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LABOR MARKET EFFECTS OF TECHNOLOGY SHOCKS BIASED TOWARD THE TRADED SECTOR*

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Abstract

Motivated by recent evidence pointing at an increasing contribution of asymmetric shocks across sectors to economic fluctuations, we explore the labor market effects of technology shocks biased toward the traded sector. Our VAR evidence for seventeen OECD countries reveals that the non-traded sector alone drives the increase in total hours worked following a technology shock that increases permanently traded relative to non-traded TFP. The shock generates a reallocation of labor toward the non-traded sector which contributes to 35% on average of the rise in non-traded hours worked. Both labor reallocation and variations in labor income shares are found empirically connected with factor-biased technological change. Our quantitative analysis shows that a two-sector open economy model with flexible prices can reproduce the labor market effects we document empirically once we allow for imperfect mobility of labor, gross substitutability between home- and foreign-produced traded goods, and factor-biased technological change. When calibrating the model to country-specific data, its ability to account for the cross-country reallocation and redistributive effects we estimate increases once we let factor-biased technological change vary between sectors and across countries.

Keywords: Sector-biased technology shocks; Factor-augmenting efficiency; Open economy; Labor reallocation; CES production function; Labor income share.
JEL Classification: E25; E32; F11; F41; 033;

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1 Introduction

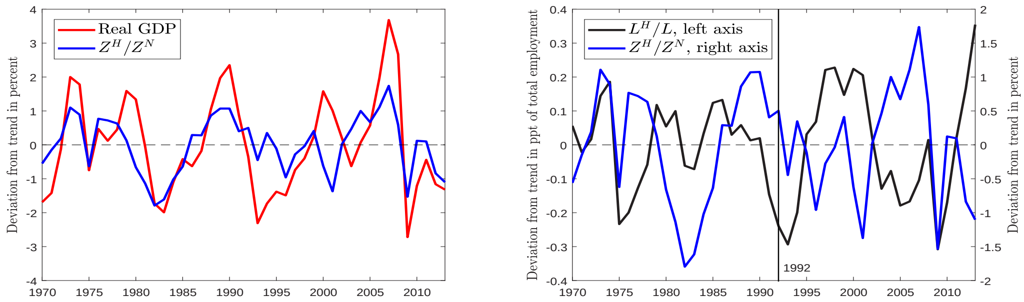
The pioneering work of Galí [1999] has sparked a broad literature investigating the labor market effects of technology shocks.[1] This literature commonly identifies technology shocks as shocks that increase permanently aggregate productivity. Because variations in aggregate total factor productivity (TFP thereafter) can be driven by movements that are both common across sectors and sector-specific, shocks to aggregate TFP can be broken down into symmetric and asymmetric technology shocks across sectors. As documented empirically by Foerster et al. [2011], Garìn et al. [2018] on U.S. data, the contribution of asymmetric shocks has increased dramatically during the great moderation relative to the period before 1984. Despite the growing importance of asymmetric shocks across sectors for economic fluctuations, a systematic exploration of the effects of sector-biased technology shocks in open economy is still lacking.

Since exporting firms have more scope for productivity improvements than non-exporting firms, a natural way to allow for asymmetric technology shifts is to make the distinction between a traded vs. a non-traded sector, see e.g., Benigno et al. [2020] who review the evidence supporting the assumption that the traded sector is the engine of productivity growth. By investigating the labor market effects of a technology shock that increases permanently traded relative to non-traded TFP, the purpose of this paper is to address two questions: Is the change in total hours worked uniformly distributed across sectors and if not which sector benefits from labor reallocation? Does the magnitude of labor reallocation vary across OECD countries and which factors are responsible for these international differences?

Answering these questions is important since economic expansions come along with an acceleration in technological change concentrated in traded industries while a fall in the relative productivity of tradables accompanies recessions. As is evident in Fig. 1(a), the cyclical component of real GDP (displayed by the red line) co-moves with the detrended (logged) ratio of traded to non-traded TFP (displayed by the blue line) for the seventeen OECD countries of our sample. Because asymmetric variations in sectoral TFPs provide incentives for labor reallocation, the traded goods-sector share of total hours worked and the relative productivity of tradables should be negatively correlated as a result of the gross complementarity between traded and non-traded goods. Such a negative correlation should materialize only during the great moderation because the contribution of asymmetric shocks is substantial during this period.[2] Since three-fourth of our sample consists of European

[1] While Galí [1999] uses labor productivity, like Chang and Hong [2006], we measure technological change with TFP. We provide a short survey of the literature in the Online Appendix B.

[2] Labor reallocation is driven by asymmetric shocks across sectors which are not necessarily technological. If the contribution of asymmetric technology shocks to economic fluctuations is negligible, cyclical components of the labor share and the relative productivity of tradables will be uncorrelated or won't display the negative conditional correlation we estimate following asymmetric technology shocks.



(a) Real GDP and Relative productivity

(b) Labor Share of Tradables and Relative Productivity

Figure 1: Relative Productivity of Tradables, Real GDP and Labor Reallocation. Notes: TFP of tradables, Z_t^H, and TFP of non-tradables, Z_t^N, are the Solow residuals. The labor share of tradables is calculated as the ratio of hours worked in the traded sector to total hours worked. Detrended relative productivity and real GDP are calculated as the difference between the logarithm of actual series and the trend of logged time series. The trend is obtained by applying a Hodrick-Prescott filter with a smoothing parameter of $\lambda = 100$ (as we use annual data) to the (logged) time series. Detrended labor share of tradables is computed as the difference between actual time series for L_t^H/L_t and the trend of the labor share of tradables, the latter being obtained by applying a Hodrick-Prescott filter with a smoothing parameter of $\lambda = 100$. Sample: 17 OECD countries, 1970-2013, annual data.

countries for which the great moderation occurs in the post-1992 period, we choose 1992 as the cutoff year for the whole sample.[3] In Fig. 1(b), we plot the detrended (logged) ratio of traded to non-traded TFP (displayed by the blue line) and the detrended labor share of tradables (displayed by the black line). The time series appear to be uncorrelated until 1992 while they move in opposite direction after 1992. More specifically, the correlation between the relative productivity and the labor share of tradables is essentially zero over 1970-1992 and is negative (i.e., at -0.35) in the post-1992 period. Evidence on U.S. data further corroborates the growing importance of asymmetric shifts in sectoral TFPs during the great moderation as the correlation between the labor share and relative productivity of tradables is zero before 1984 and stands at -0.67 from 1984 to 2013.[4]

By adapting the identification scheme of technology shocks proposed by Galí [1999], we document a set of VAR evidence which confirms the empirical facts we describe above. Our estimates reveal that the contribution of identified asymmetric technology shocks across sectors to the forecast error variance of aggregate TFP growth has increased dramatically over time and stands at about 40% in the post-1992 period while asymmetric technology shocks play a negligible role before 1992. When we estimate the effects of technology shocks biased toward the traded sector, we find that real GDP growth originates from the traded sector while the non-traded sector alone drives total hours worked growth. Our results also show that productive resources, especially labor, shift toward non-traded industries. Labor reallocation contributes to 43% of the rise in non-traded hours worked on impact and 35% on average (over ten years). To rationalize the shift of labor toward the non-traded sector that we document empirically, we put forward a two-sector semi-small open economy model with flexible prices. Likewise Kehoe and Ruhl [2009], we assume that the

[3]See e.g., Benati [2008] for the U.K. and González Cabanillas and Ruscher [2008] for the euro area.

[4]In the Online Appendix A, we show additional evidence for four OECD countries, including the U.S., as well as for the whole sample when time series are calculated as the working age population weighted sum of the seventeen OECD countries.

economy is small in world capital markets so that the world interest rate is given, but large enough in the world goods market to influence the relative price of its export good. We find quantitatively that the model can account for the magnitude of the decline in the traded goods-sector share in total hours worked once it contains a combination of three elements: high substitutability between home- and foreign-produced traded goods, imperfect mobility of labor and factor-biased technological change (FBTC henceforth).

These three specific features are necessary to mitigate the labor reallocation movement caused by the combined effect of financial openness and a low value for the elasticity between traded and non-traded consumption goods. Intuitively, the biasedness of the technology shock toward tradables generates an excess supply for traded goods and an excess demand for non-traded goods. By producing a disproportionate appreciation in the relative price of non-tradables, the gross complementarity between traded and non-traded goods increases the share of non-tradables in total expenditure which provides incentives for shifting labor toward the non-traded sector. Our quantitative analysis reveals that the model considerably overstates the reallocation of labor across sectors however and thus the decline in the labor share of tradables. The reason is that we consider an open economy setup where the access to foreign borrowing significantly biases labor demand toward the non-traded sector.

To mitigate labor reallocation, we first allow for endogenous terms of trade. As a result of an elasticity of substitution between home- and foreign-produced traded goods larger than one, as our evidence suggests, the decline in the relative price of home-produced traded goods caused by the excess supply for traded goods has a positive impact on hiring by traded firms, thus curbing the decline in the labor share of tradables. The second key element is imperfect mobility of labor. In line with our evidence indicating that the labor reallocation process is associated with mobility costs, we allow for limited substitutability in hours worked across sectors which further hampers labor reallocation. Even with the two aforementioned ingredients, the model still overstates the shift of labor toward the non-traded sector and does not replicate well the responses of sectoral hours worked.

The third and pivotal element is FBTC which is recovered from our estimation of redistributive effects. More specifically, our evidence reveals that the labor income share (LIS henceforth) increases in both sectors which implies that technological change is not Hicks-neutral but rather biased toward labor. Intuitively, when technological change is Hicks-neutral, the LIS is a function of the capital-labor ratio only. The gross complementarity between capital and labor in production found in the data (see e.g., Klump et al. [2007], Herrendorf et al. [2015], Oberfield and Raval [2014], Chirinko and Mallick [2017]) and corroborated by our own estimates implies that the LIS and the capital-labor ratio move in the same direction. Because a technology shock biased toward the traded sector drives capital out of the traded sector while labor is subject to mobility costs, the capital-labor ratio falls dramatically, thus driving down the traded LIS under the assumption of Hicks-neutral technological change. Since the non-traded capital-labor ratio is unresponsive to the shock, this assumption also implies that the non-traded LIS should remain unchanged, in contradiction with our evidence. To account for the rise in LISs that we estimate empirically, we assume that capital relative to labor efficiency increases which in turn biases technological change toward labor within each sector.[5] While the model can account for the redistributive effects once we allow for FBTC, the differential in FBTC between sectors increases the performance of the model with imperfect mobility of labor and endogenous terms of trade in reproducing the labor reallocation effects we document empirically.

To assess quantitatively the contribution of each element of our model to the sectoral effects we compute numerically, we consider a simplified version of our setup which collapses to the small open model with tradables and non-tradables developed by Fernández de Córdoba and Kehoe [2000] with no labor mobility costs, and add one ingredient at a time. While the restricted version of the model generates a decline in the labor share of tradables which is almost six times larger to what we estimate empirically on impact, adding labor mobility costs halves the reallocation of labor toward the non-traded sector. When we allow for imperfect mobility of labor and endogenous terms of trade, the model performance improves but the fall in the traded goods-sector share of total hours worked is still 50% larger to what is estimated. Once we allow for technological change biased toward labor varying across sectors, the fall in the labor share of tradables is further mitigated and matches the evidence because technological change is more biased toward labor in the traded than in the non-traded sector which leads traded firms to hire more workers, thus hampering the shift of labor toward the non-traded sector.

We further investigate about the role in FBTC in driving international differences in labor market outcomes by taking advantage of the panel data dimension of our sample. When estimating the redistributive effects at a country level, we find that LISs may fall or rise by a magnitude which varies considerably between OECD countries. In the lines of Caselli [2016], we construct time series for sectoral FBTC and detect empirically a strong and positive cross-country relationship between the responses of LISs and FBTC. While the responses of LISs vary between countries as a result of cross-country differences in FBTC, international differences in the labor reallocation effects we estimate empirically are driven by cross-sector differences in FBTC which vary significantly across OECD economies. More specifically, we find that the labor share of tradable falls less in countries where technological change is more biased toward labor in the traded than in the non-traded sector. Once calibrated to country-specific data, numerical results show that the model can account for international differences in the redistributive and reallocation effects we

[5] Technically, we adapt the methodology by Caselli and Coleman [2006] and make inference about FBTC from the demand for factors of production and a technology frontier which maps sectoral TFP shocks we estimate empirically into factor-augmenting technological shifts.

document empirically once we let FBTC vary between sectors and across countries.

The remainder of the paper is organized as follows. In section 2, we investigate empirically the labor market effects of a technology shock biased toward the traded sector. In section 3, we develop a two-sector open economy model with flexible prices and FBTC. In section 4, we report the results of our numerical simulations and assess the ability of the model to account for the evidence on the reallocation and redistributive effects of a technology shock which increases permanently traded relative to non-traded TFP. In section 5, we summarize our main results and we conclude with a discussion of some possible avenues for future research. The Online Appendix presents further empirical and numerical results, conducts robustness checks to address the SVAR critique, provides the steps to solve the model, and discusses analytical results from a restricted version of our setup.

Related Literature. Our paper fits into several different literature strands as we bring several distinct threads in the existing literature together. First, our setup includes several key features which have been put forward by the literature to rationalize the response of aggregate hours worked to a positive productivity shock. Like Collard and Dellas [2007], the open economy dimension of our setup greatly enhances the flexible price model's ability to account for the labor market effects of technology shocks through the terms of trade deterioration. In contrast to Collard and Dellas who generate a decline in total hours worked by assuming that home- and foreign-produced traded goods are gross complements, the ability of our model to account for the dynamics of sectoral hours worked increases when home- and foreign-produced traded goods are gross substitutes. Like Cantore et al. [2014], we put forward FBTC to account for the responses of hours worked to a technology shock. The authors show that technology shocks biased toward capital allow the RBC model to generate a negative response of hours worked while we find that sectoral technological shifts are biased toward labor (for the whole sample and the U.S. as well). The reason for this discrepancy lies in the fact that aggregate technology shocks are a combination of symmetric and asymmetric technology shocks, the former shock being biased toward capital and the latter biased toward labor.

The contribution of asymmetric technology shocks across sectors to economic fluctuations has received attention only very recently. Using U.S. data over 1961-2008 and distinguishing between a consumption and an investment sector, Chen and Wemy [2015] find that technology shocks biased toward the capital-producing sector explain more than 50% of TFP fluctuations. In the same vein, our evidence reveals that the contribution of technology shocks biased toward the traded sector to TFP fluctuations stands at 40% in OECD countries over 1993-2013. Drawing on the pioneering work by Long and Plosser [1983] and revitalized later by Horvath [2000], Holly and Petrella [2012] quantify the contribution of industry specific shocks to aggregate hours worked by considering input-output linkages.

Differently, we explore the sectoral composition effects driven by a shock to TFP taking place at uneven rates across sectors and uncover the key role of heterogenous substitutability across sectoral goods and FBTC in the same spirit as the structural change literature, see e.g., Ngai and Pissarides [2007] and Alvarez-Cuadrado et al. [2018], respectively. Our study differs from the structural change literature because the VAR methodology allows us to quantify empirically the extent of the reallocation of economic activity conditional on a technology shock biased toward the traded sector. Therefore, we are exclusively interested in characterizing the behavior of the economy moving from one initial steady-state to a new steady-state following a permanent increase in traded relative to non-traded TFP rather than studying the convergence of the open economy toward a balanced growth path.

Our work also complements the literature which analyzes sectoral reallocation in open economy within a RBC model, e.g., Fernández de Córdoba and Kehoe [2000], Benigno and Fornaro [2014], Arrellano et al. [2018], Fornaro [2018], Kehoe and Ruhl [2009]. The first two works show that capital inflows episodes have contributed to shifting productive resources out of the traded sector. Similarly, in our open economy setup, financial openness amplifies the incentives to shift labor toward the non-traded sector. In contrast to Arrellano et al. [2018] and Fornaro [2018] who consider a default risk and a deleveraging shock, respectively, to rationalize the shift of labor toward the traded sector during the sovereign debt crisis in Europe after 2008, this movement of labor is the result of the dramatic decline in the TFP in tradables relative to non-tradables in our setup. Whilst we emphasize the key role of the terms of trade in shaping the labor movement across sectors like Kehoe and Ruhl [2009], none of the aforementioned articles allow for FBTC.

2 Technology Shocks Biased toward Tradables: VAR Evidence

To guide our quantitative analysis, we document evidence on the labor market effects driven by a technology shock biased toward the traded sector by estimating a structural VAR model in panel format on annual data. We first present the data and detail our identification strategy, and then we discuss empirical results. We denote below the percentage deviation from initial steady-state (or the rate of change) with a hat.

2.1 Data Construction

Before presenting our empirical strategy and VAR evidence, we briefly discuss the dataset we use. Our sample contains annual observations over the period 1970-2013 and consists of a panel of 17 OECD countries. Online Appendix K provides the list of countries. We use the EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases which provide domestic currency series of value added in current and constant prices, labor compensation and hours worked at an industry level. All quantities are scaled by the working age population. We use the subscripts i and t to index countries and time periods (years), respectively, and we use the superscript j to index sectors below.

Since our primary objective is to investigate the sectoral composition effects, we describe below how we construct time series at a sectoral level. We make the distinction between a traded (indexed by the superscript H) vs. non-traded sector (indexed by the superscript N). Our sample covers eleven 1-digit ISIC-rev.3 industries which are split into traded and non-traded sectors by adopting the classification by De Gregorio et al. [1994]. Agriculture, hunting, forestry and fishing; Mining and quarrying; Total manufacturing; Transport, storage and communication are classified as traded industries. Following Jensen and Kletzer [2006], we updated the classification by De Gregorio et al. [1994] by treating Financial intermediation as a traded industry. Electricity, gas and water supply; Construction; Wholesale and retail trade; Hotels and restaurants; Real estate, renting and business services; Community, social and personal services are classified as non-traded industries.[6]

Once industries have been classified as traded or non-traded, series for sectoral value added in current (constant) prices are constructed by adding value added in current (constant) prices for all sub-industries k in sector $j = H, N$, i.e., $P^j_{it}Y^j_{it} = \sum_k P^j_{k,it}Y^j_{k,it}$ ($\bar{P}^j_{it}Y^j_{it} = \sum_k \bar{P}^j_{k,it}Y^j_{k,it}$ where the bar indicates that prices P^j are those of the base year), from which we construct price indices (or sectoral value added deflators), P^j_{it}. Normalizing base year price indices $\bar{P}^j$ to 1, the relative price of non-tradables, P_{it}, is defined as the ratio of the non-traded value added deflator to the traded value added deflator (i.e., $P_{it} = P^N_{it}/\mathsf{P}^H_{it}$). The relative price of home-produced traded goods (or the terms of trade, denoted by P^H_{it}) is constructed as the ratio of the traded value added deflator (P^H_{it}) to the price deflator of imported goods and services (P^F_{it}). The same logic applies to constructing series for hours worked ($L^j = \sum_k L^j_{k,it}$) and labor compensation in the traded and the non-traded sectors which allow us to construct sectoral wages, W^j_{it}. The real consumption wage in sector j, $W^j_{C,it}$, is defined as the sectoral nominal wage, W^j_{it}, divided by the consumption price index, $P_{C,it}$. To construct time series for the aggregate nominal wage, W_{it}, we divide aggregate labor compensation by total hours worked. We also construct hours worked and valued added shares of sector j (at constant prices), denoted by $\nu^{L,j}_{it}$ and $\nu^{Y,j}_{it}$, see Online Appendix D.[7] To estimate the redistributive effects, we calculate the LIS for each sector

[6] Because "Financial Intermediation" and "Real Estate, Renting and Business Services" are made up of sub-sectors which display a high heterogeneity in terms of tradability and "Hotels and Restaurants" has experienced a large increase in tradability over the last fifty years, we perform a sensitivity analysis with respect to the classification for the three aforementioned sectors in Online Appendix N.3. Treating "Financial Intermediation" as non-tradables or classifying "Hotels and Restaurants" or "Real Estate, Renting and Business Services" as tradables does not affect our main results.

[7] We consider an open economy which produces a traded and a non-traded good while the foreign good is the numeraire and its price is normalized to 1. Real GDP, $Y_{R,t}$, is equal to the sum of traded and non-traded value added at constant prices, i.e., $Y_{R,t} = P^H Y^H_t + P^N Y^N_t$ where prices at the initial steady-state are those at the base year so that real GDP collapses to nominal GDP, Y, initially; henceforth, the value added share at current prices also collapses to the value added share at constant prices initially.

j, denoted by $s^j_{L,it}$, as the ratio of labor compensation to valued added at current prices in sector j.

Like Chang and Hong [2006], we use sectoral TFPs, Z^j, to approximate technical change. Sectoral TFPs are constructed as Solow residuals from constant-price (domestic currency) series of value added, Y^j_{it}, capital stock, K^j_{it}, and hours worked, L^j_{it}:

$$\hat{Z}^j_{it} = \hat{Y}^j_{it} - s^j_{L,i}\hat{L}^j_{it} - \left(1 - s^j_{L,i}\right)\hat{K}^j_{it}, \tag{1}$$

where $s^j_{L,i}$ is the LIS in sector j averaged over the period 1970-2013. To obtain series for sectoral capital stock, we first compute the overall capital stock by adopting the perpetual inventory approach, using constant-price investment series taken from the OECD's Annual National Accounts. Following Garofalo and Yamarik [2002], we split the gross capital stock into traded and non-traded industries by using sectoral valued added shares. While in the main text, we measure technology change with the Solow residual, we alternatively constructed time series for utilization-adjusted-sectoral-TFPs, as recommended by Basu et al. [2006], by adapting the methodology proposed by Imbs [1999]. As shown in Online Appendix T.5, our results are little sensitive to the correction of sectoral TFPs with the (sectoral) capital utilization rate.

2.2 VAR Identification of Asymmetric Technology Shocks

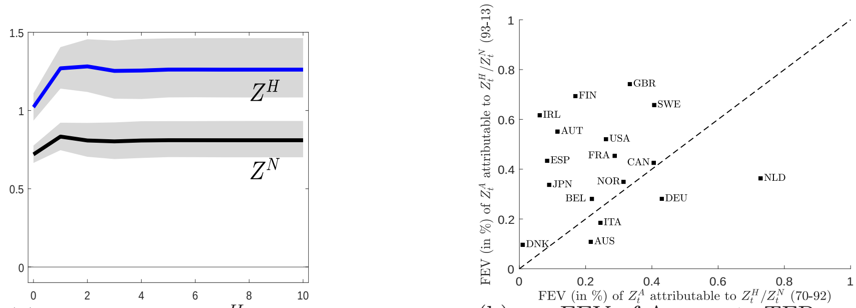
In this subsection, we present our identification strategy of asymmetric technology shocks and document some evidence pointing at their increasing importance over time. Like Galí [1999], permanent productivity shocks are identified by assuming that technology shocks are the only source of movements in long-run productivity. Because we adapt the SVAR approach by Galí [1999] to the identification of asymmetric technology shocks, we first answer to two questions below: Are shocks to aggregate TFP evenly distributed across sectors? If not, what is the contribution of asymmetric technology shocks across sectors to the variance of aggregate TFP growth? Beyond the fact that answering these questions will allow us to gain further insight about the mapping between aggregate and asymmetric technology shocks, it will pave the way for our identification strategy.

Sector distribution of shocks to aggregate TFP. We first write down the sectoral decomposition of the percentage deviation of aggregate TFP relative to its initial steady-state, denoted by $\hat{Z}^A_{it}$ (see Online Appendix C):

$$\hat{Z}^A_{it} = \nu^{Y,H}_i \hat{Z}^H_{it} + \left(1 - \nu^{Y,H}_i\right)\hat{Z}^N_{it}, \tag{2}$$

where $\hat{Z}^H_{it}$ and $\hat{Z}^N_{it}$ are the percentage deviation of TFP relative to initial steady-state in the traded and the non-traded sector, respectively, and $\nu^{Y,j}_i$ is the share of value added of sector $j = H, N$ in GDP.

According to eq. (2), variations in aggregate TFP, $\hat{Z}^A_{it}$, can be associated with shifts in sectoral TFPs which are common across sectors (i.e., $\hat{Z}^H_{it} = \hat{Z}^N_{it}$ in the long-run) or



(a) Responses of Z_t^H and Z_t^N to Aggregate Technology Shock

(b) FEV of Aggregate TFP Growth Attributable to the Shock to Z_t^H/Z_t^N

Figure 2: Symmetric and Asymmetric Technology Shocks across Sectors. Notes: In Fig. 2(a), we plot the responses of traded TFP, Z_t^H (shown in the blue line), and non-traded TFP, Z_t^N (shown in the black line), to identified shock to aggregate TFP, Z_t^A. Shaded area indicates the 90 percent confidence bounds obtained by bootstrap sampling. Fig. 2(b) plots the FEV of aggregate TFP growth attributable to shocks to the ratio of sectoral TFPs over 1970-1992 against the FEV of $\hat{Z}_t^A$ attributable to shocks to Z_t^H/Z_t^N over 1993-2013. We compute the FEVD by estimating a VAR model $[\hat{Z}_t^H - \hat{Z}_t^N, \hat{Z}_t^A, \hat{L}_t]$ for one country at a time. To identify symmetric vs. asymmetric technology shocks, we impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_t^A while only asymmetric technology shocks increase permanently Z_t^H/Z_t^N in the long-run. Sample: 17 OECD countries, 1970-2013, annual data.

take place at uneven rates across sectors (i.e., $\hat{Z}_{it}^H \neq \hat{Z}_{it}^N$ in the long-run). To investigate whether a shock to aggregate TFP is evenly or unevenly distributed across sectors, we first identify a shock to aggregate TFP, denoted by ε_{it}^{ZA}, by estimating a VAR model with two lags in panel format on annual data that includes aggregate TFP and total hours worked, both in growth rate, i.e., $[\hat{Z}_{it}^A, \hat{L}_{it}]$. To identify aggregate technology shocks, we impose restrictions on the long-run cumulative matrix such that only aggregate technology shocks increase permanently Z_{it}^A. In the second step, we consider a VAR model which includes identified technology shocks, ε_{it}^{ZA}, ordered first, the rate of growth of traded, non-traded and aggregate TFP, and adopt a Cholesky decomposition. Next, we plot in Fig. 2(a) the responses for Z_{it}^H shown in the blue line and Z_{it}^N shown in the black line following a 1% permanent increase in Z_{it}^A in the long-run. Estimates show that aggregate technology shocks are not evenly distributed since traded TFP increases significantly more than non-traded TFP.

Above VAR evidence can be mapped into the sectoral decomposition of aggregate TFP by rearranging eq. (2) as follows:

$$\hat{Z}_{it}^A = \hat{Z}_{it}^N + \nu_i^{Y,H}\left(\hat{Z}_{it}^H - \hat{Z}_{it}^N\right). \tag{3}$$

According to our estimates shown in Fig. 2(a), an aggregate technology shock which raises Z_{it}^A by 1% in the long-run gives rise to an increase in Z_{it}^N by 0.8% augmented by a productivity differential between tradables and non-tradables of 0.4% (weighted by $\nu_i^{Y,H}$). The RHS of eq. (3) paves the way for the identification of symmetric and asymmetric technology shocks across sectors. When the shock is asymmetric, both the ratio Z_{it}^H/Z_{it}^N and Z_{it}^A are permanently increased while Z_{it}^H and Z_{it}^N rise by the same amount when the shock is symmetric so that the last term of eq. (3) vanishes.

Contribution of asymmetric technology shocks to FEV of aggregate TFP

growth. To identify symmetric vs. asymmetric technology shocks, we consider the same VAR model as above augmented with the ratio of traded to non-traded TFP, Z_{it}^H/Z_{it}^N (in growth rate), i.e., $[\hat{Z}_{it}^H - \hat{Z}_{it}^N, \hat{Z}_{it}^A, \hat{L}_{it}]$. We impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_{it}^A while only asymmetric technology shocks increase permanently Z_{it}^H/Z_{it}^N in the long-run. Once we have identified symmetric and asymmetric technology shocks across sectors, we can gauge their contribution to aggregate TFP growth by computing a forecast error variance decomposition (FEVD). To explore whether the contribution of shocks to Z^H/Z^N has changed over time, we estimate the VAR model over two sub-periods, i.e., 1970-1992 and 1993-2013, respectively. Estimates reveal that the share of the FEV of aggregate TFP growth attributable to the shock to the ratio of sectoral TFPs, Z_{it}^H/Z_{it}^N, is negligible over 1970-1992 and stands at about 40% over 1993-2013. Empirical results are shown in Table 2 relegated to Online Appendix F. In Fig. 2(b) we re-estimate the same VAR model but for one country at a time by imposing long-run restrictions detailed above and plot the FEV of $\hat{Z}_t^A$ attributable to the shock to Z_t^H/Z_t^N over 1970-1992 (horizontal axis) against the FEV of $\hat{Z}_t^A$ attributable to the asymmetric shock over 1993-2013 (vertical axis). Except for four countries (Australia, Germany, Italy, the Netherlands), all OECD countries are above the bisecting line and thus experience a rise in the contribution of asymmetric technology shocks across sectors to the FEV of aggregate TFP growth over time (i.e., in the post-1992 period).

Construction of sector TFP differential index. As in Gali [1999], we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of TFP. Differently, we focus on the effects of technology shocks biased toward the traded sector and thus identify technology shocks that increase permanently the ratio of traded to non-traded TFP. The empirical strategy is detailed in Appendix B. In line with the Balassa-Samuelson literature, we construct a weighted productivity differential index between tradables and non-tradables by augmenting sectoral TFPs with weights in order to get an economic meaningful normalization (see Online Appendix E):

$$\hat{Z}_{it} = a_i \hat{Z}_{it}^H - b_i \hat{Z}_{it}^N, \tag{4}$$

where $a = \left[(1-\alpha_J) + \alpha_J \frac{s_L^H}{s_L^N}\right]^{-1}$, and $b = a\frac{s_L^H}{s_L^N}$ are country-specific and time-invariant weights which are functions of the labor income share (LIS henceforth) in sector j, s_L^j, and the tradable share in total investment expenditure, α_J, both averaged over 1970-2013. Adding weights a and b 're-scales' sectoral TFP growth so that when the weighted productivity differential increases by 1%, the relative price of non-tradables also appreciates by 1% when terms of trade are exogenous and inputs' mobility costs are absent. Intuitively, higher TFP gains in the traded sector put upward pressure on wages. To compensate for lower productivity gains, non-traded firms increase prices, and all the more so as the production is more intensive in labor, thus explaining why the weighted productivity differential is increasing in s_L^N/s_L^H. In the rest of the paper, for simplicity purposes, we refer to $Z = (Z^H)^a/(Z^N)^b$ as the ratio of traded to non-traded TFP. Note that a and b are close to 1 for the whole sample.

2.3 Labor Market Effects: VAR Evidence

To estimate the sectoral composition effects of a technology shock biased toward tradables, we consider VAR models which include the ratio of traded to non-traded TFP, Z_{it}, and a vector of sectoral variables such as value added at constant prices, Y_{it}^j, hours worked, L_{it}^j, and the real consumption wage, $W_{C,it}^j$ in sector j or alternatively the value added share, $\nu_{it}^{Y,j}$, the labor share, $\nu_{it}^{L,j}$, and the relative wage, W_{it}^j/W_{it}, in sector j. We also consider a VAR model which includes relative prices to inspect the transmission mechanism. All variables enter the VAR model in rate of growth. We estimate the reduced form of VAR models by panel OLS regression with country and time fixed effects. VAR specifications are detailed in Online Appendix G. While we focus on labor market effects, we also estimate the effects on value added to guide our quantitative analysis as their adjustment allows us to discriminate between models.[8]

We generated impulse response functions which summarize the responses of variables to a 1% permanent increase in traded relative to non-traded TFP (see eq. (4)). Fig. 3 displays the estimated effects of a technology shock. The horizontal axis measures time after the shock in years and the vertical axis measures percentage deviations from trend. In each case, the solid line represents the point estimate, while the shaded area indicates 90% confidence bounds obtained by bootstrap sampling. In Online Appendix F, Table 3 shows point estimates on impact (i.e., at $t = 0$), and in the long-run (i.e., at a 10-year horizon).

Adjustment of sectoral TFPs. As displayed by the solid blue line in Fig. 3(a), the relative productivity of tradables rises by 0.9% on impact and increases gradually to reach 1% after 10 years. While TFP of tradables increases by 0.72%, its rise is not large enough to raise Z by 0.9% on impact and thus TFP of non-tradables must decline by 0.17%. Fig. 3(e) shows that traded TFP grows over time while Z^N remains fairly constant. See Online Appendix L.3 for further details about how we determine empirically the responses of sectoral TFPs.

Sectoral composition effects. The second and third column of Fig. 3 show the output and labor distributional effects of a 1% permanent increase in TFP in tradables relative to

[8]Because we consider alternative VAR models, one might be concerned by the fact that identified technology shocks display substantial differences across VAR specifications. To address this issue, we ran a robustness check by augmenting each VAR model with the same identified technology shock, ordered first. In the quantitative analysis, we take the VAR model which includes the relative productivity of tradables, Z_{it}, real GDP, $Y_{R,it}$, total hours worked, L_{it}, the real consumption wage, $W_{C,it}$, i.e., $x_{it}^A = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$, as our benchmark model to calibrate the technology shock. Augmenting each VAR model with the technology shock identified for this benchmark specification, we find that the responses lie within the confidence bounds and thus differences are not statistically significant. Results can be found in Online Appendix N.6.

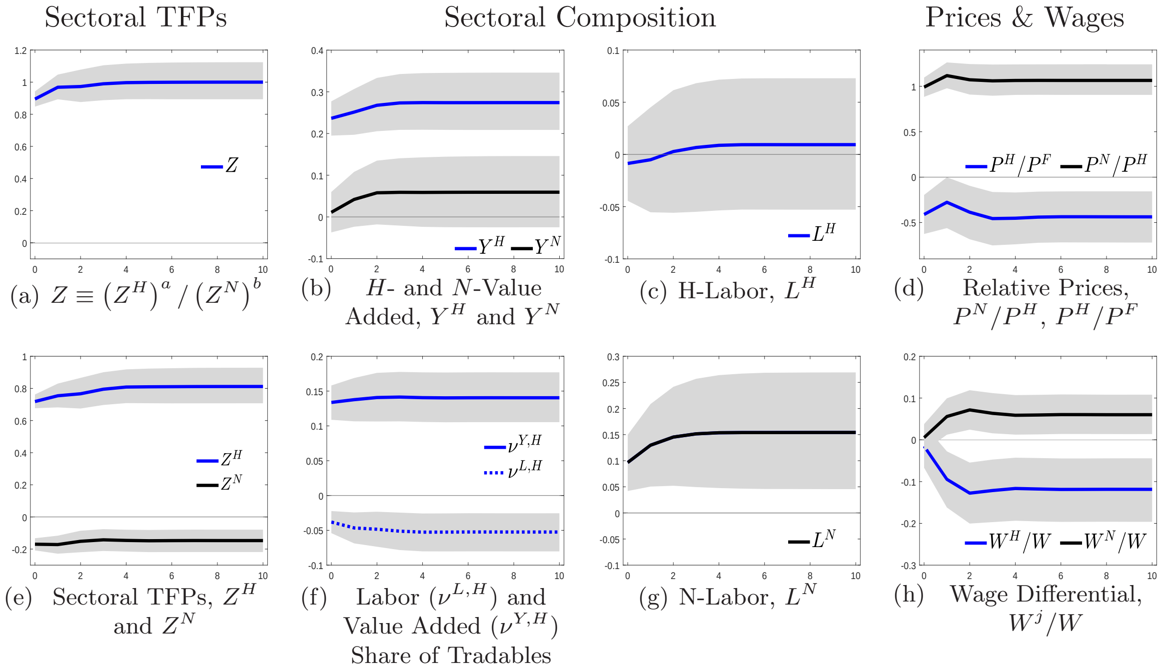
non-tradables. The asymmetric technology shock gives rise to an increase in traded value added by 0.24% of GDP on impact whilst non-traded value added is virtually unchanged. As shown in Fig. 3(b), Y^H grows over time while the response of Y^N is not statistically significant, thus indicating that real GDP growth originates from traded industries. The solid blue line of Fig. 3(f) shows that higher relative productivity of tradables has an expansionary effect on the value added share of tradables (i.e., $\nu^{Y,H}$) which stabilizes at 0.14% of GDP.

While higher traded productivity growth relative to average increases the value added share of tradables, $\nu_{it}^{Y,H}$, the reallocation of productive resources lowers it. As can be seen in the dashed blue line in Fig. 3(f), the labor share of tradables, $\nu^{L,H}$, declines by about 0.04% of total hours worked on impact. The shift of labor toward the non-traded sector contributes to 43% of the rise in L^N on impact which stands at 0.1% of total hours worked. Labor keeps on shifting toward the non-traded sector over time while the contribution of labor reallocation to the rise in L^N somewhat declines at 34%. On average, 35% of the increase in L^N is attributable to labor movements between sectors.[9] Conversely, as can be seen in the third column of Fig. 3, hours worked do not respond at any horizon in the traded sector. Thus the non-traded sector alone drives the increase in total hours worked.

Incentives for labor reallocation. The evidence documented in the last column of Fig. 3 enables us to shed some light on the transmission mechanism. As displayed by the black line in Fig. 3(d), a shock to the productivity differential generates an excess demand for non-traded goods which appreciates the relative price of non-tradables by 0.99%. Because the magnitude of the appreciation in P^N/P^H is larger than the productivity differential we estimate on impact (i.e., 0.90%), the share of non-tradables at current prices increases which has an expansionary effect on hiring in the non-traded sector.

Factors hampering labor reallocation. Our VAR evidence in Fig. 3 are in line with the class of neoclassical models such as Ngai and Pissarides's [2007] where the sector having greater productivity gains experiences a rise in its value added share whilst the sector where productivity growth is smaller, increases its labor share. Loosely speaking, the low substitutability between traded and non-traded goods allows non-traded firms to set higher prices which more than offsets their productivity disadvantage and attracts productive resources. However, the reallocation of productive resources, especially labor, is hampered in an open economy where domestic and foreign goods are highly substitutable and workers experience costs of switching sectors.

[9] To ensure that $d\nu_{it}^{L,H} + d\nu_{it}^{L,N} = 0$ and compute the contribution of labor reallocation consistently, we reconstructed responses in sectoral labor shares at all horizons by plugging estimated responses of $\hat{L}_{it}^j$ and $\hat{L}_{it} = \alpha_{L,i}\hat{L}_{it}^H + (1-\alpha_{L,i})\hat{L}_{it}^N$ into $d\nu_{it}^{L,j} = \alpha_{L,i}^j\left(\hat{L}_{it}^j - \hat{L}_{it}\right)$ where $\alpha_{L,i}$ is the labor compensation share of tradables averaged over 1970-2013 in country i, see Online Appendix G for further details. Differences between reconstructed and estimated responses of $d\nu_{it}^{L,N}$ remain very small. Dividing $d\nu_{it}^{L,j}$ by $\alpha_{L,i}^j\hat{L}_{it}^j$ gives the contribution of labor reallocation to the rise in hours worked in sector j.



(a) $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$ (b) H- and N-Value Added, Y^H and Y^N (c) H-Labor, L^H (d) Relative Prices, P^N/P^H, P^H/P^F

(e) Sectoral TFPs, Z^H and Z^N (f) Labor ($\nu^{L,H}$) and Value Added ($\nu^{Y,H}$) Share of Tradables (g) N-Labor, L^N (h) Wage Differential, W^j/W

Figure 3: Sectoral Effects of a Permanent Increase in Traded Relative to Non-Traded TFP.
Notes: Exogenous 1% increase of TFP in tradables relative to non-tradables (as measured by eq. 4). Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added, sectoral value added share), percentage deviation from trend in total hours worked units (sectoral hours worked, sectoral hours worked share), percentage deviation from trend (sectoral TFPs, relative price of non-tradables, terms of trade, relative wage). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for tradables while the black line shows the response for non-tradables. Sample: 17 OECD countries, 1970-2013, annual data.

As displayed by the blue line in Fig. 3(d), a 1% permanent increase in TFP of tradables relative to non-tradables leads to a significant deterioration in the terms of trade which fall by more than 0.4%. If home- and foreign-produced traded goods are gross substitutes, as evidence (see Bajzik et al. [2020]) and our own estimates (see Online Appendix L.6) suggest, then lower home-produced traded goods prices have an expansionary effect on tradable hiring, see Online Appendix D for a formal argument. Through this channel, the terms of trade deterioration hampers the outflow of workers experienced by the traded sector. Fig. 3(h) reveals that the shift of labor toward the non-traded sector is further mitigated by the presence of labor mobility costs. Such mobility costs give rise to a positive wage differential for non-tradables by 0.06% in the long-run (see panel E of Table 3), as displayed by the black line, and a fall in the relative wage of tradables by 0.12%, as shown in the blue line.

Capital reallocation and redistributive effects. We now analyze the implications for capital reallocation and sectoral LISs of a permanent increase in the relative productivity of tradables to determine whether sectoral TFP shifts are Hicks-neutral or rather factor-biased. We compute the LIS like Gollin [2002], i.e., labor compensation is defined as the sum of compensation of employees plus compensation of self-employed. We find that our results are robust to alternative constructions of the LIS, see Online Appendix N.5. To explore empirically the redistributive effects, we consider a VAR specification which includes the sector TFP differential index, Z_{it}, the LIS, s_L^j, and the capital-labor ratio in sector j,

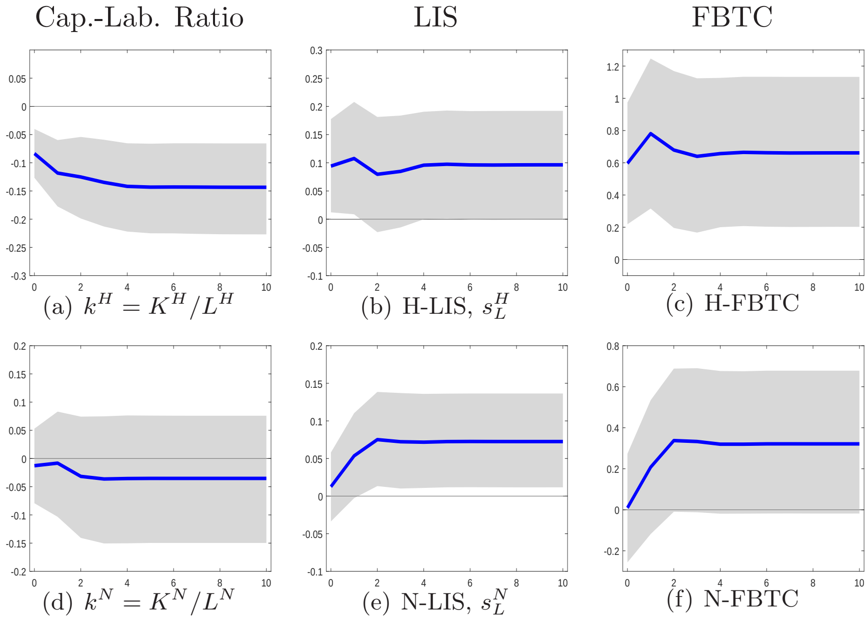


Figure 4: Redistributive Effects of a Permanent Increase in Traded Relative to Non-Traded TFP. Notes: Exogenous increase of TFP in tradables relative to non-tradables by 1%. The first two columns show the responses of capital-labor ratios and LISs for tradables and non-tradables. Horizontal axes indicate years. Vertical axes measure deviations from trend in percentage of value added for the LIS, and percentage deviation from trend in capital stock units for the capital-labor ratio. The third column plots the response of FBTC in sector $j = H, N$ which is obtained by running a simple VAR $[\hat{Z}_{it}, \text{FBTC}^j_{it}]$ where details about the construction of time series for FBTC^j_{it} can be found in Online Appendix H. Results for baseline specification are displayed by solid lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. Sample: 17 OECD countries, 1970-2013, annual data.

$k^j \equiv K^j/L^j$, both in rate of growth.

The first and second column of Fig. 4 shows the dynamic responses of capital-labor ratios and LISs, respectively. Our VAR evidence reveals that k^H falls significantly by 0.08% of the aggregate capital stock while k^N is almost unaffected because the rise in non-traded hours worked offsets the capital inflow.[10] If production functions were Cobb-Douglas, the shift of capital would have no impact on sectoral LISs. However, as shown in the second column of Fig. 4, s_L^H increases by more than 0.09% of traded value added on impact while s_L^N increases gradually up to 0.07% of non-traded value added in the long-run. This finding suggests that sectoral goods are produced from CES production functions which is corroborated by our estimates indicating that the elasticity of substitution between capital and labor in production is smaller than one (see Online Appendix L.5).[11]

FBTC hypothesis. The positive and significant response of the LIS in the traded sector together with the fall in k^H calls into question the assumption of Hicks-neutral technological change (HNTC henceforth). The reason is that when capital and labor are

[10] Due to limited data availability, in the line of Garofalo and Yamarik [2002], we split the aggregate capital stock into tradables and non-tradables in accordance with their value added share. In Online Appendix N.7, we estimate the same VAR model by using databases which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for nine countries of our sample over the entire period 1970-2013. The Garofalo and Yamarik's [2002] methodology we adopt in this paper gives very similar results to those obtained when using disaggregated capital stock data.

[11] We are aware that the traded and non-traded sectors are made-up of several industries and variations in the LISs of aggregate sectors could be the result of changes in the value added share of sub-sectors (between-effect) rather than the rise in their LISs (within-effect). We find that on average, 2/3 (80%) of the impact response of the LIS in tradables (non-tradables) can be attributed to the within-effect, see Online Appendix N.4.

gross complements in production, as our evidence and those documented by the existing literature on the subject suggests, see e.g., Klump et al. [2007], Herrendorf et al. [2015], Oberfield and Raval [2014], Chirinko and Mallick [2017], the decline in k^H drives down s_L^H, in contradiction with our empirical findings. A natural candidate to reconcile theory with our evidence is factor-biased technological change (FBTC henceforth). When capital and labor are gross complements, an increase in capital relative to labor efficiency biases technological change toward labor which raises the LIS. To test this hypothesis, we construct time series for FBTC by drawing on Caselli and Coleman [2006] and Caselli [2016] and we estimate a simple VAR model that includes the productivity differential, $\hat{Z}_{it}$, and FBTC_{it}^j, see Online Appendix H which details the construction of FBTC_{it}^j. The third column of Fig. 4 shows the responses of FBTC following a 1% permanent increase in the relative productivity of tradables. Our estimates reveal that FBTC increases significantly in the traded sector and thus technological change is biased toward labor which is consistent with the rise in s_L^H we estimate empirically. While technological change is also biased toward labor in the non-traded sector, the rise in FBTC^N is not statistically significant. Wide confidence bounds suggest that FBTC varies across countries as corroborated by our evidence documented in the next subsection. Before investigating cross-country effects, we discuss the robustness of our empirical findings below.

SVAR critique: Robustness analysis. Because the SVAR estimation allows for a limited number of lags (2 lags on annual data), the SVAR model might face some difficulties to disentangle pure technology shocks from other shocks which have long-lasting effects on productivity when capital adjusts sluggishly. Following the SVAR critique by Faust and Leeper [1997], Erceg et al. [2005] and Chari et al. [2008], we have assessed the robustness of our inference under the long-run scheme in Online Appendix T. In the lines of Francis and Ramey [2005], in Online Appendix T.3, we have run exogeneity tests and find that identified asymmetric technology shocks are not correlated with changes in the labor or capital tax, identified government spending shocks, and variations in the labor wedge while non-technology shocks are strongly correlated with the aforementioned variables. In Online Appendix T.4, in line with the recommendation of Chari et al. [2008], we have increased the number of lags from two to eight to estimate the IRFs and find that dynamic responses remain qualitatively unchanged and quantitatively lie within the initial confidence bounds. Chaudourne et al. [2014] demonstrate that the use of 'purified' TFP to measure technological change ensures the robustness of the identification of technology shocks. In Online Appendix T.5, we identify shocks to traded relative to non-traded utilization-adjusted-TFP and find that the dynamic responses are merely affected when we correct sectoral TFPs with a measure of capital utilization. In Online Appendix T.6, we adopt the ingenious idea of Dupaigne and Fève [2009] and replace the country-level sectoral TFP with their 'world' counterpart which by construction cannot be contaminated by country-level non-technology shocks. We find that the labor share of tradables declines and the value added share of tradables increases whilst the dynamics lie within the confidence bounds of the baseline VAR model. In the lines of Francis et al. [2014], we conduct an additional robustness check where the Maximum Forecast Error Variance (Max Share) approach extracts the shock that best explains the FEV at a medium (i.e., ten years) horizon of the ratio of traded to non-traded TFP. We find that the median of responses falls within the confidence interval of the baseline VAR model where we adopt a long-run identification approach, see Online Appendix T.7. To conclude, all the robustness checks we have conducted confirm the ability of the long-run identified VAR model to reliably estimate the dynamic responses to an asymmetric technology shock across sectors.

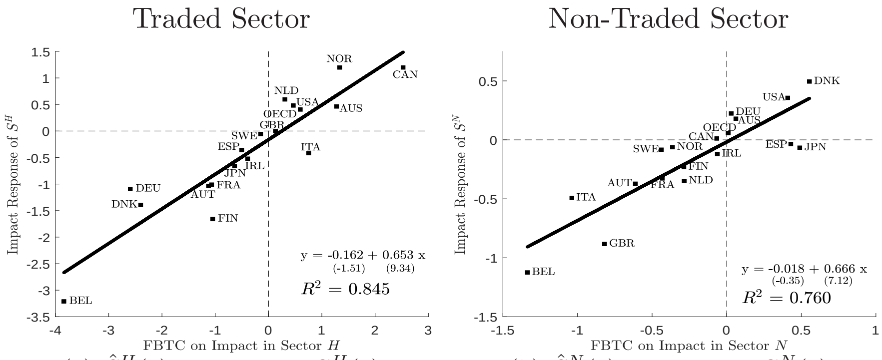
2.4 Cross-Country Differences in Reallocation and Redistributive Effects

In this subsection, we take advantage of the panel data dimension of our sample to answer two economic questions: Do redistributive (i.e., responses of sectoral LISs) and reallocation (especially labor) effects of a permanent increase in the relative productivity of tradables vary across countries? What are the determinants of these cross-country differences?

Cross-country redistributive effects and FBTC. As shown in Online Appendix H, the ratio of the demand of labor to the demand of capital implies a direct mapping between FBTC^j_{it} and the ratio of labor to capital income share denoted by $S^j_{it} = \frac{s^j_{L,it}}{1-s^j_{L,it}}$. Since $\hat{S}^j_{it} = \frac{\hat{s}^j_{L,it}}{1-s^j_{L,i}}$ and thus the percentage deviation of the ratio of labor to capital income share relative to its initial steady-state is proportional to the percentage change in the LIS, $\hat{s}^j_{L,t}$, we estimate the responses of s^j_L for one country at a time and scale its response by dividing point estimates by $1 - s^j_{L,i}$ averaged over 1970-2013. Because the responses of S^j and s^j_L differ only by a scaling factor, we refer interchangeably to the LIS or the ratio of factor income share as long as it does not cause confusion.

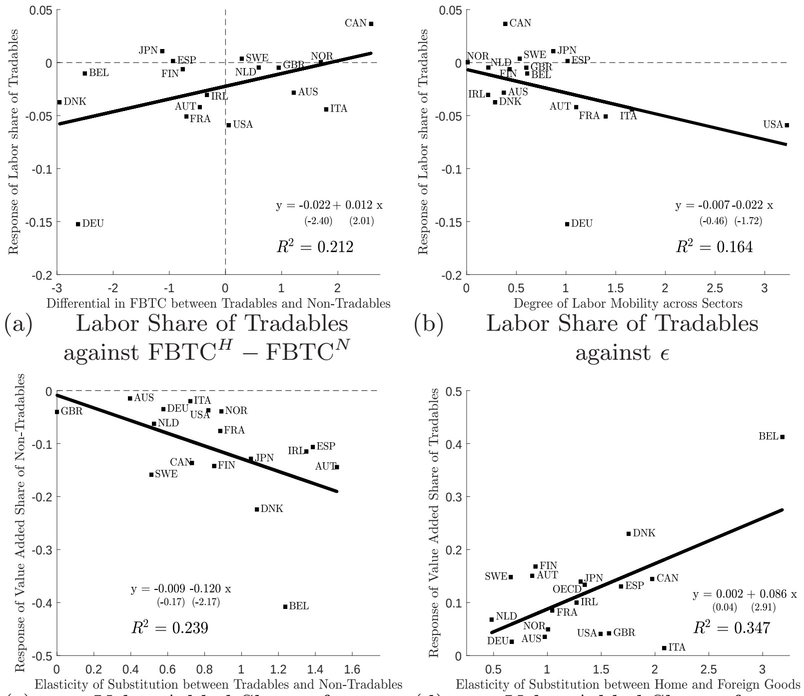
Fig. 5 plots impact responses of S^j_t on the vertical axis against estimated responses of sectoral FBTC on the horizontal axis. The first conclusion that emerges is that the responses of LISs vary greatly across countries and this dispersion is the result of international differences in FBTC since we detect a positive cross-country relationship between the responses of LISs and FBTC for both the traded and the non-traded sector. More specifically, countries which lie in the north-east experience simultaneously a rise in the LIS and technological change biased toward labor while countries which lie in the south-west experience simultaneously a fall in the LIS and technological change biased toward capital. While FBTC varies greatly across countries, the second conclusion that emerges from Fig. 5 is that FBTC varies significantly across sectors within the same country. We explore its implications for the reallocation of labor across sectors below.

Cross-country labor reallocation effects and differential in FBTC across sec-



(a) $\hat{S}^H(0)$ against $\mathrm{FBTC}^H(0)$ (b) $\hat{S}^N(0)$ against $\mathrm{FBTC}^N(0)$

Figure 5: Cross-Country Redistributive Effects of a Permanent Increase in Traded Relative to Non-Traded TFP. Notes: Exogenous increase of TFP in tradables relative to non-tradables by 1%. Fig. 5 plots impact responses of the ratio of factor income shares, $\hat{S}^j_t = \frac{\hat{s}^j_{L,t}}{1-s^j_L}$, on the vertical axis against FBTC in sector $j = H, N$ on the horizontal axis. The response of FBTC in sector $j = H, N$ is obtained by running a simple VAR $[\hat{Z}_t, \mathrm{FBTC}^j_t]$ for one country at a time. Details about the construction of time series for FBTC^j_t can be found in Online Appendix H. Sample: 17 OECD countries, 1970-2013, annual data.



(a) Labor Share of Tradables against $\mathrm{FBTC}^H - \mathrm{FBTC}^N$ (b) Labor Share of Tradables against ϵ

(c) Value Added Share of Non-Tradables against ϕ (d) Value Added Share of Tradables against ρ^A

Figure 6: Cross-Country Effects of a Permanent Increase in Traded Relative to Non-Traded TFP. Notes: Fig. 6 plots impact responses of sectoral labor and sectoral value added shares to a 1% permanent increase in the relative productivity of tradables against four key estimated parameters. Impact responses shown on the vertical axis are obtained by running a VAR model for one country at a time and are expressed in percentage point. Horizontal axis in Fig. 6(b), Fig. 6(c), Fig. 6(d) display the elasticity of labor supply across sectors, ϵ (which captures the degree of labor mobility across sectors), the elasticity of substitution between traded and non-traded goods, ϕ, the aggregate elasticity of substitution between home- and foreign-produced traded goods, ρ^A, respectively. Panel data estimates for ϵ, ϕ are taken from columns 16 and 15 of Table 6, respectively. Values for the aggregate elasticity ρ^A are calculated from the weighted sum of panel data estimations of the elasticity of substitution between home- and foreign-produced traded goods for consumption ρ and investment ρ_J, i.e., $\rho^A_i = 1 - \alpha^{C,H}_i (1-\rho_i) - \left(1-\alpha^{C,H}_i\right)(1-\rho_{J,i})$, where $\alpha^{C,H}_i$ is the share of consumption in expenditure on home-produced traded goods in country i. Values for ρ^A are taken from column 4 of Table 12. The horizontal axis in Fig. 6(a) displays the differential in FBTC between tradables and non-tradables where estimates are obtained by running the VAR model $[\hat{Z}_t, \mathrm{FBTC}^j_t]$ for one country at a time.

tors. Fig. 6(a) plots the impact response of the labor share of tradables to a 1% permanent increase in traded to non-traded TFP (on the vertical axis) we estimate for one country at a time against the differential in FBTC between tradables and non-tradables (on the horizontal axis). The difference between traded FBTC and non-traded FBTC displays a significant cross-country dispersion as it varies between -2.9% for Denmark and +2.6% for Canada. We expect the reallocation of labor toward the non-traded sector and thus the decline in the labor share of tradables to be less pronounced in countries where technological change is more biased toward labor in the traded than in the non-traded sector. Indeed, in Fig. 6(a), we detect a positive cross-country relationship indicating that the response of the labor share of tradables to a shock to the relative productivity of tradables is increasing in the differential in FBTC between tradables and non-tradables. Intuitively, when technological change is more biased toward labor in tradables than in non-tradables, it has an expansionary effect on hiring by traded firms which mitigates the fall in $\nu_t^{L,H}$ and may increase it like in Canada. Conversely, in Denmark and Germany, technological change is more biased toward labor in non-tradables which amplifies the decline in $\nu_t^{L,H}$. As we shall see when discussing numerical results, the assumption of FBTC increases the ability of our model to account for the labor reallocation effects we document empirically.

Cross-country labor reallocation effects and labor mobility costs. Besides the differential in FBTC between tradables and non-tradables, labor mobility costs can influence the extent of labor reallocation toward the non-traded sector. We expect countries with a higher degree of labor mobility to experience a greater decline in the labor share of tradables. To explore the cross-country relationship between changes in $\nu_t^{L,H}$ and the magnitude of workers' costs of switching sectors, we need a measure of the degree of labor mobility. In the lines of Horvath [2000], we estimate the elasticity of labor supply across sectors for each country i denoted by ϵ_i; see Online Appendix M.3 for further details about the derivation of the testable equation and the empirical strategy. Higher values of ϵ imply that workers experience lower labor mobility costs caused by sector-specific human capital which may not be perfectly transferable across sectors (see e.g., Lee and Wolpin [2006], Dix-Carneiro [2014]). In Fig. 6(b), we plot impact responses of the labor share of tradables to a 1% permanent increase in the relative productivity of tradables on the vertical axis against our measure of the degree of labor mobility, ϵ_i, on the horizontal axis. In line with our hypothesis, Fig. 6(b) shows that $\nu_t^{L,H}$ declines more on impact in countries where labor mobility costs are lower (i.e., ϵ takes higher values).

Cross-country reallocation effects and substitutability across goods. While both labor mobility costs and the FBTC differential across sectors determine the extent of the decline in the labor share of tradables, the substitutability between traded and non-traded goods determines the extent of the reallocation of both labor and capital, and thus the extent of the decline in the value added share of non-tradables at constant prices, $\nu_t^{Y,N}$.

In a two-sector model with flexible prices, a low elasticity of substitution ϕ between sectoral goods leads to a shift of productive resources to the sector with low TFP growth which in turn mitigates the decline in its value added share. Because less productive resources shift toward the non-traded sector as the elasticity of substitution between traded and non-traded goods, ϕ, takes higher values, we should observe a larger decline in $\nu_t^{Y,N}$ in countries where the substitutability between the two goods is higher. In Fig. 6(c), we plot impact responses of $\nu_t^{Y,N}$ against ϕ_i we estimate empirically for each country; see Online Appendix M.2 for further details about the empirical strategy to estimate ϕ_i. While all countries experience a fall in $\nu_t^{Y,N}$ on impact, the trend line reveals that the value added share of non-tradables declines more in countries where ϕ is higher. As shown later when discussing numerical results, international capital flows reinforce the reallocation incentives driven by a low value of ϕ.

While low values of ϕ cause productive resources to shift toward the non-traded sector following a technology shock biased toward the traded sector, high substitutability between home- and foreign-produced traded goods mitigates the reallocation of capital and labor toward the non-traded sector. As home- and foreign-produced traded goods become more substitutable, the depreciation in the terms of trade caused by higher traded relative to non-traded TFP exerts a greater positive impact on the demand of labor and capital in the traded sector which mitigates the shift of factors toward the non-traded sector. Therefore we expect the rise in the value added share of tradables at constant prices to be more pronounced in countries where the substitutability between home- and foreign-produced traded goods is higher. In Fig. 6(d), we plot impact responses of $\nu_t^{Y,H}$ against the elasticity of substitution between domestic and imported goods ρ_i^A we estimate empirically for each country; see Online Appendix L.6 which details the empirical strategy and shows panel data estimations. Inspection of the trend line corroborates our hypothesis as the value added share of tradables increases more on impact following a technology shock biased toward tradables in countries where home- and foreign-produced traded goods are higher substitutes.

Summary of evidence motivating the key elements of the model. To summarize, our evidence shows that a technology shock biased toward the traded sector leads to a shift of labor toward the non-traded sector which is less pronounced in countries where labor mobility costs are higher or where technological change is more biased toward labor in the traded than in the non-traded sector. Although productive resources shift away from the traded sector due to the low substitutability between traded and non-traded goods, the value added share of tradables at constant prices increases and all the more so in countries where the home- and foreign-produced traded goods are more highly substitutable. To account for the sectoral composition effects we document empirically, we develop an open economy version of the neoclassical model with tradables and non-tradables which includes the elements uncovered in our cross-country analysis, i.e., imperfect mobility of labor across sectors, imperfect substitutability across goods, CES production functions and sectoral FBTC.

3 A Semi-Small Open Economy Model with Tradables and Non-Tradables

We consider a semi-small open economy that is populated by a constant number of identical households and firms that have perfect foresight and live forever. The country is assumed to be semi-small in the sense that it is price-taker in international capital markets, and thus faces a given world interest rate, $r^{\star}$, but is large enough on world good markets to influence the price of its export goods. The open economy produces a traded good which can be exported, consumed or invested and imports consumption and investment goods. Besides the home-produced traded good, denoted by the superscript H, a non-traded sector produces a good, denoted by the superscript N, for domestic absorption only. The foreign good is chosen as the numeraire. We focus on the competitive equilibrium for the open economy because we want to emphasize the role of relative prices in driving the sectoral effects. Time is continuous and indexed by t.

3.1 Households

At each instant the representative household consumes traded and non-traded goods denoted by $C^T(t)$ and $C^N(t)$, respectively, which are aggregated by means of a CES function:

$$C(t) = \left[\varphi^{\frac{1}{\phi}} \left(C^T(t)\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} \left(C^N(t)\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{5}$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The traded consumption index $C^T(t)$ is defined as a CES aggregator of home-produced traded goods, $C^H(t)$, and foreign-produced traded goods, $C^F(t)$:

$$C^T(t) = \left[\left(\varphi^H\right)^{\frac{1}{\rho}} \left(C^H(t)\right)^{\frac{\rho-1}{\rho}} + \left(1-\varphi^H\right)^{\frac{1}{\rho}} \left(C^F(t)\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{6}$$

where $0 < \varphi^H < 1$ is the weight of the home-produced traded good and ρ corresponds to the elasticity of substitution between home- and foreign-produced traded goods. The consumption-based price index $P_C(t)$ is a function of traded and non-traded prices, denoted by $P^T(t)$ and $P^N(t)$, respectively:

$$P_C(t) = \left[\varphi \left(P^T(t)\right)^{1-\phi} + (1-\varphi) \left(P^N(t)\right)^{1-\phi}\right]^{\frac{1}{1-\phi}}, \tag{7}$$

where the price index for traded goods is a function of the terms of trade denoted by P^H(t):

$$P^T(t) = \left[\varphi^H \left(P^H(t)\right)^{1-\rho} + \left(1-\varphi^H\right)\right]^{\frac{1}{1-\rho}}. \tag{8}$$

As shall be useful later in the quantitative analysis, we denote the relative price of non-tradables by $P(t) = P^N(t)/P^H(t)$.

The representative household supplies labor to the traded and non-traded sectors, denoted by $L^H(t)$ and $L^N(t)$, respectively. To rationalize the sectoral wage differential which accompanies an asymmetric technology shock across sectors, we assume that hours worked in the traded and the non-traded sectors are imperfect substitutes in the lines of Horvath [2000]:

$$L(t) = \left[\vartheta^{-1/\epsilon}\left(L^H(t)\right)^{\frac{\epsilon+1}{\epsilon}} + (1-\vartheta)^{-1/\epsilon}\left(L^N(t)\right)^{\frac{\epsilon+1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon+1}}, \tag{9}$$

where $0 < \vartheta < 1$ parametrizes the weight attached to the supply of hours worked in the traded sector and ϵ is the elasticity of substitution between sectoral hours worked. The case of perfect mobility of labor is nested under the assumption that ϵ tends toward infinity which makes our results directly comparable with those obtained in the special case where workers no longer experience switching costs. The aggregate wage index $W(.)$ associated with the above defined labor index (9) is:

$$W(t) = \left[\vartheta\left(W^H(t)\right)^{\epsilon+1} + (1-\vartheta)\left(W^N(t)\right)^{\epsilon+1}\right]^{\frac{1}{\epsilon+1}}, \tag{10}$$

where $W^H(t)$ and $W^N(t)$ are wages paid in the traded and the non-traded sectors.

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1 - L(t)$ as leisure. At any instant of time, households derive utility from their consumption and experience disutility from working. Assuming that the felicity function is additively separable in consumption and labor, the representative household maximizes the following objective function:

$$U = \int_0^\infty \left\{\frac{1}{1-\frac{1}{\sigma_C}} C(t)^{1-\frac{1}{\sigma_C}} - \frac{1}{1+\frac{1}{\sigma_L}} L(t)^{1+\frac{1}{\sigma_L}}\right\} e^{-\beta t}\mathrm{d}t, \tag{11}$$

where $\beta > 0$ is the discount rate, $\sigma_C > 0$ the intertemporal elasticity of substitution for consumption, and $\sigma_L > 0$ the Frisch elasticity of (aggregate) labor supply.

Factor income is derived by supplying labor $L(t)$ at a wage rate $W(t)$, and capital $K(t)$ at a rental rate $R(t)$. In addition, households accumulate internationally traded bonds, $N(t)$, that yield net interest rate earnings of $r^\star N(t)$. Households' flow budget constraint states that real disposable income (on the RHS of the equation below) can be saved by accumulating traded bonds, consumed, $P_C(t)C(t)$, or invested, $P_J(t)J(t)$:

$$\dot{N}(t) + P_C(t)C(t) + P_J(t)J(t) = r^\star N(t) + R(t)K(t) + W(t)L(t), \tag{12}$$

where $P_J(t)$ is the investment price index defined below and $J(t)$ is total investment.

The investment good is (costlessly) produced using inputs of the traded good and the non-traded good by means of a CES technology:

$$J(t) = \left[\iota^{\frac{1}{\phi_J}}\left(J^T(t)\right)^{\frac{\phi_J-1}{\phi_J}} + (1-\iota)^{\frac{1}{\phi_J}}\left(J^N(t)\right)^{\frac{\phi_J-1}{\phi_J}}\right]^{\frac{\phi_J}{\phi_J-1}}, \tag{13}$$

where $0 < \iota < 1$ is the weight of the investment traded input and ϕ_J corresponds to the elasticity of substitution between investment traded goods and investment non-traded goods. The index $J^T(t)$ is defined as a CES aggregator of home-produced traded inputs, $J^H(t)$, and foreign-produced traded inputs, $J^F(t)$:

$$J^T(t) = \left[\left(\iota^H\right)^{\frac{1}{\rho_J}} \left(J^H(t)\right)^{\frac{\rho_J - 1}{\rho_J}} + \left(1 - \iota^H\right)^{\frac{1}{\rho_J}} \left(J^F(t)\right)^{\frac{\rho_J - 1}{\rho_J}} \right]^{\frac{\rho_J}{\rho_J - 1}}, \tag{14}$$

where $0 < \iota^H < 1$ is the weight of the home-produced traded input and ρ_J corresponds to the elasticity of substitution between home- and foreign-produced traded inputs. The investment-based price index $P_J(t)$ is a function of traded and non-traded prices:

$$P_J(t) = \left[\iota \left(P_J^T(t)\right)^{1-\phi_J} + (1-\iota) \left(P^N(t)\right)^{1-\phi_J} \right]^{\frac{1}{1-\phi_J}}, \tag{15}$$

where the price index for traded investment goods reads:

$$P_J^T(t) = \left[\iota^H \left(P^H(t)\right)^{1-\rho_J} + \left(1 - \iota^H\right) \right]^{\frac{1}{1-\rho_J}}. \tag{16}$$

Installation of new investment goods involves convex costs, assumed quadratic. Thus, total investment $J(t)$ differs from effectively installed new capital:

$$J(t) = I(t) + \frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K \right)^2 K(t), \tag{17}$$

where the parameter $\kappa > 0$ governs the magnitude of adjustment costs to capital accumulation. Denoting the fixed capital depreciation rate by $0 \leq \delta_K < 1$, aggregate investment, $I(t)$, gives rise to capital accumulation according to the dynamic equation:

$$\dot{K}(t) = I(t) - \delta_K K(t). \tag{18}$$

Households choose consumption, worked hours and investment in physical capital by maximizing lifetime utility (11) subject to (12) and (18) together with (17). Denoting by λ and Q' the co-state variables associated with (12) and (18), the first-order conditions characterizing the representative household's optimal plans are:

$$C(t) = \left(P_C(t)\lambda\right)^{-\sigma_C}, \tag{19a}$$

$$L(t) = \left(W(t)\lambda\right)^{\sigma_L}, \tag{19b}$$

$$\frac{I(t)}{K(t)} = \frac{1}{\kappa} \left(\frac{Q(t)}{P_J(t)} - 1 \right) + \delta_K, \tag{19c}$$

$$\dot{\lambda}(t) = \lambda(t) \left(\beta - r^\star\right), \tag{19d}$$

$$\dot{Q}(t) = \left(r^\star + \delta_K\right) Q(t) - \left\{ R(t) + P_J(t) \frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K \right) \left(\frac{I(t)}{K(t)} + \delta_K \right) \right\}, \tag{19e}$$

and the transversality conditions $\lim_{t \to \infty} \lambda N(t) e^{-\beta t} = 0$, $\lim_{t \to \infty} Q(t) K(t) e^{-\beta t} = 0$ where $Q(t) = Q'(t)/\lambda$. In an open economy model with a representative agent having perfect foresight, a constant rate of time preference and perfect access to world capital markets, we impose $\beta = r^\star$ in order to generate an interior solution. Setting $\beta = r^\star$ into (19d) implies that the shadow value of wealth is constant over time, i.e., $\lambda(t) = \lambda$. When new information about the technology shock arrives, λ jumps (to fulfill the intertemporal solvency condition determined later) and remains constant afterwards. For the sake of clarity, we drop the time argument below provided this causes no confusion.

Applying Shephard's lemma (or the envelope theorem) yields the following demand for the home- and the foreign-produced traded good for consumption and investment:

$$C^H = \varphi \left(\frac{P^T}{P_C}\right)^{-\phi} \varphi^H \left(\frac{P^H}{P^T}\right)^{-\rho} C, \qquad C^F = \varphi \left(\frac{P^T}{P_C}\right)^{-\phi} \left(1-\varphi^H\right) \left(\frac{1}{P^T}\right)^{-\rho} C, \tag{20a}$$

$$J^H = \iota \left(\frac{P^T_J}{P_J}\right)^{-\phi_J} \iota^H \left(\frac{P^H}{P^T_J}\right)^{-\rho_J} J, \qquad J^F = \iota \left(\frac{P^T_J}{P_J}\right)^{-\phi_J} \left(1-\iota^H\right) \left(\frac{1}{P^T_J}\right)^{-\rho_J} J, \tag{20b}$$

and the demand for non-traded consumption and investment goods, respectively:

$$C^N = (1-\varphi)\left(P^N/P_C\right)^{-\phi} C, \qquad J^N = (1-\iota)\left(P^N/P_J\right)^{-\phi_J} J. \tag{21}$$

The substitutability across goods has important implications for the labor market effects of asymmetric technology shocks across sectors. First, rearranging the first equality of eq. (21) reveals that the share of non-traded goods in aggregate consumption expenditure, i.e., $1 - \alpha_C = \frac{P^N C^N}{P_C C} = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{1-\phi}$, is increasing in non-traded prices when $\phi < 1$ as evidence suggests. Conversely, the home content of consumption and investment expenditure in tradables, i.e., $\alpha^H = \frac{P^H C^H}{P^T C^T} = \varphi^H \left(\frac{P^T}{P^H}\right)^{\rho-1}$ and $\alpha^H_J = \frac{P^H J^H}{P^T_J J^T} = \iota^H \left(\frac{P^T_J}{P^H}\right)^{\rho_J-1}$, increases as the terms of trade, P^H, decline since home- and foreign-produced traded goods are gross substitutes, i.e., $\rho > 1$ and $\rho_J > 1$, in line with our estimates. These parameters, ϕ, ρ and ρ_J, will play an important role in the transmission mechanism of an increase in the relative productivity of tradables by affecting the share of expenditure in sectoral goods and thus sectoral labor demand.

Given the aggregate wage index, we can derive the allocation of aggregate labor supply to the traded and the non-traded sector:

$$L^H = \vartheta \left(W^H/W\right)^{\epsilon} L, \qquad L^N = (1-\vartheta)\left(W^N/W\right)^{\epsilon} L, \tag{22}$$

where the elasticity of labor supply across sectors ϵ captures the degree of labor mobility.

3.2 Firms

Each sector consists of a large number of identical firms which use labor, L^j, and physical capital, K^j, according to a technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j \left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)K^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{23}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and $A^j(t)$ and $B^j(t)$ are labor- and capital-augmenting efficiency.

Firms lease the capital from households and hire workers. They face two cost components: a capital rental cost equal to $R(t)$, and the wage rate equal to $W^j(t)$ in sector $j = H, N$. Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given. While capital can move freely between the two sectors, costly labor mobility implies a wage differential across sectors:

$$P^j(t)\gamma^j \left(A^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(y^j(t)\right)^{\frac{1}{\sigma^j}} = W^j, \tag{24a}$$

$$P^j(t)\left(1-\gamma^j\right)\left(B^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(k^j(t)\right)^{-\frac{1}{\sigma^j}} \left(y^j(t)\right)^{\frac{1}{\sigma^j}} = R, \tag{24b}$$

where we denote by $k^j(t) \equiv K^j(t)/L^j(t)$ the capital-labor ratio for sector $j = H, N$, and $y^j(t) \equiv Y^j(t)/L^j(t)$ refers to value added per hour worked.

Demand for inputs can be rewritten in terms of their respective cost in value added; for labor, we have $s_L^j(t) = \gamma^j \left(\frac{A^j(t)}{y^j(t)}\right)^{\frac{\sigma^j-1}{\sigma^j}}$. Applying the same logic for capital and denoting by $S^j(t) \equiv \frac{s_L^j(t)}{1-s_L^j(t)}$ the ratio of labor to capital income share, we have:

$$S^j(t) \equiv \frac{s_L^j(t)}{1-s_L^j(t)} = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j(t)k^j(t)}{A^j(t)}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{25}$$

When technological change is assumed to be Hicks-neutral, productivity increases uniformly across inputs, i.e., $\hat{A}^j(t) = \hat{B}^j(t)$. Hence sectoral LISs are only affected through changes in $k^j(t)$. When capital shifts away from sector j, $s_L^j(t)$ declines since evidence reveals that capital and labor are gross complements in production, i.e., $\sigma^j < 1$. By contrast, when technological change is factor-biased, an increase in capital relative to labor efficiency, $B^j(t)/A^j(t)$, impinges on the sectoral LIS directly and indirectly through changes in $k^j(t)$. The measure of FBTC in sector j is: $\text{FBTC}^j(t) = \frac{1-\sigma^j}{\sigma^j}\left(\hat{B}^j(t) - \hat{A}^j(t)\right)$. Technological change biased toward labor in sector j, i.e., $\text{FBTC}^j(t) > 0$, stimulates the demand of labor and lowers the demand of capital in this sector. As we shall see in the quantitative analysis, because $\text{FBTC}^j(t) > 0$ overturns the negative impact on the LIS caused by the decline in k^j, s_L^j increases.

Finally, aggregating over the two sectors gives us the resource constraint for capital:

$$K^H(t) + K^N(t) = K(t). \tag{26}$$

3.3 Technology Frontier

Eq. (25) can be used to determine the direction and the extent of the change in relative capital efficiency which is consistent with observed changes in S^j and k^j. In order to be consistent with our empirical strategy, we need to specify a technology frontier which determines how TFP in sector j is split between capital and labor efficiency for a given change in relative capital efficiency inferred from (25). A natural way to map A^j and B^j into Z^j is to assume that besides optimally choosing factor inputs, firms also optimally choose the technology of production. Following Caselli and Coleman [2006] and Caselli [2016], the menu of possible choices of the technology of production is represented by a set of possible (A^j, B^j) pairs which are chosen along a technology frontier which is assumed to take a Cobb-Douglas form:

$$Z^j(t) = \left(A^j(t)\right)^{\alpha^j(t)} \left(B^j(t)\right)^{1-\alpha^j(t)}, \tag{27}$$

where Z^j measures the height of the technology frontier and α^j is a positive parameter which determines the weight of labor-augmenting efficiency. In Online Appendix S.7, we alternatively assume that labor- and capital-augmenting efficiency are aggregated by means of a CES function and find that the same results we derive below hold. Firms choose labor and capital efficiency, A^j and B^j, along the technology frontier described by eq. (27) that minimize the unit cost function. The optimal trade-off between A^j and B^j that minimizes the unit cost is such that the weight of labor efficiency (i.e., α^j) collapses to its contribution to the decline in the unit cost (i.e., s_L^j) so that (27) can be rewritten as follows:

$$Z^j(t) = \left(A^j(t)\right)^{s_L^j(t)} \left(B^j(t)\right)^{1-s_L^j(t)}, \tag{28}$$

where the weight s_L^j is time-varying because the production function (23) takes a CES form with $\sigma^j \neq 1$. While the technological frontier imposes a structure on the mapping between TFP and factor-augmenting efficiency, as described by (28), it has the advantage to ensure a consistency between the theoretical and the empirical approach where technological shifts can be Hicks-neutral or factor-biased.

3.4 Model Closure and Equilibrium

To fully describe the equilibrium, we impose goods market clearing conditions for non-traded and home-produced traded goods:

$$Y^N(t) = C^N(t) + J^N(t), \qquad Y^H(t) = C^H(t) + J^H(t) + X^H(t), \tag{29}$$

where X^H stands for exports of home-produced goods. In the lines of Kehoe and Ruhl [2009], we assume that the size of the open economy on world goods market is large enough to influence the price of its export good. Foreign demand for the home-produced traded good is a decreasing function of terms of trade, $P^H(t)$:

$$X^H(t) = \varphi_X \left(P^H(t)\right)^{-\phi_X}, \tag{30}$$

where $\varphi_X > 0$ is a scaling parameter, and ϕ_X is the elasticity of exports w.r.t. P^H.

Log-linearizing (28) shows that sectoral TFPs dynamics are driven by the dynamics of labor- and capital-augmenting efficiency, i.e., $\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right) \hat{B}^j(t)$. We drop the time index below to denote steady-state values. Like Galí [1999], we abstract from trend growth and consider a technology shock that increases permanently traded relative to non-traded productivity. The adjustment of $A^j(t)$ and $B^j(t)$ toward their long-run (higher) level expressed in percentage deviation from initial steady-state is governed by the following continuous time process:[12]

$$\hat{A}^j(t) = \hat{A}^j + \bar{a}^j e^{-\xi^j t}, \quad \hat{B}^j(t) = \hat{B}^j + \bar{b}^j e^{-\xi^j t}, \tag{31}$$

where $\bar{a}^j$ and $\bar{b}^j$ are parameters, and $\xi^j > 0$ measures the speed at which productivity closes the gap with its long-run level. Once $A^j(t)$ and $B^j(t)$ have completed their adjustment, they increase permanently to a new higher level, i.e., letting time tend toward infinity into (31) leads to $\hat{A}^j(\infty) = \hat{A}^j$ and $\hat{B}^j(\infty) = \hat{B}^j$ where $\hat{A}^j$ and $\hat{B}^j$ are steady-state (permanent) changes in labor- and capital-augmenting efficiency in percentage. Inserting (31) into the log-linearized version of the technology frontier allows us to recover the dynamics of TFP in sector j:

$$\hat{Z}^j(t) = \hat{Z}^j + \bar{z}^j e^{-\xi^j t}, \tag{32}$$

where $\bar{z}^j = s_L^j \bar{a}^j + \left(1 - s_L^j\right) \bar{b}^j$ and $\hat{Z}^j(\infty) = \hat{Z}^j = s_L^j \hat{A}^j + \left(1 - s_L^j\right) \hat{B}^j$ is the permanent change (in percentage) in TFP in sector j.

The adjustment of the open economy toward the steady-state is described by a dynamic system which comprises six equations that are functions of $K(t)$, $Q(t)$, $A^j(t)$, $B^j(t)$:

$$\dot{K}(t) = \Upsilon\left(K(t), Q(t), A^H(t), B^H(t), A^N(t), B^N(t)\right), \tag{33a}$$

$$\dot{Q}(t) = \Sigma\left(K(t), Q(t), A^H(t), B^H(t), A^N(t), B^N(t)\right), \tag{33b}$$

$$\dot{A}^j(t) = -\xi^j \left(A^j(t) - \tilde{A}^j\right), \qquad \dot{B}^j(t) = -\xi^j \left(B^j(t) - \tilde{B}^j\right), \tag{33c}$$

where $j = H, N$. The first dynamic equation corresponds to the non-traded goods market clearing condition (29) and the second dynamic equation corresponds to (19e) which equalizes the rates of return on domestic equities and foreign bonds, $r^\star$, once we have substituted appropriate first-order conditions. Equations (33c) are the law of motion of labor- and capital-augmenting efficiency, respectively, in sector j. Linearizing (33a)-(33b) around the steady-state and denoting by ω_k^i the kth element of eigenvector ω^i related to eigenvalue ν_i, the general solution that characterizes the adjustment toward the new steady-state can be written as follows: $V(t) - V = \sum_{i=1}^{6} \omega^i D_i e^{\nu_i t}$ where V is the vector of state and control variables. Denoting the positive eigenvalue by $\nu_2 > 0$, we set $D_2 = 0$ to eliminate explosive

[12] We assume that the economy starts from an initial steady-state and is hit by a technology shock which increases permanently traded relative to non-traded TFP. In the same spirit as Galí [1999], the accumulation of permanent technology shocks give rise to a unit root in the time series for the relative productivity of tradables, an assumption we use to identify a permanent technology shock biased toward tradables in the empirical part. We do not characterize the convergence of the economy toward a balanced growth path which is supposed to exist, in line with the theoretical findings by Acemoglu and Guerrieri [2008], Alvarez-Cuadrado et al. [2018], Kehoe et al. [2018] who allow labor income shares to vary across sectors. In the lines of Kehoe et al. [2018], the balanced growth path we have in mind is one where sectoral productivity growth rates must eventually be equal. Indeed, the data reveals an asymptotic (and hump-shaped) but very persistent convergence of traded toward non-traded TFP productivity growth which started in the 90s. This convergence is consistent with our identifying assumption since it is a very lengthy process. Panel unit root tests reported in Appendix N.1 show clearly that time series for the ratio of traded to non-traded TFP are I(1), thus confirming that the convergence process is far from being completed.

paths and determine the five arbitrary constants D_i (with $i = 1, ..., 6$, $i \neq 2$) by using the five initial conditions, i.e., $K(0) = K_0$, $A^j(0) = A^j_0$, and $B^j(0) = B^j_0$ for $j = H, N$.

Using the properties of constant returns to scale in production, identities $P_C(t)C(t) = \sum_g P^g(t)C^g(t)$ and $P_J(t)J(t) = \sum_g P^g(t)J^g(t)$ (with $g = F, H, N$) along with market clearing conditions (29), the current account equation (12) can be rewritten as a function of the trade balance (last two terms on the RHS of the equation below):

$$\dot{N}(t) = r^\star N(t) + P^H(t)X^H(t) - M^F(t), \tag{34}$$

where $M^F(t) = C^F(t) + J^F(t)$ stands for imports of foreign-produced consumption and investment goods. Eq. (34) can be written as a function of state and control variables, i.e., $\dot{N}(t) \equiv r^\star N(t) + \Xi\left(K(t), Q(t), A^H(t), B^H(t), A^N(t), B^N(t)\right)$. Linearizing around the steady-state, inserting the solutions for $K(t)$, $Q(t)$ together with (33c), solving and invoking the transversality condition, yields the solution for traded bonds:

$$N(t) - N = \sum_{i=1, i\neq 2}^{6} \Phi^i_N e^{\nu_i t}, \tag{35}$$

where $\Phi^i_N = \frac{E_i D_i}{r^\star - \nu_i}$ with $E_i = \Xi_K \omega^i_1 + \Xi_Q \omega^i_2 + \Xi_{A^H} \omega^i_3 + \Xi_{B^H} \omega^i_4 + \Xi_{A^N} \omega^i_5 + \Xi_{B^N} \omega^i_6$; partial derivatives of Ξ w.r.t. K, Q, A^j, B^j, are evaluated at the steady-state. Eq. (35) gives the trajectory for $N(t)$ consistent with the intertemporal solvency condition:

$$N - N_0 = \sum_{i=1, i\neq 2}^{6} \Phi^i_N. \tag{36}$$

4 Quantitative Analysis

In this section, we take the model to the data. For this purpose we solve the model numerically.[13] Therefore, first we discuss parameter values before turning to the effects of a technology shock biased toward the traded sector.

4.1 Calibration

To ensure that the initial steady-state with CES production functions is invariant when σ^j is changed, we normalize CES production functions by choosing the initial steady-state in a model with Cobb-Douglas production functions as the normalization point. Once we have calibrated the initial steady-state with Cobb-Douglas production functions, we calibrate the CES economy to the data such that Z^j and γ^j together with other parameters are endogenously calibrated to reproduce the ratios of the Cobb-Douglas economy, including the sectoral LISs, see Online Appendix P.3. This normalization procedure guarantees that we start from the same initial steady-state regardless of the value of σ^j. To calibrate

[13] Technically, the assumption $\beta = r^\star$ requires the joint determination of the transition and the steady state since the constancy of the marginal utility of wealth implies that the intertemporal solvency condition (36) depends on eigenvalues' and eigenvectors' elements, see e.g., Turnovsky [1997].

the reference model we use to normalize the CES economy, we estimated a set of ratios and parameters for the seventeen OECD economies in our dataset. Our reference period for the calibration corresponds to the period 1970-2013. Table 6 in Online Appendix L.1 summarizes our estimates of the ratios and estimated parameters for all countries in our sample.

We first calibrate the model to a representative OECD country and investigate whether the model can account for the evidence we document empirically when one parameter at a time is modified. Later, we move a step further and calibrate the model to country-specific data and explore whether the model can rationalize our empirical findings once we let all parameters of interest vary across countries. To capture the key properties of a typical OECD economy, we take unweighted average values of ratios which are shown in the last line of Table 6. Among the 24 parameters that the model contains, 18 have empirical counterparts while the remaining 6 parameters, i.e., φ, ι, φ^H, ι^H, ϑ, δ_K together with initial conditions (N_0, K_0) must be endogenously calibrated to match ratios $1-\alpha_C$, $1-\alpha_J$, α^H, α^H_J, $\frac{L^N}{L}$, ω_J, and $\upsilon_{NX} = \frac{NX}{P^H Y^H}$ with $NX = P^H X^H - C^F - I^F$. More details about the calibration procedure can be found in Online Appendix P.1-P.2. We choose the model period to be one year and set the world interest rate, $r^\star$, which is equal to the subjective time discount rate, β, to 4%. Table 7 in Online Appendix L.1 summarizes the parameter values.

The degree of labor mobility which is measured by the elasticity of labor supply across sectors, ϵ, is set to 1.6 to allow the model to replicate the long-run wage differential we document empirically for tradables and non-tradables (see Fig. 3(h)). As summarized in column 16 of Table 6, our panel data estimates of ϵ over the period 1970-2013 range from a low of 0.01 for Norway to a high of 3.2 for the U.S. and thus a value of 1.6 is halfway between these two estimates. See Online Appendix M.3 for the derivation of the testable equation and Online Appendix L.4 for panel data estimations.

Following Stockman and Tesar [1995], we choose a value for the elasticity of substitution ϕ between traded and non-traded goods of 0.44 which is the value commonly used in the international RBC literature. This value falls in the range of our panel data estimates for the whole sample which vary between 0.66 and 0.33 depending on whether the testable equation includes or not a country-specific linear time trend, see Online Appendix L.4 which shows our panel data estimations of ϕ and Online Appendix M.2 which details the steps of derivation of the testable equation. The weight of consumption in non-tradables $1-\varphi$ is set to target a non-tradable content in total consumption expenditure (i.e., $1-\alpha_C$) of 53%, in line with the average of our estimates. In accordance with our empirical findings, see Online Appendix L.6, we set the elasticity of substitution, ρ, in consumption between home- and foreign-produced traded goods to 1.5 which corresponds to value commonly adopted in the literature, see e.g., Backus et al. [1994]. The weight of consumption in home-produced traded goods φ^H is set to target a home content of consumption expenditure in tradables (i.e. α^H) of 77%, in line with the average of our estimates.

While an elasticity of intertemporal substitution around one is a typical choice in the business cycle literature, we choose a value of two for σ_C which squares well with the estimates documented by Crossley and Low [2011], Gourinchas and Parker [2002], and Gruber [2013]. As is well known (and demonstrated analytically in Online Appendix O), when $\sigma_C = 1$, the wealth and substitution effect cancel out and total hours worked remain unresponsive to a technology shock. A value of two mitigates the negative impact of the wealth effect on labor supply and enables us to generate a positive response of total hours worked to the shock on impact in line with our evidence.[14] We conduct a sensitivity analysis w.r.t. the IES for consumption in Online Appendix U.5. We find that choosing values for σ_C equal or lower than one leads the model to understate the responses of sectoral hours worked but has little impact on the value added and labor share of tradables together with relative prices. Based on the estimates of the macro Frisch elasticity of labor supply documented by Peterman [2016] which vary between 1.5 and 1.75 for the population aged between 20 and 55, and between 20 and 60, respectively, we choose a value of 1.6 for σ_L; this value enables us to generate the increase in total hours worked by 0.09% we estimate empirically on impact (see Fig. 15(a) in Online Appendix L.2). The weight of labor supply to the non-traded sector, $1 - \vartheta$, is set to 0.6 to target a share of non-tradables in total hours worked of 63% in line with our estimates.

We now describe the calibration of production-side parameters. We assume that physical capital depreciates at a rate $\delta_K = 9.3\%$ to target an investment-GDP ratio of 24%. In line with our estimates, the shares of labor income in traded and non-traded value added, s_L^H and s_L^N, are set to 0.63 and 0.68, respectively. We consider an initial steady-state with HNTC and normalize $A^j = B^j = Z^j$ to 1. We set the elasticity of substitution, ϕ_J, between J^T and J^N to 1, in line with the empirical findings documented by Bems [2008] for OECD countries. Further, the weight of non-traded investment $(1 - \varphi_I)$ is set to target a non-tradable content of investment expenditure of 62%. In accordance with our estimates, we set the elasticity of substitution, ρ_J, in investment between home- and foreign-produced traded inputs to 1.5. The weight of home-produced traded investment ι^H is set to 0.62 to target a home content of investment expenditure in tradables (i.e. α_J^H) of 51%. We choose the value of parameter κ so that the elasticity of I/K with respect to Tobin's q, i.e., Q/P_J, is equal to the value implied by estimates in Eberly, Rebelo, and Vincent [2008].

[14] When we restrict attention to the period 1970-2007, we find that total hours worked are unresponsive to asymmetric technology shocks across sectors and thus a value of one for the intertemporal elasticity of substitution (IES) squares well with our evidence over this period. Since we find that total hours worked increase significantly following a shock to a productivity differential, the positive response is caused by the period 2007-2013. During this period, the value for the IES has increased sharply, as suggested by the empirical study by Cundy [2018] who reports a value of 2.8 for the IES between 2009 and 2014.

The resulting value of κ is equal to 17.

Government spending on traded G^T and non-traded goods G^N are considered for calibration purposes. We set government spending on non-traded goods G^N and traded goods G^T so as to yield a non-tradable share of government spending, ω_{G^N}, of 90%, and government spending as a share of GDP, ω_G, of 20%. We choose initial conditions so that trade is initially balanced. Since net exports are nil, the investment-to-GDP ratio, ω_J, and government spending as a share of GDP, ω_G, implies a consumption-to-GDP ratio of $\omega_C = 56\%$. It is worth mentioning that the tradable content of GDP is endogenously determined by the market clearing condition for traded goods, i.e., $P^H Y^H / Y = \omega_C \alpha_C + \omega_J \alpha_J + \omega_{G^T} \omega_G = 38\%$. Building on structural estimates of the price elasticities of aggregate exports documented by Imbs and Mejean [2015], we set the export price elasticity, ϕ_X, to 1.7 in the baseline calibration (see column 19 of Table 6). Because trade is balanced, export as a share of GDP, $\omega_X = P^H X^H / Y$, is endogenously determined by the import content of consumption, $1 - \alpha^H$, and investment expenditure, $1 - \alpha_J^H$, along with ω_C and ω_J.

Since the model with Cobb-Douglas production functions is the normalization point, when we calibrate the model with CES production functions, φ, ι, φ^H, ι^H, ϑ, δ_K, N_0, K_0, Z^j, γ^j are endogenously set to target $1 - \bar{\alpha}_C$, $1 - \bar{\alpha}_J$, $\bar{\alpha}^H$, $\bar{\alpha}_J^H$, $\bar{L}^N / \bar{L}$, $\bar{\omega}_J$, $\bar{\upsilon}_{NX}$, $\bar{K}$, $\bar{y}^j$, $\bar{s}_L^j$, respectively, where a bar indicates that the ratio is obtained from the Cobb-Douglas economy, and we consider an initial steady-state with HNTC, i.e., $A^j = B^j = Z^j$, see Online Appendix P.3 which provides more details. Drawing on Antràs [2004], we estimate the elasticity of substitution between capital and labor for tradables and non-tradables and set σ^H and σ^N, to 0.69 and 0.72 (see the last line of columns 17 and 18 of Table 6); see Online Appendix L.5 for the empirical strategy and panel data estimations of σ^j.

4.2 Factor-Augmenting Efficiency and Sectoral TFP Dynamics

Since our VAR evidence documented in subsection 2.3 reveals that technological change is factor-biased, we need to set the dynamics for factor efficiency, $B^j(t)$ and $A^j(t)$. We first derive the change in capital relative to labor efficiency, by log-linearizing (25) which describes the demand for factors of production:

$$\left(\hat{B}^j(t) - \hat{A}^j(t)\right) = \frac{\sigma^j}{1 - \sigma^j} \hat{S}^j(t) - \hat{k}^j(t), \tag{37}$$

all variables being expressed in percentage deviation from the initial steady-state. Next, given the adjustment of relative capital efficiency inferred from (37), we have to determine the dynamics of $B^j(t)$ and $A^j(t)$ consistent with the dynamics of sectoral TFP we estimate empirically. Log-linearizing the technology frontier (28) in the neighborhood of the initial steady-state leads to $\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right) \hat{B}^j(t)$. The latter equation together with

(37) can be solved for labor and capital-augmenting efficiency:

$$\hat{A}^j(t) = \hat{Z}^j(t) - \left(1 - s_L^j\right) \left[\left(\frac{\sigma^j}{1-\sigma^j} \right) \hat{S}^j(t) - \hat{k}^j(t) \right], \tag{38a}$$

$$\hat{B}^j(t) = \hat{Z}^j(t) + s_L^j \left[\left(\frac{\sigma^j}{1-\sigma^j} \right) \hat{S}^j(t) - \hat{k}^j(t) \right]. \tag{38b}$$

Plugging estimated values for σ^j and empirically estimated responses for $s_L^j(t)$ and $k^j(t)$ (see Fig. 4), $Z^j(t)$ (see Fig. 3(e)), into the above equations enables us to recover the dynamics for $A^j(t)$ and $B^j(t)$ consistent with the demand of factors of production (37) and adjustment of sectoral TFPs. To ensure that our method to generate time series for sectoral FBTC captures technological change, in Online Appendix J, we test Acemoglu's [2003] model assumptions who endogeneizes FBTC. We find that countries where TFP gains are concentrated in capital (labor) intensive industries also experience a rise in capital (labor) relative to labor (capital) efficiency, in accordance with Acemoglu's [2003] model assumptions, which lends credence to the ability of the time series of B^j/A^j we generate to reflect FBTC.

Once we have determined the underlying dynamic process for labor and capital efficiency by using (38), we have to choose values for exogenous parameters $\bar{a}^j$, $\bar{b}^j$, and ξ^j, which are consistent with the law of motion (31). We choose $\bar{a}^j$, $\bar{b}^j$ by setting $t = 0$ into (31) which yields $\bar{a}^j = -\left(\hat{A}^j - \hat{A}^j(0)\right)$, and $\bar{b}^j = -\left(\hat{B}^j - \hat{B}^j(0)\right)$. Making use of the time series generated by (38a) and (38b) gives us $\bar{a}^H = -0.029840$, $\bar{b}^H = -0.202769$, $\bar{a}^N = 0.234035$, $\bar{b}^N = -0.500629$. By using the fact that $\bar{z}^j = s_L^j \bar{a}^j + \left(1 - s_L^j\right) \bar{b}^j$ (see eq. (32)), we have $\bar{z}^H = -0.093566$ and $\bar{z}^N = 0.000164$ for the parameters governing the gap which must be fulfilled when sectoral TFP converges toward its long-run equilibrium. To determine the value for the speed of adjustment of sectoral TFP, we solve (32) for ξ^j, i.e., $\xi^j = -\frac{1}{t} \ln \left(\frac{\hat{Z}^j(t) - \hat{Z}^j}{\bar{z}^j} \right)$; setting $t = 3$ leads to $\xi^H = 0.570885$ for the traded sector and $\xi^N = 1.166821$ for the non-traded sector which gives us the best fit of the response of $\hat{Z}^j(t)$ estimated empirically. Once we have the dynamic paths for $\hat{Z}^H(t)$ and $\hat{Z}^N(t)$, we can compute the dynamics for the shock to the TFP differential between tradables and non-tradables (see eq. (4)):

$$\hat{Z}(t) = a\hat{Z}^H(t) - b\hat{Z}^N(t), \tag{39}$$

where $\hat{Z}(\infty) = \hat{Z} = a\hat{Z}^H - b\hat{Z}^N$ is normalized to 1% in the long-run.

In Fig. 11 which is relegated to Online Appendix I for reason of space, we contrast the empirical response functions (shown in blue lines) of the TFP differential between tradables and non-tradables as well as sectoral TFPs with the theoretical response functions (shown in black lines with squares) generated by the law of motion (31)-(32) together with (39). As can be seen in Fig. 11, the theoretical responses perform well in reproducing the evidence and thus the dynamic equations (31)-(32) which govern the adjustment of factor-augmenting efficiency and $Z^j(t)$ are consistent with data.

4.3 Reallocation and Redistributive Effects: Model Performance

In this subsection, we analyze the role of FBTC, terms of trade, and imperfect mobility of labor in shaping the reallocation and redistributive effects in an open economy in response to a 1% permanent increase in TFP of tradables relative to TFP of non-tradables. In order to assess quantitatively the role of each ingredient in driving the sectoral effects of a technology shock biased toward tradables, we report results from restricted versions of the baseline model. These restricted versions collapse to the international RBC model by Fernández de Córdoba and Kehoe [2000] (FK henceforth) who consider variants of a small open economy setup with tradables and non-tradables. Our quantitative analysis reveals that the model can account for the sectoral composition effects of asymmetric technology shocks we estimate empirically once we allow for imperfect mobility of labor (i.e., $\epsilon < \infty$), assume home- and foreign-produced traded goods to be gross substitutes (i.e., $\rho > 1$ and $\rho_J > 1$), and let technological change be factor-biased. Whilst the latter ingredient is key to replicating the dynamics of the sectoral LISs, the differential in FBTC between tradables and non-tradables increases the ability of the model to account for the reallocation of labor we estimate empirically.

In Table 1, we report the simulated impact (i.e., at $t = 0$) and long-run (i.e., at $t = 10$) effects. While columns 1 and 7 show impact and long-run responses from our VAR model for comparison purposes, columns 2 and 8 show results for the baseline model. Columns 5 and 11 display results for a restricted version of our model which collapses to the FK model with capital adjustment costs. In this restricted model, we impose perfect mobility of labor, exogenous terms of trade and Cobb-Douglas production functions. In the next columns, we add one ingredient at a time. In columns 4 and 10, we consider the same model except that we allow for imperfect mobility of labor across sectors (i.e., we set $\epsilon = 1.6$). This version collapses to the FK model with capital adjustment as well as labor mobility costs. In columns 3 and 9, we allow for imperfect mobility of labor and endogenous terms of trade (i.e., we set $\rho = \rho_J = 1.5$). We also allow for CES production functions while assuming HNTC.

Baseline model. We first assess the ability of the baseline model with imperfect mobility of labor, endogenous terms of trade and FBTC to account for our evidence on the reallocation and redistributive effects. Columns 2 and 8 of Table 1 show impact and long-run effects for the baseline model. To begin with, as can be seen in panel A of Table 1, the baseline model is able to account for the sectoral composition effects we estimate empirically. First, as in the data, the traded sector drives real GDP growth since Y^H and Y^N increases by 0.22% and 0.01% of GDP, respectively, close to our VAR evidence (0.24% and 0.01%, resp.). Conversely, the non-traded sector drives the rise in total hours worked as L^H remains unresponsive on impact and L^N rises by 0.11% of total hours worked, in line with our empirical findings (-0.01% for L^H and 0.10% for L^N). As can be seen in panel C, incentives for increasing L^N are brought about by an appreciation in the relative price of non-tradables (i.e., 0.97% at $t = 0$ and 1.08% at $t = 10$) which is larger than the productivity differential, in accordance with our estimates (0.99% at $t = 0$ and 1.06% at $t = 10$). Intuitively, a technology shock generates a positive wealth effect which encourages households to increase consumption in both traded and non-traded goods. Since the technology shock is biased toward the traded sector, an excess demand for non-traded goods and an excess supply for traded goods show up. Because the elasticity of substitution between traded and non-traded goods is smaller than one (i.e., $\phi < 1$), the relative price of non-tradables appreciates disproportionately which has an expansionary effect on labor (and capital) demand in the non-traded sector. The movement of productive resources, especially labor, toward non-tradable sectors is stronger in a financially open economy as the access to foreign borrowing amplifies the demand boom for non-tradables.

The labor outflow experienced by the traded sector is mitigated however by the fall in the relative price of home-produced traded goods brought about by the excess supply for domestically produced traded goods. Panel C shows that the terms of trade deteriorate by 0.27% on impact (0.41% in the data) and 0.37% in the long-run (0.44% in the data). Since home- and foreign-produced traded goods are gross substitutes, the terms of trade deterioration has a positive impact on labor demand in the traded sector. Intuitively, when $\rho > 1$ and $\rho_J > 1$, a fall in P^H increases the home content of tradable expenditures for consumption (i.e., α^H) and investment (i.e., α_J^H) goods. The reallocation of labor toward the non-traded sector is further mitigated by the presence of labor mobility costs. As can be seen in panel B, non-traded firms pay higher wages to encourage workers to shift, thus producing a positive wage differential for non-tradables and a negative wage differential for tradables, close to our estimates, especially in the long-run (see column 8).

As can be seen in panel B, the model generates a decline in the share of tradables in total hours worked (i.e., $\nu^{L,H}$) by the same amount that is estimated empirically (i.e., 0.04% of total hours worked). The reason is that technological change is more biased toward labor in the traded than in the non-traded sector which has a positive impact on labor demand in the former sector and thus hampers the shift of labor toward the non-traded sector. Labor reallocation accounts for 38% (43% in the data) of the rise in non-traded hours worked on impact. In the long-run, the contribution of the shift of labor is lower at 33% (34% in the data).

In addition to producing a labor outflow, the large appreciation in $P = P^N/P^H$ also drives capital out of the traded sector. Since labor is subject to mobility costs and technological change is biased toward labor, the capital-labor ratio, k^H, falls substantially (see panel D). Because technological change biased toward labor overturns the negative impact on the LIS caused by the decline in k^H, s_L^H unambiguously increases. If capital and labor were immobile across sectors, the change in the value added share of tradables would collapse to $d\nu^{Y,H} = \nu^{Y,H}\left(1-\nu^{Y,H}\right)\left(\hat{Z}^H - \hat{Z}^N\right)$. Since $\nu^{Y,H} = 0.4$ approximately and the productivity differential is 1% in the long-run, a back of the envelope calculation indicates that $\nu^{Y,H}$ would increase by 0.24% of GDP in the long-run. As can be seen in the second line of panel B, the reallocation of productive resources away from the traded sector mitigates the rise in $\nu^{Y,H}$ which increases by 0.16% (0.14% in the data) of GDP only.

Restricted model: perfect mobility of labor, exogenous terms of trade and HNTC. In columns 5 and 11, we consider a restricted model imposing perfect mobility of labor across sectors (i.e., we set $\epsilon \to \infty$), exogenous terms of trade (i.e., we let ρ and ρ_J tend toward ∞) and Cobb-Douglas production functions. When we contrast VAR evidence reported in column 1 with numerical results displayed by column 5, we find that the restricted model can generate qualitatively the sectoral effects we estimate empirically but fails to account for their magnitude. A direct implication of abstracting from labor mobility costs is that the model cannot account for the sectoral wage differential which materializes after one year (see the last two rows of panel B of Table 1). When labor mobility costs are absent and terms of trade remain fixed, the restricted model considerably overstates the decline in the labor share of tradables. The fall in $\nu^{L,H}$ is almost six times larger to what we estimate empirically on impact (i.e., -0.22% vs. -0.04% in the data, see the first row of panel B). As a result, the model predicts a dramatic fall in traded hours worked (-0.23% vs. -0.01% in the data) and considerably understates the rise in traded value added (0.05% vs. 0.24% in the data). By overestimating the reallocation of labor toward the non-traded sector, the model overpredicts the rise in L^N (0.21% vs. 0.10% in the data, see panel A) as well as in Y^N (0.11% vs. 0.01% in the data). The excess demand for non-traded goods is thus mitigated which leads the model to predict an appreciation in the relative price of non-tradables (see panel C of Table 1) by 0.90% below what is estimated empirically (0.99%).

Restricted model: Exogenous terms of trade and HNTC. Columns 4 and 10 show results for the same restricted model as above except that we allow for imperfect mobility of labor across sectors (i.e., we set $\epsilon = 1.6$). As expected, labor mobility costs substantially hamper the reallocation of labor away from the traded sector. More specifically, as shown in the first row of panel B, labor mobility costs almost halve the fall in the labor share of tradables, i.e., $d\nu^{L,H}(0) = -0.12\%$ instead of -0.22% in a model imposing perfect mobility of labor. However, the decline in $\nu^{L,H}(0)$ is still three time larger to what is estimated empirically. The reason is that keeping P^H fixed leads the model to overstate the demand boom for non-tradables, as reflected in an appreciation in the relative price of non-tradables by 1.1% above what is estimated empirically (0.99% in the data, see the first row of panel C of Table 1). Because the model imposing $\rho \to \infty$ overstates the shift of

Table 1: Impact and Long-Run Effects of a 1% Permanent Increase in Traded Relative to Non-Traded TFP

	VAR ($t=0$)	Impact ($t=0$) Theoretical Responses					VAR ($t=10$)	Long-run ($t=10$) Theoretical Responses				
	Data	Bench	HNTC	FK-IML	FK-PML	Subst.	Data	Bench	HNTC	FK-IML	FK-PML	Subst.
		FBTC	$\hat{A}^j(t)=\hat{B}^j(t))$	$(\rho\to\infty)$	$(\epsilon\to\infty)$	$(\phi=1.2)$		FBTC	$\hat{A}^j(t)=\hat{B}^j(t)$	$(\rho\to\infty)$	$(\epsilon\to\infty)$	$(\phi=1.2)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Labor and VA												
Traded labor, $dL^H(t)$	-0.01	-0.00	-0.03	-0.10	-0.23	0.03	0.01	0.01	-0.02	-0.02	-0.06	0.05
Non-traded labor, $dL^N(t)$	0.10	0.11	0.12	0.14	0.21	0.05	0.15	0.15	0.13	0.15	0.18	0.06
Traded value added, $dY^H(t)$	0.24	0.22	0.22	0.14	0.05	0.32	0.27	0.27	0.28	0.29	0.27	0.39
Non-traded value added, $dY^N(t)$	0.01	0.01	0.00	0.06	0.11	-0.07	0.06	0.02	0.03	0.07	0.09	-0.04
B. Labor Reallocation												
Labor share of tradables, $d\nu^{L,H}(t)$	-0.04	-0.04	-0.06	-0.12	-0.22	0.00	-0.05	-0.05	-0.06	-0.07	-0.10	0.01
Output share of tradables, $d\nu^{Y,H}(t)$	0.13	0.13	0.13	0.06	-0.01	0.21	0.14	0.16	0.16	0.15	0.13	0.25
Non-traded wage, $\left(\hat{W}^N(t)-\hat{W}(t)\right)$	0.01	0.04	0.06	0.12	0.00	0.00	0.06	0.04	0.06	0.07	0.00	-0.00
Traded wage, $\left(\hat{W}^H(t)-\hat{W}(t)\right)$	-0.02	-0.07	-0.11	-0.20	0.00	0.00	-0.12	-0.07	-0.11	-0.11	-0.00	0.00
C. Relative Prices												
Relative price of non-trad., $\hat{P}(t)$	0.99	0.97	1.00	1.10	0.90	0.89	1.06	1.08	1.10	1.11	0.99	0.97
Terms of trade, $\hat{P}^H(t)$	-0.41	-0.27	-0.29	0.00	0.00	-0.37	-0.44	-0.37	-0.40	0.00	0.00	-0.47
D. FBTC and LISs												
Traded FBTC	0.50	0.51	0.00	0.00	0.00	0.00	0.58	0.58	0.00	0.00	0.00	0.00
Non-Traded FBTC	0.07	0.11	0.00	0.00	0.00	0.00	0.36	0.36	0.00	0.00	0.00	0.00
Traded capital-labor, $dk^H(t)$	-0.08	-0.13	-0.06	-0.03	-0.08	-0.04	-0.14	-0.12	-0.02	0.01	-0.02	0.00
Non-traded capital-labor, $dk^N(t)$	-0.01	0.03	-0.01	-0.04	0.07	-0.05	-0.04	-0.04	0.03	0.01	0.07	-0.01
Traded LIS, $ds_L^H(t)$	0.09	0.08	-0.01	0.00	0.00	-0.01	0.10	0.10	-0.01	0.00	0.00	0.00
Non-traded LIS, $ds_L^N(t)$	0.01	0.02	-0.00	0.00	0.00	-0.01	0.07	0.07	0.00	0.00	0.00	-0.00

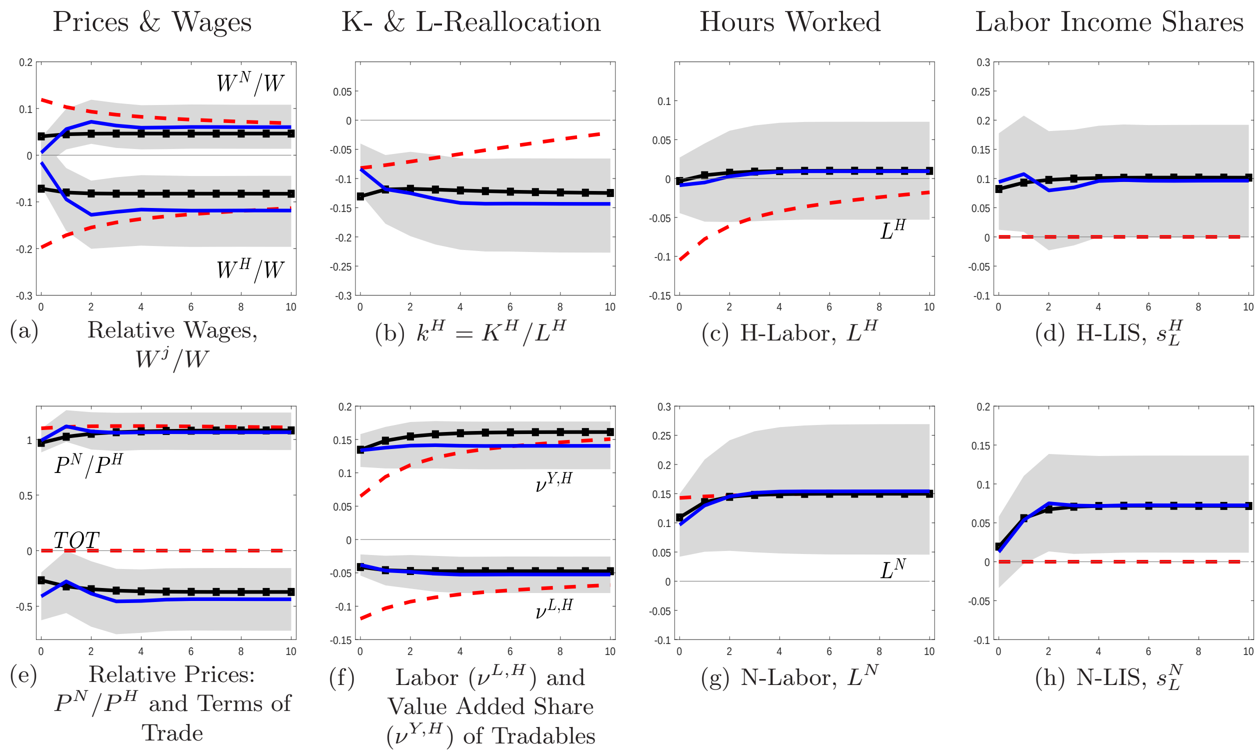
Notes: Impact ($t=0$) and long-run ($t=10$) effects of a 1% permanent increase in traded relative to non-traded TFP. Panels A,B,C,D show the deviation in percentage relative to steady-state for sectoral variables. Panel A shows the effects on sectoral sectoral hours worked and sectoral value added while panel B displays the responses of the labor share and value added share of tradables together with changes in sectoral wages relative to the aggregate wage. Panel C shows the responses of the relative price of non-tradables and the terms of trade. Panel D displays FBTC, changes in sectoral capital-labor ratios and sectoral LISs. Responses of relative wages and relative prices are percentage deviation from initial steady-state (denoted with a hat). Sectoral value added and value added share are expressed in percent of initial GDP while sectoral labor and labor shares are expressed in percent of initial total hours worked; changes in capital-labor ratios are expressed in percent of the aggregate stock of capital while responses of sectoral LISs are measured in percent of value added of the corresponding sector. In columns 3-6 and 9-12, we consider restricted versions of our baseline model, results of which are shown in columns 2 and 8. 'FK-PML' refers to the small open economy model by Fernández de Córdoba and Kehoe [2000] with tradables and non-tradables, capital adjustment costs and perfect mobility of labor (we let the elasticity of labor supply across sectors tend toward infinity and assume that home-produced and foreign-produced traded goods are perfect substitutes). 'FK-IML' corresponds to the FK model augmented with imperfect mobility of labor across sectors (we set $\epsilon=1.6$ while keeping $\rho=\rho_J\to\infty$ so that terms of trade remain fixed). 'HNTC' refers to a semi-small open economy model with endogenous terms of trade, labor mobility costs, CES production functions while imposing Hicks-neutral technological change (i.e., $\hat{A}^j(t)=\hat{B}^j(t)$). In columns 6 and 12, we consider the same model as 'HNTC' and set ϕ to 1.2 instead of 0.44 to shut down labor reallocation across sectors. In our baseline calibration (labelled 'Bench' in columns 2 and 8), we set $\epsilon=1.6$, $\phi=0.44$, $\sigma_L=1.6$, $\kappa=17$, $\rho=\rho_J=1.5$, $\phi_X=1.7$, $\sigma^H=0.69$, $\sigma^N=0.72$ and allow for labor- and capital-augmenting technological change inferred from (38a)-(38b).

labor between sectors, it considerably understates the rise in traded value added (see the third row of panel A of Table 1) and thus the increase in the value added share of tradables (see the second row of panel B of Table 1, i.e., $d\nu^{Y,H}(0)$).

Restricted model: HNTC. In columns 3 and 9 of Table 1, we consider a model with endogenous terms of trade and labor mobility costs together with CES production functions. While the latter ingredient has no impact on results because we impose HNTC, the combination of the adjustment in the relative price of home-produced traded goods and imperfect mobility of labor improves the performance of the model. Overall, on impact, the model assuming HNTC performs as well as the baseline model, except for the reallocation of labor and the responses of LISs. To have a clearer picture of the performance of the model imposing HNTC, it is useful to start with the redistributive effects shown in panel D of Table 1. Contrasting the long-run responses for k^j and s_L^j (column 9) with responses estimated empirically (column 7) reveals that a model assuming HNTC significantly overstates the demand for capital in both sectors (e.g., $\hat{k}^H = -0.02\%$ instead of -0.14% in the data). The decline in k^H drives down the traded LIS in contradiction with our evidence which reveals that s_L^H increases by 0.10%. Conversely, by allowing for technological change biased toward labor, as captured by a rise in $\left(B^j(t)/A^j(t)\right)^{\frac{1-\sigma^j}{\sigma^j}}$ (see the first two rows of panel D), the baseline model can generate an increase in sectoral LISs (see columns 2 and 8) in line with our estimates. The model imposing HNTC also overstates the fall in the labor share of tradables, as can be seen in columns 3 and 9 of Table 1 (see the first row of panel B, i.e., $d\nu^{L,H}$). Conversely, because $\text{FBTC}^H(t) > \text{FBTC}^N(t)$ has a positive impact on tradable hiring which hampers the movement of labor toward the non-traded sector, the decline in $\nu^{L,H}(t)$ predicted by the baseline model squares well with the evidence.

Dynamics. While in Table 1, we restrict our attention to impact and long-run responses, in Fig. 7, we contrast theoretical (displayed by solid black lines with squares) with empirical (displayed by solid blue lines) dynamic responses. In each panel, the responses display the point estimate of the VAR model, with the shaded area indicating the 90% confidence bounds. We also contrast theoretical responses from the baseline model with the predictions of the Fernández de Córdoba and Kehoe [2000] model which includes frictions in factor mobility between sectors (generated by capital adjustment as well as labor mobility costs). The results for the FK model which shuts down the terms of trade channel and imposes HNTC are shown in dashed red lines.

By abstracting from endogenous terms of trade and FBTC, the restricted (i.e., FK) model fails to account for the evidence along a number of dimensions. It overpredicts the wage differential, understates the decline in the traded capital-labor ratio, overstates the decline in the labor share of tradables and as displayed by the last column, it cannot account for the rise in sectoral LISs.



(a) Relative Wages, W^j/W (b) $k^H = K^H/L^H$ (c) H-Labor, L^H (d) H-LIS, s_L^H

(e) Relative Prices: P^N/P^H and Terms of Trade (f) Labor ($\nu^{L,H}$) and Value Added Share ($\nu^{Y,H}$) of Tradables (g) N-Labor, L^N (h) N-LIS, s_L^N

Figure 7: Sectoral Effects of a Permanent Technology Shock Biased Toward Tradables: Model vs. Data. Notes: Solid blue lines display point estimates of VAR model with shaded area indicating 90% confidence bounds; solid black lines with squares display baseline model predictions, i.e., when we allow for IML ($\epsilon = 1.6$), endogenous terms of trade ($\rho = \rho_J = 1.5$), gross complementarity between capital and labor in production (i.e., $\sigma^H = 0.687$, $\sigma^N = 0.716$), and technological change biased toward labor, i.e., $\text{FBTC}^H = 0.58\%$ and $\text{FBTC}^N = 0.36\%$ in the long-run; dashed red lines show predictions of a restricted model where terms of trade are exogenous and technological change is Hicks-neutral.

The performance of the model increases once we allow for endogenous terms of trade, CES production functions together with FBTC. As shown by the solid black line with squares in Fig. 7, the dynamics of relative prices and the sectoral wage differential which materializes after one year are captured fairly well by the baseline model (see the first column). The increase in the productivity differential over time further appreciates the relative price of non-tradables, P^N/P^H, and amplifies the terms of trade deterioration. The time-increasing appreciation in P^N/P^H has an expansionary effect on L^N as displayed by Fig. 7(g) while L^H remains unresponsive (see Fig. 7(c)). Despite the fact that labor keeps on shifting toward the non-traded sector as can be seen in the lower part of Fig. 7(f), the rise in the productivity of tradables prevents the value added share of tradables, $\nu^{Y,H}$, from declining (see the upper part of Fig. 7(f)).

As can be seen in Fig. 7(d) and Fig. 7(h), the combined effect of the rise in capital relative to labor efficiency and the gross complementarity between capital and labor in production generates an increase in sectoral LISs whilst Fig. 7(b) shows that the decline in k^H is amplified in line with the evidence. In Online Appendix I, we contrast the model predictions with empirical estimates for k^N. Whilst it misses the decline in k^N on impact, the baseline model gives rise to a declining path for k^N driven by technology change biased toward labor, in accordance with the evidence.

4.4 Sensitivity Analysis and Extensions

In this subsection, we explore the role of financial openness for asymmetric technology shocks, summarize the main findings of the sensitivity analysis we have conducted w.r.t. preferences' assumptions and the reliability of empirical IRFs, and discuss how the increasing importance of asymmetric technology shocks could modify the response of total hours worked to aggregate technology shocks.

Implications of financial openness. In columns 6 and 12 of Table 1, we consider the same model with HNTC as in columns 3 and 9, and set the elasticity of substitution between traded and non-traded goods, ϕ, to 1.2 instead of 0.44. This value is such that the labor share of tradables, $\nu^{L,H}$, remains unchanged on impact, as can be seen in the first row of panel B, and thus there is no labor reallocation between the two sectors. Interestingly, this threshold value of 1.2 for ϕ is higher than the value of 1 in a closed economy setup, see e.g., Ngai and Pissarides [2007]. As demonstrated analytically in the Online Appendix O.1, this threshold value of 1 also holds in an open economy setup without capital since the net foreign asset position remains fixed so that $\nu^{L,H}$ increases only when ϕ is above one. By contrast, in an open economy setup with capital accumulation, the threshold value for ϕ is higher. Intuitively, access to foreign borrowing allows households to increase consumption and to avoid a large increase in labor supply which amplifies the excess demand for non-traded goods because traded goods can be imported. The current account deficit thus amplifies the reallocation of labor toward the non-traded sector. Note that we impose HNTC in columns 6 and 12 to shut down the effect of FBTC and thus to isolate the pure effect caused by financial openness.

Robustness to preferences' assumptions. In Online Appendix U.2-U.4, we conduct a robustness check with respect to preferences' assumptions, i.e., we re-estimate the dynamic effects of a permanent increase in traded relative to non-traded TFP by considering the preferences proposed by Greenwood et al. [1988] (GHH thereafter) which eliminate the wealth effect (from labor supply), by allowing for non-separability in preferences between consumption and leisure in the lines of Shimer [2009], by allowing for external habits (which generate time non separability in preferences) in the lines of Carroll et al. [2000] in addition to non-separability between consumption and leisure. We find that a model assuming GHH [1988] preferences performs as well as our model with MaCurdy [1981] preferences as long as we assume a low value for the Frisch elasticity of labor supply for GHH preferences because these preferences eliminate the wealth effect and make labor supply more elastic to the technology shock. Conversely, the performance of a model assuming Shimer [2009] preferences augmented or not with external habits is lower than the performance of our baseline model. The reason is that the coefficient of relative risk aversion collapses to the parameter determining the substitutability between consumption and leisure. When we allow consumption and leisure to be gross substitutes, the IES for consumption is low so that the wealth effect exerts a strong negative impact on hours worked.

Further investigation of reliability of empirical IRFs. The SVAR critique questions the reliability of empirical IRFs generated from the estimation of the VAR model which in turn casts doubt on the performance of the model. As stressed by Christiano et al. [2006], the identification of temporary technology shocks is not subject to biases. In Online Appendix U.6, we estimate empirically the dynamic effects of a temporary shock shock to aggregate TFP and contrast them with the baseline model's predictions. We find that the baseline model with the same calibration as that described in section 4.1 can account for the empirical IRFs we generate following a temporary aggregate technology shock. Not only does it mean that the model is validated by the data, it also means that the empirical IRFs obtained from long-run restrictions in section 2 are unbiased because they fit the theoretical responses of the model.

Implications for the response of total hours worked to aggregate technology shocks. We view our analysis of asymmetric technology shocks across sectors as a step toward a better understanding of the labor market effects of aggregate technology shocks which are a combination of symmetric and asymmetric technology shocks across sectors. By generating an expansionary effect on hiring in the non-traded sector which accounts for two-thirds of labor, asymmetric technology shocks have a positive impact on total hours worked and all the more so in countries where sectoral technological change is biased toward labor. Conversely, symmetric technology shocks have a negative impact on total hours worked through two channels. By giving rise to a fall in non-traded prices which lowers labor demand in the non-traded sector (because $\phi < 1$), symmetric technology shocks exert a negative impact on total hours worked. In addition, technological change is biased toward capital in both sectors following symmetric technology shocks, as evidence documented in Online Appendix U.9 shows, which amplifies the negative impact on $L(t)$. When we compute numerically the effects of a 1% permanent increase in aggregate TFP, see Online Appendix U.9, we find that the response of total hours worked increases as asymmetric technology shocks account for a greater share of the variations in aggregate TFP. The growing importance of asymmetric technology shocks could therefore rationalize the time-increasing response of total hours worked to aggregate technology shocks, as documented empirically by Galí and Gambetti [2009], and Cantore et al. [2017].

4.5 Redistributive and Reallocation Effects across Countries: Model vs. Data

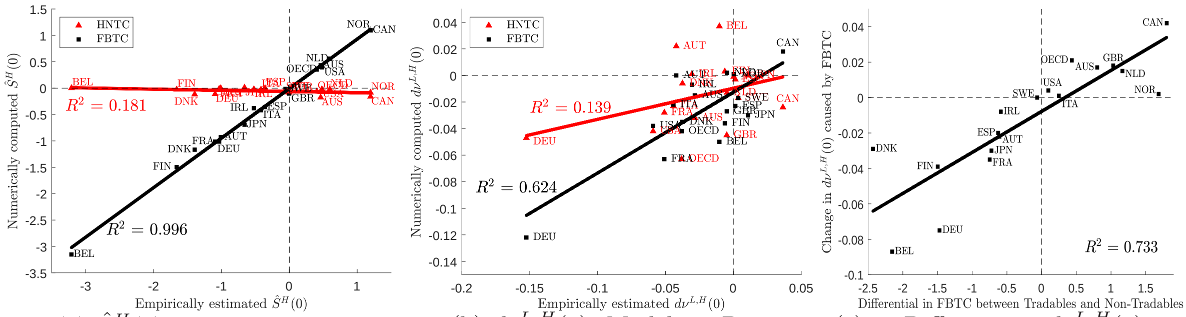
We now move a step further and calibrate our model to country-specific data. Our objective is to assess the ability of our baseline model to account for the cross-country dispersion in the reallocation and redistributive effects we estimate empirically by shedding some light on the role of FBTC.

Calibration to country-specific data. To conduct this analysis, we calibrate our model to match key ratios of the 17 OECD economies in our sample, as summarized in Table 6 in Online Appendix L.1, while ϵ, ϕ, σ^j, ϕ_X, ρ, ρ_J, are set in accordance with estimates shown in the last seven columns of Table 6. The remaining parameters, i.e., σ_L, σ_C, ϕ_J, κ take the same values as those summarized in Table 7 in Online Appendix L.1. As discussed in subsection 4.1, we consider the initial steady-state with Cobb-Douglas production functions as the normalization point and calibrate the reference model to the data. Next exogenous parameters in the CES economy are endogenously calibrated to replicate the ratios targeted in the Cobb-Douglas economy.

To compute FBTC for each country, we proceed as in subsection 4.2 except that to estimate (38a)-(38b), we use country-specific estimates of σ^j and country-specific estimated responses of $s_L^j(t)$, $k^j(t)$, $Z^j(t)$. Once we have recovered time series for FBTC in sector $j = H, N$ for each country, we choose parameters $\bar{a}^j$ and $\bar{b}^j$ by setting $t = 0$ into (31) and we choose parameter ξ^j by choosing time t in eq. (32) which gives the best fit of sectoral TFP dynamics to the data. Once the model is calibrated, we estimate numerically the effects of a 1% permanent increase in traded relative to non-traded TFP.

Redistributive effects across countries. We first assess the ability of the model to account for the cross-country dispersion in the responses of LISs we estimate empirically. In the first column of Fig 8, we plot impact responses of the ratio of factor income shares in the traded sector, S^H, we compute numerically (vertical axis) against impact responses of S^H we estimate empirically (horizontal axis). To have a sense of the importance of FBTC in driving the cross-country redistributive effects, we contrast the model predictions when we impose HNTC which are displayed by red triangles with the model predictions when assuming FBTC shown in black squares. It is worth mentioning that $\hat{S}^j(t) = \frac{\hat{s}_L^j(t)}{1-s_L^j}$ and thus the response of S^j is similar to that of the LIS which is scaled by the capital income share. As it stands out, a model imposing HNTC cannot account for international differences in the responses of sectoral LISs. Intuitively, the shifts of capital between sectors generated by a model imposing HNTC are not large enough on their own to reproduce the cross-country dispersion in the responses of LISs. Conversely, by influencing sectoral LISs directly and indirectly through the shifts of capital, the baseline model with FBTC is able to generate a wide cross-country dispersion in the responses of LISs which fits well the data as the correlation between model predictions and the data is 0.99 for the traded sector. A similar conclusion is reached for the non-traded sector relegated to the Online Appendix I.

Reallocation effects across countries. In the second column of Fig. 8, we plot impact responses of the labor share of tradables we compute numerically (vertical axis) against impact responses of the same variable we estimate empirically (horizontal axis).



(a) $\hat{S}^H(0)$: Model vs. Data (b) $d\nu^{L,H}(0)$: Model vs. Data (c) Difference in $d\nu^{L,H}(0)$ caused by FBTC

Figure 8: Cross-Country Relationships under FBTC and HNTC Hypothesis: Model vs. Data. Notes: The first two columns of Fig. 8 plot impact responses of the traded LIS and labor share of tradables computed numerically (vertical axis) against the responses of the corresponding variables estimated empirically (horizontal axis). In each panel, we contrast the predictions from a model imposing HNTC shown in red triangles with the predictions of the baseline model assuming FBTC shown in black squares. The red trend line shows the fit of the model to the data when imposing HNTC while the black trend line shows the fit of the model to the data when assuming FBTC. The last column plots the change in labor reallocation caused by sector differences in FBTC (vertical axis) against the differential in FBTC between tradables and non-tradables (horizontal axis) on impact and in the long-run, respectively.

Black squares show model predictions when we allow for FBTC while red triangles show model predictions when we impose HNTC. The red trend line shows the fit of the model to the data when imposing HNTC and the black trend line shows the model fit when we assume FBTC. As is evident from trend lines, the ability of the model to account for the cross-country dispersion in the responses of $\nu^{L,H}$ is higher when we allow for FBTC (as shown in the black trend line). The correlation between numerical and empirical estimates stands at 0.79 with FBTC and falls to 0.38 when we shut down this feature. Intuitively, a sectoral differential in FBTC modifies sectoral labor demand and thus either amplifies or mitigates the shift of labor across sectors in a way that increases the ability of the baseline model to account for the cross-country dispersion in the reallocation effects. One most prominent example is Germany which experiences technological change biased toward capital in the traded sector and technological change biased toward labor in the non-traded sector. The former lowers labor demand in the traded sector while the latter stimulates labor demand in the non-traded sector. The shift of labor toward the non-traded sector is thus amplified which allows the baseline model to generate a decline in $\nu^{L,H}$ by 0.12% close to our estimates (i.e., -0.15%). Conversely, a model imposing HNTC produces a decline in $\nu^{L,H}$ which is more than three times smaller to what we estimate empirically.

Reduction or amplification of labor reallocation caused by sector differences in FBTC. The differential in FBTC between tradables and non-tradables varies considerably across countries and influences the shift of labor across sectors. To give a sense of the variation of labor reallocation caused by sector differences in FBTC, we compute the difference in the change in the labor share of tradables, $d\nu^{L,H}(t)$, between the baseline model assuming FBTC and a model imposing HNTC. Fig. 8(c) plots the change in $\nu^{L,H}(t)$ caused by sector differences in FBTC (vertical axis) against the differential in FBTC between tradables and non-tradables (horizontal axis) on impact. For countries which lie in the north-east, technological change is more biased toward labor in the traded than the non-traded sector (i.e., $\text{FBTC}^H - \text{FBTC}^N > 0$) which in turn exerts a positive impact on $\nu^{L,H}$ and thus reduces labor reallocation toward the non-traded sector (compared with a model imposing HNTC). The reduction in labor reallocation toward the non-traded sector averages 0.012% of total hours worked which represents 42% of the cross-country average labor reallocation. Conversely, for countries which lie in the south-west, technological change is more biased toward labor in the non-traded than in the traded sector (i.e., $\text{FBTC}^H - \text{FBTC}^N < 0$). For these economies, the decline in the labor share of tradables doubles because technology makes non-traded production more labor intensive and tilts labor demand toward the non-traded sector.

5 Conclusion

Motivated by the evidence documented by Foerster et al. [2011] and Garìn et al. [2018], we explore the labor market effects caused by asymmetric technology shocks across sectors in an open economy setup. To conduct this analysis, we use a panel of 17 OECD countries over 1970-2013 and adopt the identification approach of technology shocks proposed by Galí [1999]. Since we consider an open economy, we differentiate between a traded and a non-traded sector. When we estimate the effects of a technology shock which increases permanently traded relative to non-traded TFP, our evidence reveals that the non-traded sector alone drives total hours worked growth; 35% of the rise in non-traded hours worked is attributable to the reallocation of labor on average which lowers the labor share of tradables by 0.05 percentage point of total hours worked.

To rationalize our VAR evidence, we put forward an open economy version of the neoclassical model with tradables and non-tradables. Our quantitative analysis reveals that the low substitutability between traded and non-traded goods in consumption and financial openness leads the model to substantially overstate the decline in the labor share of tradables. To account for the magnitude of the reallocation effects we document empirically, we consider three key elements. Like Kehoe and Ruhl [2009], we allow for endogenous terms of trade. Since domestically and foreign-produced traded goods are gross substitutes, the terms of trade deterioration stimulates hiring in the traded sector and thus curbs the shift of labor toward the non-traded sector. The second element is labor mobility costs which strengthen the terms of trade channel by further hampering labor reallocation.

We put forward FBTC as a third key ingredient. Adapting the methodology of Caselli and Coleman [2006] to our setup, we use the demand of inputs and our estimates of the elasticity of substitution between capital and labor to construct time series for FBTC. Our VAR estimates reveal that technological change is biased toward labor in both sectors following a shock to traded relative to non-traded TFP which is consistent with the rise in sectoral LISs we find in the data. Once we include the three aforementioned elements, the model reproduces well the labor market effects we estimate empirically for the whole sample.

Taking advantage of the panel data dimension of our sample, we detect empirically a strong and positive cross-country relationship between the responses of sectoral LISs and factor-biased technological shifts. When focusing on the reallocation effects, we find empirically that countries where technological change is more biased toward labor in the traded than the non-traded sector experience a smaller decline in the labor share of tradables. When we calibrate the model to country-specific data, our model can account for the cross-country redistributive and reallocation effects we estimate empirically once we let FBTC vary across sectors and between countries.

In this work, we exclusively focus on a permanent increase in traded relative to non-traded TFP and restrict our attention to its sectoral composition effects. A fruitful extension of our analysis would be to analyze the effects of aggregate TFP shocks driven by both symmetric and asymmetric technology shocks across sectors in the same spirit as Garìn et al. [2018]. As mentioned at the end of section 4.4, the growing importance of asymmetric technology shocks (relative to symmetric technology shocks) over time could rationalize the time-increasing correlation between labor growth and productivity growth, a finding documented by Galí and Gambetti [2009], and Cantore et al. [2017].

While in our paper, we restrict attention to industrialized countries, emerging countries also experience technological change biased toward the traded sector, see e.g., Rodrik [2013]. When we extend our analysis to emerging countries, our preliminary results confirm that labor shifts toward the non-traded sector following a permanent rise in traded relative to non-traded productivity whereas the relative price of non-tradables merely appreciates or even falls in Latin American countries.[15] This result is puzzling because the shift of labor toward the non-traded sector is driven by the appreciation in the relative price of non-tradables. One potential explanation to this puzzle lies in the international transmission of technology shocks, see e.g., Miyamoto and Nguyen [2017] who find that U.S. technology shocks appreciate the terms of trade in Canada and thus should potentially mitigate the appreciation in the relative price of non-tradables. Because our model treats the rest of the world as exogenous, extending our framework to a two-country model would be a fruitful avenue for future research to rationalize the effects of technology shocks in Latin American countries.

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[15]Results for emerging countries can be found in Online Appendix V.

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A Labor Share and Relative Productivity: Empirical Facts for Selected Countries

While in the introduction of the main text, we restrict attention to our sample of seventeen OECD countries by considering the unweighted sum of time series of the labor share and the relative productivity, in this subsection, we show evidence for selected OECD countries as well as for the whole sample when sectoral TFPs and the labor share of tradables are calculated as the working age population weighted sum of the seventeen OECD countries

As a result of the importance of asymmetric shocks for economic fluctuations during the great moderation, we expect cyclical components of the relative productivity of tradables and the traded goods-sector share of total hours worked to be more correlated over the post-1984 period than from 1970 to 1983 for the United States. To explore this hypothesis, we plot in Fig. 9(a) the detrended (logged) ratio of traded to non-traded TFP (displayed by the blue line) and the detrended labor share of tradables (displayed by the black line) for the United States. The correlation is essentially zero over 1970-1983 and stands at -0.67 from 1984 to 2013. The United Kingdom for which the great moderation occurs in the post-1992 period, see Benati [2008], has also experienced a sharp increase (in absolute terms) in the correlation between the relative productivity and the labor share of tradables which has doubled, passing from -0.38 from 1970-1992 to -0.76 over the post-1992 period. As can be seen in Fig. 9(c), the pre-financial crisis period is characterized by an acceleration in technological change concentrated in traded industries and a fall in the labor share of tradables while the other way around is true after 2008. Like the U.K, a reallocation of labor toward the traded sector accompanies the fall in the relative productivity of tradables in Ireland and Spain in the aftermath of the financial crisis, as can be seen in Fig. 9(d) and Fig. 9(e). The growing importance of asymmetric technology shocks across sectors and the subsequent shift of labor between industries is not limited to the aforementioned countries. For the whole sample shown in Fig. 9(b), the correlation between the relative productivity and the labor share of tradables is 0.23 over 1973-1992 and stands at -0.58 from 1993 to 2013.

B Identification of Technology Shocks

In this section we detail the identification strategy of technology shocks biased toward the traded sector. We also provide a short survey of the literature and motivate the choice of our method described below.

Empirical identification of permanent shocks to traded relative to non-traded TFP. To explore empirically the dynamic effects of a shock to the relative productivity of tradables, we consider a vector of n observables $\hat{X}_{it} = [\hat{Z}_{it}, \hat{V}_{it}]$ where $\hat{Z}_{it}$ consists of the first difference of the (logarithm of the) ratio of traded to non-traded TFP (as defined in eq. (4)) and $\hat{V}_{it}$ denotes the $n-1$ variables of interest (in growth rate) detailed later. Let us consider the following reduced form of the VAR(p) model:

$$C(L)\hat{X}_{it} = \eta_{it}, \tag{40}$$

where $C(L) = I_n - \sum_{k=1}^{p} C_k L^k$ is a p-order lag polynomial and η_{it} is a vector of reduced-form innovations with a variance-covariance matrix given by Σ. We estimate the reduced form of the VAR model by panel OLS regression with country and time fixed effects which are omitted in (40) for expositional convenience. The matrices C_k and Σ are assumed to be invariant across time and countries and all VARs have two lags. The vector of orthogonal structural shocks $\varepsilon_{it} = [\varepsilon^Z_{it}, \varepsilon^V_{it}]$ is related to the vector of reduced form residuals η_{it} through:

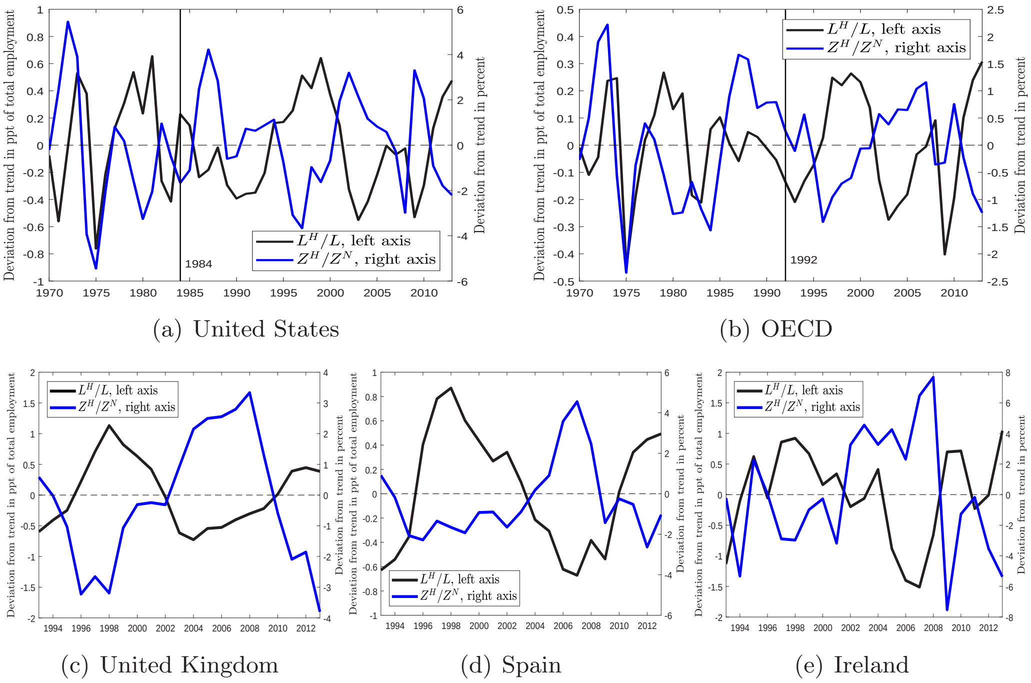
$$\eta_{it} = A_0 \varepsilon_{it}, \tag{41}$$

which implies $\Sigma = A_0 A_0'$ with A_0 the matrix that describes the instantaneous effects of structural shocks on observables. The linear mapping between the reduced-form innovations and structural shocks leads to the structural moving average representation of the VAR model:

$$\hat{X}_{it} = B(L) A_0 \varepsilon_{it}, \tag{42}$$

where $B(L) = C(L)^{-1}$. Let us denote $A(L) = B(L)A_0$ with $A(L) = \sum_{k=0}^{\infty} A_k L^k$. To identify shocks to the productivity differential, ε^Z_{it}, we use the restriction that the unit root in the ratio of sectoral TFPs originates exclusively from technology shocks biased toward the traded sector which implies that the upper triangular elements of the long-run cumulative matrix $A(1) = B(1)A_0$ must be zero. Once the reduced form has been estimated using OLS, structural shocks can then be recovered from $\varepsilon_{it} = A(1)^{-1} B(1) \eta_{it}$ where the matrix $A(1)$ is computed as the Cholesky decomposition of $B(1)\Sigma B(1)'$.

Brief survey of the literature. While we adopt the identification of permanent technology shocks pioneered by Gali [1999], and assume that per capita hours worked enter the VAR model



(a) United States (b) OECD

(c) United Kingdom (d) Spain (e) Ireland

Figure 9: Relative Productivity and Labor Share of Tradables (1970-2013/1993-2013). Notes: In Fig. 9, we plot the detrended ratio of TFP of tradables to TFP of non-tradables (or the relative productivity of tradables) shown in the blue line, against the detrended labor share of tradables shown in the black line. TFP of tradables, Z_t^H, and TFP of non-tradables, Z_t^N, are the Solow residuals. The labor share of tradables is calculated as the ratio of hours worked in the traded sector to total hours worked. Detrended relative productivity of tradables is computed as the difference between the logarithm of actual time series for Z_t^H/Z_t^N and the trend of (logged) relative productivity of tradables. The trend of logged relative productivity of tradables is obtained by applying a Hodrick-Prescott filter with a smoothing parameter of $\lambda = 100$ (as we use annual data) to the (logged) time series Z_t^H/Z_t^N. Detrended labor share of tradables is computed as the difference between actual time series for L_t^H/L_t and the trend of the labor share of tradables, the latter being obtained by applying a Hodrick-Prescott filter with a smoothing parameter of $\lambda = 100$. Sample: United States, United Kingdom, Ireland, Spain. For the last three economies, we restrict attention to the period 1993-2013 as the great moderation starts in the post-1992 period in European countries, see González Cabanillas and Ruscher [2008]. Fig. 9(b) plots detrended relative productivity of tradables and detrended labor share of tradables for the whole sample where sectoral TFPs and the labor share of tradables are calculated as the working age population weighted sum of the seventeen OECD countries. Sample: 17 OECD countries, 1970-2013, annual data.

in growth rate, Christiano, Eichenbaum, and Vigfusson [2004] argue in favor of using per capita hours in log-levels rather than in growth rates and find the opposite to Gali's result, say hours worked rise after a positive technology shock. We conducted unit root tests in panel data and find that all variables entering the VAR model are integrated of order one, see Technical Appendix N.1. Several papers have questioned Galí's identifying assumption that technology shocks are the only shocks that increase permanently labor productivity. First, Mertens and Ravn [2011] find that permanent changes in income tax rates induce permanent changes in hours worked as well as in labor productivity which leads to a violation of the standard long-run identification strategy for technology shocks. Second, Francis, Owyang, Rousch, DiCecio [2014] identify the technology shock as the one associated with the maximum forecast-error variance share in labor productivity at a long, finite horizon, and find that hours worked decline. One advantage of this method is that it lets other shocks influence labor productivity after a certain horizon of time. Like Chang and Hong [2006], we measure technological change with TFP and this measure should mitigate the effects of other shocks. Finally, Basu, Fernald and Kimball [2006] find that when technology improves, utilization falls so that TFP initially rises less than technology does. The authors construct a measure of aggregate technological change controlling for varying utilization of capital and labor. While in the main text, we measure technology change with the Solow residual, we alternatively constructed time series for utilization-adjusted-sectoral-TFPs, as recommended by Basu et al. [2006], by adapting the methodology proposed by Imbs [1999]. As shown in Online Appendix T.5, our results are little sensitive to the correction of sectoral TFPs with the (sectoral) capital utilization rate.

C Sectoral Decomposition of Aggregate TFP

We consider an open economy which produces domestic traded goods, denoted by a superscript H, and non-traded goods, denoted by a superscript N. The foreign-produced traded good is the numeraire and its price is normalized to 1. We consider an initial steady-state where prices are those at the base year so that initially real GDP, denoted by Y_R, and the value added share at constant prices, denoted by $\nu^{Y,j}$, collapse to nominal GDP (i.e., Y) and the value added share at current prices, respectively.

Summing value added at constant prices across sectors gives real GDP:

$$Y_{R,t} = P^H Y_t^H + P^N Y_t^N, \tag{43}$$

where P^H and P^N stand for the price of home-produced traded goods and non-traded goods, respectively, which are kept fixed since we consider value added at constant prices.

Log-linearizing (43), and denoting the percentage deviation from initial steady-state by a hat leads to:

$$\hat{Y}_{R,t} = \nu^{Y,H}\hat{Y}_t^H + \left(1-\nu^{Y,H}\right)\hat{Y}_t^N, \tag{44}$$

where $\nu^{Y,H} = \frac{P^H Y^H}{Y}$ is the value added share of home-produced traded goods evaluated at the initial steady-state. We drop the time index below as long as it does not cause confusion.

Capital K^j can be freely reallocated across sectors while labor L^j is subject to mobility costs which creates a sectoral wage differential. We denote the capital rental cost by R and the wage rate in sector j by W^j (with $j = H, N$). Under assumption of perfect competition in product and input markets, factors of production are paid their marginal product in both sectors:

$$P^j \frac{\partial Y^j}{\partial L^j} = W^j, \tag{45a}$$

$$P^j \frac{\partial Y^j}{\partial K^j} = R. \tag{45b}$$

Assuming constant returns to scale in production and making use of (45), the log-linearized version of the production function reads:

$$\hat{Y}^j = \hat{Z}^j + s_L^j \hat{L}^j + \left(1-s_L^j\right)\hat{K}^j, \tag{46}$$

where s_L^j and Z^j are the labor income share and TFP in sector j, respectively.

Using the fact that $WL = W^H L^H + W^N L^N$, and $RK = RK^H + RK^N$, dividing both sides of these identities by GDP enables us to express the aggregate labor income share, s_L, and capital income share, $1-s_L$, as a weighted sum of sectoral factor income shares:

$$s_L = \nu^{Y,H} s_L^H + \left(1-\nu^{Y,H}\right) s_L^N, \tag{47a}$$

$$1-s_L = \nu^{Y,H}\left(1-s_L^H\right) + \left(1-\nu^{Y,H}\right)\left(1-s_L^N\right). \tag{47b}$$

Since we assume perfect capital mobility, the resource constraint for capital reads as follows $K = K^H + K^N$. Totally differentiating, multiplying both sides by the capital rental cost R, and dividing by GDP leads to:

$$\left(1 - s_L\right) \hat{K} = \nu^{Y,H} \left(1 - s_L^H\right) \hat{K}^H + \left(1 - \nu^{Y,H}\right) \left(1 - s_L^N\right) \hat{K}^N. \tag{48}$$

The same logic applies to labor except that we assume imperfect mobility of labor across sectors. In this case, the percentage deviation of total hours worked relative to its initial steady-state is defined as the weighted sum of the percentage deviation of sectoral hours worked relative to initial steady-state, i.e., $\hat{L} = \alpha_L \hat{L}^H + (1 - \alpha_L) \hat{L}^N$, where $\alpha_L = \frac{W^H L^H}{WL}$ is the labor compensation share for tradables. Multiplying both sides by total compensation of employees, WL, and dividing by GDP leads to:

$$s_L \hat{L} = \nu^{Y,H} s_L^H \hat{L}^H + \left(1 - \nu^{Y,H}\right) s_L^N \hat{L}^N. \tag{49}$$

Inserting (46) into (44):

$$\begin{aligned} \hat{Y}_R \quad = \quad & \left[\nu^{Y,H} \hat{Z}^H + \left(1 - \nu^{Y,H}\right) \hat{Z}^N\right] + \left[\nu^{Y,H} s_L^H \hat{L}^H + \left(1 - \nu^{Y,H}\right) s_L^N \hat{L}^N\right] \\ & + \left[\nu^{Y,H} \left(1 - s_L^H\right) \hat{K}^H + \left(1 - \nu^{Y,H}\right) \left(1 - s_L^N\right) \hat{K}^N\right]. \end{aligned}$$

Next plugging (48) and (49) into the above equation and denoting aggregate TFP by Z^A leads to:

$$\hat{Y}_R = \hat{Z}^A + s_L \hat{L} + \left(1 - s_L\right) \hat{K}, \tag{50}$$

where we set

$$\hat{Z}^A = \nu^{Y,H} \hat{Z}^H + \left(1 - \nu^{Y,H}\right) \hat{Z}^N. \tag{51}$$

Eq. (51) corresponds to eq. (2) in the main text.

D Construction of Sectoral Shares

In this section, we provide more details about the construction of sectoral shares. We also derive a formal expression for the labor share of tradables.

Sectoral labor share. Dropping the country index i, in an economy where labor is imperfectly mobile across sectors, the percentage deviation of total hours worked relative to its initial steady-state (i.e., $\hat{L}_t$) following a technology shock is equal to the weighted sum of the percentage deviation of sectoral hours worked relative to initial steady-state (i.e., $\hat{L}_t^j$):

$$\hat{L}_t = \alpha_L \hat{L}_t^H + \left(1 - \alpha_L\right) \hat{L}_t^N, \tag{52}$$

where α_L is the labor compensation share of tradables. If we subtract the share of higher total hours worked received by each sector from the change in sectoral hours worked, we obtain the change in the labor share of sector j, denoted by $\nu^{L,j}$, which measures the contribution of the reallocation of labor across sectors to the change in hours worked in sector j:[16]

$$d\nu_t^{L,j} = \alpha_L^j \cdot \left(\hat{L}_t^j - \hat{L}_t\right) \qquad j = H, N. \tag{53}$$

The differential between the responses of sectoral and total hours worked on the RHS of eq. (53) can be viewed as the change in labor in sector j if L remained fixed and thus reflects higher employment in this sector resulting from the reallocation of labor.

Sectoral value added share. If we subtract the share of higher real GDP received by each sector from the change in sectoral value added in GDP units, we obtain the change in the value added share at constant prices of sector j, denoted by $\nu_t^{Y,j}$, which reads as follows:

$$d\nu_t^{Y,j} = \nu^{Y,j} \left(\hat{Y}_t^j - \hat{Y}_{R,t}\right), \tag{54}$$

where Y_R is real GDP. A rise in the value added share at constant prices of sector j can be brought about by a high productivity growth relative to average, and/or a labor inflow, and/or a greater capital intensity. Formally, the decomposition of the change in the value added share of sector j reads:

$$d\nu_t^{Y,j} = \nu^{Y,j} \left[\left(\hat{Z}_t^j - \hat{Z}_t^A\right) + \left(\hat{L}_t^j - \hat{L}_t\right) + \left(1 - s_L^j\right)\left(\hat{k}_t^j - \hat{k}_t\right)\right], \tag{55}$$

where Z^A is aggregate TFP growth defined by eq. (51) and s_L^j is the LIS in sector j; $k^j = K^j/L^j$ stands for the capital-labor ratio in sector j and $k = K/L$ is the aggregate capital-labor ratio where

[16] While the two measures are equivalent in level, we differentiate between $\nu^{L,j}$ and α_L since the change in the labor share is calculated by keeping W^j/W constant.

$K = K^H + K^N$ and $L = L\left(L^H, L^N\right)$ (since we assume IML and sectoral hours worked are aggregated by means of a CES function).

To obtain (55), we proceed as follows. First, the percentage change in real GDP is a weighted sum of the percentage change in sectoral value added at constant prices: $\hat{Y}_R = \nu^{Y,H}\hat{Y}^H + \left(1-\nu^{Y,H}\right)\hat{Y}^N$. Subtracting the percentage change in real GDP from both sides, changes in sectoral value added shares cancel out:

$$0 = \nu^{Y,H}\left(\hat{Y}_t^H - \hat{Y}_{R,t}\right) + \left(1-\nu^{Y,H}\right)\left(\hat{Y}_t^N - \hat{Y}_{R,t}\right) = d\nu_t^{Y,H} + d\nu_t^{Y,N}. \tag{56}$$

Second, we use the fact that the percentage change in real GDP and the percentage change in sectoral value added can be rewritten as $\hat{Y}_R = \hat{Z}^A + \hat{L} + (1-s_L)\,\hat{k}$ and $\hat{Y}^j = \hat{Z}^j + \hat{L}^j + \left(1-s_L^j\right)\hat{k}^j$, respectively. Inserting these equations into the sectoral decomposition of the percentage change in real GDP and making use of (47b), we find that:

$$\begin{aligned} 0 \;&=\; \nu^{Y,H}\left[\left(\hat{Z}_t^H - \hat{Z}_t^A\right) + \left(\hat{L}_t^H - \hat{L}_t\right) + \left(1-s_L^H\right)\left(\hat{k}_t^H - \hat{k}_t\right)\right] \\ &\quad + \left(1-\nu^{Y,H}\right)\left[\left(\hat{Z}_t^N - \hat{Z}_t^A\right) + \left(\hat{L}_t^N - \hat{L}_t\right) + \left(1-s_L^N\right)\left(\hat{k}_t^N - \hat{k}_t\right)\right]. \end{aligned} \tag{57}$$

From (57) and (56), we have (55).

Capital reallocation. Because we assume perfect mobility of capital across sectors, we have $K = K^H + K^N$. Log-linearizing the resource constant for capital and denoting $\alpha_K = RK^H/RK = K^H/K$ the share of traded capital into the aggregate capital stock, leads to:

$$\hat{K}_t = \alpha_K \hat{K}_t^H + (1-\alpha_K)\,\hat{K}_t^N. \tag{58}$$

Subtracting (52) from (58) and assuming that $\alpha_K \simeq \alpha_L$ leads to:

$$\hat{K}_t - \hat{L}_t = \hat{k}_t = \alpha_L \hat{k}_t^H + (1-\alpha_L)\,\hat{k}_t^N,$$

where $k^j = K^j/L^j$. Subtracting $\hat{k}_t$ from $\hat{k}_t^H$ by using the above equation leads to:

$$\hat{k}_t^H - \hat{k}_t = (1-\alpha_L)\left(\hat{k}_t^H - \hat{k}_t^N\right). \tag{59}$$

Assumption $\alpha_K \simeq \alpha_L$ amounts to assuming that the LIS in sector j is close to the aggregate LIS which is defined as a value added weighted average of sectoral LIS. For the whole sample, we have $s_L^H = 0.63$ and $s_L^N = 0.69$ while the aggregate LIS stands at 0.66 which makes assumption $\alpha_K \simeq \alpha_L$ reasonable.

Determinants of the labor share of tradables. We assume perfectly competitive markets and constant returns to scale in production. Under these assumptions, labor is paid its marginal product. Denoting the traded labor income share by $s_{L,t}^H$, the marginal revenue product of labor, $s_{L,t}^H \frac{P_t^H Y_t^H}{L_t^H}$, must equate the wage rate W_t^H. The same logic applies at an aggregate level, i.e., $s_{L,t}\frac{Y_t}{L_t} = W_t$ where $s_{L,t}$ is the aggregate LIS, Y_t is GDP at current prices. Dividing W_t^H by W_t, making use of the labor supply schedule, i.e., $L_t^H/L_t = \vartheta\left(W_t^H/W_t\right)^{\epsilon}$, to eliminate the relative wage W_t^H/W_t and solving for the labor share of tradables leads to:

$$\frac{L_t^H}{L_t} = \vartheta^{\frac{1}{1+\epsilon}}\left(\frac{s_{L,t}^H}{s_{L,t}}\right)^{\frac{\epsilon}{1+\epsilon}}\left(\omega_t^{Y,H}\right)^{\frac{\epsilon}{1+\epsilon}}, \tag{60}$$

where $\omega_t^{Y,H} = \frac{P_t^H Y_t^H}{Y_t}$ is the value added share of tradables at current prices. Because a rise in Z_t^H/Z_t^N lowers $\omega_t^{Y,H}$ when traded and non-traded goods are gross complements, i.e., $\phi < 1$, L_t^H/L_t falls. As ϵ takes higher values, a shock to Z_t^H/Z_t^N generates a greater reallocation of labor toward the non-traded sector and thus a larger decline in L_t^H/L_t.

Eq. (60) shows that the decline in L_t^H/L_t can be mitigated through two channels. First, the decline in L_t^H/L_t is less when $s_{L,t}^H/s_{L,t}$ increases. We show in the paper that for $s_{L,t}^H/s_{L,t}$ to increase, we have to allow for CES production function and let technological change to be more biased toward labor in the traded than in the non-traded sector. Second, the decline in the terms of trade increases the home content of traded goods and has a positive impact on L_t^H/L_t. To see it, we multiply both sides of the market clearing condition for traded goods (29) by P_t^H and next we divide by GDP at current prices Y_t which leads to (we drop the time index below):

$$\frac{P^H Y^H}{Y} = \frac{P^H C^H}{P^T C^T}\frac{P^T C^T}{P_C C}\omega_C + \frac{P^H J^H}{P_J^T J^T}\frac{P_J^T J^T}{P_J J}\omega_J + \frac{P^H X^H}{Y}, \tag{61}$$

where $\omega_C = \frac{P_C C}{Y}$ and $\omega_J = \frac{P_J J}{Y}$. When $\phi < 1$, a rise in Z^H/Z^N produces an appreciation in P^N/P^H which lowers the tradable content of consumption expenditure $\frac{P^T C^T}{P_C C}$. When we allow for endogenous terms of trade, because a rise in Z^H/Z^N lowers P^H, the fall in the relative price of home-produced traded goods increases $\alpha^H = \frac{P^H C^H}{P^T C^T} = \varphi^H \left(\frac{P^T}{P^H}\right)^{\rho-1}$ if and only if $\rho > 1$ since $\hat{\alpha}^H = -(\rho-1)\left(1-\alpha^H\right)\hat{P}^H > 0$ only when $\rho > 1$ following $\hat{P}^H < 0$. The same logic applies to investment and exports. Since $X^H = \varphi_X \left(P^H\right)^{-\phi_X}$, the value of exports as a share of GDP will increase only if $\phi_X > 1$ following a decline in P^H.

To summarize, a permanent increase in Z^H/Z^N lowers $\omega^{Y,H}$ when $\phi < 1$ which leads to a decline in the labor share of tradables. As long as $\rho < \infty$, a technology shock biased toward the traded sector also lowers P^H. When $\rho > 1$ (and $\rho_J > 1$) and $\phi_X > 1$, the fall in the terms of trade has a positive impact on the share of tradables by increasing the home content of expenditure on tradables (i.e., α^H and α^H_J) and the share of exports in GDP. By mitigating the decline in $\omega^{Y,H}$, the deterioration in the terms of trade also mitigates the decline in L^H/L.

E Construction of the TFP Differential Index

In this section, we show that when investment is both traded and non-traded, a technology shock biased toward the traded sector must be consistently measured by the rate of change of the expression below:

$$\left[\frac{Z^H}{\left(Z^N\right)^{\frac{s_L^H}{s_L^N}}}\right]^{\frac{1}{(1-\alpha_J)+\alpha_J\left(\frac{s_L^H}{s_L^N}\right)}}. \tag{62}$$

Both the traded and non-traded sectors use physical capital, K^j, and labor, L^j, according to constant returns to scale production functions which are assumed to take a CES form:

$$Y^j = \left[\gamma^j \left(A^j L^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j K^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{63}$$

where γ^j and $1-\gamma^j$ are the weight of labor and capital in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, A^j and B^j are labor- and capital-augmenting efficiency. Both sectors face two cost components: a capital rental cost equal to R, and a labor cost equal to the wage rate, i.e., W^H in the traded sector and W^N in the non-traded sector.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{K^j, L^j} \Pi^j = \max_{K^j, L^j} \left\{P^j Y^j - W^j L^j - R K^j\right\}. \tag{64}$$

Since capital can move freely between the two sectors, the value of marginal products in the traded and non-traded sectors equalizes while costly labor mobility implies a wage differential across sectors:

$$P^H\left(1-\gamma^H\right)\left(B^H\right)^{\frac{\sigma^H-1}{\sigma^H}}\left(k^H\right)^{-\frac{1}{\sigma^H}}\left(y^H\right)^{\frac{1}{\sigma^H}} = P^N\left(1-\gamma^N\right)\left(B^N\right)^{\frac{\sigma^N-1}{\sigma^N}}\left(k^N\right)^{-\frac{1}{\sigma^N}}\left(y^N\right)^{\frac{1}{\sigma^N}} \equiv R, \tag{65a}$$

$$P^H\gamma^H\left(A^H\right)^{\frac{\sigma^H-1}{\sigma^H}}\left(L^H\right)^{-\frac{1}{\sigma^H}}\left(Y^H\right)^{\frac{1}{\sigma^H}} \equiv W^H, \tag{65b}$$

$$P^N\gamma^N\left(A^N\right)^{\frac{\sigma^N-1}{\sigma^N}}\left(L^N\right)^{-\frac{1}{\sigma^N}}\left(Y^N\right)^{\frac{1}{\sigma^N}} \equiv W^N, \tag{65c}$$

where we denote by $k^j \equiv K^j/L^j$ the capital-labor ratio for sector $j = H, N$, and $y^j \equiv Y^j/L^j$ value added per hours worked described by

$$y^j = \left[\gamma^j\left(A^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j k^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}. \tag{66}$$

Combining the return on domestic capital with the return on labor leads to the capital-labor ratio in sector $j = H, N$:

$$k^j = \left(\frac{1-\gamma^j}{\gamma^j}\right)^{\sigma^j}\left(\frac{W^j}{R}\right)^{\sigma^j}\left(\frac{B^j}{A^j}\right)^{\sigma^j-1}. \tag{67}$$

We assumed that the economy is initially at the steady-state and we calculate steady-state changes in percentage denoted by a hat. As shall be useful, we totally differentiate the technology frontier (27)

$$\hat{Z}^j = s_L^j \hat{A}^j + \left(1-s_L^j\right)\hat{B}^j, \tag{68}$$

where s_L^j is the LIS in sector j. Differentiating (66) by making use of (68) and eliminating the capital-labor ratio by using (67) leads to:

$$\hat{y}^j = \hat{Z}^j + \left(1 - s_L^j\right)\left[\sigma^j\left(\hat{W}^j - \hat{R}\right) + \left(\sigma^j - 1\right)\left(\hat{B}^j - \hat{A}^j\right)\right]. \tag{69}$$

Dividing (65c) by (65b), differentiating, inserting (69) and making use of (68), solving for the sectoral price differential leads to:

$$\hat{P}^N - \hat{P}^H = \hat{Z}^H - \hat{Z}^N + s_L^N \hat{W}^N - s_L^H \hat{W}^H + \left(s_L^H - s_L^N\right)\hat{R}. \tag{70}$$

Differentiating (65a) and eliminating k^j by using (67) leads to:

$$\begin{aligned}
\hat{W}^H &= \hat{P}^H\left(\frac{\sigma^H - 1}{\sigma^H}\right)\hat{A}^H + \frac{\hat{Z}^H}{\sigma^H} + \frac{\left(1-\sigma^H\right)}{\sigma^H}\hat{k}^H, \\
&= \frac{\hat{P}^H}{s_L^H} + \frac{\hat{Z}^H}{s_L^H} - \left(\frac{1 - s_L^H}{s_L^H}\right)\hat{R}.
\end{aligned} \tag{71}$$

Adding and subtracting the term $s_L^N \hat{W}^H$ into the RHS of eq. (70), then inserting (71) enables us to find an expression for the rate of change of non-traded prices:

$$\begin{aligned}
\hat{P}^N &= \hat{Z}^H - \hat{Z}^N + s_L^N\left(\hat{W}^N - \hat{W}^H\right) + \hat{P}^H + \left(s_L^N - s_L^H\right)\hat{W}^H + \left(s_L^H - s_L^N\right)\hat{R}, \\
&= \frac{s_L^N}{s_L^H}\hat{Z}^H - \hat{Z}^N + s_L^N\left(\hat{W}^N - \hat{W}^H\right) + \frac{s_L^N}{s_L^H}\hat{P}^H + \left(\frac{s_L^H - s_L^N}{s_L^H}\right)\hat{R}.
\end{aligned} \tag{72}$$

Totally differentiating the capital rental cost $R = P_J\left(P^H, P^N\right)\left(r^\star + \delta_K\right)$ where P_J is the investment price index and δ_K the capital depreciation rate, yields:

$$\hat{R} = \alpha_J \alpha_J^H \hat{P}^H + \left(1 - \alpha_J\right)\hat{P}^N, \tag{73}$$

where α_J is the tradable share in total investment expenditure and α_J^H is the home-produced goods content of investment expenditure on traded goods.

Inserting (73) into (72), the rate of change of the non-traded prices can be rewritten as follows:

$$\begin{aligned}
\hat{P}^N &= \left(\frac{s_L^N}{s_L^H}\right)\hat{Z}^H - \hat{Z}^N + \left(\frac{s_L^N}{s_L^H}\right)\hat{P}^H + s_L^N\left(\hat{W}^N - \hat{W}^H\right) \\
&+ \left(\frac{s_L^H - s_L^N}{s_L^H}\right)\left[\alpha_J\alpha_J^H\hat{P}^H + \left(1-\alpha_J\right)\hat{P}^N\right], \\
\hat{P}^N\left[s_L^H + \left(s_L^N - s_L^H\right)\left(1-\alpha_J\right)\right] &= s_L^N\hat{Z}^H - s_L^H\hat{Z}^N + s_L^N s_L^H\left(\hat{W}^N - \hat{W}^H\right) \\
&+ \left[s_L^N + \left(s_L^H - s_L^N\right)\alpha_J\alpha_J^H\right]\hat{P}^H, \\
\hat{P}^N\left[\left(1-\alpha_J\right) + \alpha_J\frac{s_L^H}{s_L^N}\right] &= \left(\hat{Z}^H - \frac{s_L^H}{s_L^N}\hat{Z}^N\right) + s_L^H\left(\hat{W}^N - \hat{W}^H\right) \\
&+ \left[1 + \left(\frac{s_L^H - s_L^N}{s_L^N}\right)\alpha_J\alpha_J^H\right]\hat{P}^H.
\end{aligned} \tag{74}$$

The change in non-traded prices in percentage is thus given by:

$$\begin{aligned}
\hat{P}^N &= \frac{\left(\hat{Z}^H - \frac{s_L^H}{s_L^N}\hat{Z}^N\right)}{\left[\left(1-\alpha_J\right) + \alpha_J\frac{s_L^H}{s_L^N}\right]} + \frac{s_L^H\left(\hat{W}^N - \hat{W}^H\right)}{\left[\left(1-\alpha_J\right) + \alpha_J\frac{s_L^H}{s_L^N}\right]} \\
&+ \frac{\left[1 + \left(\frac{s_L^H - s_L^N}{s_L^N}\right)\alpha_J\alpha_J^H\right]\hat{P}^H}{\left[\left(1-\alpha_J\right) + \alpha_J\frac{s_L^H}{s_L^N}\right]}.
\end{aligned} \tag{75}$$

To calculate the change in price of non-traded goods relative to traded goods, we subtract $\hat{P}^T = \alpha^H \hat{P}^H$ from both sides of (75) by assuming that $\alpha^H \simeq \alpha_J^H$:

$$\hat{P}^N - \hat{P}^T = \frac{\left(\hat{Z}^H - \frac{s_L^H}{s_L^N}\hat{Z}^N\right)}{\left[\left(1-\alpha_J\right) + \alpha_J\frac{s_L^H}{s_L^N}\right]} + \frac{s_L^H\left(\hat{W}^N - \hat{W}^H\right)}{\left[\left(1-\alpha_J\right) + \alpha_J\frac{s_L^H}{s_L^N}\right]} + \frac{\left(1-\alpha^H\right)\hat{P}^H}{\left[\left(1-\alpha_J\right) + \alpha_J\frac{s_L^H}{s_L^N}\right]}. \tag{76}$$

Eq. (76) shows that sector j's TFP must be adjusted with sectoral labor income shares, s_L^j, along with the tradable content of investment expenditure, α_J. Thus, denoting by:

$$a = \frac{1}{\left[(1-\alpha_J) + \alpha_J \frac{s_L^H}{s_L^N}\right]}, \tag{77a}$$

$$b = a\frac{s_L^H}{s_L^N}, \tag{77b}$$

the measure of the technology bias toward tradables is given by:

$$\frac{\left(Z^H\right)^a}{\left(Z^H\right)^b}. \tag{78}$$

It is worth mentioning that:

- if the country is small on world goods market, then the terms of trade are fixed, i.e., $\hat{P}^H = 0$, or if the country does not import consumption and investment goods, i.e., $\alpha^H = 1$, the last term on the RHS of eq. (76) vanishes;
- if we assume perfect mobility of labor across sectors, then sectoral wages grow at the same speed, i.e., $\hat{W}^N = \hat{W}^H$, and thus the second term on the RHS of eq. (76) vanishes;
- if we consider a small open economy model with perfect mobility of labor across sectors, then a labor share adjusted productivity differential of 1%, i.e., $\frac{\left(\hat{Z}^H - \frac{s_L^H}{s_L^N}\hat{Z}^N\right)}{\left[(1-\alpha_J)+\alpha_J\frac{s_L^H}{s_L^N}\right]} = 1\%$, appreciates the price of non-traded goods relative to traded goods by 1% in the long-run, i.e., $\hat{P}^N - \hat{P}^T = 1\%$.

F More VAR Results: Forecast Error Variance Decomposition and Point Estimates

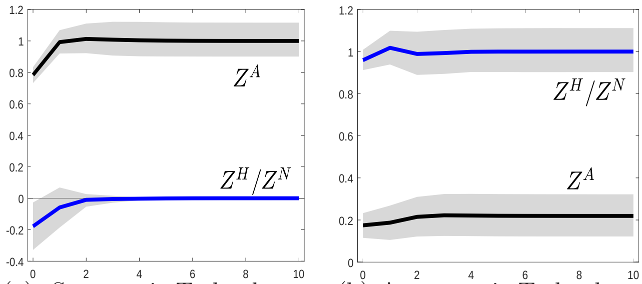
To identify symmetric vs. asymmetric technology shocks, we consider a standard VAR model augmented with the ratio of traded to non-traded TFP, Z_{it}^H/Z_{it}^N (in growth rate), i.e., $[\hat{Z}_{it}^H - \hat{Z}_{it}^N, \hat{Z}_{it}^A, \hat{L}_{it}]$. We impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_{it}^A (see the black line in Fig. 10(a) and Fig. 10(b)) while only asymmetric technology shocks increase permanently Z_{it}^H/Z_{it}^N in the long-run (see the blue line in Fig. 10(a) and Fig. 10(b)). Columns 1, 4, 7 of Table 2 report the share of the FEV of aggregate TFP growth attributable to the shock to the ratio of sectoral TFP, Z_{it}^H/Z_{it}^N, over the whole period and over two sub-periods. As shown in columns 4 and 7, respectively, the contribution of shocks to Z_{it}^H/Z_{it}^N is negligible over 1970-1992 and stands at about 40% over 1993-2013.

Table 3 reports point estimates on impact (i.e., at $t = 0$), and in the long-run (i.e., at a 10-year horizon). Point estimates are obtained by running a VAR model $[Z_{it}, V_{it}]$ where Z_{it} is the relative productivity of tradables and V_{it} is a vector which includes aggregates variables or sectoral variables.

Table 2: The Share of the FEV of Aggregate TFP Growth Attributable to Asymmetric Technology Shocks across Sectors in %

Horizon	FEVD for Z^A								
	1970-2013			1970-1992			1993-2013		
	Z^H/Z^N (1)	Z^A (2)	L (3)	Z^H/Z^N (4)	Z^A (5)	L (6)	Z^H/Z^N (7)	Z^A (8)	L (9)
0	19.065	68.970	11.964	2.589	87.143	10.268	41.187	50.816	7.997
5	17.634	68.902	13.464	2.961	81.842	15.197	39.878	50.487	9.635
10	17.632	68.897	13.472	2.960	81.804	15.236	39.878	50.487	9.635

Notes: FEVD: Forecast Error Variance Decomposition. The number in columns 1-9 denotes the fraction of the total forecast error variance of aggregate TFP growth $\hat{Z}_t^A$ attributable to identified asymmetric technology shocks across sectors (shock to Z_t^H/Z_t^N, see columns 1,4,7), symmetric technology shocks across sectors (shock to Z_t^A leaving unaffected Z_t^H/Z_t^N, see columns 2,5,8), and a third shock to which we do not attach any structural interpretation (shock to L_t, see columns 3,6,9). We consider a forecast horizon of 1, 5, 10 years and compute the FEVs in the three-variable VAR model which includes Z^H/Z^N, Z^A, and L, all in growth rate. Sample: 17 OECD countries, 1970-2013, annual data.



(a) Symmetric Technology Shocks

(b) Asymmetric Technology Shocks

Figure 10: Symmetric and Asymmetric Technology Shocks across Sectors. Notes: Fig. 10(a) and Fig. 10(b) show the effects of symmetric and asymmetric technology shocks where the blue line and the black line display the responses for Z_t^H/Z_t^N and Z_t^A, respectively. Shaded area indicates the 90 percent confidence bounds obtained by bootstrap sampling; sample: 17 OECD countries, 1970-2013, annual data.

Table 3: Sectoral Composition Effects of a Technology Shock Biased toward Tradables: Point Estimates

Variables	Impact $(t=0)$ (1)	Long-run $(t=10)$ (2)	Impact $(t=0)$ (3)	Long-run $(t=10)$ (4)
	Tradables		Non-Tradables	
A.Sectoral TFP				
Z^j	0.718*	0.812*	−0.170*	−0.147*
B.Distributional Effects				
Value added	0.236*	0.274*	0.011	0.059
Hours worked	-0.009	0.009	0.097*	0.154*
C.Reallocation Effects				
Value added Share	0.134*	0.140*	−0.137*	−0.137*
Labor Share	−0.038*	−0.052*	0.043*	0.059*
D.Relative Price				
P^H & P	−0.411*	−0.437*	0.991*	1.065*
E.Relative Wage				
W^j/W	−0.015	−0.119*	0.005	0.060*
F.Redistributive Effects				
LIS	0.094*	0.096	0.013	0.073*
Capital-Labor Ratio	−0.084*	−0.143*	−0.013	−0.035

Notes: * denote significance at 10% level. Standard errors are bootstrapped with 10000 replications.

G VAR Specifications

In order to explore empirically the labor market effects of asymmetric technology shocks across sectors and inspect the transmission mechanism, we consider four VAR models. The choice of variables is motivated in part by the variables discussed in the quantitative analysis. All variables enter the VAR model in growth rate (denoted by a hat):

- **Estimation of sectoral composition effects**. To investigate the sectoral composition effects of a technology shock, we consider a VAR model that includes (in growth rate) value added at constant prices in sector j, $\hat{Y}^j_{it}$, hours worked in sector j, $\hat{L}^j_{it}$, and the real consumption wage in sector j, $\hat{W}^j_{C,it}$ where $W^j_{C,it}$ is defined as the sectoral nominal wage W^j_{it} divided by the consumption price index $P_{C,it}$. Our vector of endogenous variables, is given by: $x^{S,j}_{it} = \left[\hat{Z}_{it}, \hat{Y}^j_{it}, \hat{L}^j_{it}, \hat{W}^j_{C,it}\right]$ with $j = H, N$, where $\hat{Z}_{it}$ is the productivity growth differential (see eq. (4)).
- **Estimation of labor reallocation effects**. To estimate the magnitude of the reallocation effects caused by an asymmetric technology shock, we consider a VAR model where we divide quantities and wages of sector $j = H, N$ by their aggregate counterpart (in rate of change): $x^{R,j}_{it} = \left[\hat{Z}_{it}, \hat{Y}^j_{it} - \hat{Y}_{R,it}, \hat{L}^j_{it} - \hat{L}_{it}, \hat{W}^j_{it} - \hat{W}_{it}\right]$ where $Y_{R,it}$ is real GDP.
- **Estimation of relative price effects**. To shed some light on the transmission mechanism of asymmetric technology shocks, we investigate the relative price effects and estimate the following VAR model: $x^P_{it} = \left[\hat{Z}_{it}, \hat{Y}^H_{it} - \hat{Y}^N_{it}, \hat{P}_{it}\right]$ where we consider the ratio of sectoral quantities since changes in relative prices are associated with variations in relative sectoral quantities. When investigating the response of the terms of trade to a technology shock, we replace $\hat{P}_{it}$ with $\hat{P}^H_{it}$ in the VAR model.
- **Estimation of capital reallocation and redistributive effects**. To explore empirically the redistributive effects, we consider a VAR specification, $x^{LIS,j}_{it} = \left[\hat{Z}_{it}, \hat{s}^j_{L,it}, \hat{k}^j_{it}\right]$, which includes the LIS, s^j_L, and the capital-labor ratio, $k^j \equiv K^j/L^j$, both in rate of growth.

Sectoral responses and aggregation. Once the VAR model $x^{S,j}$ is estimated for both sectors, we expressed the responses of sectoral value added in GDP units and responses of sectoral hours worked in % of total hours worked to ensure that aggregation of sectoral responses collapses to real GDP ($\hat{Y}_{R,it}$) and total hours worked ($\hat{L}_{it}$) responses, respectively, i.e., $\nu^{Y,H}_i \hat{Y}^H_{it} + \left(1 - \nu^{Y,H}_i\right) \hat{Y}^N_{it} = \hat{Y}_{R,it}$ and $\alpha_{L,i} \hat{L}^H_{it} + (1 - \alpha_{L,i}) \hat{L}^N_{it} = \hat{L}_{it}$ where $\nu^{Y,H}$ and $\alpha_{L,i}$ are the value added and labor compensation share of tradables averaged over 1970-2013.[17]

Responses of sectoral shares and labor reallocation. Turning to the estimation of reallocation effects, i.e., $x^{R,j}$, we express the response of the value added share at constant prices of sector j in percentage point of GDP, i.e., $d\nu^{Y,j}_{it} = \nu^{Y,j}_i \left(\hat{Y}^j_{it} - \hat{Y}_{R,it}\right)$. This scaling ensures that the change in the value added of tradables, $d\nu^{Y,H}_{it}$, is the mirror image of that of non-tradables, so that $d\nu^{Y,H}_{it} + d\nu^{Y,N}_{it} = 0$. For the sum of labor flows between sectors to cancel out, we express the change in the labor share of sector j, in percentage point of total hours worked, i.e.,

$$d\nu^{L,j}_{it} = \alpha^j_{L,i} \cdot \left(\hat{L}^j_{it} - \hat{L}_{it}\right), \qquad j = H, N. \tag{79}$$

Eq. (79) captures the change in hours worked in sector j if total hours worked remained constant and thus measures the variation in sectoral hours worked caused by labor reallocation alone. By construction, we have $d\nu^{L,H}_{it} + d\nu^{L,N}_{it} = 0$. Dividing $d\nu^{L,j}_{it}$ by $\alpha^j_{L,i} \hat{L}^j_{it}$ gives the contribution of labor reallocation to the rise in hours worked in sector j.

H Construction of Time Series for FBTC

To explore empirically the role of FBTC in driving the dynamic adjustment of sectoral LISs following a permanent increase in the relative productivity of tradables, we first construct time series for FBTC by drawing on Caselli and Coleman [2006] and Caselli [2016]. Assuming that production functions display constant returns to scale and using the fact that factors are paid their marginal product, the ratio of labor to capital income share for country i at time t, denoted by $S^j_{it} = \frac{s^j_{L,it}}{1 - s^j_{L,it}}$, is equal

[17] Note that when labor is imperfectly mobile across sectors, the rate of change in total hours worked is a weighted sum of the rate of change in sectoral hours worked where the weight is the sectoral labor compensation share instead of the share of sectoral hours worked in total hours worked.

to the ratio of the elasticity of output w.r.t. input, i.e., $S_{it} = \frac{\hat{Y}^j_{it}/\hat{L}^j_{it}}{\hat{Y}^j_{it}/\hat{K}^j_{it}}$. Totally differentiating this equality and denoting the elasticity of substitution between capital and labor in sector j by σ^j, leads to an expression which enables us to make inference of FBTC in sector j:

$$\mathrm{FBTC}^j_{it} = \hat{S}^j_{it} - \left(\frac{1-\sigma^j_i}{\sigma^j_i}\right)\hat{k}^j_{it}. \tag{80}$$

An increase in FBTC^j means that technological change is biased toward labor. As shall be clear later in section 3.2, FBTC^j_{it} is a function of σ^j. When $\sigma^j < 1$, the rise in FBTC^j_{it} is driven by an increase in capital relative to labor efficiency.

To get estimates of σ^j at a sectoral level, following Antràs [2004], we run the regression of logged real value added per hours worked on the logged real wage in this sector with country-specific linear trends over 1970-2013. Since all variables display unit root process, we use the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000] to estimate the cointegrating relationship. Columns 17 and 18 of Table 6 report estimates for σ^H and σ^N we use to recover FBTC from (80). FMOLS estimated values for the whole sample, i.e., $\sigma^H = 0.687$ and $\sigma^N = 0.716$, reveal that capital and labor are gross complements in both sectors.[18] Once we have values for σ^j, we plug time series for k^j and s^j_L into the RHS of eq. (80) to recover time series for FBTC in sector j. Next, we estimate a simple VAR model that includes the productivity differential, $\hat{Z}_{it}$, and FBTC^j_{it}.

I More Numerical Results

For reason of space, we have relegated some numerical results to the Online Appendix.

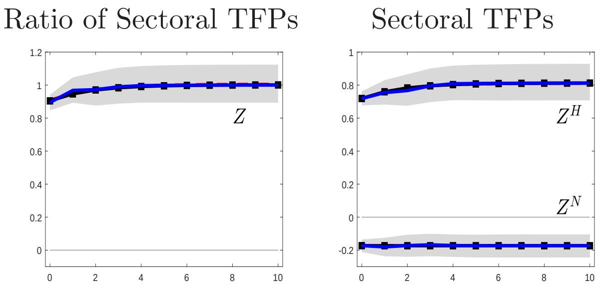
Calibration of the model to OECD representative economy. Fig. 11 shows the fit of the model to the data regarding the dynamic adjustment of traded to non-traded TFP and the responses of sectoral TFPs. As can be seen in Fig. 11(a), the dynamics of the productivity differential that we generate theoretically by specifying the law of motions (31)-(32) together with (39) reproduces the dynamic adjustment from the VAR model very well as the black line with squares and the blue line can merely be differentiated. The productivity differential is mostly driven by the adjustment in $Z^H(t)$ while $Z^N(t)$ remains constant, in line with our VAR estimates, as shown in Fig. 11(b).

As shown in Fig. 12(a), the baseline model also reproduces well the dynamics for traded output, Y^H, while it underestimates the rise in Y^N which is not statistically significant however. On the contrary, a model imposing exogenous terms of trade and HNTC substantially understates the rise in traded value added. While the restricted model reproduces well the dynamics of Y^N after two-years, this performance relies on the excess of labor reallocation predicted by the model. Fig. 12(b) shows that the restricted model with HNTC overstates the capital inflow experienced by the non-traded sector, thus leading to an increase to k^N, in contradiction with the evidence. On the contrary, technological change biased towards labor lowers the demand for capital in the non-traded sector and allows the baseline model to reproduce very well the dynamic adjustment of k^N although the model misses the initial decline in the non-traded capital-labor ratio. When we adjust time series for sectoral TFPs with capital-utilization, we find empirically that the capital-labor ratio increases instead of declining, see Online Appendix T.5.

Cross-country differences. Fig. 13(a) plots impact responses of the ratio of the non-traded labor to capital income share we estimate numerically (vertical axis) against the impact response of S^N estimated empirically. To have a sense of the importance of FBTC in driving the cross-country redistributive effects, we contrast the model predictions when we impose HNTC which are displayed by red triangles with the model predictions when assuming FBTC shown in black squares. By influencing sectoral LISs directly and indirectly through the shifts of capital, the baseline model with FBTC is able to generate a wide cross-country dispersion in the responses of LISs which fits well the data as the correlation between model predictions and the data is 0.97 for the non-traded traded sector.

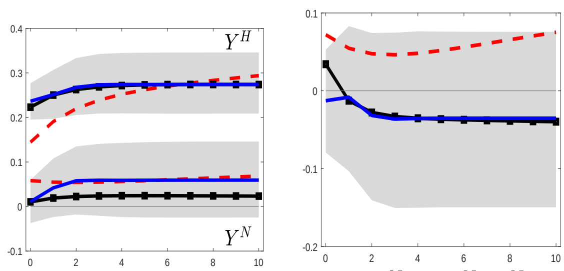
In the second column of Fig. 13, we plot impact responses of the value added share of non-tradables we compute numerically (vertical axis) against impact responses of $\nu^{Y,N}$ we estimate empirically (horizontal axis). Black squares show model predictions when we allow for FBTC while red triangles shows model predictions when we impose HNTC. The red trend line shows the fit of the model to the data when imposing HNTC and the black trend line shows the model fit when we assume FBTC. Inspection of trend lines in Fig. 13(b) reveals that both models (i.e., with either

[18] Online Appendices L.5 and M.4 provide more details about our empirical strategy to estimate σ^j. While the bulk of the FMOLS estimated coefficients are positive and statistically significant, the estimated value for σ^H is negative for Ireland while estimates of σ^N are not statistically significant for Italy and Sweden. As in Antràs [2004], we alternatively run the regression of the ratio of value added to capital stock at constant prices on the real capital cost R/P^j in sector j and replace inconsistent estimates for σ^j obtained from labor demand with those obtained from the demand of capital.



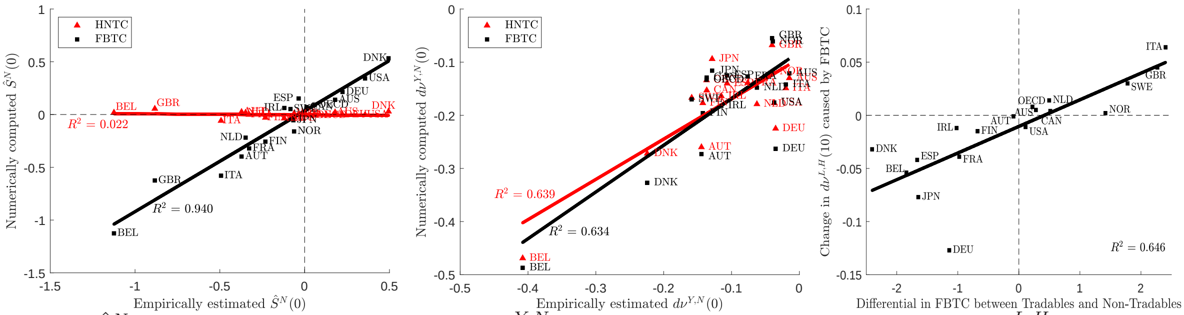
(a) $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$ (b) Sectoral TFPs, Z^H and Z^N

Figure 11: Dynamic Adjustment of Sectoral TFPs following a 1% Permanent Increase in Traded relative to Non-Traded TFP: Empirical vs. Theoretical IRF. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds; solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Fig. 11(a) shows the dynamic adjustment of the ratio of traded to non-traded TFP. Fig. 11(b) shows the dynamic adjustment of traded as well as non-traded TFP.



(a) H- and N-Sectoral Value Added, Y^H and Y^N (b) $k^N = K^N/L^N$

Figure 12: Effects of a Permanent Technology Shock Biased Toward Tradables on Sectoral Value Added and Non-Traded Capital-Labor Ratio: Model vs. Data. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds; solid black lines with squares display model's predictions in the baseline scenario with IML across sectors ($\epsilon = 1.6$), endogenous terms of trade ($\rho = \rho_J = 1.5$), gross complementarity between capital and labor in production (i.e., $\sigma^H = 0.687$, $\sigma^N = 0.716$), and technological change biased toward labor, i.e., $\text{FBTC}^H = 0.58\%$ and $\text{FBTC}^N = 0.36\%$ in the long-run); dashed red lines show predictions of a restricted model where terms of trade are exogenous and technological change is Hicks-neutral.



(a) $\hat{S}^N(0)$: Model vs. Data

(b) $d\nu^{Y,N}(0)$: Model vs. Data

(c) Excess of $d\nu^{L,H}$ caused by FBTC (long-run)

Figure 13: Cross-Country Relationships under FBTC and HNTC Hypothesis: Model vs. Data. Notes: The first two columns of Fig. 8 plots impact responses of $S^N = \frac{s_L^N}{1-s_L^N}$ and value added share of non-tradables computed numerically (vertical axis) against the responses of the corresponding variables estimated empirically (horizontal axis). In each panel, we contrast the predictions from a model imposing HNTC shown in red triangles with the predictions of the baseline model assuming FBTC shown in black squares. The red trend line shows the fit of the model to the data when imposing HNTC while the black trend line shows the fit of the model to the data when assuming FBTC. The last column plots the change in labor reallocation caused by sector differences in FBTC (vertical axis) against the differential in FBTC between tradables and non-tradables (horizontal axis) in the long-run, respectively.

HNTC or FBTC) reproduce well the cross-country dispersion in the responses of $\nu^{Y,N}$. This finding suggests that international differences in the responses of sectoral value added shares are mostly driven by international differences in the elasticity of substitution between traded and non-traded goods (i.e., ϕ) and sectoral TFP shocks (which we allow to vary across countries).

The differential in FBTC between tradables and non-tradables varies considerably across countries and influences the shift of labor across sectors. To give a sense of the variation of labor reallocation caused by sector differences in FBTC, we compute the difference in the change in the labor share of tradables, $d\nu^{L,H}(t)$, between the baseline model assuming FBTC and a model imposing HNTC. While in the main text, we show the change in labor reallocation driven by the FBTC differential between tradables and non-tradables on impact, Fig. 13(c) plots the reduction or the excess of labor reallocation caused by sector differences in FBTC (vertical axis) against the differential in FBTC between tradables and non-tradables (horizontal axis) in the long-run. For countries which lie in the north-east, technological change is more biased toward labor in the traded than the non-traded sector (i.e., $\text{FBTC}^H - \text{FBTC}^N > 0$) which in turn reduces labor reallocation (compared with a model imposing HNTC). The reduction in labor reallocation averages 0.023 ppt of total hours worked on impact and in the long-run, respectively. This decline represents 61% of the (cross-country average) change in $\nu^{L,H}$. Conversely, for countries which lie in the south-west, technological change is more biased toward labor in the non-traded than in the traded sector (i.e., $\text{FBTC}^H - \text{FBTC}^N < 0$). For these economies, the decline in the labor share of tradables doubles as a result of the differential in FBTC between sectors.

J A Test for FBTC Hypothesis

In the main text, we have put forward international differences in FBTC as an explanation of the cross-country redistributive and reallocation effects. To provide some support for our hypothesis of FBTC, we draw on Acemoglu's [2003] model. In Acemoglu's setup, capital-augmenting technological change is the result of innovation by capital intensive firms and labor-augmenting technological change is the result of innovation by labor intensive firms. Because asymmetric technology shocks across sectors are caused by higher productivity of tradables in most of the countries of the sample, we restrict our attention to the traded sector below.[19]

To implement our empirical strategy, we proceed as follows. We identify technology shocks biased toward the traded sector, ϵ_t^Z, for each country in our sample by estimating a VAR model which includes aggregate variables $x_t^A = \left[\hat{Z}_t, \hat{Y}_{R,t}, \hat{L}_t, \hat{W}_{C,t}\right]$. For each industry k, we estimate the VAR model which includes the identified shock to the productivity differential, ϵ_t^Z, TFP in industry k denoted by $Z^{H,k}$ and the ratio of traded to non-traded TFP, i.e., $x_t^{Z,k} = [\epsilon_t^Z, \hat{Z}_t^{H,k}, \hat{Z}_t]$, and adopt

[19] Since the home-produced traded goods sector is highly intensive in R&D, whilst the non-traded sector displays a low R&D intensity, Acemoglu's setup is less relevant for non-traded industries. More specifically, the evidence documented by Galindo-Rueda and Verger [2016] for manufacturing and non-manufacturing activities reveals that industries we classify as tradables (except for financial and insurance activities which are classified as low R&D intensity industries) display high intensity in R&D.

a Cholesky decomposition. Then, we generate impulse response functions in order to recover the percentage change in TFP in industry k in the traded sector, denoted by $\hat{Z}_t^{H,k}$, triggered by the productivity differential, $\hat{Z}$, normalized to one percent in the long-run. The percentage deviation of TFP of tradables relative to initial steady-state is a weighted average of industries' TFPs changes, i.e., $\hat{Z}_t^H = \sum_k \nu^{Y,H,k} \hat{Z}_t^{H,k}$ where $\nu^{Y,H,k}$ is the share of industry k's value added in traded value added at constant prices. Substituting the linearized version of the technology frontier (32) for each industry k shows that TFP growth of the broad sector is driven by labor- or capital-augmenting technological change performed by traded industries:

$$\hat{Z}_t^H = \sum_k \nu^{Y,H,k} \left[s_L^{H,k} \hat{A}_t^{H,k} + \left(1 - s_L^{H,k}\right) \hat{B}_t^{H,k} \right] \tag{81}$$

Drawing on Acemoglu's [2003] model, HNTC corresponds to a situation where all industries have the same LIS so that $s_L^{H,k}$ collapses to the LIS of the broad sector, s_L^H; in this situation, eq. (81) reduces to

$$\hat{\bar{Z}}_t^H = \sum_k \nu^{Y,H,k} \left[s_L^H \hat{A}_t^{H,k} + \left(1 - s_L^H\right) \hat{B}_t^{H,k} \right], \tag{82}$$

where a bar above Z^H on the LHS of (82) refers to traded TFP if LISs were identical across traded industries. When $s_L^{H,k} = s_L^H$ for all industries k of the traded sector, we have $\hat{A}_t^{H,k} = \hat{B}_t^{H,k}$ for each industry k so that technological change in the traded sector is Hicks-neutral. Subtracting (82) from (81) leads to a measure of the deviation from HNTC:

$$\hat{Z}_t^H - \hat{\bar{Z}}_t^H = \sum_k \nu^{Y,H,k} \left[\left(1 - s_L^{H,k}\right) - \left(1 - s_L^H\right) \right] \left(\hat{B}_t^{H,k} - \hat{A}_t^{H,k} \right). \tag{83}$$

Like Acemoglu [2003], we assume that industries which are more capital (labor) intensive only perform capital- (labor-) augmenting technological change so that the change in TFP in traded industry k we estimate empirically reduces to the change in capital (labor) efficiency. These assumptions can be summarized as follows:

$$\begin{cases} \hat{Z}_t^{H,k} = \hat{B}_t^{H,k} & \text{if} \quad \left(1 - s_L^{H,k}\right) > \left(1 - s_L^H\right), \\ \hat{Z}_t^{H,k} = -\hat{A}_t^{H,k} & \text{if} \quad s_L^{H,k} > s_L^H, \end{cases} \tag{84}$$

where s_L^H is the LIS averaged across all industries in the traded sector. It is worth mentioning that the minus in front of $\hat{A}_t^{H,k}$ (see the second line of (84)) allows us to differentiate graphically countries where labor-intensive industries contribute more to the TFP growth in the traded sector from those where a greater part of $\hat{Z}^H$ can be attributed to capital-intensive industries. More precisely, if labor-intensive industries contribute more to TFP growth in the traded sector, then the measure of the deviation from HNTC is negative. Conversely, (83) turns out to be positive for countries where capital-intensive industries contribute more to $\hat{Z}^H$.

Next, we contrast deviation from HNTC from empirical estimates with measure (83) computed numerically. To construct the latter measure, we make inference of $\hat{A}^H$ and $\hat{B}^H$ by using (38a) and (38b), respectively and we further assume that capital-augmenting technological change is identical across capital-intensive industries and thus $\hat{B}_t^{H,k} = \hat{B}_t^H$. The same logic applies for labor-intensive industries, i.e., $\hat{A}_t^{H,k} = \hat{A}_t^H$. Analogously to empirical estimates, we add a minus for labor-augmenting technological change in order to differentiate labor- from capital-augmenting technological change graphically. In Fig. 14, we plot measure (83) of the deviation from HNTC estimated empirically (on the horizontal axis) against the measure estimated numerically (on the vertical axis). The left panel of Fig. 14 contrasts empirical with numerical estimates of (83) on impact (i.e., $t = 0$) when we allow for two lags in the VAR model (to estimate $\hat{Z}_t^{H,k}$) while the right panel compares both measures by allowing for one lag.[20] If technology shocks were Hicks neutral, all countries would be positioned at point (0,0). By contrast, we find that capital- and labor-augmenting efficiency increases at uneven rates. More specifically, countries positioned in the north-east of the scatter-plot are those where TFP changes in the traded sector are mostly driven by capital-intensive industries while those located in the south-west are those where labor-intensive industries contribute more to $\hat{Z}_t^H$. Importantly, we detect a positive cross-country relationship which is robust to the number of lags included in the VAR model. In the working paper version, we plot the measure (83) of the deviation from HNTC estimated empirically against the measure estimated numerically in the long-run and find that our conclusion holds at a longer horizon. Such a finding

[20] There is substantial uncertainty surrounding point estimates when estimating the VAR model at a country level given the relatively small number of observations available per country. Since the magnitude of the responses of TFP at a country/industry level may vary substantially with the number of lags, we find it appropriate to show estimates with one or two lags.

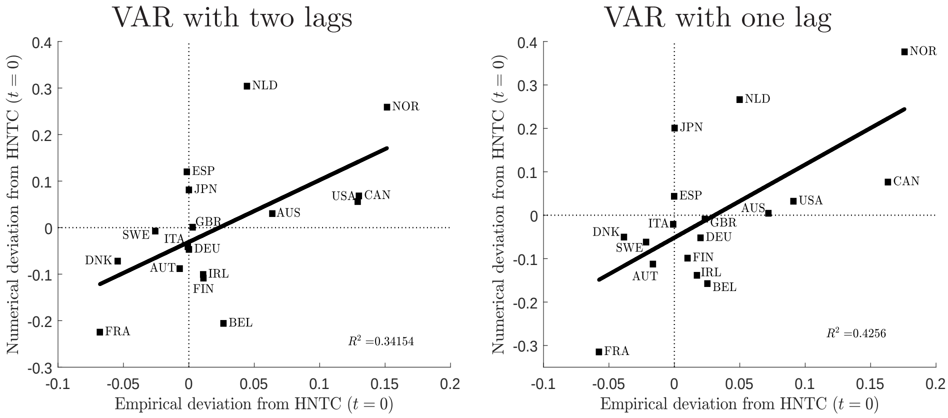


Figure 14: Deviation from HNTC: Model vs. Data. Notes: According to Acemoglu's [2003] model assumptions, capital- (labor-) intensive industries perform capital- (labor-) augmenting technological change. In Fig. 14, we investigate whether in countries where capital relative to labor efficiency increases, capital-intensive industries contribute more to TFP changes on impact. To perform this investigation, we compute a measure of the deviation from HNTC. This index is a weighted average of TFP shocks within each industry; each industry's TFP shock is weighted by the product of its valued added share and the difference between this industry's capital income share and the broad sector's capital income share. On the horizontal axis, we report estimated values of our measure of deviation from HNTC. When this measure takes positive (negative) values, relative capital (labor) efficiency increases. The vertical axis shows the same measure computed numerically. According to Acemoglu's [2003] model, if capital income shares were equal across industries, then technological change would be Hicks-neutral so that capital and labor efficiency would increase at the same speed and all observations would be positioned at point (0,0).

reveals that in line with Acemoglu model's assumptions, in countries where capital-intensive industries contribute more to TFP growth in the traded sector, capital relative labor efficiency increases so that technological change favors the use of labor (as long as $\sigma_i^H < 1$). Conversely, in countries where TFP gains are concentrated on labor-intensive industries, labor relative to capital efficiency rises which biases technological change toward capital (as long as $\sigma_i^H < 1$).

K Data Description for Empirical Analysis

Coverage: Our sample consists of a panel of 17 countries: Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Denmark (DNK), Finland (FIN), France (FRA), Germany (DEU), Ireland (IRL), Italy (ITA), Japan (JPN), the Netherlands (NLD), Norway (NOR), Spain (ESP), Sweden (SWE), the United Kingdom (GBR) and the United States (USA). The baseline period is running from 1970 to 2013, except for Japan (1974-2013). Although sectoral data are available over the period 1970-2015 (see below), our preferred time span is 1970-2013. The reason is that all quantity variables entering the VAR model are scaled by the working age population for which data are spotty for last years, making it impractical to work with it for periods that extend after 2013. Table 4 summarizes our dataset.

Sources: Our primary sources for sectoral data are the OECD and EU KLEMS databases. We use data from EU KLEMS ([2011], [2017]) March 2011 and July 2017 releases. The EU KLEMS dataset covers all countries of our sample, with the exceptions of Canada and Norway. For these two countries, sectoral data are taken from the Structural Analysis (STAN) database provided by the OECD ([2011], [2017]). For both EU KLEMS and STAN databases, the March 2011 release provides data for eleven 1-digit ISIC-rev.3 industries over the period 1970-2007 while the July 2017 release provides data for thirteen 1-digit-rev.4 industries over the period 1995-2013.

The construction of time series for sectoral variables over the period 1970-2013 involves two steps. First, we identify tradable and non-tradable sectors. To do so, we adopt the classification proposed by De Gregorio et al. [1994]. Following Jensen and Kletzer [2006], we have updated this classification by treating the financial sector as a traded industry. We map the ISIC-rev.4 classification into the ISIC-rev.3 classification in accordance with the concordance Table 5. Once industries have been classified as traded or non-traded, for any macroeconomic variable X, its sectoral counterpart X^j for $j = H, N$ is constructed by adding the X_k of all sub-industries k classified in sector $j = H, N$ as follows $X^j = \sum_{k \in j} X_k$. Second, series for tradables and non-tradables variables from EU KLEMS [2011] and OECD [2011] databases (available over the period 1970-2007) are extended forward up to 2013 using annual growth rate estimated from EU KLEMS [2017] and OECD [2017] series (available over the period 1995-2013).

Relevant to our work, the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases provide data, for each industry and year, on value added at current and constant prices, permitting the construction of sectoral deflators of value added, as well as details on labor compensation and hours worked data, allowing the construction of sectoral wage rates. All quantity variables

Table 4: Sample Range for Empirical and Numerical Analysis

Country	Code	Period	Obs.
Australia	(AUS)	1970 - 2013	44
Austria	(AUT)	1970 - 2013	44
Belgium	(BEL)	1970 - 2013	44
Canada	(CAN)	1970 - 2013	44
Germany	(DEU)	1970 - 2013	44
Denmark	(DNK)	1970 - 2013	44
Spain	(ESP)	1970 - 2013	44
Finland	(FIN)	1970 - 2013	44
France	(FRA)	1970 - 2013	44
Great Britain	(GBR)	1970 - 2013	44
Ireland	(IRL)	1970 - 2013	44
Italy	(ITA)	1970 - 2013	44
Japan	(JPN)	1974 - 2013	40
Netherlands	(NLD)	1970 - 2013	44
Norway	(NOR)	1970 - 2013	44
Sweden	(SWE)	1970 - 2013	44
United States	(USA)	1970 - 2013	44
Total number of obs.			744
Main data sources		EU KLEMS & OECD STAN	

Notes: Column 'period' gives the first and last observation available. Obs. refers to the number of observations available for each country.

Table 5: Summary of Sectoral Classifications

Sector	ISIC-rev.4 Classification (sources: EU KLEMS [2017] and OECD ([2017]))		ISIC-rev.3 Classification (sources: EU KLEMS [2011] and OECD ([2011]))	
	Industry	Code	Industry	Code
Tradables (H)	Agriculture, Forestry and Fishing	A	Agriculture, Hunting, Forestry and Fishing	AtB
	Mining and Quarrying	B	Mining and Quarrying	C
	Total Manufacturing	C	Total Manufacturing	D
	Transport and Storage	H	Transport, Storage and Communication	I
	Information and Communication	J		
	Financial and Insurance Activities	K	Financial Intermediation	J
Non Tradables (N)	Electricity, Gas and Water Supply	D-E	Electricity, Gas and Water Supply	E
	Construction	F	Construction	F
	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles	G	Wholesale and Retail Trade	G
	Accommodation and Food Service Activities	I	Hotels and Restaurants	H
	Real Estate Activities	L	Real Estate, Renting and Business Services	K
	Professional, Scientific, Technical, Administrative and Support Service Activities	M-N		
	Community Social and Personal Services	O-U	Community Social and Personal Services	LtQ

are scaled by the working age population (15-64 years old). Source: OECD ALFS Database for the working age population (data coverage: 1970-2013). Normalizing base year price indices $\bar{P}^j$ to 1, we describe below the construction for the sectoral data employed in the main text (mnemonics are given in parentheses):

- **Sectoral value added**, Y^j: sectoral value added at constant prices in sector $j = H, N$ (VA_QI). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Relative value added**, Y^H/Y^N: ratio of traded value added to non-traded value added at constant prices.
- **Sectoral value added share**, $\nu^{Y,j}$: ratio of value added at constant prices in sector j to GDP at constant prices, i.e., $Y^j/(Y^H + Y^N)$ for $j = H, N$.
- **Relative price of non-tradables**, P: ratio of the non-traded value added deflator to the traded value added deflator, i.e., $P = P^N/P^H$. The sectoral value added deflator P^j for sector $j = H, N$ is calculated by dividing value added at current prices (VA) by value added at constant prices (VA_QI) in sector j. EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Terms of Trade**, P^H/P^F: ratio of the traded value added deflator to price deflator of imports of goods and services, i.e., P^H/P^F. The traded value added deflator P^H is calculated by dividing value added at current prices (VA) by value added at constant prices (VA_QI) in sector H. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) for P^H and OECD National Accounts Database for P^F.
- **Sectoral hours worked**, L^j: total hours worked by persons engaged in sector j (H_EMP).EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Relative hours worked**, L^H/L^N: ratio of hours worked in the traded sector to hours worked in the non-traded sector.
- **Sectoral labor share**, $\nu^{L,j}$: ratio of hours worked in sector j to total hours worked, i.e., $L^j/(L^H + L^N)$ for $j = H, N$.
- **Sectoral real consumption wage**, W^j_C: nominal wage in sector j divided by the consumer price index (CPI), i.e. $W^j_C = W^j/P_C$. Source: OECD Prices and Purchasing Power Parities for the consumer price index. The sectoral nominal wage W^j for sector $j = H, N$ is calculated by dividing labor compensation in sector j (LAB) by total hours worked by persons engaged (H_EMP) in that sector. Labor compensation is total labor costs that include compensation of employees and labor income of the self-employed and other entrepreneurs. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Relative wage**: ratio of the nominal wage in the sector j to the aggregate nominal wage W, i.e., W^j/W.
- **Labor income share (LIS)**, s^j_L: ratio of labor compensation in sector $j = H, N$ (LAB) to value added at current prices (VA) of that sector. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Capital-labor ratio**, k^j: ratio of capital stock in sector $j = H, N$ to total hours worked by persons engaged in that sector (H_EMP). Aggregate capital stocks are estimated from the perpetual inventory approach by using real gross capital formation from OECD Economic Outlook Database (data in millions of national currency, constant prices) and assuming a depreciation rate of 5%. Following Garofalo and Yamarik [2002], the capital stock is then allocated to traded and non-traded industries by using sectoral output shares $K^j = \omega^{Y,j}K$ where $\omega^{Y,j}$ is the value added share of sector j at current prices, see Appendix N.7. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Relative productivity of tradables**, Z : labor share-adjusted ratio of traded TFP, Z^H, to the non-traded TFP, Z^N, i.e., $Z = \left(Z^H\right)^a / \left(Z^N\right)^b$ where $a = \left[(1-\alpha_J) + \alpha_J \frac{s^H_L}{s^N_L}\right]^{-1}$, and $b = a\frac{s^H_L}{s^N_L}$. Sectoral TFPs, Z^j, for $j = H, N$ are constructed as Solow residuals from constant-price domestic currency series of value added (VA_QI), capital, LIS s^j_L, and hours worked (H_EMP) in sector j. s^j_L is the ratio of the compensation of employees (LAB) to value added (VA) in sector $j = H, N$, averaged over the period 1970-2013 (except Japan: 1974-2013). Sources: EU EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. α_J is the tradable share in total investment expenditure averaged over the period 1970-2013. Source: OECD Input-Output database [2017].

In the following, we provide details on data construction for aggregate variables (mnemonics are in parentheses):

- **Gross domestic product**, Y_R: real gross domestic product (GDPV). Source: OECD Economic Outlook Database. Data coverage: 1970-2013.
- **Total hours worked**, L: total hours worked by persons engaged (H_EMP). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Real consumption wage**, $W_C = W/P_C$: nominal aggregate wage divided by the consumer price index (CPI). Source: OECD Prices and Purchasing Power Parities for the consumer price index. The nominal aggraget wage is calculated by dividing labor compensation (LAB) by total hours worked by persons engaged (H_EMP). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

L Data for Calibration

L.1 Non-Tradable Content of GDP and its Demand Components

Table 6 shows the non-tradable content of GDP, consumption, investment, government spending, labor and labor compensation (columns 1 to 6). In addition, it gives information about the sectoral labor income shares (columns 10 and 11). The home content of consumption and investment expenditure in tradables together with the ratio of final goods imports to GDP are reported in columns 7 to 9. Columns 12 to 14 display the labor income share, investment-to-GDP ratio and government spending in % of GDP, respectively, for the whole economy. Our sample covers the 17 OECD countries mentioned in Section C. Our reference period for the calibration corresponds to the period 1970-2013. The choice of this period has been dictated by data availability. In the following, statistics for the sample as a whole represent (unweighted) averages of the corresponding variables.

To calculate the non-tradable share of value added (column 1), labor (column 5) and labor compensation (column 6), we split the eleven industries into traded and non-traded sectors by adopting the classification proposed by De Gregorio et al. [1994] and updated by Jensen and Kletzer [2006]. Details about data construction for sectoral output and sectoral labor are provided above. We calculate the non-tradable share of labor compensation as the ratio of labor compensation in the non-traded sector (i.e., $W^N L^N$) to overall labor compensation (i.e., WL). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 for all countries (except Japan: 1974-2013). The non-tradable content of GDP, labor and labor compensation, shown in columns 1, 5 and 6 of Table 6, average to 60%, 63% and 63% respectively.

To split consumption expenditure (at current prices) into consumption in traded and non-traded goods, we made use of the Classification of Individual Consumption by Purpose (COICOP) published by the United Nations (Source: United Nations [2017]). Among the twelve items, the following ones are treated as consumption in traded goods: "Food and Non-Alcoholic Beverages", "Alcoholic Beverages Tobacco and Narcotics", "Clothing and Footwear", "Furnishings, Household Equipment and Routine Maintenance of the House" and "Transport". The remaining items are treated as consumption in non-traded goods: "Housing, Water, Electricity, Gas and Fuels", "Health", "Communications", "Recreation and Culture", "Education", "Restaurants and Hotels". Because the item "Miscellaneous Goods and Services" is somewhat problematic, we decided to consider it as both tradable (50%) and non-tradable (50%) with equal shares. Data coverage: AUS (1970-2013), AUT (1995-2013), BEL (1995-2013), CAN (1981-2013), DEU (1995-2013), DNK (1970-2013), ESP (1995-2013), FIN (1975-2013), FRA (1970-2013), GBR (1995-2013), IRL (1995-2013), ITA (1995-2013), JPN (1994-2013), NLD (1995-2013), NOR (1970-2013), SWE (1993-2013) and USA (1970-2013). The non-tradable share of consumption shown in column 2 of Table 6 averages to 53%.

To calculate the non-tradable share of investment expenditure, we follow the methodology proposed by Burstein et al. [2004] who treat "Total Construction" as non-tradable investment and "Transport Equipment", "ICT Equipment", "Cultivated Biological Resources", "Intellectual Property Product" as tradable investment expenditure. The item "Other machinery and equipment and weapon system" is considered as both tradable (50%) and non-tradable (50%) with equal shares. Source: OECD Input-Output database [2017]. Data coverage: AUS (1970-2013), AUT (1995-2013), BEL (1995-2013), CAN (1970-2013), DEU (1995-2013), DNK (1970-2013), ESP (1995-2013), FIN (1980-2013), FRA (1978-2013), GBR (1997-2013), IRL (1995-2013), ITA (1995-2013), JPN (1994-2013), NLD (1995-2013), NOR (1970-2013), SWE (1993-2013) and USA (1970-2013). non-tradable share of investment shown in column 3 of Table 6 averages to 62%, in line with estimates provided by Burstein et al. [2004] and Bems [2008].

Sectoral government expenditure data (at current prices) are taken from the OECD General Government Accounts database (Source: COFOG, OECD [2017]). The following four items pertaining to "Economic Affairs" are treated as traded: "Fuel and Energy", "Agriculture, Forestry, Fishing, and Hunting", "Mining, Manufacturing, and Construction", "Transport and Communications". Items treated as non-traded are: "General Public Services", "Defence", "Public Order and Safety", "Environment Protection", "Housing and Community Amenities", "Health", "Recreation, Culture and Religion", "Education" and "Social Protection". Data coverage: AUS (1998-2013), AUT (1995-2013), BEL (1995-2013), DEU (1995-2013), DNK (1995-2013), ESP (1995-2013), FIN (1990-2013), FRA (1995-2013), GBR (1995-2013), IRL (1995-2013), ITA (1995-2013), JPN (2005-2013), NLD (1995-2013), NOR (1995-2013), SWE (1995-2013) and USA (1970-2013). Data are not available for CAN. Thus, for this country, when we calibrate the model to each OECD country, we choose a non-tradable content of government expenditure that is given by the unweighed average, i.e., 0.90, as can be seen in column 4 of Table 6.

To compute the home content of consumption and investment expenditure in tradables, we use the Comtrade database from the United Nations. There are three basic classes of goods in SNA in the categories of classification of Broad Economic Categories (BEC): capital goods, intermediate goods and consumption goods. Since we focus on sectoral value added and its final use, we exclude intermediate goods. The sum of capital and consumption goods imports as a share of GDP averages 10.4% as can be seen in column 7 of Table 6. When we calibrate the model to a representative OECD economy, we assume that trade is initially balanced. This assumption is roughly consistent with the data which indicate that exports of consumption and capital goods as a share of GDP average 10.8%. Excluding trade on intermediate goods, the Comtrade database enables us to construct time series for the content of imports in consumption goods, C^F/M^F, and investment goods, J^F/M^F. Since we can compute consumption and investment goods as a share of GDP, i.e., C^F/Y and J^F/Y, we can determine the import content of consumption and investment expenditure in tradables, by using the following decomposition:

$$1-\alpha^H = \frac{C^F}{P^H C^H} = \frac{C^F}{Y}\frac{1}{\omega_C \alpha_C}, \tag{85a}$$

$$1-\alpha_J^H = \frac{J^F}{P_J^H J^H} = \frac{J^F}{Y}\frac{1}{\omega_J \alpha_J}, \tag{85b}$$

where $\omega_C = 1-\omega_J-\omega_G$ with ω_J and ω_G shown in columns 13 and 14 of Table 6; the tradable content of consumption expenditure, α_C, can be calculated by using column 2 which gives $1-\alpha_C$. Once we have computed $1-\alpha^H$ and $1-\alpha_J^H$, we can compute the home content of consumption and investment expenditure in tradables which are shown in columns 8 and 9. The home content of consumption expenditure in tradables, α^H, averages 77% while the home content of investment expenditure in tradables, α_J^H, averages 51%. Source: United Nations Comtrade database [2017]. Data coverage: 1998-2013 for all countries.

The labor income share for sector j denoted by s_L^j is calculated as the ratio of labor compensation of sector j to value added of sector j at current prices. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 for all countries (except Japan: 1974-2013). As shown in columns 10 and 11 of Table 6, s_L^H and s_L^N average 0.63 and 0.68, respectively.

Column 12 of Table 6 gives the aggregate labor income share which averages 0.66 in our sample. Columns 13 and 14 of Table 6 display gross capital formation and final consumption expenditure of general government as a share of GDP, respectively. Source: OECD National Accounts Database. Data coverage: 1970-2013 for all countries.

Columns from 15 to 21 of Table 6 display estimates of the elasticity of substitution between tradables and non-tradables in consumption, ϕ, the elasticity of labor supply across sectors, ϵ, the elasticity of substitution between capital and labor in the traded and the non-traded sector, i.e., σ^H and σ^N, respectively, the elasticity of exports w.r.t. the terms of trade, ϕ_X, the elasticity of substitution between home- and foreign-produced traded goods for consumption and investment, ρ and ρ_J, respectively. In subsections L.4, L.5, L.6, we detail the empirical strategy to estimate these parameters, except for the price elasticity of exports ϕ_X shown in column 19 of Table 6 whose estimates are taken from Imbs and Mejean [2015].

Because data source and construction are heterogenous across variables as a result of different nomenclatures, Table 8 provides a summary of the classification adopted to split value added and its demand components as well into traded and non-traded goods.

L.2 Responses of Aggregate Hours Worked to Asymmetric and Symmetric Technology Shocks across Sectors

We explore empirically below the response of total hours worked to the asymmetric technology shock because this variable receives a lot of attention in the literature pioneered by Gali [1999]. We consider the VAR model which includes aggregate variables (all in growth rate) such a real GDP, total hours worked, the real consumption wage in addition to the productivity differential ordered first. Interestingly, a shock to the ratio of traded to non-traded TFP increases significantly hours

Table 6: Data to Calibrate the Two-Sector Model (1970-2013)

Countries	Non-tradable share						Home share			Labor Share		Aggregate ratios			Elasticities						
	GDP	Cons.	Inv.	Gov.	Labor	Lab. comp.	Imp./Y	Cons.	Inv.	LIS^H	LIS^N	s_L	I/Y	G/Y	ϕ	ϵ	σ^H	σ^N	ϕ_X	ρ	ρ_J
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
AUS	0.60	0.53	0.62	0.88	0.64	0.63	0.07	0.86	0.64	0.59	0.67	0.64	0.27	0.18	0.40	0.37	0.47	0.53	1.64	1.04	0.65
AUT	0.61	0.54	0.60	0.88	0.60	0.61	0.14	0.70	0.44	0.68	0.68	0.68	0.25	0.18	1.52	1.10	0.77	1.30	1.70	0.76	1.20
BEL	0.62	0.53	0.58	0.89	0.64	0.63	0.25	0.32	0.19	0.66	0.67	0.67	0.23	0.22	1.24	0.61	0.83	1.07	n.a.	3.34	2.02
CAN	0.62	0.53	0.68	0.90	0.67	0.65	0.10	0.81	0.28	0.54	0.62	0.59	0.22	0.21	0.75	0.39	0.48	0.67	2.25	2.13	0.57
DEU	0.61	0.52	0.64	0.91	0.60	0.57	0.09	0.81	0.52	0.76	0.64	0.69	0.23	0.19	0.58	1.01	0.64	0.99	1.47	2.02	1.57
DNK	0.65	0.51	0.62	0.94	0.66	0.67	0.12	0.72	0.40	0.65	0.70	0.68	0.21	0.25	1.08	0.29	0.42	1.28	n.a.	1.81	1.29
ESP	0.60	0.55	0.79	0.87	0.60	0.62	0.08	0.81	0.42	0.60	0.66	0.63	0.24	0.16	1.39	1.02	1.03	0.48	1.87	1.75	1.15
FIN	0.57	0.50	0.65	0.89	0.58	0.60	0.09	0.83	0.51	0.65	0.74	0.70	0.25	0.20	0.85	0.43	0.76	0.79	1.62	0.89	n.a.
FRA	0.66	0.49	0.64	0.91	0.64	0.66	0.08	0.82	0.61	0.72	0.69	0.70	0.23	0.22	0.89	1.40	0.87	0.92	1.66	1.07	0.85
GBR	0.59	0.57	0.60	0.94	0.65	0.61	0.09	0.78	0.60	0.70	0.74	0.72	0.20	0.19	0.00	0.60	0.60	0.56	1.51	1.66	0.82
IRL	0.52	0.54	0.60	0.87	0.58	0.60	0.14	0.72	0.29	0.51	0.69	0.60	0.22	0.18	1.35	0.22	0.74	0.63	n.a.	1.31	0.84
ITA	0.60	0.48	0.64	0.91	0.58	0.58	0.07	0.87	0.68	0.74	0.67	0.70	0.22	0.18	0.72	1.66	0.84	0.47	1.72	2.33	0.86
JPN	0.61	0.57	0.58	0.90	0.61	0.63	0.04	0.90	0.90	0.60	0.66	0.64	0.29	0.16	1.05	0.87	1.16	0.64	1.60	0.70	3.12
NLD	0.63	0.54	0.60	0.90	0.67	0.67	0.16	0.65	0.15	0.61	0.74	0.69	0.22	0.22	0.52	0.22	0.91	0.44	n.a.	n.a.	0.48
NOR	0.54	0.46	0.67	0.89	0.62	0.64	0.08	0.85	0.53	0.44	0.63	0.54	0.26	0.20	0.89	0.01	0.63	0.56	1.78	1.00	1.02
SWE	0.62	0.56	0.47	0.92	0.65	0.64	0.10	0.74	0.65	0.67	0.74	0.71	0.24	0.25	0.51	0.53	0.61	0.38	1.78	0.58	1.06
USA	0.66	0.59	0.56	0.89	0.70	0.66	0.05	0.89	0.77	0.62	0.62	0.62	0.22	0.16	0.82	3.22	0.77	0.88	1.45	1.37	1.94
OECD	0.61	0.53	0.62	0.90	0.63	0.63	0.10	0.77	0.51	0.63	0.68	0.66	0.24	0.20	0.44	1.60	0.69	0.72	1.70	1.50	1.50

Notes: Columns 1-6 show the GDP share of non-tradables, the non-tradable content of consumption, investment and government expenditure, the share of non-tradables in labor, and the non-tradable content of labor compensation. Column 7 gives the ratio of final goods imports to GDP; columns 8 and 9 show the home share of consumption and investment expenditure in tradables; LIS^j stands for the LIS in sector $j = H, N$ while s_L is the aggregate LIS; I/Y is the investment-to-GDP ratio and G/Y is government spending as a share of GDP; ϕ is the elasticity of substitution between traded and non-traded goods in consumption; ϵ is the elasticity of labor supply across sectors; σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$; estimates of the elasticity of exports w.r.t. terms of trade, ϕ_X, are taken from Imbs and Mejean [2015]. ρ and ρ_J are the elasticity of substitution between home- and foreign-produced traded goods for consumption and investment respectively.

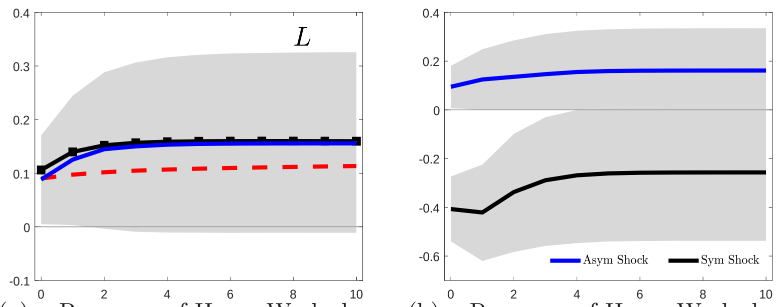
Table 7: Baseline Parameters (Representative OECD Economy)

Definition	Value		Reference
	OECD	Sensitivity	
Period of time	year	year	data frequency
A.Preferences			
Subjective time discount rate, β	4%	4%	equal to the world interest rate
Intertemporal elasticity of substitution for consumption, σ_C	2	2	Gruber [2013]
Intertemporal elasticity of substitution for labor, σ_L	1.6	1.6	Peterman [2016]
Elasticity of substitution between C^T and C^N, ϕ	0.44	0.44	Stockman and Tesar [1995]
Elasticity of substitution between J^T and J^N, ϕ_J	1	1	Bems [2008]
Elasticity of substitution between C^H and C^F, ρ	1.5	∞	Our own estimates and Backus, Kehoe and Kydland [1994]
Elasticity of substitution between J^H and J^F, ρ_J	1.5	∞	Our own estimates and Backus, Kehoe and Kydland [1994]
Elasticity of labor supply across sectors, ϵ	1.6	1.6	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
B.Non-tradable share			
Weight of consumption in non-traded goods, $1-\varphi$	0.49	0.49	set to target $1-\alpha_C = 53\%$ (United Nations, COICOP [2017])
Weight of labor supply to the non-traded sector, $1-\vartheta$	0.6	0.6	set to target $L^N/L = 63\%$ (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Weight of non-traded investment, $1-\iota$	0.62	0.62	set to target $\alpha_J = 62\%$ (OECD Input-Output database [2017])
Non-tradable content of government expenditure, ω_{G^N}	0.9	0.9	our estimates (COFOG, OECD [2017])
Labor income share in the non-traded sector, s_L^N	0.68	0.68	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Labor income share in the traded sector, s_L^H	0.63	0.63	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
TFP index, Z^j	1	1	normalization
C.Home share			
Weight of consumption in home traded goods, φ^H	0.84	0.84	set to target $\alpha^H = 77\%$ (United Nations, Comtrade [2017])
Weight of home traded investment, ι^H	0.62	0.62	set to target $\alpha_J^H = 51\%$ (United Nations, Comtrade [2017])
Export price elasticity, ϕ_X	1.7	1.7	Imbs and Mejean [2015]
D.GDP demand components			
Physical capital depreciation rate, δ_K	9.3%	9.3%	set to target $\omega_J = 24\%$ (Source: OECD Economic Outlook Database)
Parameter governing capital adjustment cost, κ	17	17	set to match the elasticity I/K to Tobin's q (Eberly et al. [2008])
Government spending as a ratio of GDP, ω_G	20%	20%	our estimates (Source: OECD Economic Outlook Database)
E.Technology shock			
Exogenous shock to productivity differential, $\hat{Z}$	1%	1%	to generate $\hat{Z} = 1\%$ in the long-run
Scaling parameter for $\hat{Z}^H(0)$, $\bar{z}^H$	-0.0936	-0.0936	set to target $\hat{Z}^H(0)$
Scaling parameter for $\hat{Z}^N(0)$, $\bar{z}^N$	0.0002	0.0002	set to target $\hat{Z}^N(0)$
Speed of adjustment of Z^H, ξ^H	0.5709	0.5709	set to target $-\frac{1}{3}\ln\left(\frac{\hat{Z}^H(3)-\hat{Z}^H}{\bar{z}^H}\right)$
Speed of adjustment of Z^N, ξ^N	1.1668	1.1668	set to target $-\frac{1}{3}\ln\left(\frac{\hat{Z}^N(3)-\hat{Z}^N}{\bar{z}^N}\right)$

Table 8: Construction of Variables and Data Sources

Variable	Countries covered	Period	Construction and aggregation	Database
Value added Y^H & Y^N (constant prices)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	T: Agriculture, Mining, Manufacturing, Transport, Finance Intermediation N: Electricity, Construction, Trade, Hotels, Real Estate, Personal Services	EU KLEMS & STAN
Value added $P^H Y^H$ & $P^N Y^N$ (current prices)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	T: Agriculture, Mining, Manufacturing, Transport, Finance Intermediation N: Electricity, Construction, Trade, Hotels, Real Estate, Personal Services	EU KLEMS & STAN
Labor L^H & L^N (total hours worked by persons engaged)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	T: Agriculture, Mining, Manufacturing, Transport, Finance Intermediation N: Electricity, Construction, Trade, Hotels, Real Estate, Personal Services	EU KLEMS & STAN
Labor compensation LAB^H & LAB^N (current prices)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	T: Agriculture, Mining, Manufacturing, Transport, Finance Intermediation N: Electricity, Construction, Trade, Hotels, Real Estate, Personal Services	EU KLEMS & STAN
Relative Output Y^H/Y^N	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Value added at constant prices in tradables (Y^H) over value added at constant prices in non-tradables (Y^N)	authors' calculations
Output Share $\nu^{Y,H}$ & $\nu^{Y,N}$	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Value added at constant prices (Y^j) over value added at constant prices in total economy ($Y^H + Y^N$)	authors' calculations
Relative Labor L^H/L^N	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Total hours worked by persons engaged in tradables (L^H) over total hours worked by persons engaged in non-tradables (L^N)	authors' calculations
Labor Share $\nu^{L,H}$ & $\nu^{L,N}$	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Total hours worked by persons engaged (L^j) over total hours worked by persons engaged in total economy ($L^H + L^N$)	authors' calculations
Price P^H & P^N (value added deflator)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Value added at current prices ($P^j Y^j$) over value added at constant prices (Y^j)	authors' calculations
Relative Price P (index 1995=100)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Value added deflator of non-traded goods (P^N) over value added deflator of traded goods (P^H)	authors' calculations
Wage W^H & W^N (nominal and per hour)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Labor compensation (LAB^j) over total hours worked by persons engaged (L^j)	authors' calculations
Wage W (nominal and per hour)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Labor compensation (LAB) over total hours worked by persons engaged (L)	authors' calculations
Wage W^H/P_C & W^N/P_C (real and per hour)	AUS, AUT, BEL, CAN, ESP, DNK, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Nominal wage (W^j) divided by the consumer price index (P_C)	authors' calculations
Wage W/P_C (real and per hour)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Nominal wage (W) divided by the consumer price index (P_C)	authors' calculations
Relative Wage Ω (index 1995=100)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Nominal wage in non-tradables (W^N) over nominal wage in tradables (W^H)	authors' calculations
Labor income shares s_L^H & s_L^N	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Labor compensation (LAB^j) over value added at current prices ($P^j Y^j$)	authors' calculations
Capital stock K (constant prices)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Computed from the perpetual inventory approach using data of aggregate investment in constant prices (depreciation rate: 5%)	authors' calculations
Sectoral capital stocks K^H & K^N	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Computed from Garofalo and Yamarik [2002] using sectoral current prices output shares ($P^j Y^j / (P^H Y^H + P^N Y^N)$)	authors' calculations
Capital-labor ratios k^H & k^N	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Capital stock (K^j) over total hours worked by persons engaged (L^j)	authors' calculations
Sectoral TFPs Z^H & Z^N (index 1995=100)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	Computed as Solow residuals from $\log Z^j = \log Y^j - s_L^j \log L^j - (1 - s_L^j) \log K^j$ where is s_L^j the labor share in value added averaged over 1970-2013	authors' calculations
Relative TFP Z	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013 (JPN: 74-13)	TFP in tradables (Z^H) over TFP in non-tradables (Z^N) adjusted by labor shares (s_L^H and s_L^N) and the tradable share in investment (α_J)	authors' calculations
Consumer Price Index P_C (index 1995=100)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL , ITA, JPN, NLD, NOR, SWE, USA	1970-2013	Consumer prices, all items index	OECD Prices
Gross domestic product Y_R (constant prices)	AUS, AUT, BEL, CAN, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, NOR, SWE, USA	1970-2013	Gross domestic product (GDPV)	OECD Outlook
Investment $P^H I^H$ & $P^N I^N$ (current prices)	AUS (70-13), AUT (95-13), BEL (95-13), CAN (70-13), DEU (95-13), DNK (70-13), ESP (95-13), FIN (80-13), FRA (78-13), GBR (97-13), IRL (95-13), ITA (95-13) JPN (94-13), NLD (95-13), NOR (70-13), SWE (93-13), USA (70-13)		T: Transport, ICT, Biological Resources, Property Product, Other N: Construction, Other (Other: defined as 50% tradable and 50% non-tradable)	OECD Input-Output
Consumption $P^H C^H$ & $P^N C^N$ (current prices)	AUS (70-13), AUT (95-13), BEL (95-13), CAN (81-13), DEU (95-13), DNK (70-13), ESP (95-13), FIN (75-13), FRA (70-13), GBR (95-13), IRL (95-13), ITA (95-13), JPN (94-13), NLD (95-13), NOR (70-13), SWE (93-13), USA (70-13)		T: Food, Beverages, Clothing, Furnishings, Transport, Miscellaneous N: Housing, Health, Communications, Recreation, Education, Restaurants and Miscellaneous (defined as 50% tradable and 50% non-tradable)	COICOP
Government spending $P^H G^H$ & $P^N G^N$ (current prices)	AUS (98-13), AUT (95-13), BEL (95-13), DEU (95-13), DNK (95-13), ESP (95-13), FIN (90-13), FRA (95-13), GBR (95-13), IRL (95-13), ITA (95-13), JPN (05-13), NLD (95-13), NOR (95-13), SWE (95-13), USA (70-13)		T: Energy, Agriculture, Manufacturing, Transport N: Public Services, Defence, Safety, Education, Health, Housing, Recreation Environment, Social Protection	COFOG

Notes: time series for $P^H G^H$ & $P^N G^N$ are not available for CAN.



(a) Response of Hours Worked: Model vs. Data

(b) Response of Hours Worked: Asymmetric vs. Symmetric Technology Shock

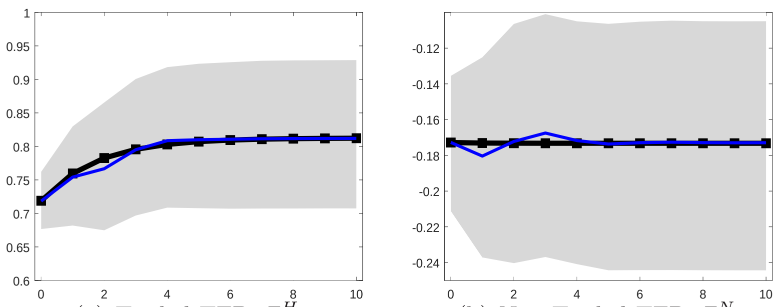
Figure 15: Dynamic Adjustment of Hours Worked: Empirical vs. Theoretical IRF. Notes: Fig. 15(a) contrasts the empirical response of total hours worked shown in the blue line with the baseline model's prediction with FBTC displayed by the black line with squares. The dashed red line shows the theoretical response from the reference model for the calibration with Cobb-Douglas production functions and HNTC. Fig. 15(b) shows empirical responses of total hours worked to identified symmetric (black line) and asymmetric (blue line) technology shocks across sectors. Sample: 17 OECD countries, 1970-2013, annual data.

worked. While it is beyond the scope of this article, we estimated the response of total hours worked to a symmetric technology shock across sectors (i.e., a shock to Z^A leaving unchanged the ratio Z^H/Z^N) and we find empirically that total hours worked decline substantially, see Fig. 15(b). The discrepancy in the response of hours worked between symmetric and asymmetric technology shocks is caused by the reallocation incentives we focus on in this work. While a technology shock biased toward the traded sector appreciates the relative price of non-tradables and has an expansionary effect on hiring by non-traded firms, a symmetric technology shock across sectors depreciates the relative price of non-tradables which lowers the share of non-tradables in expenditure and thus exerts a negative impact on labor demand by non-traded firms. Since the labor share of non-tradables is two-third, more hiring in this sector increases total hours worked while less incentives to hire in this sector lower total hours worked. In this regard, the gross complementarity between traded and non-traded goods and the gross substitutability between home- and foreign-produced traded goods play a pivotal role in the response of total hours worked to aggregate technology shocks. In addition, as mentioned in the main text, aggregate technology shocks are a combination of asymmetric and symmetric technology shocks whose contribution varies over time, and thus the response of hours worked is most likely to increase over time because the contribution of asymmetric technology shocks increases.

Empirical and theoretical impulse response functions following a permanent increase in traded relative to non-traded TFP are contrasted in Fig. 15(a). Empirical responses are displayed by the solid blue line and theoretical responses from the baseline model with FBTC are displayed by the solid black line with squares. The dashed red line shows model's predictions when we consider Cobb-Douglas production functions which correspond to the normalization point (since we normalize CES production functions by taking the steady-state in a Cobb-Douglas economy as the reference point). We set σ_L to 1.6 in order to let the reference model with Cobb-Douglas production functions reproduce the impact response of total hours worked. While the impact response is almost identical, the baseline model with CES production functions and FBTC reproduces very well the dynamics of total hours worked while the model with Cobb-Douglas production functions somewhat understates the growing time profile of total hours worked.

L.3 Calibration of the Technology Shock Biased toward Tradables

Once the model has been calibrated to reproduce the key features of a representative OECD economy, we have to generate shocks to sectoral TFPs which are in line with the data. To determine the dynamic adjustment of Z^j following a long-run permanent increase in $\hat{Z}$ by 1%, we first estimate the VAR model that includes (in growth rate) the relative productivity of tradables, real GDP, total hours worked, and the real consumption wage and identify technology shocks as shocks that increase permanently the ratio of traded relative to non-traded TFP. Then, we consider a VAR model in panel format on annual data that includes identified technology shocks, ϵ^Z_{it}, ordered first, TFP in the traded sector, Z^H_{it}, TFP in the non-traded sector, Z^H_{it}, and the ratio of sectoral TFPs, Z_{it}, where all variables are measured in growth rate. We estimate the VAR model $x^Z_{i,t} = [\epsilon^Z_{it}, \hat{Z}^H_{it}, \hat{Z}^N_{it}, \hat{Z}_{it}]$ and adopt a Cholesky decomposition. While the weights a and b are assumed to be constant over time, we find a slight discrepancy in the estimated technology shock biased toward the traded sector because $\hat{Z}_t$ slightly differs from the weighted average $a\hat{Z}^H_t - b\hat{Z}^N_t$. We thus take the following route. We compute $\hat{Z}^N_t$ at various horizons by using the following formula $\hat{Z}^N_t = \frac{aZ^H_t - \hat{Z}_t}{b}$ so that the



(a) Traded TFP, Z^H (b) Non-Traded TFP, Z^N

Figure 16: Dynamic Adjustment of Sectoral TFP following a 1% Permanent Increase in Traded relative to non-traded TFP: Empirical vs. Theoretical IRF. Notes: The empirical responses of TFP in the traded sector (i.e., Z^H) and non-traded sector (i.e., Z^N) to the identified (in the baseline VAR model) technology shock biased toward the traded sector are displayed by solid blue lines with shaded area indicating the 90 percent confidence bounds obtained by bootstrap sampling; the model's prediction is shown in the solid black line with squares. Sample: 17 OECD countries, 1970-2013, annual data.

asymmetric technology shock is equal to the labor share-adjusted TFP differential at each point of time. It is worth mentioning that the difference between the actual and rescaled response of non-traded TFP is negligible.

To set the law of motion of sectoral TFPs, we proceed as follows. We assume that the adjustment of labor- and capital-augmenting efficiency is governed by the following continuous time path:

$$\hat{A}^j(t) - \hat{A}^j = \bar{a}^j e^{-\xi^j t}, \quad \hat{B}^j(t) - \hat{B}^j = \bar{b}^j e^{-\xi^j t}, \tag{86}$$

where $\xi^j > 0$ measures the speed at which productivity closes the gap with its long-run level. When parameters $\bar{a}^j$ or $\bar{b}^j$ take negative values, productivity undershoots its new steady-state value on impact. Log-linearizing the technology frontier (27) in the neighborhood of the initial steady-state leads to:

$$\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right) \hat{B}^j(t), \tag{87}$$

where s_L^j is the LIS in sector j at the initial steady-state. Inserting (86) into (87) and using the fact the $\hat{Z}^j = s_L^j \hat{A}^j + \left(1 - s_L^j\right) \hat{B}^j$ in the long-run enables us to map the dynamics for labor- and capital-augmenting efficiency into the law of motion for TFP in sector $j = H, N$:

$$\hat{Z}^j(t) - \hat{Z}^j = \bar{z}^j e^{-\xi^j t}, \tag{88}$$

where $\bar{z}^j = s_L^j \bar{a}^j + \left(1 - s_L^j\right) \bar{b}^j$. We choose $\bar{a}^j$, $\bar{b}^j$ by setting $t = 0$ into (86) which yields $\bar{a}^j = -\left(\hat{A}^j - \hat{A}^j(0)\right)$, and $\bar{b}^j = -\left(\hat{B}^j - \hat{B}^j(0)\right)$. Making use of the time series generated by (38a) and (38b) gives us $\bar{a}^H = -0.029840$, $\bar{b}^H = -0.202769$, $\bar{a}^N = 0.234035$, $\bar{b}^N = -0.500629$. To determine the value for the speed of adjustment of sectoral TFP, we solve (88) for ξ^j:

$$\xi^j = -\frac{1}{t} \ln\left(\frac{\hat{Z}^j(t) - \hat{Z}^j}{\bar{z}^j}\right). \tag{89}$$

We choose time t for which we calculate ξ^j that gives us the best fit of the response of $\hat{Z}^j(t)$ estimated empirically. Setting $t = 3$ leads to $\xi^H = 0.570885$ for the traded sector and $\xi^N = 1.166821$ for the non-traded sector which gives us the best fit of the response of $\hat{Z}^j(t)$ estimated empirically.

Given the values for $\bar{z}^j$, ξ^j and $\hat{Z}^j$, we can compute the transitional path for $\hat{Z}^j(t)$ by using (88) and thus the dynamics for the productivity differential (39) where we assume that weights a and b are constant over time. In Fig. 16, we contrast empirical responses shown in blue lines with theoretical responses displayed by the solid black lines with squares. We may notice that the law of motion (88) we impose to capture the dynamic adjustment of sectoral TFPs allows us to reproduce well the responses of $Z^j(t)$ we estimate empirically. When we calibrate the model to country-specific data, we adopt the same approach as for the calibration to a representative economy.

L.4 Estimates of ϵ and ϕ: Empirical Strategy

Table 9 shows our estimates of the elasticity of labor supply across sectors, ϵ, while Table 10 shows our estimates of the elasticity of substitution in consumption between traded and non-traded goods, ϕ. We present our empirical strategy to estimate these two parameters. More details can be found in Appendix M.3 and M.2, respectively.

Table 9: Estimates of Elasticity of Labor Supply across Sectors (ϵ)

Country	Elasticity of labor supply across Sectors (ϵ), eq. (90)
AUS	0.375^{a} (3.20)
AUT	1.103^{a} (3.00)
BEL	0.610^{a} (3.57)
CAN	0.390^{a} (4.12)
DEU	1.012^{a} (3.52)
DNK	0.286^{a} (2.50)
ESP	1.015^{a} (3.73)
FIN	0.431^{a} (4.39)
FRA	1.400^{a} (2.83)
GBR	0.601^{a} (3.91)
IRL	0.216^{a} (3.74)
ITA	1.664^{a} (3.01)
JPN	0.873^{a} (3.55)
NLD	0.219^{b} (2.05)
NOR	0.011 (0.34)
SWE	0.534^{a} (4.28)
USA	3.222^{c} (1.83)
Countries	17
Observations	1456
Data coverage	1971-2013
Country fixed effects	yes
Time trend	no

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

Elasticity of labor supply across sectors. Drawing on Horvath [2000], we derive a testable equation by combining optimal rules for labor supply and labor demand and estimate ϵ by running the regression of the worker inflow in sector $j = H, N$ of country i at time t arising from labor reallocation across sectors computed as $\hat{L}^j_{i,t} - \hat{L}_{i,t}$ on the relative labor's share percentage changes in sector j, $\hat{\beta}^j_{i,t}$:

$$\hat{L}^j_{i,t} - \hat{L}_{i,t} = f_i + f_t + \gamma_i \hat{\beta}^j_{i,t} + \nu^j_{i,t}, \tag{90}$$

where $\nu^j_{i,t}$ is an i.i.d. error term; country fixed effects are captured by country dummies, f_i, and common macroeconomic shocks by year dummies, f_t. The LHS term of (90) is calculated as the difference between changes (in percentage) in hours worked in sector j, $\hat{L}^j_{i,t}$, and in total hours worked, $\hat{L}_{i,t}$. The RHS term β^j corresponds to the fraction of labor's share of value added accumulating to labor in sector j. Denoting by $P^j_t Y^j_t$ value added at current prices in sector $j = H, N$ at time t, β^j_t is computed as $\frac{s^j_L P^j_t Y^j_t}{\sum_{j=H}^{N} s^j_L P^j_t Y^j_t}$ where s^j_L is the LIS in sector $j = H, N$ defined as the ratio of the compensation of employees to value added in the jth sector, averaged over the period 1970-2013. Because hours worked are aggregated by means of a CES function, percentage change in total hours worked, $\hat{L}_{i,t}$, is calculated as a weighted average of sectoral hours worked percentage changes, i.e., $\hat{L}_t = \sum_{j=H}^{N} \beta^j_{t-1} \hat{L}^j_t$. The parameter we are interested in, say the degree of substitutability of hours worked across sectors, is given by $\epsilon_i = \gamma_i/(1-\gamma_i)$. In the regressions that follow, the parameter γ_i is assumed to be different across countries when estimating ϵ_i for each economy ($\gamma_i \neq \gamma_{i'}$ for $i \neq i'$). To construct $\hat{L}^j$ and $\hat{\beta}^j$ we combine raw data on hours worked L^j, nominal value added $P^j Y^j$ and labor compensation $W^j L^j$. All required data are taken from the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. The sample includes the 17 OECD countries mentioned above over the period 1971-2013 (except for Japan: 1975-2013). Table 9 reports empirical estimates that are consistent with $\epsilon > 0$. All values are statistically significant at 10%, except for Norway. Overall, we find that ϵ ranges from a low of 0.01 for NOR to a high of 3.222 for USA.

Elasticity of substitution between traded and non-traded goods in consumption. To estimate the elasticity of substitution in consumption, ϕ, between traded and non-traded goods, we derive a testable equation by rearranging the optimal rule for optimal demand for non-traded goods, i.e., $C_t^N = (1-\varphi)\left(\frac{P_t^N}{P_{C,t}}\right)^{-\phi} C_t$, since time series for consumption in non-traded goods are too short. More specifically, we derive an expression for the non-tradable content of consumption expenditure by using the market clearing condition for non-tradables and construct time series for $1-\alpha_{C,t}$ by using time series for non-traded value added and demand components of GDP while keeping the non-tradable content of investment and government expenditure fixed, in line with the evidence documented by Bems [2008] for the share of non-traded goods in investment and building on our own evidence for the non-tradable content of government spending. After verifying that the (logged) share of non-tradables and the (logged) ratio of non-traded prices to the consumption price index are both integrated of order one and cointegrated, we run the regression by adding country and time fixed effects by using a FMOLS estimator. We consider two variants, one including a country-specific time trend and one without the time trend. We provide more details below.

Multiplying both sides of $C_t^N = (1-\varphi)\left(\frac{P_t^N}{P_{C,t}}\right)^{-\phi} C_t$ by P^N/P_C leads to the non-tradable content of consumption expenditure:

$$1-\alpha_{C,t} = \frac{P_t^N C_t^N}{P_{C,t} C_t} = (1-\varphi)\left(\frac{P_t^N}{P_{C,t}}\right)^{1-\phi}. \tag{91}$$

Because time series for non-traded consumption display a short time horizon for most of the countries of our sample while data for sectoral value added and GDP demand components are available for all of the countries of our sample over the period running from 1970 to 2013, we construct time series for the share of non-tradables by using the market clearing condition for non-tradables:

$$\frac{P_t^N C_t^N}{P_{C,t} C_t} = \frac{1}{\omega_{C,t}}\left[\frac{P_t^N Y_t^N}{Y_t} - (1-\alpha_J)\,\omega_{J,t} - \omega_{G^N}\omega_{G,t}\right]. \tag{92}$$

Since the time horizon is too short at a disaggregated level (for I^j and G^j) for most of the countries, we draw on the evidence documented by Bems [2008] which reveals that $1-\alpha^J = \frac{P^N J^N}{P^J J}$ is constant over time; we further assume that $\frac{P^N G^N}{G} = \omega_{G^N}$ is constant as well in line with our evidence. We thus recover time series for the share of non-tradables by using time series for the non-traded value added at current prices, $P_t^N Y_t^N$, GDP at current prices, Y_t, consumption expenditure, gross fixed capital formation, I_t, government spending, G_t while keeping the non-tradable content of investment and government expenditure, $1-\alpha_J$, and ω_{G^N}, fixed.

Once we have constructed time series for $1-\alpha_{C,t} = \frac{P_t^N C_t^N}{P_{C,t} C_t}$ by using (92), we take the logarithm of both sides of (91) and run the regression of the logged share of non-tradables on the logged ratio of non-traded prices to the consumption price index:

$$\ln\left(1-\alpha_{C,it}\right) = f_i + f_t + \alpha_i\ .t + (1-\phi)\ln\left(P^N/P_C\right)_{it} + \mu_{it}, \tag{93}$$

where f_i captures the country fixed effects, f_t are time dummies, and μ_{it} are the i.i.d. error terms. Because parameter φ in (91) may display a trend over time, we add country-specific trends, as captured by $\alpha_i t$. It is worth mentioning that P^N is the value added deflator of non-tradables.

Data for non-traded value added at current prices, $P_t^N Y_t^N$ and GDP at current prices, Y_t, are taken from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases (data coverage: 1970-2013 for all countries, except Japan: 1974-2013). To construct time series for consumption, investment and government expenditure as a percentage of nominal GDP, i.e., $\omega_{C,t}$, $\omega_{J,t}$ and $\omega_{G,t}$, respectively, we use data at current prices obtained from the OECD Economic Outlook Database (data coverage: 1970-2013). Sources, construction and data coverage of time series for the share of non-tradables in investment $(1-\alpha_J)$ and in government spending (ω_{G^N}) are described in depth in Appendix K; P^N is the value added deflator of non-tradables. Data are taken from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases (data coverage: 1970-2013 for all countries, except Japan: 1974-2013). Finally, data for the consumer price index $P_{C,t}$ are obtained from the OECD Prices and Purchasing Power Parities database (data coverage: 1970-2013).

Since both sides of (93) display trends, we ran unit root and then cointegration tests. Having verified that these two assumptions are empirically supported, we estimate the cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000], [2001]. FMOLS estimates of (93) are reported in Table 10. When we include a country-specific time trend, the vast majority (15 out of 17) of the FMOLS estimated coefficients are positive; yet, only ten out of seventeen are statistically significant, including AUS, AUT, CAN, DEU, DNK, ESP, IRL, JPN, NOR, USA. We thus also run the same regression as in eq. (93) by ignoring country-specific time trends. We replace inconsistent (i.e., negative or no statistically significant) estimates for ϕ when adding a country-specific time trend with those obtained when we excluded the country-specific time trend. Except for GBR for which estimates are negative in both cases and BEL for which estimates are not statistically significant, one out of the two regressions leads to consistent estimates for the elasticity of substitution. For the countries mentioned below, estimates for ϕ obtained with a time trend are replaced with those when we drop the time trend: $\phi = 0.852$ ($t = 8.97$) for FIN, $\phi = 0.885$ ($t = 2.76$) for FRA, $\phi = 0.723$ ($t = 5.54$) for ITA, $\phi = 0.526$ ($t = 2.89$) for NLD and $\phi = 0.513$ ($t = 2.59$) for SWE. For BEL, we take the estimate obtained when we remove country-specific time trend (i.e. $\phi = 1.236$) since the t-stat is close to the threshold of 10%. For GBR, the estimate is negative whether there is a time trend in the regression or not and thus we set ϕ to zero for the rest of the analysis for this country. Table 10 shows estimates for ϕ for each country. We add the superscript * when estimates come from regression (93) without country-specific linear time trend. The last line of Table 6 reveals that ϕ stands at 0.66 when adding a time trend while the estimate for the parameter is twice as small when dropping the time trend. The unweighted average of these two estimates, say 0.49, is close to the value of ϕ which is commonly set in the international RBC literature and taken from Stockman and Tesar [1995] who find a value for ϕ of 0.44. One point merits comments. When running eq. (93), data for the RHS variable, i.e., P^N/P_C, has a good coverage for all countries of our sample. Indeed, we are able to cover our baseline period 1970-2013 for this variable (except for JPN: 1974-2013). By contrast, the LHS variable is constructed by using the share of non-tradables in investment $(1-\alpha_J)$ and in government spending (ω_{G^N}), averaged over the period 1995-2013 (due to data availability). In light of these limitations, we also run eq. (93) for the overlap period 1995-2013. Over this period of time, we have a balanced panel and time series of a reasonable length. Using again the FMOLS estimator, we obtain $\phi = 0.474$ for the whole sample. As a robustness check, we also used the DOLS estimator with one lead/lag which gives a value of 0.415. The unweighted average of these two estimates is $\phi = 0.445$ for the whole sample, in accordance with the estimated value of 0.44 documented by Stockman and Tesar [1995].

L.5 Estimates of σ^j: Empirical strategy

To estimate the elasticity of substitution between capital and labor, σ^j, we draw on Antràs [2004]. We let labor- and capital-augmenting technological change grow at a constant rate:

$$A_t^j = A_0^j e^{a^j t}, \tag{94a}$$

$$B_t^j = B_0^j e^{b^j t}, \tag{94b}$$

where a^j and b^j denote the constant growth rate of labor- and capital-augmenting technical progress and A_0^j and B_0^j are initial levels of technology. Inserting first (94a) and (94b) into the demand for labor and capital (24a)-(24b), taking logarithm and rearranging gives:

$$\ln(Y_t^j/L_t^j) = \alpha_1 + \left(1-\sigma^j\right) a^j t + \sigma_j \ln(W_t^j/P_t^j), \tag{95a}$$

$$\ln(Y_t^j/K_t^j) = \alpha_2 + \left(1-\sigma^j\right) b^j t + \sigma_j \ln(R_t/P_t^j), \tag{95b}$$

where $\alpha_1 = \left[(1-\sigma^j)\ln A_0^j - \sigma^j \ln \gamma^j\right]$ and $\alpha_2 = \left[(1-\sigma^j)\ln B_0^j - \sigma^j \ln(1-\gamma^j)\right]$ are constants. Above equations describe firms' demand for labor and capital respectively.

We estimate the elasticity of substitution between capital and labor in sector $j = H, N$ from first-order conditions (95a)-(95b) in panel format on annual data. Adding an error term and controlling for country fixed effects, we explore empirically the following equations:

$$\ln(Y_{it}^j/L_{it}^j) = \alpha_{1i} + \lambda_{1i} t + \sigma_i^j \ln(W_{it}^j/P_{it}^j) + u_{it}, \tag{96a}$$

$$\ln(Y_{it}^j/K_{it}^j) = \alpha_{2i} + \lambda_{2i} t + \sigma_i^j \ln(R_{it}/P_{it}^j) + v_{it}, \tag{96b}$$

where i and t index country and time and u_{it} and v_{it} are i.i.d. error terms. Country fixed effects are represented by dummies α_{1i} and α_{2i}, and country-specific trends are captured by λ_{1i} and λ_{2i}. Since all variables display unit root process, we estimate cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000].

Estimation of (96a) and (96b) requires data for each sector $j = H, N$ on sectoral value added at constant prices Y^j, sectoral hours worked L^j, sectoral capital stock K^j, sectoral value added deflator P^j, sectoral wage rate W^j and capital rental cost R. Data for sectoral value added Y^H and Y^N, hours worked L^H and L^N, value added price deflators P^H and P^N, and, nominal wages W^H and W^N are taken form the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. To construct the national stock of capital K, we use the perpetual inventory method with a fixed depreciation rate of 5% and the time series of constant-price investment from the OECD Economic Outlook Database. Next, following Garofalo and Yamarik [2002], the capital stock is allocated to traded and non-traded industries by using sectoral output shares. Finally, we measure the aggregate rental price of capital R as the ratio of capital income to capital stock. Capital income is derived

Table 10: Elasticity of Substitution between Tradables and Non-Tradables (ϕ)

Country	Elasticity of substitution between C^T and C^N (ϕ) , eq. (93)
AUS	0.396^{b} (2.25)
AUT	1.518^{a} (6.35)
BEL	$1.236^{\star}$ (1.29)
CAN	0.748^{a} (4.32)
DEU	0.577^{a} (2.79)
DNK	1.083^{a} (3.77)
ESP	1.387^{b} (2.19)
FIN	$0.852^{a\star}$ (8.97)
FRA	$0.885^{a\star}$ (2.76)
GBR	0
IRL	1.352^{a} (3.70)
ITA	$0.723^{a\star}$ (5.54)
JPN	1.052^{a} (5.12)
NLD	$0.526^{a\star}$ (2.89)
NOR	0.891^{a} (3.33)
SWE	$0.513^{a\star}$ (2.59)
USA	0.821^{a} (3.73)
Whole Sample	$0.662^{a}/0.333^{a\star}$ (12.03) (6.05)
Countries	17
Observations	739
Data coverage	1970-2013
Country fixed effects	yes
Time trend	yes

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. The superscript * indicates that the estimate is obtained in a regression without a country-specific linear time trend.

Table 11: FMOLS Estimates of the Sectoral Elasticity of Substitution between Capital and Labor (σ^j)

Country	Tradables (σ^H)		Non-Tradables (σ^N)	
Dependent variable	$\ln(Y^H/K^H)$	$\ln(Y^H/L^H)$	$\ln(Y^N/K^N)$	$\ln(Y^N/L^N)$
Explanatory variable	$\ln(R/P^H)$	$\ln(W^H/P^H)$	$\ln(R/P^N)$	$\ln(W^N/P^N)$
AUS	0.607^a (6.67)	0.474^a (3.79)	0.459^a (4.03)	0.529^a (5.69)
AUT	0.235^a (2.65)	0.774^a (6.04)	0.105 (1.22)	1.298^a (13.04)
BEL	0.389^a (3.01)	0.829^a (8.89)	0.266^a (7.37)	1.069^a (7.10)
CAN	0.595^a (3.99)	0.480^a (2.94)	0.855^a (8.62)	0.668^a (7.65)
DEU	−0.123 (−0.68)	0.642^a (8.56)	0.512^a (8.88)	0.987^a (6.97)
DNK	0.267^c (1.84)	0.417^a (4.32)	0.502^a (7.83)	1.282^a (6.74)
ESP	0.747^a (7.11)	1.033^a (10.62)	0.682^a (3.65)	0.476^a (3.35)
FIN	0.249^a (2.90)	0.764^b (1.98)	0.560^a (6.64)	0.794^a (8.30)
FRA	0.267^a (4.82)	0.870^a (4.82)	0.294^a (11.04)	0.916^a (4.21)
GBR	0.242 (0.95)	0.603^a (6.42)	0.008 (0.08)	0.561^a (2.68)
IRL	0.737^a (18.46)	−0.125 (−0.50)	0.762^a (5.73)	0.627^a (3.16)
ITA	0.506^a (3.82)	0.837^a (8.80)	0.471^a (3.23)	0.259 (1.51)
JPN	0.622^a (8.16)	1.164^a (6.73)	0.417^a (7.97)	0.635^b (2.47)
NLD	0.645^a (5.13)	0.910^a (5.98)	0.287^a (9.14)	0.444^a (3.74)
NOR	0.798^a (4.60)	0.629^a (4.39)	0.653^a (10.17)	0.556^a (4.72)
SWE	0.052 (0.35)	0.607^a (8.56)	0.378^a (6.71)	0.194 (0.95)
USA	1.485^a (6.85)	0.766^a (9.51)	0.723^a (6.64)	0.876^a (4.96)
Whole Sample	0.489^a (19.56)	0.687^a (24.70)	0.467^a (26.42)	0.716^a (21.16)
Countries	17	17	17	17
Observations	745	745	745	745
Data coverage	1970-2013	1970-2013	1970-2013	1970-2013
Country fixed effects	yes	yes	yes	yes
Time trend	yes	yes	yes	yes

Notes: [a], [b] and [c] denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

as nominal value added minus labor compensation. For all aforementioned variables, the sample includes includes the 17 OECD countries over the period 1970-2013 (except for Japan: 1974-2013).

While we take the demand for labor as our baseline model (i.e. eq. (96a), Table 11 provides FMOLS estimates of σ^j for the demand of labor and capital. The bulk (3 out of 34) of the FMOLS estimated coefficients from eq. (96a) are positive and statistically significant. One estimated coefficient is negative (σ^H for IRL) while estimates of σ^N for ITA and SWE are positive but not statistically significant. As in Antràs [2004], we alternatively run the regression of the ratio of value added to capital stock at constant prices on the real capital cost R/P^j in sector j, i.e., eq. (96b). We then replace inconsistent estimates for σ^j obtained from labor demand with those obtained from the demand of capital. Columns 17-18 of Table 6 report estimates for σ^H and σ^N.

L.6 Estimates of ρ and ρ_J: Empirical strategy

In this subsection, we detail our empirical strategy to estimate the elasticity between home- and foreign-produced traded goods for consumption, ρ, and investment , ρ_J.

Empirical strategy. Making use of (20a) and (20b), the demand for home- relative to foreign-produced traded goods for consumption and investment reads $\frac{C_t^H}{C_t^F} = \frac{\varphi^H}{1-\varphi^H}\left(\frac{P_t^H}{P_t^F}\right)^{-\rho}$ and $\frac{J_t^H}{J_t^F} =$

$\frac{\iota^H}{1-\iota^H}\left(\frac{P_t^H}{P_t^F}\right)^{-\rho_J}$. Left multiplying by $\frac{P_t^H}{P_t^F}$ leads to

$$\frac{P_t^H C_t^H}{P_t^F C_t^F} = \frac{\varphi^H}{1-\varphi^H}\left(\frac{P_t^H}{P_t^F}\right)^{1-\rho}, \tag{97a}$$

$$\frac{P_t^H J_t^H}{P_t^F J_t^F} = \frac{\iota^H}{1-\iota^H}\left(\frac{P_t^H}{P_t^F}\right)^{1-\rho_J}. \tag{97b}$$

Denoting current expenditure on home-produced traded goods by $D_{X,t}^H = P_t^H X_t^H$ for $X = C, J$ and current expenditure on foreign-produced traded goods by $D_{X,t}^F = P_t^F X_t^F$ for $X = C, J$, taking the logarithm of both sides of (97a)-(97b), indexing countries by i and adding an error term, we run the regression of logged expenditure on home-produced traded goods relative to expenditure on foreign-produced traded goods on logged terms of trade (TOT thereafter):

$$\ln\left(D_{C,it}^H/D_{C,it}^F\right) = g_i + g_t + (1-\rho_i)\ln \mathrm{TOT}_{it} + \mu_{it}, \tag{98a}$$

$$\ln\left(D_{J,it}^H/D_{J,it}^F\right) = h_i + h_t + (1-\rho_{J,i})\ln \mathrm{TOT}_{it} + \nu_{it}, \tag{98b}$$

where g_i, h_i capture the country fixed effects, g_t, h_t are time dummies, μ_{it} and ν_{it} are the i.i.d. error terms. Because parameter φ^H, ι^H in (97a)-(97b) may display a trend over time, we also estimate both equations by adding country-specific linear time trends, as captured by $\beta_{c,i}t$ and $\beta_{j,i}t$.

Data Construction. To construct $D_{C,it}^H$, $D_{C,it}^F$, $D_{J,it}^H$, $D_{J,it}^F$, we use the World Input-Output Database (WIOD [2013], [2016]). The 2013 release provides data for eleven 1-digit ISIC-rev.3 industries over the period 1995-2011 while the 2016 release provides data for thirteen 1-digit-rev.4 industries over the period 2000-2014. As sectoral data are classified using identical ISIC revisions in both the EU KLEMS and WIOD datasets, we map the WIOD ISIC-rev.4 classification (the 2016 release) into the WIOD ISIC-rev.3 classification (the 2013 release) in accordance with the concordance Table 5. Consistent with the methodology we used to extend series taken from the EU KLEMS ([2011], [2017]), time series for traded and non-traded variables from the WIOD [2013] dataset (available over the period 1995-2011) are extended forward up to 2014 using annual growth rate estimated from WIOD [2016] series (available over the period 2000-2014). WIOD provides data (at current prices) by industry for expenditure on home-produced traded goods, $D_{X,it}^H$, and foreign-produced traded goods, $D_{X,it}^F$, with $X = C, J$, for consumption and investment. We construct time series for $D_{C,it}^H$, $D_{C,it}^F$, $D_{J,it}^H$, $D_{J,it}^F$. Coverage: 1995-2014 except for NOR (2000-2014).

To construct time series for the terms of trade, we consider two measures. The first measure is the ratio of the traded value added deflator to the deflator of imports of goods and services, i.e., $\mathrm{TOT}_{it} = P_{it}^H/P_{it}^F$. The second measure is the ratio of the traded value added deflator of the home country i to the weighted sum of the traded value added deflator of the sixteen trade partners of the corresponding country i, the weight being equal to the share $\alpha^{M,i,k}$ of imports from the trade partner k, i.e, $\mathrm{TOT}_{it} = P_{it}^H/P_{it}^{H,\star}$ where $P_{it}^{H,\star} = \Pi_{k\neq i}\alpha^{M,i,k}P_t^{H,k}$. While in our model, both measures are equivalent since foreign good prices are exogenous and fixed, the second measure of terms of trade is our preferred measure to estimate ρ and ρ_J because $D_{X,it}^H$ and $D_{X,it}^F$ abstract from intermediate inputs in production, and thus the price indexes and quantities in equation (98a)-(98b) correspond to a value-added concept. The Direction of Trade Statistics (DOTS, IMF) gives the share of imports $\alpha^{M,i,k}$ of country i by trade partner k for all countries of our sample over 1995-2014. While the sixteen trade partners of a representative home country do not fully account for the totality of trade between country i and its trade partners $k \neq i$, it covers two-third of total trade on average for a representative OECD country of our sample. Source: Direction of Trade Statistics [2017]. Period: 1995-2014 for all countries except for Belgium (1997-2014).

Estimates. Since both sides of (98a)-(98b) display trends, we ran unit root and then cointegration tests. Having verified that these two assumptions are empirically supported, we estimate the cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000], [2001]. FMOLS estimates of (98a)-(98b) are reported in Table 12. When we include country and year effects only, the majority (12 out of 17 for ρ) of the FMOLS estimated coefficients of ρ are positive and statistically significant. When the estimate for ρ or ρ_J is negative or not significant, we alternatively take the dynamic OLS (DOLS) estimator proposed by Pedroni [2000], [2001]. Otherwise, we use the estimate with country fixed effects and country-specific linear time trend or country fixed effects plus year effects plus a country-specific linear time trend. Only for a few countries, neither the DOLS estimator nor alternative empirical specifications give consistent results. In this situation, we replace $\mathrm{TOT}_{it} = P_{it}^H/P_{it}^{H,\star}$ with $\mathrm{TOT}_{it} = P_{it}^H/P_{it}^F$. If the estimates are still inconsistent, we leave the cell blank.

Cross-country mean. Table 12 shows empirical estimates for ρ and ρ_J in columns 1 and 2. The last row shows the cross-country mean. We find that the elasticity of substitution between home- and foreign-produced traded goods for consumption averages 1.485 across countries when we include only year effects and averages 1.407 when we include a country-specific linear time trend.

For reasons of space, we don't show the values for the specification with a country-specific linear time trend. The elasticity of substitution between home- and foreign-produced traded goods for investment averages 1.214 across countries when we include only year effects and averages 1.714 when we include a country-specific linear time trend. Hence ρ and ρ_J averages 1.45 across the empirical specifications. Because the cross-country mean of the elasticity of substitution between home- and foreign-produced traded goods is 1.45 for both consumption and investment, we set ρ and ρ_J to 1.5 when we calibrate the semi-small open economy to a representative OECD economy. By contrast, as mentioned above and detailed below, ρ and ρ_J are no longer set to 1.5 at a country level and instead are allowed to vary across countries.

Estimated values for ρ at a country level. Column 1 of Table 12 shows estimates for the elasticity of substitution between home- and foreign-produced traded consumption goods, ρ. When we include country and year effects only, twelve out of seventeen FMOLS estimated coefficients of ρ are positive and statistically significant. Because FMOLS estimates of ρ with country and year effects are negative for Austria and Canada and not statistically significant for Denmark, we took estimates when adding a country-specific linear time trend as the estimated values were positive and statistically significant. For Germany, FMOLS estimates of ρ are negative without a time trend and positive but not statistically significant with a time trend. When we replace $\text{TOT}_{it} = P_{it}^H/P_{it}^{H,\star}$ with $\text{TOT}_{it} = P_{it}^H/P_{it}^F$ and run again the regression of (98a), we find a statistically significant and positive estimate for ρ which amounts to 2.02. For Netherlands, none of estimates were consistent since estimates are either negative or not statistically significant. So we leave the cell blank for this country.

Estimated values for ρ_J at a country level. Column 2 of Table 12 shows estimates for the elasticity of substitution between home- and foreign-produced traded investment goods, ρ_J. Out of 17 estimated coefficients, nine are positive and statistically significant for the baseline specification with country fixed effects and time dummies (and no trend) and thus we replace inconsistent values with alternative specifications we detail in this paragraph. For Japan, the Netherlands and Norway, (FMOLS and DOLS) estimates of ρ_J are negative or are not statistically significant and we replace them with the estimates when we allow for country fixed effects and a country-specific linear time trend, i.e., ρ_J stands at 3.12 for Japan, 0.48 for the Netherlands, and 1.02 for Norway. For Germany, either the FMOLS or DOLS estimate of ρ_J is negative with country fixed effects and time effects. When we run the regression by adding a country-specific linear time trend, in addition to country fixed effects and time effects, we find a positive and statistically significant estimate of 1.57. For Ireland, either the FMOLS or DOLS estimate of ρ_J is not statistically significant with country fixed effects and time effects. When we run the regression by adding a country-specific linear time trend and by considering the DOLS estimator, we find a positive and statistically significant estimate of 0.84 for ρ_J for Ireland. For Canada and the United States, FMOLS or DOLS estimates are all negative or not statistically significant. We replace them with consistent FMOLS estimates when we use time series $\text{TOT}_{it} = P_{it}^H/P_{it}^F$ instead of $\text{TOT}_{it} = P_{it}^H/P_{it}^{H,\star}$. The FMOLS estimates for Canada and the U.S. for ρ_J stand at 0.57 and 1.94. For Finland, none of the estimates of ρ_J are consistent so we leave the cell blank.

Column 4 shows the aggregate elasticity of substitution between home- and foreign-produced traded goods denoted by ρ^A. The aggregate elasticity ρ^A is constructed as a weighted sum of the elasticity of substitution for consumption and investment, i.e., $\rho_i^A = 1 - \alpha_i^{C,H}(1-\rho_i) - \left(1-\alpha_i^{C,H}\right)(1-\rho_{J,i})$ where $\alpha_i^{C,H}$ is the share of consumption in expenditure on home-produced traded goods, i.e., $\alpha_{it}^{C,H} = \frac{D_{C,it}^H}{D_{C,it}^H + D_{J,it}^H}$. We average $\alpha_i^{C,H}$ for each country i over 1995-2014. As shown in the last line of column 3, the consumption content of home-produced traded goods expenditure averages 85% over 1995-2014 and thus the investment content stands at 15% on average. We find an aggregate elasticity between home- and foreign produced traded goods of 1.35, close to the value of 1.5 which is commonly assumed in the international RBC literature, see e.g., Backus, Kehoe, and Kydland [1994]. Note that for Germany, column 4 does not return one minus the weighted sum of $1-\rho$ and $1-\rho_J$. The reason is that ρ receives a weight of 86% for Germany and thus mostly determines the magnitude of the ρ^A. Because none of (FMOLS or DOLS) estimates for ρ are positive or statistically significant for Germany when using our preferred time series for the terms of trade $\text{TOT}_{it} = P_{it}^H/P_{it}^{H,\star}$, we found more appropriate to aggregate consumption and investment expenditure and run the regression of $\ln\left(D_{C,it}^H/D_{C,it}^F\right)$ on $\text{TOT}_{it} = P_{it}^H/P_{it}^{H,\star}$ where $D_{it}^H = D_{C,it}^H + D_{J,it}^H$ and $D_{it}^F = D_{C,it}^F + D_{J,it}^F$. When we allow for country fixed effects and time dummies together with country-specific linear time trend, we find a positive and statistically significant estimate of ρ^A of 0.67 for Germany. We thus take this estimated value to calibrate our model. It is worth mentioning that the same logic could apply for the Netherlands as we cannot find some consistent estimates for ρ. However, even when we aggregate consumption and investment expenditure, none of the estimates are consistent.

Table 12: FMOLS Estimates of the Elasticity of Substitution between Home- and Foreign-Produced Traded Goods: ρ and ρ_J

Country	ρ (1)	ρ_J (2)	$\alpha_{it}^{C,H}$ (3)	ρ^A (4)
AUS	1.036^a (25.08)	0.648^a (10.99)	0.847	0.977
AUT	0.759^a (3.18)	1.201^a (3.60)	0.773	0.859
BEL	3.344^b (2.40)	2.020^a (3.80)	0.878	3.182
CAN	2.133^a (6.63)	0.568^a (3.05)	0.899	1.974
DEU	2.016^b (2.43)	1.568^b (2.32)	0.855	0.670
DNK	1.811^c (1.95)	1.292^a (5.07)	0.891	1.755
ESP	1.746^a (8.84)	1.149^b (2.16)	0.895	1.683
FIN	0.889^a (7.38)	n.a.	0.874	0.889
FRA	1.069^a (6.05)	0.852^b (2.39)	0.892	1.046
GBR	1.661^a (6.15)	0.819^a (2.61)	0.894	1.572
IRL	1.309^a (3.40)	0.835^c (1.65)	0.918	1.270
ITA	2.332^a (9.65)	0.856^c (1.68)	0.833	2.086
JPN	0.702^a (9.48)	3.115^a (7.66)	0.748	1.309
NLD	n.a.	0.482^c (1.95)	0.893	0.482
NOR	0.999^a (23.57)	1.024^a (5.40)	0.733	1.006
SWE	0.579^a (10.66)	1.059^a (6.46)	0.831	0.660
USA	1.369^a (13.71)	1.941^b (2.49)	0.781	1.494
Mean	1.485	1.214	0.849	1.348

Notes: ρ is the elasticity of substitution between home- and foreign-produced traded consumption goods, ρ_J is the elasticity of substitution between home- and foreign-produced traded investment goods, $\alpha_{it}^{C,H} = \frac{D_{C,it}^H}{D_{C,it}^H + D_{J,it}^H}$ is the share of expenditure on home-produced traded consumption goods in total expenditure on home-produced traded goods (averaged over 1995-2014); ρ^A is the aggregate elasticity of substitution between home- and foreign-produced traded goods constructed as a weighted sum of the elasticity of substitution for consumption and the elasticity of substitution for investment, i.e., $\rho_i^A = 1 - \alpha_i^{C,H}(1-\rho_i) - \left(1-\alpha_i^{C,H}\right)(1-\rho_{J,i})$. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels.

M Data Description

In this section, we present some additional information about the data we use in the empirical and numerical analysis and the empirical strategy adopted to estimate key parameters. First, we provide details on the construction of sectoral TFP. Then, we describe empirical strategies to estimate four parameters involved in our quantitative analysis: the elasticity of substitution in consumption between traded and non-traded goods, ϕ, the degree of substitutability of hours worked across sectors, ϵ, the elasticity of substitution between capital and labor in production, σ^H and σ^N.

M.1 Construction of Sectoral TFPs

Sectoral TFPs, Z_t^j, at time t are constructed as Solow residuals from constant-price (domestic currency) series of value added, Y_t^j, capital stock, K_t^j, and hours worked, L_t^j:

$$\ln Z_t^j = \ln Y_t^j - s_L^j \ln L_t^j - \left(1 - s_L^j\right) \ln K_t^j, \tag{99}$$

where s_L^j is the LIS in sector j averaged over period 1970-2013 (1974-2013 for Japan). Data for the series of constant price value added (VA_QI) and hours worked (H_EMP) are taken from EU

KLEMS database. The sectoral LIS is calculated as the ratio of labor compensation in sector j (LAB) to value added at current prices (VA). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

To construct the series for the sectoral capital stock, we proceed as follows. Capital stocks are estimated by using the perpetual inventory method. In order to apply this method, we need (*i*) real gross capital formation series, (*ii*) the initial capital stock in the base year, which is set to be 1970 and (*iii*) the rate of depreciation of the existing capital stock. Real gross capital formation is obtained from OECD National Accounts Database [2017] (data in millions of national currency, constant prices). Consistent with the neoclassical growth model, the initial capital stock, K_{1970}, is computed using the following formula:

$$K_{1970} = \frac{I_{1970}}{g_I + \delta_K},$$

where I_{1970} corresponds to the real gross capital formation in the base year 1970, g_I is the average growth rate from 1970 to 2013 of the real gross capital formation series and δ_K is the depreciation rate which is assumed to be 5% (see Hall and Jones [1999]). The capital stock is obtained by using the standard capital accumulation equation: $K_{t+1} = (1-\delta)K_t + I_t$ for $t = 1970, \ldots, 2013$ where K_t is the capital stock at the beginning of period t. Following Garofalo and Yamarik [2002], the gross capital stock is then allocated to traded and non-traded industries by using the sectoral value added share:

$$K_t^j = \omega_t^{Y,j} K_t,$$

where $\omega_t^{Y,j}$ is the value added share of sector j at current prices.

Finally, the productivity differential variable is computed as the difference in the labor share-adjusted TFP growth between the traded sector and the non-traded sector:

$$\hat{Z}_t = a\hat{Z}_t^H - b\hat{Z}_t^N, \tag{100}$$

where $a = \left[(1-\alpha_J) + \alpha_J(s_L^H/s_L^N)\right]^{-1}$, $b = a(s_L^H/s_L^N)$, with α_J the tradable share in total investment expenditure.

M.2 Estimates of ϕ: Empirical Strategy

In this section, we detail our empirical strategy to estimate the elasticity of substitution between traded and non-traded goods ϕ. Estimates of the elasticity of substitution ϕ documented by the existing literature are rather diverse. The cross-section studies report an estimate of ϕ ranging from 0.44 to 0.74, see e.g., Stockman and Tesar [1995] and Mendoza [1995], respectively.[21] The literature adopting the Generalized Method of Moments and cointegration methods, see e.g. Ostry and Reinhart [1992] and Cashin and Mc Dermott [2003], respectively, reports a value in the range $[0.75, 1.50]$ for developing countries and in the range $[0.63, 3.50]$ for developed countries. Since estimates for ϕ display a sharp dispersion across empirical studies, we conduct an empirical analysis in order to estimate this parameter for each country in our sample.

M.2.1 Derivation of the Testable Equation

To estimate ϕ, we adopt the following strategy. At each instant of time, the representative household consumes traded and non-traded goods denoted by C^T and C^N, respectively, which are aggregated by means of a CES function:

$$C = \left[\varphi^{\frac{1}{\phi}} \left(C^T\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} \left(C^N\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{101}$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The index C^T is defined as a CES aggregator of home-produced traded goods, C^H, and foreign produced traded goods, C^F:

$$C^T = \left[\left(\varphi^H\right)^{\frac{1}{\rho}} \left(C^H\right)^{\frac{\rho-1}{\rho}} + (1-\varphi_H)^{\frac{1}{\rho}} \left(C^F\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{102}$$

where $0 < \varphi_H < 1$ is the weight of the home-produced traded good and ρ corresponds to the elasticity of substitution between home- and foreign produced traded goods.

[21] While the sample used by Stockman and Tesar [1995] covers 30 countries (including 17 developing and 13 industrialized), Mendoza [1995] uses exactly the same data set in his estimation but includes only the 13 industrialized countries. Note that the estimate of ϕ has been obtained by using the cross sectional dataset by Kravis, Heston and Summers for the year 1975.

Applying Shephard's lemma (or the envelope theorem) yields the following demand for traded and non-traded goods:

$$C^T = \varphi \left(\frac{P^T}{P_C}\right)^{-\phi} C, \tag{103a}$$

$$C^N = (1-\varphi) \left(\frac{P^N}{P_C}\right)^{-\phi} C. \tag{103b}$$

Multiplying both sides of (103b) by P^N/P_C leads to the non-tradable content of consumption expenditure:

$$1 - \alpha_C = \frac{P^N C^N}{P_C C} = (1-\varphi) \left(\frac{P^N}{P_C}\right)^{1-\phi}. \tag{104}$$

The market clearing for non-tradables reads:

$$Y^N = C^N + J^N + G^N. \tag{105}$$

Multiplying both sides by P^N and dividing by GDP at current prices, $Y = P^H Y^H + P^N Y^N$, leads to:

$$\frac{P^N Y^N}{Y} = \frac{P^N C^N}{Y} + \frac{P^N J^N}{P^J J} . \frac{P^J J}{Y} + \frac{P^N G^N}{G} . \frac{G}{Y}. \tag{106}$$

We denote the investment-to-GDP ratio by $\omega_J = \frac{P^J J}{Y}$ and the share of government spending in GDP by $\omega_G = \frac{G}{Y}$. Building on the evidence documented by Bems [2008], we assume that $1 - \alpha_J = \frac{P^N J^N}{P^J J}$ is constant over time; we further assume that $\frac{P^N G^N}{G} = \omega_{G^N}$ is constant as well in line with our evidence. Under these assumptions and by using the fact that $\frac{P^N C^N}{Y} = (1-\alpha_C)\,\omega_C$, eq. (106) can be solved for the share of non-tradables into consumption expenditure:

$$\frac{P_t^N C_t^N}{P_{C,t} C_t} = \frac{1}{\omega_{C,t}} \cdot \left[\frac{P_t^N Y_t^N}{Y_t} - (1-\alpha_J)\,\omega_{J,t} - \omega_{G^N}\omega_{G,t}\right], \tag{107}$$

where the shares $1-\alpha_J$ and ω_{G^N} are kept constant over time whilst we let the shares $\frac{P_t^N Y_t^N}{Y_t}$, $\omega_{C,t}$, $\omega_{J,t}$, $\omega_{G,t}$ vary across time.

Once we have constructed time series for $1-\alpha_{C,t} = \frac{P_t^N C_t^N}{P_{C,t} C_t}$ by using (107), we take the logarithm of both sides of (104) and we run the regression of the logged share of non-tradables on the logged ratio of non-traded prices to the consumption price index:

$$\ln(1-\alpha_C)_{i,t} = f_i + f_t + \alpha_i t + (1-\phi)\ln\left(P^N/P_C\right)_{i,t} + \mu_{i,t}, \tag{108}$$

where f_i captures the country fixed effects, f_t are time dummies, and μ_{it} are the i.i.d. error terms. Because parameter φ in (104) may display a trend over time, we add country-specific linear time trends, as captured by $\alpha_i t$. It is worth mentioning that P^N is the value added deflator of non-tradables.

M.2.2 Data Construction and Source

We provide more details below on the construction of data employed to estimate equation (108):

- Non-traded value added, $P^N Y^N$: value added at current prices in sector N (VA). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.

- Nominal GDP, Y: value added at current prices in total economy (VA), i.e. $Y = P^H Y^H + P^N Y^N$. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.

- Share of consumption expenditure in total GDP, ω_C: final consumption expenditure of households at current prices over gross domestic product (expenditure approach) at current prices. Source: OECD National Accounts Database [2017]. Data coverage: 1970-2013.

- Share of investment expenditure in total GDP, ω_J: gross fixed capital formation at current prices over gross domestic product (expenditure approach) at current prices. Source: OECD National Accounts Database [2017]. Data coverage: 1970-2013.

- Share of government spending in total GDP, ω_G: final consumption expenditure of general government at current prices over gross domestic product (expenditure approach) at current prices. Source: OECD National Accounts Database [2017]. Data coverage: 1970-2013.

- Share of non-tradables in total investment expenditure, $1-\alpha_J$: investment expenditure on non-tradables at current prices over total investment expenditure at current prices. Source: OECD Input-output database [2017]. Data coverage: AUS (1970-2013), AUT (1995-2013), BEL (1995-2013), CAN (1970-2013), DEU (1995-2013), DNK (1970-2013), ESP (1995-2013), FIN (1980-2013), FRA (1978-2013), GBR (1997-2013), IRL (1995-2013), ITA (1995-2013), JPN (1994-2013), NLD (1995-2013), NOR (1970-2013), SWE (1993-2013) and USA (1970-2013).
- Share of non-tradables in total government spending, ω_{G^N}: government spending on non-tradables at current prices over total government spending at current prices. Source: COFOG, OECD [2017]. Data coverage: AUS (1998-2013), AUT (1995-2013), BEL (1995-2013), DEU (1995-2013), DNK (1995-2013), ESP (1995-2013), FIN (1990-2013), FRA (1995-2013), GBR (1995-2013), IRL (1995-2013), ITA (1995-2013), JPN (2005-2013), NLD (1995-2013), NOR (1995-2013), SWE (1995-2013) and USA (1970-2013). Data are not available for CAN. For this country, we choose $\omega_{G^N}=0.90$ which corresponds to the cross-country unweighed average.
- Sectoral value added price deflator, P^N: value added at current prices (VA) over value added at constant prices (VA_QI) in sector N. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.
- Consumer price index, P_C: consumer price index (all items, Index, 2010=100). Source: OECD Prices and Purchasing Power Parities. Data coverage: 1970-2013.

We use data described above to construct time series for $(1-\alpha_C)_{i,t}$ and $\left(P^N/P_C\right)_{i,t}$. When estimating equation (108), all variables are converted into index 2010=100 and are expressed in log levels.

M.2.3 Empirical Results

Since the two variables of interest in regression (108) display trends, we first run panel unit root tests, see Table 13. By and large, all tests, with the exception of LLC, for the variable $\ln(1-\alpha_C)$, show that non stationarity is pervasive, making it clear that pursuing a cointegration analysis is appropriate.

Table 13: Panel Unit Root Tests (p-values)

	LLC (t-stat)	Breitung (t-stat)	IPS (W-stat)	MW (ADF)	Hadri (Z_μ-stat)
$\ln(1-\alpha_C)$	0.011	0.941	0.992	0.991	0.000
$\ln(P^N/P_C)$	0.077	0.950	0.886	0.833	0.000

Notes: For all tests, except for Hadri [2000], the null of a unit root is not rejected if p-value ≥ 0.05 at a 5% significance level. For Hadri [2000], the null of stationarity is rejected if p-value ≤ 0.05 at a 5% significance level.

We thus implement Pedroni's [2004] tests of the null hypothesis of no cointegration, see Table 14. All panel tests, with the exception of non-parametric ν statistic, reject the null hypothesis of no cointegration between $\ln(1-\alpha_C)$ and the relative price $\ln(P^N/P_C)$ at the 5% significance level. In particular, the group-mean parametric t-stat test suggest the existence of a cointegration relationship between the variables of interest at 1% significance level. In small samples, Pedroni's [2004] simulations reveal that the group-mean parametric t-stat is the most powerful. Based on this result, the null hypothesis of no cointegration is strongly rejected at the 1% level

Table 15 shows estimates of ϕ when running regression (108) where the dependent variable is the log of $(1-\alpha_C)$. The regressor is the (logged) price of non-tradables in terms of the consumer price index (P^N/P_C). The sample covers all countries we are interested in. For the whole sample, the FMOLS estimate gives a significant value of ϕ of 0.662. This estimated coefficient is statistically significant. The majority (10 out of 17) of the individual FMOLS estimated coefficients are positive and statistically significant. Two estimated coefficients are negative (GBR and SWE), although none of them are statistically significant. Focusing only on countries with positive statistically significant estimates, we find that ϕ varies from a low of 0.396 for AUS to a high of 1.518 for AUT.

M.3 Estimates of ϵ: Empirical Strategy

In this section, we detail our empirical strategy to estimate the elasticity of labor supply across sectors, ϵ, which captures the degree of labor mobility across sectors.

Table 14: Panel Cointegration Tests (p-values)

Dependent variable	$\ln(1-\alpha_C)$
Explanatory variable	$\ln(P^N/P_C)$
Panel tests	
Non-parametric ν	0.034
Non-parametric ρ	0.015
Non-parametric t	0.000
Parametric t	0.005
Group-mean tests	
Non-parametric ν	0.227
Non-parametric t	0.001
Parametric t	0.009

Notes: the null hypothesis of no cointegration is rejected if the p-value is below 0.05 (0.10 resp.) at 5% (10% resp.) significance level.

Table 15: FMOLS Estimates of ϕ

Country	$\hat{\phi}_i^{FMOLS}$
AUS	0.396^b (2.25)
AUT	1.518^a (6.35)
BEL	0.612 (0.63)
CAN	0.748^a (4.32)
DEU	0.577^a (2.79)
DNK	1.083^a (3.77)
ESP	1.387^b (2.19)
FIN	0.225 (1.16)
FRA	0.353 (1.38)
GBR	−0.267 (−0.87)
IRL	1.352^a (3.70)
ITA	0.284 (1.60)
JPN	1.052^a (5.12)
NLD	0.389 (0.93)
NOR	0.891^a (3.33)
SWE	−0.173 (−0.73)
USA	0.821^a (3.73)
Whole Sample	0.662^a (12.03)
Countries	17
Observations	739
Data coverage	1970-2013
Country fixed effects	yes
Time trend	yes

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

M.3.1 Limited Substitutability of Hours Worked across Sectors and the Derivation of the Testable Equation

The economy consists of M distinct sectors, indexed by $j = 0, 1, ..., M$ each producing a different good. Along the lines of Horvath [2000], the aggregate labor index is assumed to take the form:

$$L = \left[\int_0^M \left(\vartheta^j\right)^{-\frac{1}{\epsilon}} \left(L^j\right)^{\frac{\epsilon+1}{\epsilon}} dj\right]^{\frac{\epsilon}{\epsilon+1}}, \tag{109}$$

The agent seeks to maximize her labor income

$$\int_0^M W^j L^j dj = X, \tag{110}$$

for given utility loss; L^j is labor supply to sector j, W^j the wage rate in sector j and X total labor income. The form of the aggregate labor index (109) implies that there exists an aggregate wage index $W(.)$, whose expression will be determined later. Thus equation (110) can be rewritten as follows:

$$\int_0^M W^j L^j dj = WL. \tag{111}$$

Writing down the Lagrangian and denoting by μ the Lagrangian multiplier to the constraint, the first-order reads as:

$$\left(\vartheta^j\right)^{-\frac{1}{\epsilon}} \left(L^j\right)^{\frac{1}{\epsilon}} L^{-\frac{1}{\epsilon}} = \mu W^j. \tag{112}$$

Left-multiplying both sides of eq. (112) by L^j, summing over the M sectors and using eqs. (109) and (111) implies that $\mu = \frac{1}{W}$. Plugging the expression for the Lagrangian multiplier into (112) and rearranging terms leads to optimal labor supply L^j to sector j:

$$L^j = \vartheta^j \left(\frac{W^j}{W}\right)^{\epsilon} L. \tag{113}$$

We assume that within each sector, there is a large number of identical firms which produces Y^j by using labor L^j and capital K^j according to constant returns to scale in production. The representative firm faces two cost components: a capital rental cost equal to R, and sectoral wages W^H and W^N, respectively. Since each sector is assumed to be perfectly competitive, the representative firm chooses capital and labor by taking prices as given:

$$\max_{K^j, L^j} \Pi^j = \max_{K^j, L^j} \left\{P^j Y^j - W^j L^j - RK^j\right\}. \tag{114}$$

Since that the production function displays constant returns to scale and using the fact that factors are paid their marginal product, the demand for labor and capital are: $\partial Y^j/\partial L^j = W^j/P^j$ and $\partial Y^j/\partial K^j = R/P^j$, respectively; denoting the LIS in sector j by s_L^j, the demand for capital and labor can be rewritten as follows: $\hat{Y}^j/\hat{L}^j = s_L^j$ and $\hat{Y}^j/\hat{K}^j = 1 - s_L^j$ which leads to:

$$s_L^j \frac{P^j Y^j}{L^j} = W^j, \tag{115a}$$

$$\left(1 - s_L^j\right) \frac{P^j Y^j}{K^j} = R. \tag{115b}$$

Inserting labor demand (115a) into labor supply to sector j (113) and solving leads the share of sector j in aggregate labor:

$$\frac{L^j}{L} = \left(\vartheta^j\right)^{\frac{1}{\epsilon+1}} \left(\frac{s_L^j P^j Y^j}{\int_0^M s_L^j P^j Y^j dj}\right)^{\frac{\epsilon}{\epsilon+1}}, \tag{116}$$

where we combined (111) and (115a) to rewrite the aggregate wage as follows:

$$W = \frac{\int_0^M s_L^j P^j Y^j dj}{L}. \tag{117}$$

We denote by β^j the fraction of labor's share of value added accumulating to labor in sector j:

$$\beta^j = \frac{s_L^j P^j Y^j}{\sum_{j=1}^M s_L^j P^j Y^j}. \tag{118}$$

Using (118), the labor share in sector j (116) can be rewritten as follows:

$$\frac{L^j}{L} = \left(\vartheta^j\right)^{\frac{1}{\epsilon+1}} \left(\beta^j\right)^{\frac{\epsilon}{\epsilon+1}}. \tag{119}$$

Introducing a time subscript and taking logarithm, eq. (119) reads as:

$$\ln\left(\frac{L^j}{L}\right)_t = \frac{1}{\epsilon+1} \ln \vartheta^j + \frac{\epsilon}{\epsilon+1} \ln \beta_t^j. \tag{120}$$

Totally differentiating (120) and denoting the rate of change of the variable with a hat, we find that the change in hours worked in sector j caused by labor reallocation across sectors is driven by the change in the fraction β^j of the labor's share of aggregate output accumulating to labor in sector j:

$$\hat{L}^j_t - \hat{L}_t = \gamma \hat{\beta}^j_t, \tag{121}$$

where $\gamma = \frac{\epsilon}{\epsilon+1}$.

We use panel data to estimate (121). Including country fixed effects captured by country dummies, f_i, and common macroeconomic shocks by year dummies, f_t, (121) can be rewritten as follows:

$$\hat{L}^j_{it} - \hat{L}_{it} = f_i + f_t + \gamma_i \hat{\beta}^j_{it} + \nu^j_{it}, \tag{122}$$

where $\gamma_i = \frac{\epsilon_i}{\epsilon_i+1}$ and β^j_{it} is given by (118); j indexes the sector, i the country, and t indexes time. The LHS and RHS variables are defined as follows:

$$\hat{L}_{it} = \sum_{j=1}^{M} \beta^j_{i,t-1} \hat{L}^j_{i,t}. \tag{123}$$

and

$$\beta^j_{it} = \frac{s^j_{L,i} P^j_{it} Y^j_{it}}{\sum_{j=1}^{M} s^j_{L,i} P^j_{it} Y^j_{it}}, \tag{124}$$

where $s^j_{L,i}$ is the LIS in sector j in country i which is averaged over 1970-2013. When exploring empirically (122), the coefficient γ is alternatively assumed to be identical, i.e., $\gamma_i = \gamma$, or to vary across countries. The LHS term of (122), i.e., $\hat{L}^j_{it} - \hat{L}_{it}$, gives the percentage change in hours worked in sector j driven by the pure reallocation of labor across sectors.

To determine (123) we proceed as follows. Approximate changes in aggregate labor with differentials, we get:

$$\mathrm{d}L_t \equiv L_t - L_{t-1} = \left(L^H_{t-1}\right)^{\frac{1}{\epsilon}} \left(L_{t-1}\right)^{-\frac{1}{\epsilon}} \mathrm{d}L^H_t + \left(L^N_{t-1}\right)^{\frac{1}{\epsilon}} \left(L_{t-1}\right)^{-\frac{1}{\epsilon}} \mathrm{d}L^N_t. \tag{125}$$

Expressing (125) in percentage changes and inserting $\left(\frac{L^j}{L}\right)^{\frac{\epsilon+1}{\epsilon}} = \beta^j$, we have:

$$\begin{aligned} \hat{L}_t \equiv \frac{L_t - L_{t-1}}{L_{t-1}} &= \left(\frac{L^H_{t-1}}{L_{t-1}}\right)^{\frac{\epsilon+1}{\epsilon}} \hat{L}^H_t + \left(\frac{L^N_{t-1}}{L_{t-1}}\right)^{\frac{\epsilon+1}{\epsilon}} \hat{L}^N_t, \\ &= \beta^H_{t-1} \hat{L}^H_t + \beta^N_{t-1} \hat{L}^N_t. \end{aligned} \tag{126}$$

According to eq. (126), the percentage change in total hours worked, $\hat{L}_t$, can be approximated by a weighted average of changes in sectoral hours worked $\hat{L}^j_t$ (in percentage), the weight being equal to β^j_{t-1}.

M.3.2 Data Description

Data are taken from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. EU KLEMS data provide yearly information for the period 1970-2013 (except for JPN: 1974-2013) for 15 countries of our sample (AUS, AUT, BEL, DEU, DNK, ESP, FIN, FRA, GBR, IRL, ITA, JPN, NLD, SWE and USA). For CAN and NOR, annual sectoral data stems from the STAN database. To classify hours worked and value added as traded or non-traded, we adopt the classification described in Appendix K. We provide more details below about the data used to estimate equation (122):

- Sectoral hours worked, L^j ($j = H, N$): total hours worked by persons engaged in sector j (H_EMP). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- Sectoral value added, $P^j Y^j$ ($j = H, N$): value added at current prices in millions of national currency in sector j (VA). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- Sectoral labor income share, s^j_L ($j = H, N$): labor compensation in sector j (LAB) over value added at current prices (VA) averaged over the period 1970-2013 (1974-2013 for JPN). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

By combining s^j_L and $P^j Y^j$, we can construct time series β^j as defined by (124).

Table 16: Estimates of the Elasticity of Labor Supply across Sectors (ϵ)

Country	$\hat{\epsilon}_i$
AUS	0.375^a (3.20)
AUT	1.103^a (3.00)
BEL	0.610^a (3.57)
CAN	0.390^a (4.12)
DEU	1.012^a (3.52)
DNK	0.286^a (2.50)
ESP	1.015^a (3.73)
FIN	0.431^a (4.39)
FRA	1.400^a (2.83)
GBR	0.601^a (3.91)
IRL	0.216^a (3.74)
ITA	1.664^a (3.01)
JPN	0.873^a (3.55)
NLD	0.219^b (2.05)
NOR	0.011 (0.34)
SWE	0.534^a (4.28)
USA	3.222^c (1.83)
Countries	17
Observations	1456
Data coverage	1971-2013
Country fixed effects	yes
Time trend	no

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

M.3.3 Panel Data Estimates of ϵ

The parameter we are interested in, the degree of substitutability of hours worked across sectors, is given by $\epsilon_i = \gamma_i/(1-\gamma_i)$. In the regression below, coefficient γ_i is assumed to be different across countries, i.e., $\gamma_i \neq \gamma_{i'}$ for $i \neq i'$. The sample is running from 1971 to 2013.

Empirical results reported in Table 16 are consistent with $\epsilon > 0$. Among the 17 countries, we find that 16 have statistically significant (at the 10% level) estimates of ϵ. We find that the degree of substitutability of hours worked across sectors ranges from a low of 0.01 for NOR to a high of 3.222 for USA.

M.4 Sectoral Elasticity of Substitution between Capital and Labor in Production

We detail below the estimation strategy of the elasticity of substitution between capital and labor, σ^j, for sector $j = H, N$.

M.4.1 Empirical Strategy

We assume CES productions::

$$Y_t^j = \left[\gamma^j \left(A_t^j L_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B_t^j K_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{127}$$

where σ^j is the constant elasticity of substitution between capital and labor in sector $j = H, N$, γ^j is the weight of labor in the production technology, A_t^j and B_t^j denote the level of efficiency of labor and capital, respectively. Variations over time of A_t^j and B_t^j capture labor- and capital-augmenting technological change. Note that we allow factors efficiency to differ across sectors, i.e. $\hat{A}^H \neq \hat{A}^N$ and

$\hat{B}^H \neq \hat{B}^N$. When assuming factor-biased technological change, the identification of the parameter of interest, σ^j, turns to be problematic as the elasticity and factor-biased technical change cannot be simultaneously identified given time series of output, inputs and factors shares. To circumvent this problem, we assume that labor- and capital-augmenting technological changes grow at constant rate:

$$A_t^j = A_0^j e^{a^j t}, \tag{128a}$$

$$B_t^j = B_0^j e^{b^j t}, \tag{128b}$$

where a^j and b^j denote the constant growth rate of labor- and capital-augmenting technical progress and A_0^j and B_0^j are initial levels of technology.

We assume perfect mobility of capital across sectors so that $R = R^H = R^N$. Labor is imperfectly mobile across sectors and the wage rate in sector $j = H, N$ is denoted W^j. Profit maximization by firms in a competitive framework implies the first-order conditions:

$$P_t^j \gamma^j \left(A_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L_t^j\right)^{-\frac{1}{\sigma^j}} \left(Y_t^j\right)^{\frac{1}{\sigma^j}} = W_t^j, \tag{129a}$$

$$P_t^j \left(1-\gamma^j\right) \left(B_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(K_t^j\right)^{-\frac{1}{\sigma^j}} \left(Y_t^j\right)^{\frac{1}{\sigma^j}} = R_t, \tag{129b}$$

where P^j is the value added price deflator in sector j. Taking logarithm of (129a)-(129b) and rearranging gives:

$$\ln(Y_t^j/L_t^j) = \alpha_1 + \left(1-\sigma^j\right) a^j t + \sigma_j \ln(W_t^j/P_t^j), \tag{130a}$$

$$\ln(Y_t^j/K_t^j) = \alpha_2 + \left(1-\sigma^j\right) b^j t + \sigma_j \ln(R_t/P_t^j), \tag{130b}$$

where $\alpha_1 = \left[(1-\sigma^j)\ln A_0^j - \sigma^j \ln \gamma^j\right]$ and $\alpha_2 = \left[(1-\sigma^j)\ln A_0^j - \sigma^j \ln(1-\gamma^j)\right]$ are constants. These equations represent the first-order conditions (FOC) with respect to labor and capital and can be interpreted as describing the firms' demand for labor and capital respectively. We estimate the elasticity of substitution between capital and labor in sector $j = H, N$ from FOCs (130a)-(130b) in panel format on annual data. Adding an error term and controlling for country fixed effects yields our testable regressions:

$$\ln(Y_{it}^j/L_{it}^j) = \alpha_{1i} + \lambda_{1i} t + \sigma_i^j \ln(W_{it}^j/P_{it}^j) + u_{it}, \tag{131a}$$

$$\ln(Y_{it}^j/K_{it}^j) = \alpha_{2i} + \lambda_{2i} t + \sigma_i^j \ln(R_{it}/P_{it}^j) + v_{it}, \tag{131b}$$

where i and t index country and time and u_{it} and v_{it} are i.i.d. error terms. Country fixed effects are represented by dummies α_{1i} and α_{2i}, and country-specific linear time trends are captured by λ_{1i} and λ_{2i}.

To estimate the elasticity of substitution between capital and labor for tradables and non-tradables, we follow closely the approach suggested by Antràs [2004] who derives alternative specifications based on factor demand functions.[22] This approach possesses three particular attractive properties. First, the econometric specification allows for factor-biased technological change. The choice of the specification determines the type of technological change which can be captured within the framework of econometric estimation. For instance, in case of the FOC for labor, capital-augmenting technological change drops out. Therefore, labor-augmenting technological change can be identified, together with σ^j, from eq. (130a). Second, it allows for a clear treatment of the non-stationary nature of the data involved in the estimation. Regressions (131a) and (131b) feature two trends governed by a^j and b^j and several variables which potentially follow non-stationary processes (Y_{it}^j/L_{it}^j, Y_{it}^j/K_{it}^j, W_{it}^j/P_{it}^j and R_{it}/P_{it}^j). Following Antràs [2004], we tackle this non-stationary issue by applying the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni ([2000], [2001]) to eq. (131a) and eq. (131b). FMOLS is a nonparametric approach to adjust for the effects of endogenous regressors and serial correlation. Another econometric problem when estimating (131a) and (131b) is the potential endogeneity of regressors. As shown by Pedroni ([2000], [2001]), using the FMOLS technique can address this issue too as this estimator is also extremely accurate in panels with heterogeneous serial correlation and endogenous regressors. Third, employing Monte Carlo experiments, León-Ledesma et al. [2010] compare the different approaches for estimating the elasticity of substitution between capital and labor (single equation based on

[22] It is worth noting that Antràs [2004] derives six econometric functional forms to estimate σ: FOC with respect to labor (eq. (130a)), FOC with respect to capital (eq. (130b)), a combination of both FOCs and the remaining three are the reciprocal thereof. However, we focus on the first two because only the use of the FOCs permits the identification of growth rate of labor- and capital-augmenting technological change while the third specification captures the overall technological bias.

FOCs, system, linear, non linear and normalization). Their evidence suggests that provided that the true value of σ is below 1.3, estimates of both the elasticity of substitution and technical change are close to their true values when the FOC with respect to labor is used (eq. (130a)). Below we report sectoral elasticities well below unity when using the FOCs. The panel estimates of σ^H and σ^N obtained from the FOC with respect to labor (capital resp.) are 0.687 and 0.716 (0.489 and 0.467 resp.). Our results thus lend credence to the use of specifications (131a) and (131b) based on the FOCs as a way to obtain precise estimates of the elasticity of substitution between capital and labor at the sectoral level. In addition, results of León-Ledesma et al. [2010] show that the FOC for the demand of capital (i.e., eq. (131b)) performs worse than the FOC for the demand of labor (i.e., eq. (131a)) as estimates of σ^j are sensitive to measurement errors and endogeneity in the capital stock. Consequently, in the following, when presenting our own estimates of σ^j for both sectors, the labor demand equation, i.e., regression (131a), is preferred.

An alternative way to recover the CES production parameters is the supply-side system method (see Klump et al. [2007] and León-Ledesma et al. [2010]). This approach consists of the joint non-linear estimation of a three-equation system combining the CES production function (equation (127) in log form) together with the first-order conditions for the optimal choices of labor and capital, i.e. FOCs (130a)-(130b). Despite system approach's appealing features , we stick to the single-equation methodology developed by Antràs [2004] because, in our context, this estimation method has several advantages over the three-equation system advocated by León-Ledesma et al. [2010]. First, the supply-side system method has the disadvantage that it does rely on non-linear estimations, so the results are obtained numerically and sensitive to the choice of initial values (especially in the nonnormalized system). By contrast, we estimate eqs. (131a) and (131b) with the FMOLS approach which avoids such numerical computations. Second, estimation of the three-equation system involves the estimation of a large number of parameters which may affect estimation accuracy. Instead, the single-equation is a more parsimonious specification as it reduces considerably the number of estimated coefficients and thus is particularly well suited when estimating the elasticity of substitution at the sectoral level.

M.4.2 Data Description

Estimation of equations (131a) and (131b) requires data for each sector $j = H, N$ on value added at constant prices, Y^j, hours worked, L^j, capital stock, K^j, value added deflator, P^j, wage rate, W^j and capital rental cost, R. We describe below the time series we use in estimating σ^j (codes in EU KLEMS/STAN are reported in parentheses):

- Sectoral value added, Y^j ($j = H, N$): value added at constant prices in sector j (VA_QI). Sources: KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.
- Sectoral hours worked, L^j: total hours worked by persons engaged in sector j (H_EMP). Sources: KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.
- Sectoral capital stock, K^j: aggregate capital stocks are estimated from the perpetual inventory approach by using real gross capital formation from OECD National Accounts Database [2017] (data in millions of national currency, constant prices) and assuming a depreciation rate of 5%. Following Garofalo and Yamarik [2002], the capital stock is then allocated to traded and non-traded industries by using the sectoral value added share, i.e., $K^j = \omega_t^{Y,j} K$ where $\omega_t^{Y,j}$ is the value added share at current prices. Sources: KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.
- Sectoral value added price deflator, P^j: value added at current prices (VA) over value added at constant prices (VA_QI) in sector j. Sources: KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.
- Sectoral nominal wage, W^j: labor compensation in sector j (LAB) over total hours worked by persons engaged (H_EMP) in that sector. Labor compensation is total labor costs that include compensation of employees and labor income of the self-employed and other entrepreneurs. Sources: KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.
- Aggregate rental price of capital, R: capital income over capital stock K in the total economy. Capital income is derived as nominal value added (VA) minus labor compensation (LAB). Sources: KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2013 except for JPN 1974-2013.

The data construction merits further discussion. First, sectoral wages do not equalize ($W^H \neq W^N$) while the sectoral rental costs of capital equalize ($R^H = R^N \equiv R$). These choices are consistent with our theoretical model in which physical capital is perfectly mobile across sectors and the presence of mobility costs implies that both sectors do not pay the same wage. Second, when calculating sectoral wages, labor compensation includes total labor costs (wages, salaries and all other costs of employing labour which are borne by the employer) as well as the income of self-employed. Treating all self-employed income as labor income allows us to obtain a consistent measurement of the labor share (Gollin [2002]). As a robustness check, we also split self-employed income into capital and labor income based on the assumption that the labor income of the self-employed has the same mix of labor and capital income as the rest of the economy (in other words, total labor compensation comprises the labor compensation of employees and the self-employed income scaled by the labor share of employees only). This adjustment turns out to have only a marginal effect on the estimates of σ^j (results available upon request).

M.4.3 Empirical Results

Table 17 reports a summary of the panel unit root tests we performed on each of the series involved in the estimation of cointegrating equations. As is clear from Table 17, except for the LLC test applied to the variable $\ln(W^N/P^N)$, for none of the eight series do the LLC, Breitung, IPS and Madalla-Wu tests reject the hypothesis of a unit root at the 5% level of significance.[23] As a robustness check, we also consider the test developed by Hadri of the null that the time series for each cross section is stationary against the alternative of a unit root in the panel data. We reach the same conclusion and conclude that all eight series are nonstationary and integrated of order one.

Table 17: Panel Unit Root Tests (p-values)

	LLC (t-stat)	Breitung (t-stat)	IPS (W-stat)	MW (ADF)	Hadri (Z_μ-stat)
$\ln(Y^H/L^H)$	0.990	1.000	1.000	0.970	0.000
$\ln(Y^N/L^N)$	0.286	1.000	0.607	0.225	0.000
$\ln(Y^H/K^H)$	0.998	1.000	0.999	0.981	0.000
$\ln(Y^N/K^N)$	0.960	0.999	0.990	0.994	0.000
$\ln(W^H/P^H)$	0.636	1.000	0.758	0.735	0.000
$\ln(W^N/P^N)$	0.006	0.209	0.716	0.643	0.000
$\ln(R/P^H)$	0.866	1.000	0.679	0.498	0.000
$\ln(R/P^N)$	0.999	0.999	0.791	0.218	0.000

Notes: For all tests, except for Hadri [2000], the null of a unit root is not rejected if p-value ≥ 0.05 at a 5% significance level. For Hadri [2000], the null of stationarity is rejected if p-value ≤ 0.05 at a 5% significance level.

Table 18 presents the results from parametric and non parametric cointegration tests developed by Pedroni ([1999], [2004]). All statistics hinge on testing the stationarity of the residuals of equations (131a) and (131b). As is apparent from Table 18 the results are conclusive: for at least five of the seven tests the null hypothesis of no cointegration between $\ln(Y^j/L^j)$ ($\ln(Y^j/K^j)$ resp.) and $\ln(W^j/P^j)$ ($\ln(R/P^j)$ resp.) is rejected for all four specifications at the 10% significance level. As pointed out by Pedroni [2004], the group-mean parametric t-test is more powerful than other tests in finite samples. Based on the statistic parametric t (reported in the last row), the null hypothesis of zero cointegrating vectors is clearly rejected at the 10% significance level for any of the four specifications.

Table 19 summarizes FMOLS estimates elasticity of substitution between capital and labor for the tradables and non-tradables sectors. Results for the labor (capital resp.) demand equation are presented in columns 2 and 4 (columns 1 and 3 resp.).[24] As noted previously, on the basis of the extensive Monte Carlo simulations provided by León-Ledesma et al. [2010], the FOC for labor specification (equation (131a)) is preferred to the FOC for capital specification (equation (131b)) because in the former case the elasticity of substitution is estimated quite precisely. To ease the presentation, we therefore restrict the discussion to the results obtained with labor demand equation. For the whole sample, the FMOLS estimate of σ^H from regression (131a) (see column 2) gives a value of 0.687. The estimated coefficient is statistically different from zero with a t-statistic of 24.70. Furthermore, the null hypothesis of a panel unit elasticity is strongly rejected at the 5% significance level. However, there is substantial evidence of parameter heterogeneity across countries inside the sample. The vast majority (16 out of 17) of the individual FMOLS estimated coefficients

[23] As IPS and MW allow for heterogeneity of the autoregressive root, we prefer these tests over the LLC test for which the autoregressive coefficient is required to be identical across all units.

[24] To conserve space we only report in Table 19 the results for the elasticity of substitution σ^H and σ^N. The estimates of the parameters λ_1 and λ_2, that is estimates of the growth rate of labor- and capital-augmenting technological change are available from the authors upon request.

Table 18: Panel Cointegration Tests (p-values)

Dependent variable	$\ln(Y^H/L^H)$	$\ln(Y^H/K^H)$	$\ln(Y^N/L^N)$	$\ln(Y^N/K^N)$
Explanatory variable	$\ln(W^H/P^H)$	$\ln(R/P^H)$	$\ln(W^N/P^N)$	$\ln(R/P^N)$
	Eq. (131a)	Eq. (131b)	Eq. (131a)	Eq. (131b)
Panel tests				
Non-parametric ν	0.000	0.021	0.170	0.030
Non-parametric ρ	0.000	0.053	0.073	0.010
Non-parametric t	0.000	0.055	0.050	0.002
Parametric t	0.000	0.043	0.054	0.003
Group-mean tests				
Non-parametric ν	0.010	0.420	0.145	0.012
Non-parametric t	0.000	0.147	0.059	0.001
Parametric t	0.000	0.065	0.064	0.001

Notes: the null hypothesis of no cointegration is rejected if the p-value is below 0.05 (0.10 resp.) at 5% (10% resp.) significance level.

σ^H are positive. The only exception is IRL for which σ^H is estimated to be negative. Although the estimated value for IRL is not statistically different from zero, this negative value is difficult to justify by economic theory. In order to avoid inconsistent estimates of σ^H, we replace the negative value IRL with the one obtained when using the demand for capital (see column 1), namely we set $\sigma^H_{IRL} = 0.737$. Focusing only on countries with positive FMOLS estimates of σ^H, we find that all have statistically significant coefficients at a standard threshold, ranging from a low of 0.417 (DNK) to a high of 1.164 (JPN). Overall, out the 16 positive estimates in column 2, 14 are lower than one (exceptions are ESP and JPN with $\sigma^H = 1.033$ and $\sigma^H = 1.164$ respectively); out these 14 estimates, 8 are significantly below one at the 5% level: for AUT, BEL, ESP, FIN, FRA, ITA, JPN and NLD the null hypothesis of a unit elasticity is rejected at the 5% significance level. Columns 3 and 4 show FMOLS estimates for the non-traded sector. For labor demand (column 4), we find $\sigma^N = 0.716$ in the entire panel. This value is significantly different from zero and lower than one at the 1% level. The estimates range from 0.194 (SWE) to 1.298 (AUT). The vast majority (15 out of 17) of the individual FMOLS estimated coefficients are statistically significant except for ITA and SWE. Note also that the coefficient σ^N is found to be larger than one in only three countries (AUT, BEL and DNK). Among these three countries, the null hypothesis of a unit elasticity is not rejected at the 5% significance level in BEL and DNK. Finally, for 10 out of the 17 countries, the results lead to a rejection of the null hypothesis of a unit elasticity of substitution in the non-traded sector at the 5% significance level (AUS, AUT, CAN, ESP, FIN, GBR, ITA, NLD, NOR and SWE)

Overall, we find that, controlling for factor-biased technological change, the elasticity of substitution between capital and labor for traded and non-traded sectors is lower than one, implying that capital and labor are less substitutable than a Cobb-Douglas production function. This result is consistent with previous estimates found in the literature (see Antràs [2004], Klump et al. [2007] and León-Ledesma et al. [2010] among others).

N More VAR Results and Robustness Check

In this section, we provide more VAR results and conduct several robustness checks. Because in the main text, all variables enter in growth rate, Appendix N.1 shows panel unit tests for all variables considered in the empirical analysis. For reason of space, in the main text, we report results of selected sectoral variables and do not show aggregate effects. Appendix N.2 shows aggregate effects of a technology shock biased toward the traded sector and also reports results for all variables and all VAR models mentioned in the main text. Due to data availability, we use annual data for eleven 1-digit ISIC-rev.3 industries that we classify as tradables or non-tradables. Because at this level of disaggregation, the classification is somewhat ambiguous as some sub-industries could be classified as tradables while other sub-industries are treated as non-tradables, Appendix N.3 investigates the sensitivity of our empirical results to the classification of industries as tradables or non-tradables. Since the traded and non-traded sectors are made up of sub-sectors, we explore in Appendix N.4 whether our results for the LIS are not driven by changes in value added shares of sub-sectors. In the main text, we compute the LIS like Gollin [2002], i.e., labor compensation is defined as the sum of compensation of employees plus compensation of self-employed. Since there exists alternative ways in constructing labor compensation, we explore empirically in Appendix N.5 whether the evidence on redistributive effects we document in the main text are robust to alternative measures of the LIS. In Appendix N.6, we address a potential concern related to the fact that various VAR models

Table 19: FMOLS Estimates of the Sectoral Elasticity of Substitution between Capital and Labor (σ^j)

Country	Tradables (σ^H)		Non-Tradables (σ^N)	
Dependent variable	$\ln(Y^H/K^H)$	$\ln(Y^H/L^H)$	$\ln(Y^N/K^N)$	$\ln(Y^N/L^N)$
Explanatory variable	$\ln(R/P^H)$	$\ln(W^H/P^H)$	$\ln(R/P^N)$	$\ln(W^N/P^N)$
	(1)	(2)	(3)	(4)
AUS	0.607^a (6.67)	0.474^a (3.79)	0.459^a (4.03)	0.529^a (5.69)
AUT	0.235^a (2.65)	0.774^a (6.04)	0.105 (1.22)	1.298^a (13.04)
BEL	0.389^a (3.01)	0.829^a (8.89)	0.266^a (7.37)	1.069^a (7.10)
CAN	0.595^a (3.99)	0.480^a (2.94)	0.855^a (8.62)	0.668^a (7.65)
DEU	-0.123 (-0.68)	0.642^a (8.56)	0.512^a (8.88)	0.987^a (6.97)
DNK	0.267^c (1.84)	0.417^a (4.32)	0.502^a (7.83)	1.282^a (6.74)
ESP	0.747^a (7.11)	1.033^a (10.62)	0.682^a (3.65)	0.476^a (3.35)
FIN	0.249^a (2.90)	0.764^b (1.98)	0.560^a (6.64)	0.794^a (8.30)
FRA	0.267^a (4.82)	0.870^a (4.82)	0.294^a (11.04)	0.916^a (4.21)
GBR	0.242 (0.95)	0.603^a (6.42)	0.008 (0.08)	0.561^a (2.68)
IRL	0.737^a (18.46)	-0.125 (-0.50)	0.762^a (5.73)	0.627^a (3.16)
ITA	0.506^a (3.82)	0.837^a (8.80)	0.471^a (3.23)	0.259 (1.51)
JPN	0.622^a (8.16)	1.164^a (6.73)	0.417^a (7.97)	0.635^b (2.47)
NLD	0.645^a (5.13)	0.910^a (5.98)	0.287^a (9.14)	0.444^a (3.74)
NOR	0.798^a (4.60)	0.629^a (4.39)	0.653^a (10.17)	0.556^a (4.72)
SWE	0.052 (0.35)	0.607^a (8.56)	0.378^a (6.71)	0.194 (0.95)
USA	1.485^a (6.85)	0.766^a (9.51)	0.723^a (6.64)	0.876^a (4.96)
Whole Sample	0.489^a (19.56)	0.687^a (24.70)	0.467^a (26.42)	0.716^a (21.16)
Countries	17	17	17	17
Observations	745	745	745	745
Data coverage	1970-2013	1970-2013	1970-2013	1970-2013
Country fixed effects	yes	yes	yes	yes
Time trend	yes	yes	yes	yes

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

could identify different structural technology shocks. Finally, since we split the gross capital stock into traded and non-traded industries by using sectoral valued added shares, in Appendix N.7, we conduct a robustness check by taking time series for sectoral capital stock from KLEMS.

N.1 Panel Unit Root Tests

When estimating alternative VAR specifications, all variables enter in growth rates. In order to support our assumption of I(1) variables, we ran panel unit root tests displayed in Table 20. We consider five panel unit root tests among the most commonly used in the literature: Levin, Lin and Chu ([2002], hereafter LLC), Breitung [2000], Im, Pesaran and Shin ([2003], hereafter IPS), Maddala and Wu ([1999], hereafter MW) and Hadri [2000]. All tests, with the exception of Hadri [2000], consider the null hypothesis of a unit root against the alternative that some members of the panel are stationary. Additionally, they are designed for cross sectionally independent panels. LLC and IPS are based on the use of the Augmented Dickey-Fuller test (ADF hereafter) to each individual series of the form $\Delta x_{i,t} = \alpha_i + \rho_i x_{i,t-1} + \sum_{j=1}^{q_i} \theta_{i,j} \Delta x_{i,t-j} + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ are assumed to be i.i.d. (the lag length q_i is permitted to vary across individual members of the panel). Under the homogenous alternative the coefficient ρ_i in LLC is required to be identical across all units ($\rho_i = \rho$, $\forall i$). IPS relax this assumption and allow for ρ_i to be individual specific under the alternative hypothesis. MW propose a Fisher type test based on the p-values from individual unit root statistics (ADF for instance). Like IPS, MW allow for heterogeneity of the autoregressive root ρ_i under the alternative. We also apply the pooled panel unit root test developed by Breitung [2000] which does not require bias correction factors when individual specific trends are included in the ADF type regression. This is achieved by an appropriate variable transformation. As a sensitivity analysis, we also employ the test developed by Hadri [2000] which proposes a panel extension of the Kwiatkowski et al. [1992] test of the null that the time series for each cross section is stationary against the alternative of a unit root in the panel data. Breitung' and Hadri's tests, like LLC's test, are pooled tests against the homogenous alternative.[25]

Table 20: Panel Unit Root Tests (p-values)

	LLC (t-stat)	Breitung (t-stat)	IPS (W-stat)	MW (ADF)	Hadri (Z_μ-stat)
$\ln(Z)$	0.977	0.000	0.999	0.999	0.000
$\ln(Y_R)$	0.979	0.999	0.959	0.941	0.000
$\ln(L)$	0.173	0.996	0.941	0.950	0.000
$\ln(W/P_C)$	0.000	1.000	0.294	0.002	0.000
$\ln(W^H/W)$	0.910	0.094	0.882	0.945	0.000
$\ln(W^N/W)$	0.232	0.971	0.415	0.349	0.000
$\ln(Y^H/Y_R)$	0.472	0.924	0.827	0.859	0.000
$\ln(L^H/L)$	1.000	0.012	0.998	0.999	0.000
$\ln(Y^N/Y_R)$	0.252	0.109	0.549	0.500	0.000
$\ln(L^N/L)$	0.885	1.000	0.998	0.996	0.000
$\ln(Y^H/Y^N)$	0.451	0.882	0.819	0.858	0.000
$\ln(P^N/P^H)$	0.692	0.000	0.961	0.992	0.000
$\ln(P^H/P^F)$	0.380	0.358	0.476	0.590	0.000
$\ln(s_L^H)$	0.145	0.312	0.142	0.081	0.000
$\ln(k^H)$	0.995	0.479	0.997	0.999	0.000
D^H	0.223	0.483	0.261	0.227	0.000
$\ln(s_L^N)$	0.999	0.186	0.988	0.943	0.000
$\ln(k^N)$	0.701	0.887	0.900	0.936	0.000
D^N	0.999	0.820	0.982	0.945	0.000

Notes: LLC and Breitung are the t-statistics of Levin et al. [2002] and Breitung [2000] respectively. IPS is the W_{tbar} test proposed by Im et al. [2003] . MW (ADF) is the Maddala and Wu's [1999] P test based on Augmented Dickey-Fuller p-values. Hadri is the Hadri's [2000] Z_μ test. For all tests, except for Hadri [2000], the null of a unit root is not rejected if p-value $\geq$ 0.05 at a 5% significance level. For Hadri [2000], the null of stationarity is rejected if p-value $\leq$ 0.05 at a 5% significance level. In all tests and for all variables, we allow for individual deterministic trends and fixed effects. D^j is defined as $D^j = (B^j/A^j)^{(1-\sigma^j)/\sigma^j}$ for $j = H, N$.

As noted above, IPS and MW tests allow for heterogeneity of the autoregressive root, accordingly,

[25] In all aforementioned tests and for all variables of interest, we allow for individual deterministic trends and country-fixed effects. Conclusions of unit root tests are robust whether there are individual trends in regressions or not. Appropriate lag length q_i is determined according to the Akaike criterion.

Table 21: Aggregate and Sectoral Effects of a 1% Permanent Increase in Traded relative to Non-Traded TFP: Point Estimates

Variables	**A**.Aggregate		**B**.Tradables		**C**.Non-Tradables	
	Impact ($t=0$)	Long-run ($t=10$)	Impact ($t=0$)	Long-run ($t=10$)	Impact ($t=0$)	Long-run ($t=10$)
	(1)	(2)	(3)	(4)	(5)	(6)
Relative Prod.	0.895*	1.000*	0.934*	1.000*	0.879*	1.000*
Value Added	0.246*	0.337*	0.223*	0.259*	0.011	0.061
Labor	0.088*	0.156	-0.009	0.009	0.097*	0.154*
Real Wage	0.095*	0.235*	0.095	0.095	0.090	0.295*

Notes: Horizon measured in year units. * denote significance at 10% level. Standard errors are bootstrapped with 10000 replications.

we will focus intensively on these tests when testing for unit roots. In all cases, except for the MW test applied to W/P_C, the null hypothesis of a unit root against the alternative of trend stationarity cannot be rejected at conventional significance levels, suggesting that the set of variables of interest are integrated of order one. When considering the Hadri's test for which the null hypothesis implies stationary against the alternative of a unit root in the panel data, we reach the same conclusion and conclude again that all series are nonstationary. Taken together, unit root tests applied to our variables of interest show that non stationarity is pervasive, suggesting that all variables should enter in the VAR models in growth rate.

N.2 Aggregate and Sectoral Effects: VAR Evidence

In the main text, we concentrate on the reallocation and redistributive effects of asymmetric technology shocks across sectors. We provide below the results for the full set of aggregate and sectoral effects of technology shocks biased toward the traded sector.

To explore the magnitude of the aggregate effects empirically, we consider a VAR model that includes in the baseline specification the technology index biased toward the traded sector, $\hat{Z}_{it}$, real GDP, $\hat{Y}_{R,it}$, total hours worked, $\hat{L}_{it}$, the real consumption wage denoted by $\hat{W}_{C,it}$, all variables entering the VAR model in rate of growth. Our vector of endogenous variables, is given by: $x_{it} = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$. All data for aggregate variables are obtained from the OECD Economic Outlook. For real GDP, we use the volumes reported by the OECD. We use hours worked to measure labor.[26] All quantities are scaled by the working age population and expressed in rate of growth. The real consumption wage is the ratio of the nominal aggregate wage, W_{it}, to the consumption price index, $P_{C,it}$. The nominal wage is obtained by calculating the ratio of labor compensation to the number of hours worked. Details of data construction and the source of variables used in our estimation are provided in Appendix K.

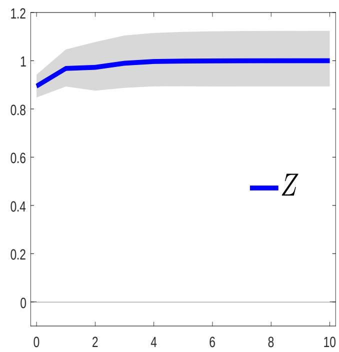
Table 21 displays point estimates on impact and in the long-run. The dynamic effects of a technology shock biased toward the traded sector on aggregate variables are shown in Fig. 17. The top left panel shows that productivity in tradables relative to non-tradables increases by 0.9% on impact and grows gradually to reach 1% after 10 years. The technology shock increases real GDP on impact by 0.25%. Higher productivity in tradables relative to non-tradables also increases significantly hours worked by 0.09% on impact and generates an initial increase in the real consumption wage by 0.1%.

The sectoral effects of a technology shock are displayed in Fig. 18 while point estimates are reported in Table 21. The responses of sectoral value added and hours worked enable us to explore empirically the breakdown of changes in real GDP and labor into the traded and non-traded sector. Whilst higher productivity of tradables has a significant expansionary effect on traded value added which increases by 0.22% GDP on impact and 0.26% in the long-run, non-traded value added is unresponsive at any horizon. Conversely, the non-traded sector experiences a significant increase in hours worked on impact by 0.10% of total hours worked while hours worked remain fairly unchanged in the traded sector.

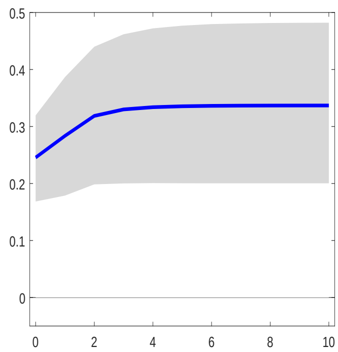
N.3 Robustness Check: Sectoral Classification

Objective. This subsection explores the robustness of our findings to the classification of the eleven 1-digit ISIC-rev.3 industries as tradables or non-tradables. When we conduct the robustness

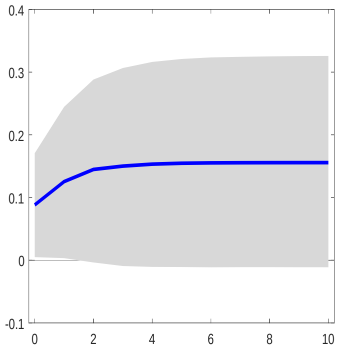
[26] Alternatively we use the number of employees as a measure of labor. All results remain almost unchanged.



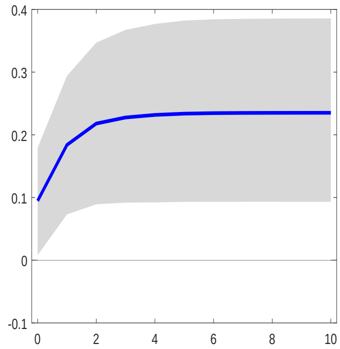
(a) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$



(b) Real GDP, Y_R



(c) Hours worked, L



(d) Real Consumption Wage, W/P_C

Figure 17: Aggregate Effects of Technology Shock Biased toward the Traded Sector. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Aggregate variables include GDP (constant prices), total hours worked, and the real consumption wage. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Results for baseline specification are displayed by solid lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling; sample: 17 OECD countries, 1970-2013, annual data.

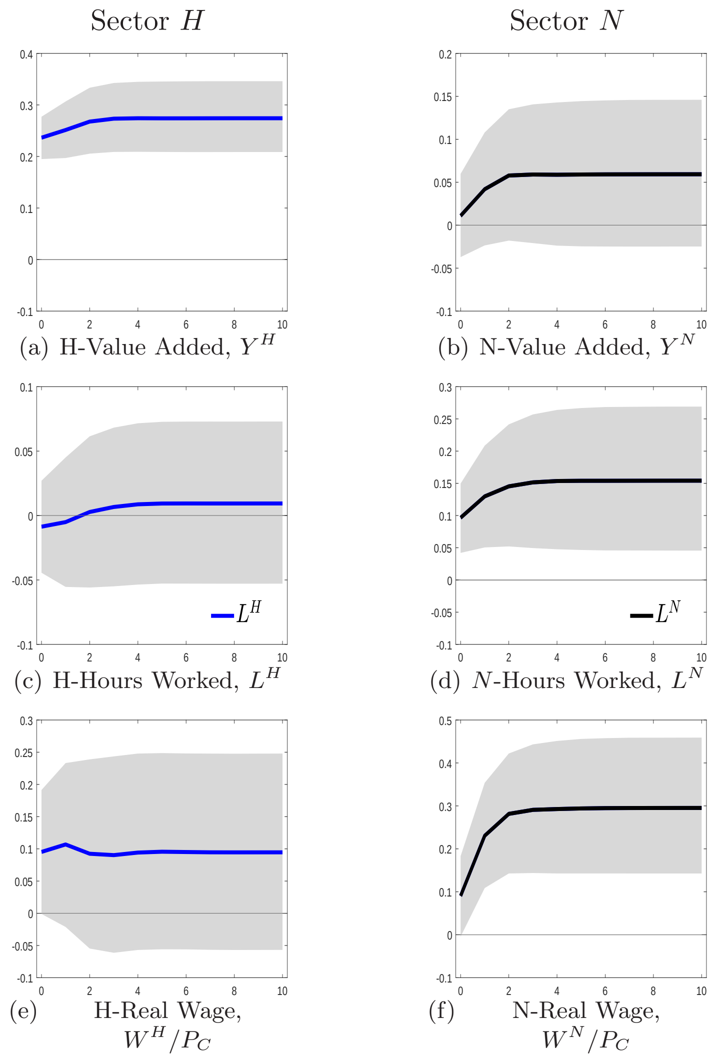


Figure 18: Sectoral Effects of Technology Shock Biased toward the Traded Sector. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added), percentage deviation from trend in total hours worked units (sectoral hours worked), and percentage deviation from trend (real wages). Results for baseline specification are displayed by solid lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling; sample: 17 OECD countries, 1970-2013, annual data.

analysis, we modify the baseline classification in a number of ways to ensure that some industries with specific characteristics are not driving the results. There are a few sectors which may display some ambiguity related to their tradability, including ”Hotels and Restaurants”, ”Financial Intermediation” and ”Real Estate, Renting and Business Services”. The reason is twofold. Some sectors such as ”Hotels and Restaurants”, ”Financial Intermediation” have experienced a large increase in tradability over the last fifty years. Since we adopt a VAR methodology, we need a long time horizon for each country which constrain us to use a less detailed sectoral disaggregation so that the sample starts from 1970 otherwise, the sample would start in 1995 for most of the countries in our sample. The lower level of sectoral disaggregation implies that ”Financial Intermediation” and ”Real Estate, Renting and Business Services” are made up of sub-sectors which display a high heterogeneity in terms of tradability. The most prominent example is ”Real Estate, Renting and Business Services” which includes ”Real Estate Activities” which displays a very low tradability and ”Professional, Scientific, Technical, Administrative, and Support Service Activities” which displays a high level of tradability. Since tradability of sectors varies across time and across subsectors, we perform a sensitivity analysis with respect to the classification for the three aforementioned sectors.

Literature on Tradedness of Industries. While we treat ”Real Estate, Renting and Business Services” and ”Hotels and Restaurants” as non-tradables, Jensen and Kletzer [2006] find that ”Professional, scientific and technical activities” included in the former sector is highly tradable whilst evidence collected by Piton [2017] who calculates the degree of openness for 18 industries over 1995-2014 reveals that ”Foods and Accommodation” included in the latter sector displays significant tradability as well. Thus, in the following, we pay particular attention of the sensitivity of our results when either ”Real Estate, Renting and Business Services” (red line) or ”Hotels and Restaurants” (yellow line) is classified as tradable instead of non-tradable. Moreover, Jensen and Kletzer [2006] find that the subsectors included in ”Financial Intermediation” vary substantially in terms of tradability. Accordingly, we also conduct a robustness check w.r.t. this subsector which includes ”Financial Intermediation” (black line) into the non-traded goods sector.

Empirical Strategy. In order to address these issues, we re-estimate the various VAR specifications for different classifications in which one of the three aforementioned industries initially marked as tradable or non-tradable is classified as non-tradable or tradable, resp., all other industries staying in their original sector. In doing so, the classification of only one industry is altered, allowing us to see if the results are sensitive to the inclusion of a particular industry in the traded or the non-traded sector. The baseline and the three alternative classifications considered in this exercise are shown in Table 22.

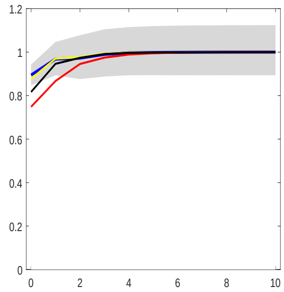
Table 22: Robustness Check: Classification of Industries as Tradables or Non-Tradables

	KLEMS code	Classification			
		Baseline	#1	#2	#3
Agriculture, Hunting, Forestry and Fishing	AtB	H	H	H	H
Mining and Quarrying	C	H	H	H	H
Total Manufacturing	D	H	H	H	H
Electricity, Gas and Water Supply	E	N	N	N	N
Construction	F	N	N	N	N
Wholesale and Retail Trade	G	N	N	N	N
Hotels and Restaurants	H	N	**H**	N	N
Transport, Storage and Communication	I	H	H	H	H
Financial Intermediation	J	H	H	H	**N**
Real Estate, Renting and Business Services	K	N	N	**H**	N
Community Social and Personal Services	LtQ	N	N	N	N
Color line in Fig. 19 to 22		blue	yellow	red	black

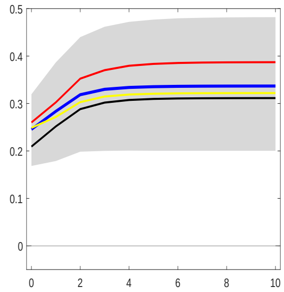
Notes: H stands for the Traded sector and N for the non-traded sector.

Results We start with the analysis of the sensitivity of aggregate effects of a technology shock to the classification of industries as tradables or non-tradables. As shown in Fig. 19, the conclusions for aggregate effects are not sensitive to sector classification. When contrasting the effects across their magnitude, treating ”Real Estate, Renting and Business Services” as tradables tends to amplify the positive response of real GDP. Conversely, treating ”Hotels and Restaurants” as tradables merely modifies the results quantitatively.

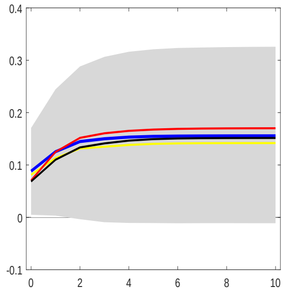
We investigate below the robustness of our results related to the effects of a technology shock biased toward the traded sector on the sectoral composition and redistributive effects. Fig. 20 and Fig. 21 contrast sectoral and reallocation effects of higher productivity of tradables relative to non-tradables according to the classification of industries. First, as shown in the red line (’Real estate, renting and business services’ classified as tradables), more labor shifts toward the non-traded sector while the relative wage of the traded sector increases instead of declining. With the exception of



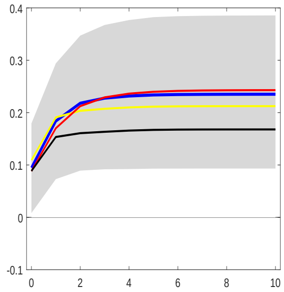
(a) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$



(b) Real GDP, Y_R



(c) Hours worked, L



(d) Real Wage, W/P_C

Figure 19: Sensitivity of Aggregate Effects of Technology Shock Biased toward the Traded Sector to the Classification of Industries as Tradable or Non-Tradable. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Aggregate variables include GDP (constant prices), total hours worked and the real consumption wage. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in output units (GDP), percentage deviation from trend in labor units (total hours worked) and percentage deviation from trend (real consumption wage). Results for baseline specification are displayed by solid lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. The yellow line and the red line show results when 'Hotels and restaurants' and 'Real Estate, renting and business services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as non-tradables. Sample: 17 OECD countries, 1970-2013, annual data.

the latter finding, all of our conclusions hold. In Fig. 22, we investigate whether our conclusion for redistributive effects (i.e., for sectoral LIS) is robust to the classification of industries. Across all scenarios, LIS in both sectors increase, except when treating "Real Estate, Renting and Business Services" (as displayed by the red line) as tradables. While sectoral LISs do not change when treating "Real Estate, Renting and Business Services" as a traded industry, the capital-labor ratio in the traded and non-traded sector falls which implies that technological change is biased toward labor in both sectors, otherwise LIS would decline. Across all scenarios in Fig. 22, the discrepancy in the estimated effect is not statistically significant.

N.4 Breaking Down Sectoral LIS into a Within- and Between-Effect

In the main text, we document evidence which reveals that LISs increase in both the traded and the non-traded sector. Because both sectors are made up of several industries, the change in the LIS of the broad sector is driven by changes in LIS within sub-sectors (keeping the value added share of sub-sectors fixed) and also by changes in the value added share of those sub-sectors (keeping the LIS of each sub-sector fixed). We break down below the change in the LIS of the broad sector $j = H, N$ into a within- and a between-effect.

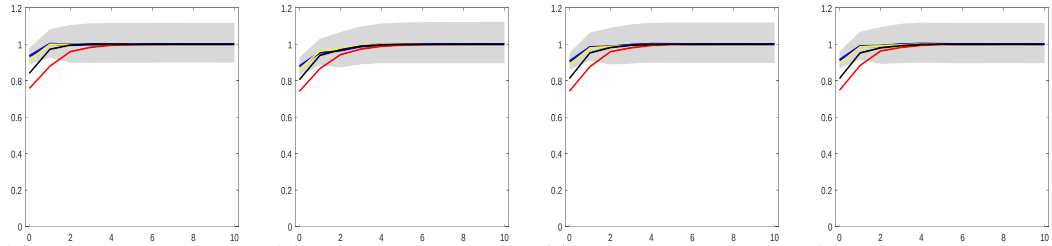
To explore empirically the contribution of the change in the LIS of each sub-sector to the change in the LIS of sector j, we proceed as follows. As shall be useful, let us write out the following relationships:

$$W_t^j L_t^j = \sum_k W_t^{k,j} L_t^{k,j}, \tag{132a}$$

$$\frac{W_t^j L_t^j}{P_t^j Y_t^j} = \sum_k \frac{W_t^{k,j} L_t^{k,j}}{P_t^{k,j} Y_t^{k,j}} .\omega_t^{Y,k,j}, \tag{132b}$$

$$s_{L,t}^j = \sum_k s_{L,t}^{k,j} .\omega_t^{Y,k,j}, \tag{132c}$$

where we denote by $\omega_t^{Y,k,j} = \frac{P_t^{k,j} Y_t^{k,j}}{P_t^j Y_t^j}$ the share of value added of sub-sector k in sector j in the

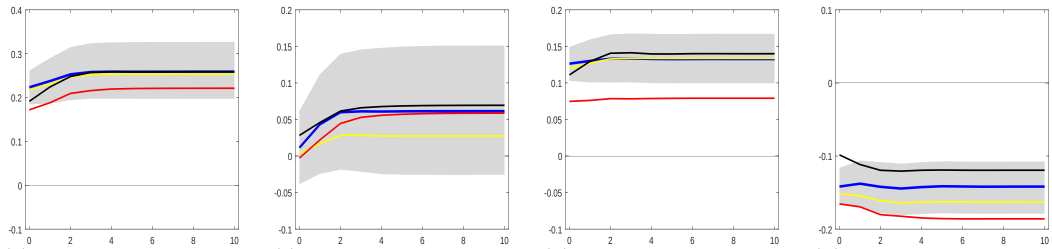


(a) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$

(b) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$

(c) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$

(d) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$

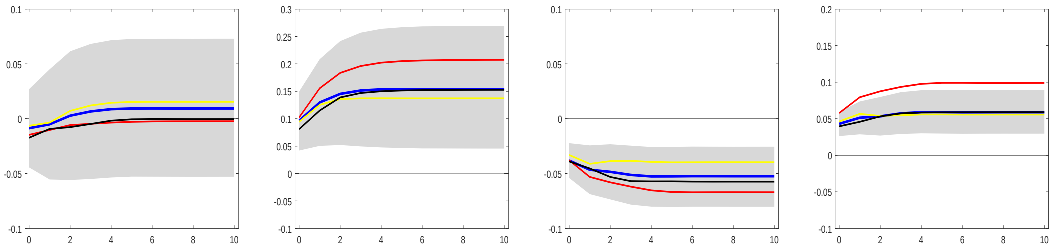


(e) H-Value Added, Y^H

(f) N-Value Added, Y^N

(g) H-Value Added Share, $\nu^{Y,H}$

(h) N-Value Added Share, $\nu^{Y,N}$

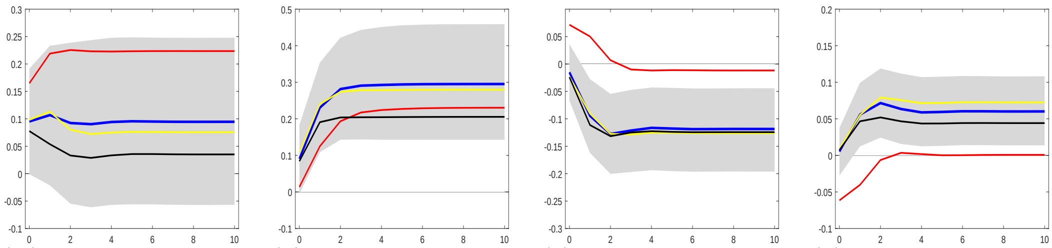


(i) H-Hours Worked, L^H

(j) N-Hours Worked, L^N

(k) H-Labor Share, $\nu^{L,H}$

(l) N-Labor Share, $\nu^{L,N}$



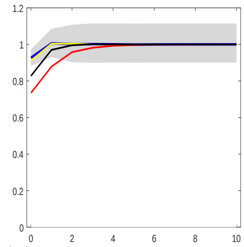
(m) H-Real Wage, W^H/P_C

(n) N-Real Wage, W^N/P_C

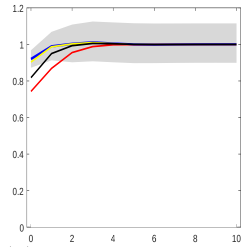
(o) H-Relative Wage, W^H/W

(p) N-Relative Wage, W^N/W

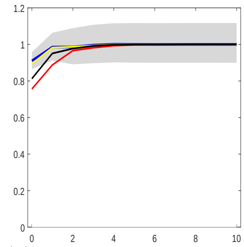
Figure 20: Sensitivity of Sectoral Effects of Technology Shock Biased toward the Traded Sector to the Classification of Industries as Tradable or Non-Tradable. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral output, sectoral value added shares), percentage deviation from trend in total hours worked units (sectoral hours worked, sectoral labor shares), and percentage deviation from trend (sectoral real consumption wages and sectoral relative wages). Results for baseline specification are displayed by solid blue lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. The yellow line and the red line show results when 'Hotels and restaurants' and 'Real Estate, renting and business services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as non-tradables. Sample: 17 OECD countries, 1970-2013, annual data.



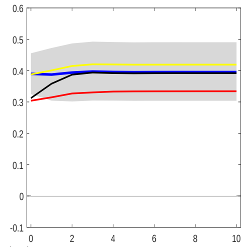
(a) Relative Productivity, $Z \equiv (Z^H)^a / (Z^N)^b$



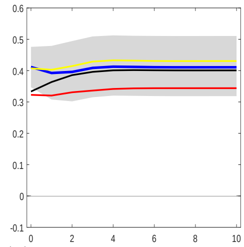
(b) Relative Productivity, $Z \equiv (Z^H)^a / (Z^N)^b$



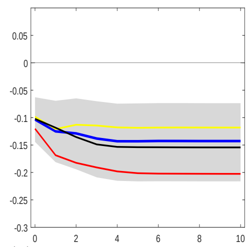
(c) Relative Productivity, $Z \equiv (Z^H)^a / (Z^N)^b$



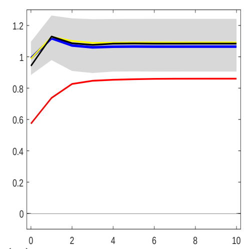
(d) Relative Value Added, Y^H/Y^N



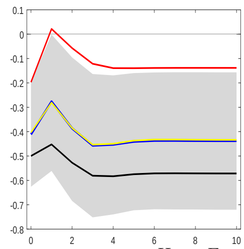
(e) Relative Value Added, Y^H/Y^N



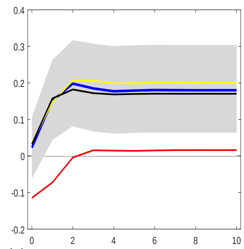
(f) Relative Hours Worked, L^H/L^N



(g) Relative Price of Non-Tradables, $P \equiv P^N/P^H$

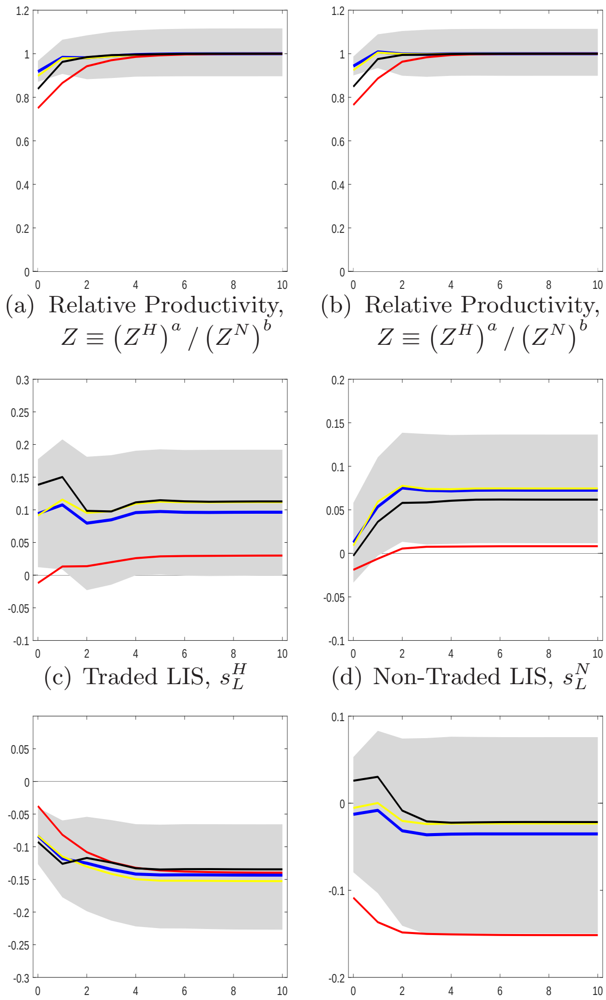


(h) TOT, P^H/P^F



(i) Relative Wage of Non-Tradables, $\Omega \equiv W^H/W^N$

Figure 21: Sensitivity of Sectoral Effects of Unanticipated Technology Shock Biased toward the Traded Sector to the Classification of Industries as Tradable or Non-tradable. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Horizontal axes indicate years. Vertical axes measure deviations from trend (ratio of traded value added to non-traded value added and ratio of hours worked of tradables to hours worked of non-tradables), percentage deviation from trend (relative price of non-tradables, terms of trade and relative wage). Results for baseline specification are displayed by solid blue lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. The yellow line and the red line show results when 'Hotels and restaurants' and 'Real Estate, renting and business services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as non-tradables. Sample: 17 OECD countries, 1970-2013, annual data.



(a) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$

(b) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$

(c) Traded LIS, s_L^H

(d) Non-Traded LIS, s_L^N

(e) Traded Capital-Labor Ratio, k^H

(f) Non-Traded Capital-Labor Ratio, k^N

Figure 22: Sensitivity of the Effects of Unanticipated Technology Shock Biased toward the Traded Sector on Sectoral Variables to the Classification of Industries as Tradable or non-tradable. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Horizontal axes indicate years. Vertical axes measure deviations from trend (ratio of labor compensation to value added at current prices) and percentage deviation from trend in capital stock units (ratio of capital to labor). Results for baseline specification are displayed by solid blue lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. The yellow line and the red line show results when 'Hotels and restaurants' and 'Real Estate, renting and business services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as tradables. Sample: 17 OECD countries, 1970-2013, annual data.

value added of sector j at current prices and at time t. Log-linearizing (132c) leads to:

$$
\begin{aligned}
ds^j_{L,t} &= \sum_k \tilde{\omega}^{Y,k,j} ds^{k,j}_{L,t} + \sum_k \tilde{s}^{k,j}_L \, d\omega^{k,j}_t, \\
\frac{ds^j_{L,t}}{\tilde{s}^j_{L,t}} &= \sum_k \tilde{\omega}^{Y,k,j} \frac{\tilde{s}^{k,j}_L}{\tilde{s}^j_L} \frac{ds^{k,j}_{L,t}}{\tilde{s}^{k,j}_L} + \sum_k \tilde{s}^{k,j}_L \frac{\tilde{\omega}^{Y,k,j}}{\tilde{s}^j_L} \frac{d\omega^{Y,k,j}_t}{\tilde{\omega}^{Y,k,j}}, \\
\hat{s}^j_{L,t} &= \sum_k \alpha^{k,j}_L \left(\hat{s}^{k,j}_{L,t} + \hat{\omega}^{Y,k,j}_t \right), \qquad (133)
\end{aligned}
$$

where $\alpha^{k,j}_L$ is the labor compensation share of sub-sector k in sector j, i.e.,

$$
\alpha^{k,j}_L = \tilde{\omega}^{Y,k,j} \frac{\tilde{s}^{k,j}_L}{\tilde{s}^j_L} = \frac{W^{k,j} L^{k,j}}{W^j L^j}. \qquad (134)
$$

From eq. (133), we are able to write the within-between decomposition for each sector j across industries k:

$$
\hat{s}^j_{L,t} = \underbrace{\sum_k \bar{\alpha}^{k,j} \hat{s}^{k,j}_{L,t}}_{\text{Within Effect}} + \underbrace{\sum_k \bar{\alpha}^{k,j} \hat{\omega}^{k,j}_t}_{\text{Between Effect}}, \qquad (135)
$$

where $\bar{\alpha}^{k,j}$ refers to the labor compensation share averaged over 1970-2013. Eq. (135) shows that the response of the LIS in sector j can be decomposed into a within-effect (keeping the value added share constant) and a between-effect (keeping the LIS constant). In accordance with (135), we first construct time series for the LIS of the broad sector $j = H, N$ as if the value added share remained constant over 1970-2013:

$$
\text{LIS}^j_{t,within} = \sum_k \bar{\alpha}^{k,j} \hat{s}^{k,j}_{L,t}. \qquad (136)
$$

Eq. (136) corresponds to the within-effect. We estimate the same VAR as in the main text, i.e., $[\hat{Z}_{it}, (\text{LIS}^j_{within})_{it}, \hat{k}^j_{it}]$ where variables enter the VAR model in growth rates, except that the LIS is constructed in accordance with eq. (136). The response of LIS^j_{within} to a shock to a productivity differential will allow us to calculate the rise in the LIS if the value added share remained constant.

Next, we construct time series for the LIS of the broad sector $j = H, N$ as if the LIS in sub-sector k remained constant over 1970-2013:

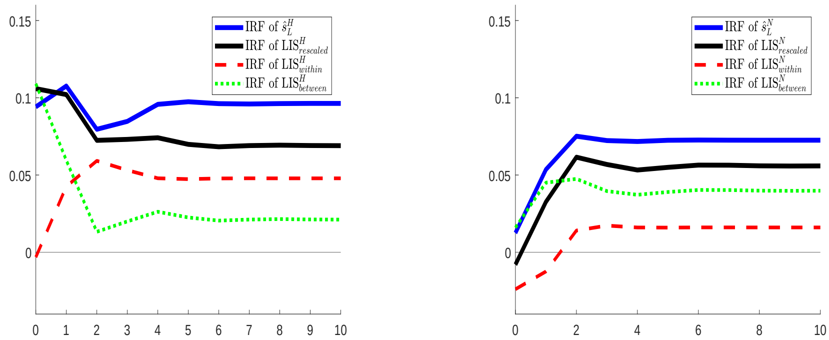
$$
\text{LIS}^j_{t,between} = \sum_k \bar{\alpha}^{k,j} \hat{\omega}^{k,j}_t. \qquad (137)
$$

Eq. (137) corresponds to the between-effect. We estimate the same VAR as in the main text, i.e., $[\hat{Z}_{it}, (\text{LIS}^j_{between})_{it}, \hat{k}^j_{it}]$ where variables enter the VAR model in growth rates, except that the LIS is constructed in accordance with eq. (137). The response of $\text{LIS}^j_{between}$ to a shock to a productivity differential will allow us to calculate the rise in the LIS driven by changes in value added shares of sub-sectors. Once we have estimated the responses of (136) and (137), we then sum the responses:

$$
\text{LIS}^j_{rescaled} = \text{LIS}^j_{within} + \text{LIS}^j_{between}. \qquad (138)
$$

We refer below to (138) as the response of the re-scaled LIS of sector j. Importantly, equation (138) allows us to also gauge the contribution of each component to the re-scaled LIS variation by calculating the share of the response of $\text{LIS}^j_{rescaled}$ attributable to the response of LIS^j_{within} and $\text{LIS}^j_{between}$, respectively.

Fig. 23 shows the responses of variables of interest to a 1% permanent increase in traded relative to non-traded TFP. For each sector $j = H, N$, the blue line shows the dynamic adjustment of the LIS ($\hat{s}^{j,t}_L$) after the technology shock while the dashed red line and the dotted green line display the within effect and the between effect respectively. The sum of the two components, the re-scaled LIS (eq. (138)), is displayed by the black line. While according to (138), the sum of the within- and between-effect should be, by construction, equal to the response of s^j_L, our results show that the discrepancy between the blue line (i.e. the empirical response of s^j_L) and the black line (corresponding to the response of the re-scaled LIS of sector j) is reassuringly small along the dynamic adjustment. For tradables, the observed increase in the labor share is mostly driven by the between effect at impact only, i.e. at time the shock occurs, the increase in s^H_L is due to changing value added shares of industries. Afterwards, the increase in the LIS in the traded sector is predominantly explained by the within component. On average, more than 60% of the LIS increase in sector H can be attributed to the rise in LIS in sub-sectors. Turning to the non-traded sector, the contribution of the within-effect is lower but remains significant at roughly 30%. But as we shall see below, this conclusion is deceptive. The reason is that for the within-effect, the LIS falls in some countries and rise in others so that on aggregate, the LIS driven by the within effect is unresponsive on impact. To address this problem, we have to estimate the within effect at a country level. In other words, we cannot draw any conclusion from the decomposition (138) when considering the whole sample.



(a) LIS of Tradables, s_L^H (b) LIS of Non-Tradables s_L^N

Figure 23: Within and Between Decomposition of Effects of Unanticipated Technology Shock Biased toward the Traded Sector on LIS. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Horizontal axes indicate years. Vertical axes measure percentage deviations from trend. In both panels the solid blue line shows the response of the LIS in sector j, $\hat{s}^j_{L,it}$, to identified technology shock biased toward the traded sector. The dashed red line displays the adjustment of the within component (eq. (136)) while the dotted green line displays the adjustment of the between component (eq. (137)). The black line represents the response of the sum of the two components (see (138)). The blue line shows baseline results for comparison purposes.

According to the evidence documented in the main text, the responses of sectoral LISs for the whole sample masks a wide cross-country dispersion since the LIS increases in half of the countries approximately and falls in the remaining sample. Accordingly, to gauge the contribution of the within-effect in a consistent way, we have re-estimated the VAR models $[\hat{Z}_t, \hat{s}^j_{L,t}, \hat{k}^j_t]$ and $[\hat{Z}_t, (\hat{\mathrm{LIS}}^j_{within})_t, \hat{k}^j_t]$ for one country at a time and plot responses of sectoral LISs on the vertical axis against estimated responses of LIS^j_{within} on the horizontal axis in Fig. 24. Impact (long-run resp.) responses, i.e., at time $t = 0$ ($t = 10$ resp.) are displayed in the first (second resp.) row of Fig. 24. In each panel, we obtain a strong and positive cross-country relationship between the change in the LIS and that of the within-effect.[27] Focusing on impact responses in sector H, 15 countries (out of 17) lie in the north-east or south-west of the scatter plot, indicating that short-run changes in s_L^H and LIS^H_{within} have the same sign (the two exceptions are CAN and NLD for which the impact response of s_L^H is positive while the impact response of LIS^H_{within} is negative). In the long-term, essentially the same picture emerges in the traded sector as the direction of the response of s_L^H collapses to the direction of the response of LIS^H_{within} for 14 countries out of 17 (exceptions are CAN, DNK and NOR). For the non-traded sector, we reach the same conclusion: at impact and in the long-run, for all countries (with the notable exception of JPN at time $t = 10$), the sign of the empirical response of s_L^H is consistent with that of the within-effect LIS^H_{within}.

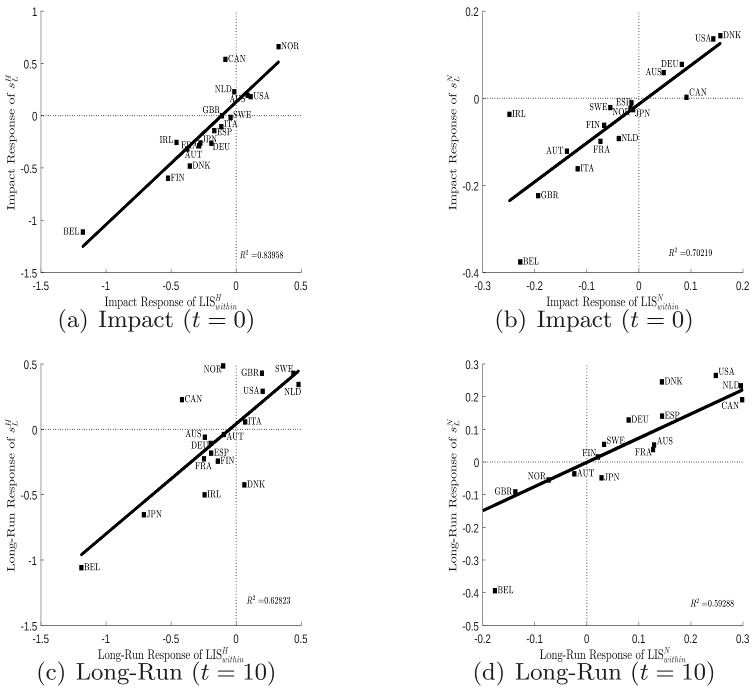
Finally, Table 23 reports the decomposition from eq. (138) and shows the contribution of the within-effect to the re-scaled LIS change in both sectors, at different time horizon. The results summarized in Table 23 show that, on average, about 60% of either short- and long-run changes in the LIS in tradables after an increase in traded relative to non-traded TFP can be attributed to the within-effect. The contribution of the within effect stands at 80% on impact and 66% in the long-run for the non-traded sector. Overall, these results confirm that the response of the LIS in sector $j = H, N$ to an asymmetric technology shock across sectors is mostly explained by the responses of LISs in sub-sectors rather than by the change in the value added composition.

N.5 Alternative Calculations of LIS

When exploring empirically the redistributive effects of a technology shock biased toward the traded sector, an issue is the way the share of labor in total income is constructed. Gollin [2002] pointed out that the treatment of self-employment income affects the measurement of the LIS. In particular, it is unclear how the income of proprietors (self-employed) should be allocated to labor income or to capital revenue. Here in this paper, our preferred measure (called benchmark *bench* hereafter) is to treat all the income of self-employed as labor income. Although this choice overstates the measure of the LIS, it has the virtue of being simple and transparent. Moreover data involved in

[27] Slope coefficients of regression lines shown in Fig. 24 range from 0.74 to 1.17 while R-squared falls in the range [0.59; 0.84].

Sector H Sector N



(a) Impact ($t = 0$) (b) Impact ($t = 0$)

(c) Long-Run ($t = 10$) (d) Long-Run ($t = 10$)

Figure 24: Cross-Country Effects of Technology Shock Biased toward the Traded Sector on LIS and LIS_{within}. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Horizontal axes report responses of LIS^j_{within} obtained by running the VAR $[\hat{Z}_t, \hat{\text{LIS}}^j_{within,t}, \hat{k}^j_t]$. Vertical axes show responses of $\hat{s}^j_{L,it}$ obtained from the VAR $[\hat{Z}_t, \hat{s}^j_{L,t}, \hat{k}^j_t]$. Impact (long-run) responses, i.e., at time $t = 0$ ($t = 10$) are shown in the first (second) row. Sample: 17 OECD countries, 1970-2013, annual data.

Table 23: Contribution of the Within-component to the re-scaled LIS Variation (in %)

Country	Sector H		Sector N	
	Impact	Long-Run	Impact	Long-Run
AUS	23.73	41.60	81.88	62.09
AUT	81.42	53.48	89.37	24.43
BEL	99.34	89.13	66.98	45.15
CAN	10.87	38.58	64.47	58.99
DEU	90.10	92.80	93.30	68.93
DNK	78.62	12.23	87.49	79.36
ESP	76.35	52.47	58.94	63.31
FIN	87.18	44.53	83.24	37.68
FRA	97.62	83.43	79.19	77.04
GBR	43.57	37.40	97.79	79.70
IRL	73.12	39.89	77.68	69.23
ITA	90.12	63.32	96.75	88.13
JPN	89.85	94.44	96.62	43.21
NLD	12.80	89.39	49.85	91.25
NOR	44.81	15.74	87.60	86.89
SWE	74.58	90.59	64.09	53.81
USA	63.71	70.74	90.83	90.93
Mean	66.93	59.40	80.36	65.89

Notes: Each entry in the table gives, for each sector $j = H, N$ and horizon $t = 0, 10$, the share of the re-scaled LIS change attributed to the within-component, i.e. $100 \times (\hat{\text{LIS}}^j_{t,within} - \hat{\text{LIS}}^j_{t,rescaled})$.

the construction of this calculation of the LIS are comparable across industries and readily available for all countries of our sample. Specifically, the LIS in sector $j = H, N$ is constructed as follows:

$$s_L^{j,bench} = \frac{W^j_{empl} L^j_{empl} + Inc^j_{self}}{P^j Y^j}, \tag{139}$$

where $W^j_{empl}L^j_{empl}$ is the labor compensation of employees, Inc_{self} is total income of self-employed and P^jY^j is the valued added at current prices in sector j. Note that labor compensation of employees includes total labor costs: wages, salaries and all other costs of employing labor which are borne by the employer whilst Inc_{self} comprises both labor and capital income components, noted $W^j_{self}L^j_{self}$ and $R^j_{self}K^j_{self}$ respectively such that $Inc^j_{self} = W^j_{self}L^j_{self} + R^j_{self}K^j_{self}$.

As a first alternative measure of the LIS, we use only employees compensation as a measure of labor income. This LIS measure, denoted by $s^{j,1}_L$, is constructed as follows:

$$s^{j,1}_L = \frac{W^j_{empl}L^j_{empl}}{P^jY^j}. \tag{140}$$

Measure (140) omits the income of the self-employed, i.e. this income is totally counted as capital income.

As a second alternative measure, we split self-employed income into capital and labor income based on the assumption that the labor income of the self-employed has the same mix of labor and capital income as the rest of the economy. In other words, total labor compensation comprises labor compensation of employees, $W^j_{empl}L^j_{empl}$, and the self-employed income scaled by the LIS of employees only, i.e. $Inc^j_{self} \times s^{j,1}_L$. With this adjustment, the LIS, denoted by $s^{j,2}_L$, is constructed as follows:

$$s^{j,2}_L = \frac{W^j_{empl}L^j_{empl} + Inc^j_{self} \times s^{j,1}_L}{P^jY^j}. \tag{141}$$

Finally, the last alternative to compute the LIS relies upon the assumption that self-employed earn the same hourly compensation as employees. Thus, we use the hourly wage earned by employees W^j_{empl} as a shadow price of labor of self-employed workers. The LIS, denoted by $s^{j,3}_L$, is constructed as follows:

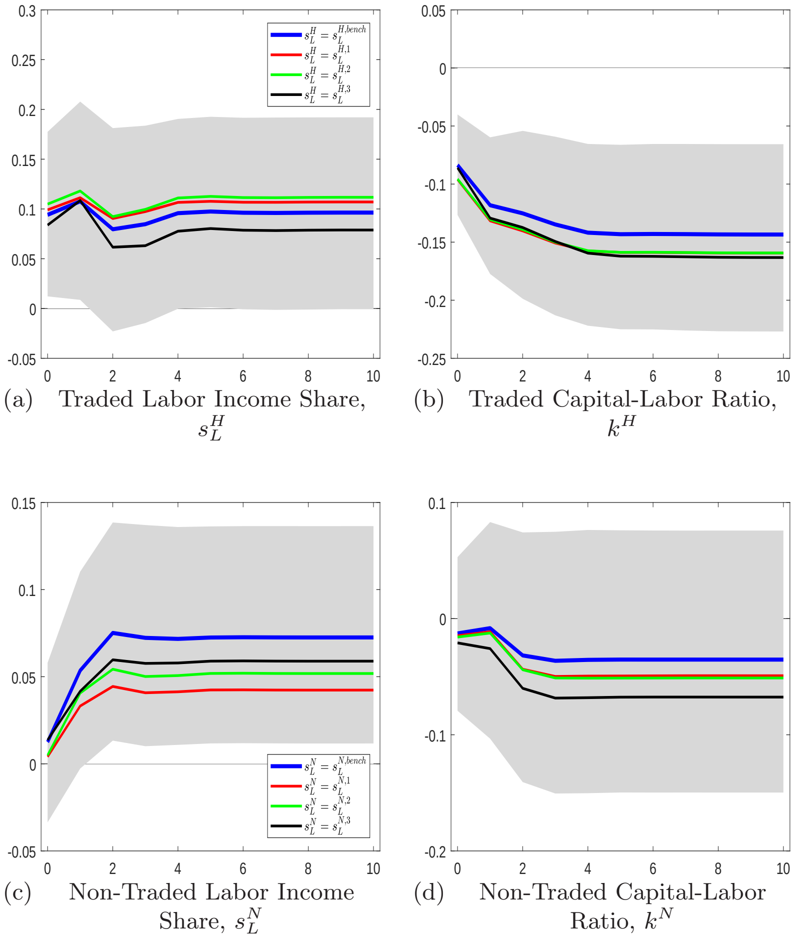
$$s^{j,3}_L = \frac{W^j_{empl} \times (L^j_{empl} + L^j_{self})}{P^jY^j}. \tag{142}$$

In Fig. 25 we display the results of this sensitivity analysis with respect to the construction of the labor income share. To do so, we measure the effects of an exogenous increase in TFP of tradables relative to non-tradables by 1% on LIS and capital-labor ratio in sector $j = H, N$ by contrasting the impulse response functions of the two variables when the LIS is measured as either $s^{j,bench}_L$ (blue line), or $s^{j,1}_L$ (red line), or $s^{j,2}_L$ (green line), or $s^{j,3}_L$ (black line). The IRFs are obtained for each specification by running the VAR model $\left[\hat{Z}_{it}, \hat{s}^H_{L,it}, \hat{k}^H_{it}\right]$ and $\left[\hat{Z}_{it}, \hat{s}^N_{L,it}, \hat{k}^N_{it}\right]$. As Fig. 25 shows, the responses of LIS and capital-labor ratios for the four specifications are qualitatively similar. In panels (a) and (c), the IRFs obtained with the three alternative measures of s^j_L are well within the confidence interval (for the benchmark specification $s^{j,bench}_L$) for all horizons. Overall, our main findings regarding the response of s^j_L and k^j for $j = H, N$ to an increase in TFP of tradables to non-tradables are robust and unsensitive to the way the share of labor in total income is constructed in the data.

N.6 Identified Technology Shocks across Alternative VAR Specifications

We address a potential concern related to the fact that the technology shock may display noticeable differences across alternative VAR specifications. Such differences could potentially make the comparison of the effects of a technology shock across sectors difficult. Because in the quantitative analysis we base our calibration on one unique technology shock, such differences could potentially undermine the comparison of theoretical with empirical responses. Before summarizing the results of our robustness exercises, it is worth mentioning that, in line with the current practice, to facilitate the interpretation of our results, we normalize the shock to a productivity differential to 1% in the long-run. Such a normalization thus makes the responses of economic variables directly comparable quantitatively across VAR models. However, even if the magnitude and the shape of the technology shock is similar across VAR specifications, different VAR models could pickup different structural technology shocks, i.e., underlying sectoral TFPs responses could differ across VAR specifications. In order to investigate the extent of the discrepancy in the estimated responses caused by potentially different technology shocks across VAR specifications, we identify the technology shock in the baseline VAR model which includes aggregate variables and augment all VAR models with the identified technology shock ordered first. Reassuringly, the discrepancy in estimated responses turns out to be insignificant.

We conduct below an elaborate investigation of the potential discrepancy in the estimated effects caused by considering alternative VAR models. To perform such an analysis, we proceed as follows. Once we have identified the technology shock in the first VAR model that includes aggregate variables, i.e., $x^A_{it} = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$, we augment each VAR model with the identified technology shock, ordered first. More precisely, we run the following VAR specifications:



(a) Traded Labor Income Share, s_L^H

(b) Traded Capital-Labor Ratio, k^H

(c) Non-Traded Labor Income Share, s_L^N

(d) Non-Traded Capital-Labor Ratio, k^N

Figure 25: Effects of Technology Shock Biased toward the Traded Sector on LISs and Capital-Labor Ratios. Notes: Exogenous increase of TFP in tradables relative to non-tradables adjusted with labor income shares by 1%. Sectoral variables include labor income shares and capital-labor ratios. Horizontal axes indicate years. Vertical axes measure deviations from trend (ratio of labor compensation to value added at current prices) and percentage deviation from trend in capital stock units (ratio of capital to labor). Results for baseline specification (eq. (139)) are displayed by solid blue lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling; sample: 17 OECD countries, 1970-2013, annual data. The red line reports results for specification (140) when $s_L^j = s_L^{j,1}$. The green and black lines shows results for specifications (141) and (142) respectively, i.e. $s_L^j = s_L^{j,2}$ for the green line and $s_L^j = s_L^{j,3}$ for the black line.

- $x_{it}^{R,j} = \left[\epsilon_{it}^{Z}, \hat{Z}_{it}, \hat{Y}_{it}^{j} - \hat{Y}_{it}, \hat{L}_{it}^{j} - \hat{L}_{it}, \hat{W}_{it}^{j} - \hat{W}_{it}\right]$ for $j = H, N$,
- $x_{it}^{P} = \left[\epsilon_{it}^{Z}, \hat{Z}_{it}, \hat{Y}_{it}^{H} - \hat{Y}_{it}^{N}, \hat{P}_{it}^{N} - \hat{P}_{it}^{H}\right]$ and $x_{it}^{P} = \left[\epsilon_{it}^{Z}, \hat{Z}_{it}, \hat{Y}_{it}^{H} - \hat{Y}_{it}^{N}, \hat{P}_{it}^{H} - \hat{P}_{it}^{F}\right]$,
- $x_{it}^{LIS} = \left[\epsilon_{it}^{Z}, \hat{Z}_{it}, \hat{s}_{L,it}^{j}, \hat{k}_{it}^{j}\right]$ for $j = H, N$,

where ϵ_{it}^{Z} is the the identified technology shock estimated in the baseline VAR model, i.e. $x_{it}^{A} = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$. Then, we contrast the responses for the baseline model with those for augmented VAR models.

Fig. 26 and Fig. 27 compare the results in the main text displayed by the solid blue line with those for the same VAR model augmented with the identified technology shock. As shown in the first row of Fig. 26 and Fig. 27, across all VAR specifications, the endogenous response of the productivity differential is quite similar, if not identical, whether the baseline VAR model is augmented (solid black line) or not with the identified technology shock (solid blue line). Turning to the sectoral composition effects shown in Fig. 26, all of the conclusions mentioned in the main text hold since the solid black line lies for all variables within the original confidence bounds of those obtained when the VAR model is not augmented with the identified technology shock. We may notice some slight differences for the relative wage in tradables and non-tradables, but the discrepancy is not statistically significant, except in the short-run. In Fig. 27, one can observe that the IRFs fall within the confidence interval for all horizons and all variables, with the exceptions of the terms of trade and the relative wage of non-tradables (but only in the short-run for the latter). Overall, reassuringly, this robustness exercise shows that our different VAR models identify similar structural technological shocks and it turns out that differences are statistically negligible.

N.7 Robustness Check to the Construction of Sectoral Physical Capital Time Series

In the main text, due to data availability, we construct time series for sectoral capital by computing the overall capital stock by adopting the perpetual inventory approach and then by splitting the gross capital stock into traded and non traded industries by using sectoral valued added shares. In this Appendix, we investigate whether the effects on k^j we estimate empirically are not driven by our assumption about the construction of time series for sectoral capital stock. To conduct this robustness check, we take time series for sectoral capital stock from EU KLEMS [2011], [2017] databases and contrast below empirical responses of k^j when sectoral capital stocks are measured by adopting the Garofalo and Yamarik's [2002] methodology (our benchmark) with those obtained by using sectoral data on K^j provided by EU KLEMS [2011], [2017] databases. In both cases, we explore empirically the VAR model $[\hat{Z}_{it}, \hat{s}_{L,it}^{j}, \hat{k}_{it}^{j}]$. Due to data availability, our results in the latter case include a sample of nine OECD countries which provide time series on sectoral capital of reasonable length. To be consistent, our benchmark also includes these nine countries only.

The methodology by Garofalo and Yamarik's [2002] is based on the assumption of perfect mobility of capital across sectors and a small discrepancy in the LIS across sectors, i.e., $s_L^H \simeq s_L^N$. The assumption of perfect capital mobility implies that the marginal revenue product of capital must equalize across sectors:

$$P_t^H \left(1 - s_L^H\right) \frac{Y_t^H}{K_t^H} = P_t^N \left(1 - s_L^N\right) \frac{Y_t^N}{K_t^N}. \tag{143}$$

Using the resource constraint for capital, $K = K^H + K^N$, dividing the numerator and the denominator in the LHS of (143) by GDP, Y, and denoting by $\omega_t^{Y,j} = \frac{P_t^j Y_t^j}{Y_t}$ the share of value added of sector j in GDP at current prices (at time t), eq. (143) can be solved for the K^H/K:

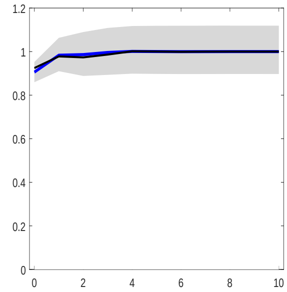
$$\frac{K_t^H}{K_t} = \frac{\omega_t^{Y,H}\left(1 - s_L^H\right)}{\left(1 - s_L^N\right)\left(1 - \omega_t^{Y,H}\right) + \left(1 - s_L^H\right)\omega_t^{Y,H}}. \tag{144}$$

Assuming that $s_L^H \simeq s_L^N$ leads to the rule we apply to split the aggregate stock of capital into tradables and non tradables:

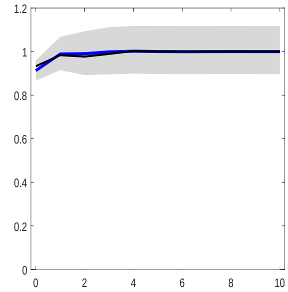
$$\frac{K_t^H}{K_t} = \omega_t^{Y,H}. \tag{145}$$

In the baseline, we adopt the methodology of Garofalo and Yamarik [2002] to split the national gross capital stock into traded and non-traded industries by using sectoral value added shares at current prices. Let $\omega^{Y,j}$ be the share of sector j's value added (at current prices) $P^j Y^j$ for $j = H, N$ in overall output (at current prices) $Y \equiv P^H Y^H + P^N Y^N$, the allocation of the national capital stock to sector j is given by the rule:

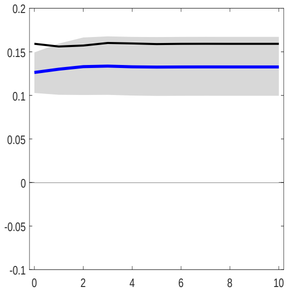
$$K_{GY}^j = \omega^{Y,j} K = \frac{P^j Y^j}{Y} K, \tag{146}$$



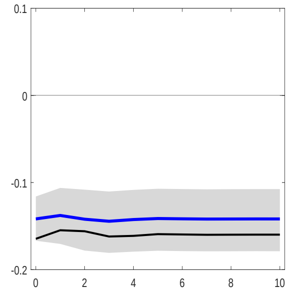
(a) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$



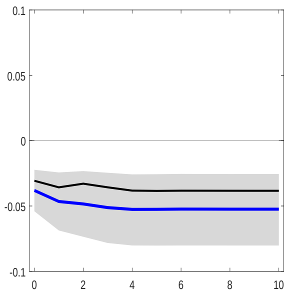
(b) Relative Productivity, $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$



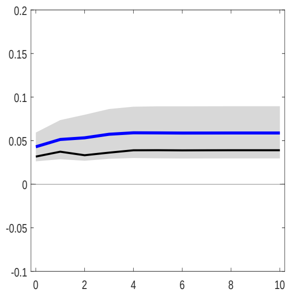
(c) H-Value Added Share, $\nu^{Y,H}$



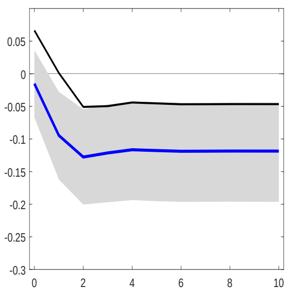
(d) N-Value Added Share $\nu^{Y,N}$



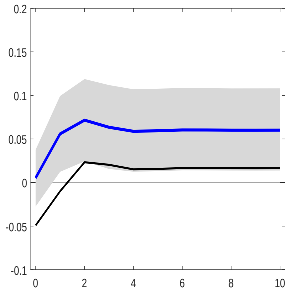
(e) H-Labor Share, $\nu^{L,H}$



(f) N-Labor Share $\nu^{L,N}$

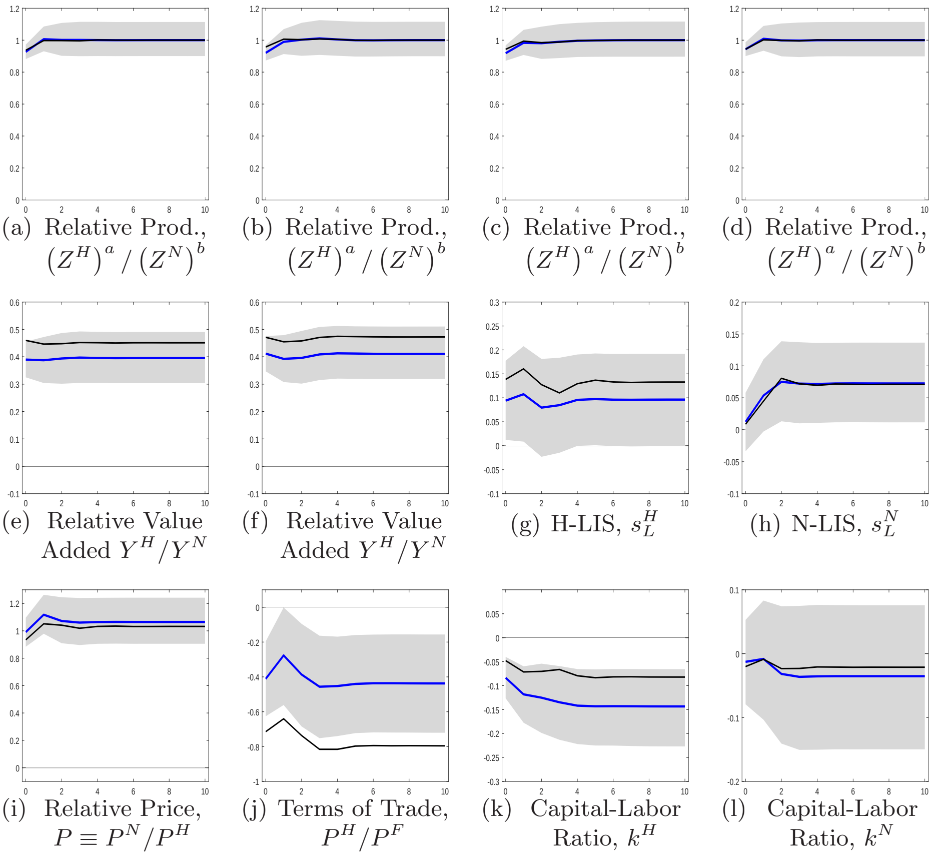


(g) H-Relative Wage, W^H/W



(h) N-Relative Wage, W^N/W

Figure 26: Assessing Differences Caused by Potentially Identifying Different Technology Shocks across VAR Models. Notes: Exogenous 1% increase in TFP of tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added shares), percentage deviation from trend in hours worked units (sectoral labor shares), and percentage deviation from trend (sectoral relative wages). Results for baseline specification are displayed by solid blue lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. The solid black line reports the results for the same VAR model which is augmented with the identified technology shock obtained in the baseline VAR model $x_{it}^A = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$. Sample: 17 OECD countries, 1970-2013, annual data.



(a) Relative Prod., $(Z^H)^a/(Z^N)^b$
(b) Relative Prod., $(Z^H)^a/(Z^N)^b$
(c) Relative Prod., $(Z^H)^a/(Z^N)^b$
(d) Relative Prod., $(Z^H)^a/(Z^N)^b$
(e) Relative Value Added Y^H/Y^N
(f) Relative Value Added Y^H/Y^N
(g) H-LIS, s_L^H
(h) N-LIS, s_L^N
(i) Relative Price, $P \equiv P^N/P^H$
(j) Terms of Trade, P^H/P^F
(k) Capital-Labor Ratio, k^H
(l) Capital-Labor Ratio, k^N

Figure 27: Assessing Differences Caused by Potentially Identifying Different Technology Shocks across VAR Models. Notes: Exogenous 1% increase in TFP of tradables relative to non-tradables adjusted. Horizontal axes indicate years. Vertical axes measure deviations from trend (ratio of traded value added to non-traded value added and ratio of labor compensation to value added at current prices), percentage deviation from trend (relative price of non-tradables, terms of trade) and percentage deviation from trend in capital stock units (ratio of capital to labor). Results for baseline specification are displayed by solid blue lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling. The solid black line reports the results for the same VAR model which is augmented with the identified technology shock obtained in the baseline VAR model $x_{it}^A = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$. Sample: 17 OECD countries, 1970-2013, annual data.

where we denote the sectoral stock of capital obtained with the decomposition by Garofalo and Yamarik [2002] by K^j_{GY}. National capital stocks are estimated from the perpetual inventory approach. Following Garofalo and Yamarik [2002], the gross capital stock is then allocated to traded and non-traded industries by using sectoral value added shares according to eq. (146). Once the series for K^j_{GY} are obtained, we can construct the sectoral capital-labor ratios, $k^j_{GY} = K^j_{GY}/L^j$, and sectoral TFPs, Z^j_{GY}, which are constructed as the Solow residual.

As a robustness check, we alternatively take capital stock series from the EU KLEMS [2011] and [2017] databases which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for up to 11 industries, but only for nine countries of our sample over the entire period 1970-2013 (AUS, CAN, DNK, ESP, FIN, GBR, ITA, NLD and the USA).[28] For future reference, we denote the sectoral stock of capital and TFP by K^j_{KL} and TFP^j_{KL}, respectively, when we take sectoral data from the EU KLEMS [2011], [2017] databases.

Before presenting VAR estimates from the sensitivity analysis with respect to the calculation of sectoral capital stocks, we show pairwise correlations between selected variables (K^j, k^j and Z^j for $j = H, N$ along with the identified structural productivity shock ϵ^Z) constructed with the Garofalo and Yamarik [2002] methodology or alternatively with the direct use of the EU KLEMS [2011] and [2017] databases. We focus on the full available sample period 1970-2013 for 9 OECD countries (AUS, CAN, DNK, ESP, FIN, GBR, ITA, NLD and the USA). Table 24 provides the summary results for pairwise correlations. Series for all variables are positively and highly correlated, the average pairwise correlation is 0.885 and the correlation coefficients range from a low 0.755 for the identified technological shock ϵ^Z to a high of 0.983 for K^N. These results are suggestive, but of course not dispositive, that Garofalo and Yamarik's [2002] approach provides consistent estimates of the capital stock at the sectoral level.

Table 24: Sectoral Capital Stocks: Correlations for Selected Variables

Variable	(K^H_{GY}, K^H_{KL})	(K^N_{GY}, K^N_{KL})	(k^H_{GY}, k^H_{KL})	(k^N_{GY}, k^N_{KL})	(Z_{GY}, Z_{KL})	$(\epsilon^Z_{GY}, \epsilon^Z_{KL})$
correlation	0.907	0.983	0.906	0.789	0.973	0.755

Notes: subscripts "GY" and "KL" refer to the two methods to construct sectoral capital stocks. K^j is the capital stock in sector $j = H, N$, k^j is the capital-labor ratio in sector $j = H, N$, $Z = (Z^H)^a/(Z^N)^b$ is the labor share-adjusted TFP ratio between traded and non-traded sectors with $a = \left[(1-\alpha_J) + \alpha_J(s^H_L/s^N_L)\right]^{-1}$ (α_J being the tradable share in total investment expenditure) and $b = a(s^H_L/s^N_L)$ and ϵ^Z is the identified technology shock obtained by running the VAR including aggregate variables, i.e., $x^A_{it} = \left[\hat{Z}_{it}, \hat{Y}_{it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$. Sample: 9 OECD countries (AUS, CAN, DNK, ESP, FIN, GBR, ITA, NLD and the USA), annual data; 1970-2013.

Next, Fig. 28 plots identified shocks to the productivity differential, ϵ^Z, obtained with the two measures of Solow residuals constructed from sectoral capital stocks by adopting the two alternative methods. We detect very small differences between the two sets of data for all considered countries. Next, in Fig. 29 we plot estimated shocks ϵ^Z using KLEMS data on the vertical axis against estimated shocks ϵ^Z using the method of Garofalo and Yamarik [2002] on the horizontal axis. In line with results presented above, the scatter-plot shows a strong positive correlation. Also reported in Fig. 29 is a regression line, whose slope coefficient and standard error are 1.040 and 0.020 respectively, implying that the estimated coefficient is significant at the 1% level (the R-squared is 0.878).

Finally, we compare the responses of k^j for the baseline method to split the national gross capital stock into tradables and non-tradables with those obtained from the alternative approach where we take data on sectoral capital from KLEMS [2011], [2017] databases. We estimate the effects of a 1% permanent increase in TFP of tradables relative to non-tradables on the capital-labor ratio in sector $j = H, N$ and contrast the IRFs whether the sectoral capital stock is measured by K^j_{GY} (blue line) or by K^j_{KL} (black line). In both cases, we estimate the VAR model which includes the LIS and the capital-labor ratios, i.e., $x^{LIS,H}_{it} = \left[\hat{Z}_{it}, \hat{s}^H_{L,it}, \hat{k}^H_{it}\right]$ and $x^{LIS,N}_{it} = \left[\hat{Z}_{it}, \hat{s}^N_{L,it}, \hat{k}^N_{it}\right]$. As shown in Fig. 30, the responses of capital-labor ratios for the two methods are qualitatively similar since the solid black line lies within the original confidence bounds of those obtained when K^j is constructed with the use of the methodology of Garofalo and Yamarik [2002]. In particular, one can observe that the discrepancy in the results is small and not statistically significant at conventional level. Overall, our main findings regarding the response of k^j for $j = H, N$ to an increase in TFP in tradables to non-tradables are robust and unsensitive to the way the sectoral capital stocks are constructed in the data.

[28] IRL and NOR do not provide disaggregated capital stock series. In efforts to have a balanced panel and time series of a reasonable length, AUT (1976-2013), BEL (1995-2013), DEU (1991-2013), FRA (1978-2013), JPN (1974-2007) and SWE (1993-2007) are removed from the sample, which leaves us with 9 OECD countries over the period 1970-2013.

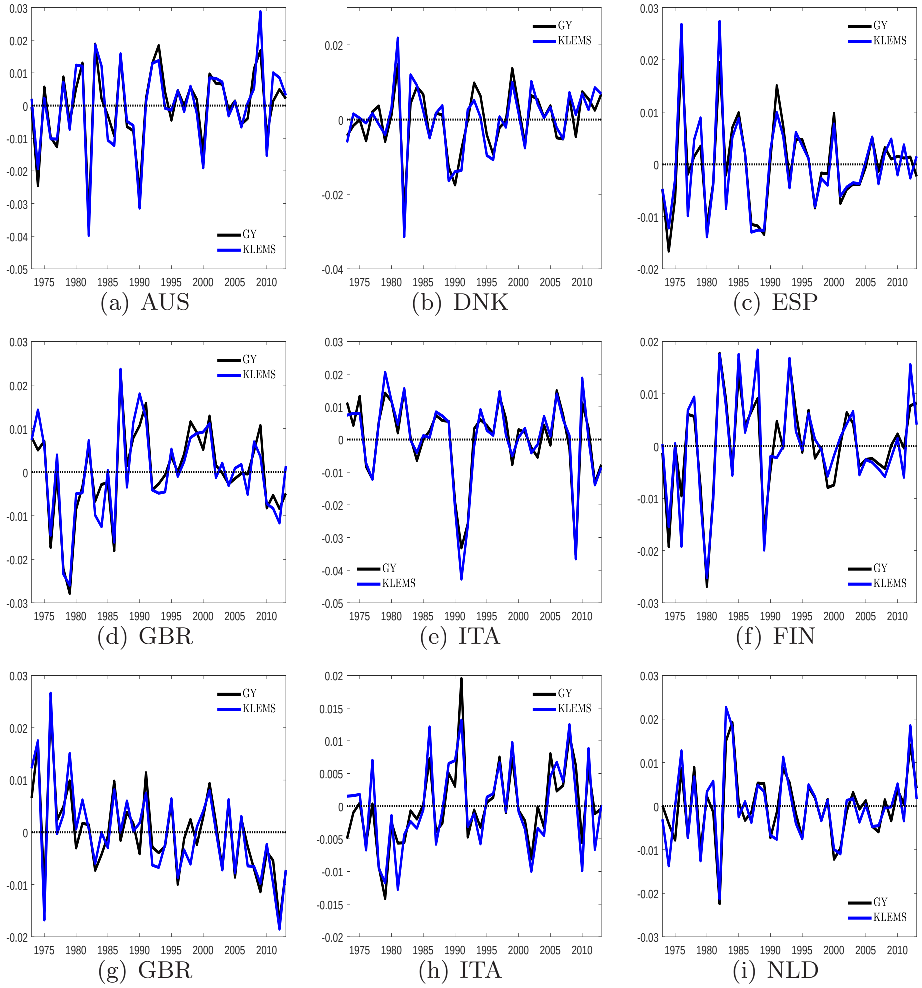


Figure 28: Identified Technology Shock ϵ^Z from Garofalo-Yamarik or KLEMS methodology: Time-series Evidence. Notes: "GY" refers to the case where we use the method of Garofalo and Yamarik [2002] to split the national gross capital stock into traded and non-traded industries. "KLEMS" refers to the case where we use the EU KLEMS [2011] and [2017] databases to construct sectoral capital stocks series. The identified technology shock ϵ^Z is obtained by running the VAR including aggregate variables, i.e., $x_{it} = [\hat{Z}_{it}, \hat{Y}_{it}, \hat{L}_{it}, \hat{W}_{C,it}]$ (sample: 9 OECD countries, 1970-2013, 2 lags).

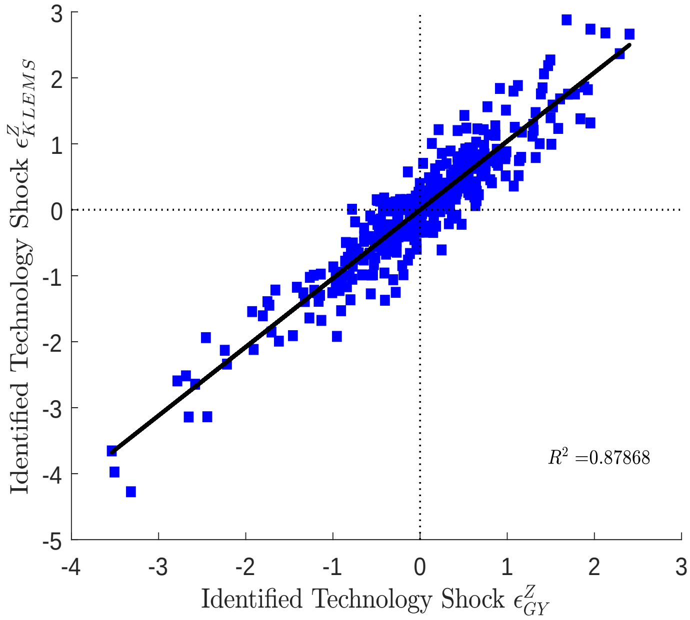
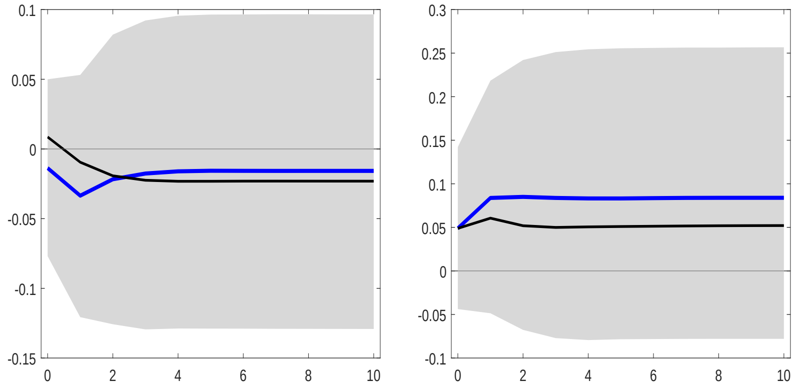


Figure 29: Identified Technology Shock ϵ^Z: Cross-Country Comparisons between Garofalo-Yamarik and KLEMS methodologies. Notes: subscript "GY" refers to the case where we use methodology of Garofalo and Yamarik [2002] to split the national gross capital stock into traded and non-traded industries. Subscript "KLEMS" refers to the case where we use the EU KLEMS [2011] and [2017] databases to construct sectoral capital stocks series.



(a) Traded Capital-Labor Ratio, k^H

(b) Non-Traded Capital-Labor Ratio, k^N

Figure 30: Effects of Technology Shock Biased toward the Traded Sector on Capital-Labor Ratios. Notes: Effects of a 1% permanent increase in TFP of tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in capital stock units. Results for baseline specification (i.e., we use the method of Garofalo and Yamarik [2002] to construct the sectoral capital stocks K^H and K^N) are displayed by blue lines with shaded area indicating 90 percent confidence bounds obtained by bootstrap sampling; sample: 9 OECD countries, 1970-2013, annual data. The black line reports results when we use the EU KLEMS [2011] and [2017] databases to construct sectoral capital stocks series K^j.

O Effects of Technology Shocks Biased Toward Tradables: Inspecting the Mechanism

In this section, we solve the model analytically by abstracting from physical capital. This enables us to derive a number of analytical results which emphasize the role of imperfect mobility of labor (IML henceforth) across sectors and endogenous terms of trade (TOT henceforth) in driving the transmission mechanism of technology shocks.

Both sectors use labor as the sole input in a constant returns to scale technology, i.e., $Y^j = A^j L^j$ with $j = H, N$. We set the productivity index in non-tradables to 1, i.e., $A^N = 1$. Because there is a difficulty in reallocating labor, sectoral wages do not equalize:

$$P^H A^H = W^H, \qquad \text{and} \qquad P^N = W^N. \tag{147}$$

The key equations characterizing optimal household behavior are given by first-order conditions described by (19a)-(19b), (20a) and (21), (22). The market clearing conditions for non-traded and home-produced traded goods read as:

$$L^N = C^N, \qquad \text{and} \qquad Y^H = C^H + X^H, \tag{148}$$

where exports, X^H, are governed by eq. (30). The current equation equation can be rewritten as $\dot{N} = r^\star N + P^H X^H - C^F$. To be able to derive useful analytical expressions which emphasize the distinct role of these two features, it is necessary to recourse to a number of assumptions. First, we solve the model by assuming that productivity in tradables increases once for all to its new long-run level, i.e., $\frac{A^H - A_0^H}{A_0^H} = a$. This assumption implies that the dynamics toward the final steady-state degenerate and the intertemporal solvency condition reduces to:

$$\tilde{N} = N_0. \tag{149}$$

Aggregation of market clearing conditions (148) leads to the standard equality between GDP, Y, and final expenditure, $P_C C - r^\star N_0$. To keep analytical expressions simple, we assume that the country starts with a zero net foreign asset position, i.e., $N_0 = 0$. This assumption implies that the consumption-to-GDP ratio, ω_C, is equal to one, since trade is initially balanced:

$$P^H X^H = C^F. \tag{150}$$

For later use, we denote $\omega_X = \frac{P^H X^H}{Y}$ the ratio of exports to GDP and $\alpha_L = \frac{P^H A^H L^H}{Y}$ the home tradable content of GDP which is equivalent to the labor compensation share of the home-produced traded goods sector.[29] Even under these assumptions, the model remains analytically untractable. Since our objective is to disentangle the role of IML across sectors and endogenous TOT, we explore below two polar cases. We first solve the model by allowing for IML across sectors while assuming that home- and foreign-produced traded goods are perfect substitutes, i.e., we let ρ tend toward infinity. Next, we consider a semi-small open economy with endogenous TOT by imposing perfect mobility of labor across sectors, i.e., we let ϵ tend toward infinity.

O.1 Model with IML

We solve the model by assuming that home- and foreign-produced traded goods are perfect substitutes. When we let ρ tend toward infinity into (6), we have $C^T = C^H + C^F$ and $P^T = 1$ so that consumption in tradables reduces to:

$$C^T = \varphi P_C^{\phi} C. \tag{151}$$

Since the traded good is the numeraire, the price of non-tradables P^N is equivalent to P. The market clearing condition for tradables (148) reads now as:

$$Y^H = C^T, \tag{152}$$

under assumption $N_0 = 0$. Inserting first (19b) into (22), (19a) into (21) and (151), and substituting the resulting expressions into the market clearing condition for non-tradables (148) and tradables (152), the steady-state can be reduced to two equations:

$$(1-\vartheta) P^{\epsilon} W^{-(\epsilon-\sigma_L)} \bar{\lambda}^{\sigma_L} = (1-\varphi) P^{-\phi} P_C^{(\phi-\sigma_C)} \bar{\lambda}^{-\sigma_C}, \tag{153a}$$

$$r^\star N_0 + \vartheta \left(A^H\right)^{1+\epsilon} W^{-(\epsilon-\sigma_L)} \bar{\lambda}^{\sigma_L} = \varphi P_C^{(\phi-\sigma_C)} \bar{\lambda}^{-\sigma_C}, \tag{153b}$$

which jointly determine the relative price of non-tradables, P, and the shadow value of wealth, $\bar{\lambda}$. Under assumption $N_0 = 0$, we have $\omega_C = \frac{P_C C}{Y} = 1$ so that $\alpha_L = \alpha_C$.

[29] Using the fact that $Y = WL$ and $P^H A^H = W^H$, we have $\alpha_L = \frac{W^H L^H}{WL}$.

A rise in the productivity index of tradables, A^H, produces a positive wealth effect reflected by a decline in the shadow value of wealth:[30]

$$\hat{\bar{\lambda}} = -\frac{\{(1+\epsilon)\left[(\sigma_L+\sigma_C)+\alpha_C(\phi-\sigma_C)\right]+\alpha_C(\epsilon-\sigma_L)(1-\phi)\}}{(\sigma_L+\sigma_C)(\epsilon+\phi)} < 0, \quad (154)$$

where the negative sign of the RHS term follows from evidence which suggests that $\phi < 1$. The positive wealth effect described by (154) encourages agents to work less and increase consumption expenditure. Because the rise in real expenditure is spread over the two goods while productivity in non-tradables is unchanged, an excess demand arises in the non-traded goods market, which in turn causes the relative price of non-tradables to appreciate:[31]

$$\hat{P} = \frac{1+\epsilon}{\phi+\epsilon} a > 0. \quad (155)$$

Eqs. (154) and (155) show that the degree of labor mobility across sectors influence both the extent of the decline in $\bar{\lambda}$ and the magnitude of the appreciation in the relative price of non-tradables. More specifically, as ϵ takes higher values, it can be shown analytically that the shadow value of wealth falls less while the relative price of non-tradables appreciates by a lower amount. Intuitively, following an increase in A^H, more labor shifts toward the non-traded sector as the degree of labor mobility increases which results in a smaller excess of demand in the non-traded goods market so that the relative price appreciates less. Since non-traded wages increase by a smaller amount as well, the positive wealth effect is mitigated. In the situation of perfect mobility of labor across sectors, we have $\lim_{\epsilon\to\infty} \hat{P} = a$, and $\lim_{\epsilon\to\infty} \hat{\bar{\lambda}} = -\frac{[(\sigma_L+\sigma_C)+\alpha_L(1-\sigma_C)]}{\sigma_L+\sigma_C} a < 0$.

Because labor shifts away from the traded to the non-traded sector, the share of non-tradables in labor, $\nu^{L,N}$, increases. To see it formally, totally differentiate (22) together with (147), and substitute (155):

$$\hat{\nu}^{L,N} = \alpha_L(1-\alpha_L)\frac{\epsilon(1-\phi)}{\epsilon+\phi} a \gtreqless 0. \quad (156)$$

Eq. (156) shows that both elasticity of substitution between traded and nontraded goods, ϕ, and the elasticity of labor supply across sectors, ϵ, matter in determining the response of the share of non-tradables in labor. Since evidence documented by the literature overwhelmingly suggest that $\phi < 1$, a technology shock biased toward the traded sector leads to a reallocation of labor toward the non-traded sector. Intuitively, when $\phi < 1$, the appreciation in the relative price, P, raises expenditure in non-tradables relative to tradables and thus boosts labor demand in the non-traded sector. Thus, $\nu^{L,N}$ increases in line with our empirical findings documented in section 2. As the elasticity of labor supply across sectors (i.e., ϵ) takes higher values, workers are more willing to shift their hours worked toward the non-traded sector and thus $\nu^{L,N}$ increases more, as long as $\phi < 1$.

While the traded sector experiences a labor outflow, the share of tradables in real GDP, $\nu^{Y,H}$, unambiguously rises. In the data, the response of the sectoral output share is calculated as the growth differential in GDP units between traded value added at constant prices and real GDP, i.e., $\hat{\nu}^{Y,H} = \alpha_L\left(\hat{Y}^H - \hat{Y}_R\right)$. Totally differentiating real GDP and inserting the resulting expression reveals that change in the share of tradables in real GDP is positively related to the appreciation in the relative price of non-tradables:

$$\hat{\nu}^{Y,H} = \alpha_L(1-\alpha_L)\phi\hat{P}, \quad (157)$$

where $\hat{P}$ is given by eq. (155). Because a higher degree of labor mobility across sectors mitigates the excess demand in the non-traded goods market, and thus the appreciation in the relative price, P, the share of tradables in real GDP increases less as more labor shifts away from the traded sector.

How do hours worked and the real consumption wage react to a technology shock biased toward the traded sector? Higher productivity in tradables increases both traded and non traded wages and thus raises the aggregate wage by an amount given by $\hat{W} = \alpha_L\hat{A}^H + (1-\alpha_L)\hat{P}$. Totally differentiating $W_C = W/P_C$ and inserting (155) gives the response of the real consumption wage, i.e., $\hat{W}_C = \alpha_C\hat{A}^H > 0$. Thus the percentage change in the real consumption wage is independent of the degree of labor mobility across sectors. By raising the aggregate wage and reducing the shadow value of wealth, a technology shock biased toward the traded sector exerts two opposite effects on labor supply. Totally differentiating (19b), i.e., $L = (W\lambda)^{\sigma_L}$, and inserting (154) along with (155) shows that total hours worked remain unaffected when $\sigma_C = 1$:

$$\hat{L} = -\frac{\sigma_L\alpha_L(1-\sigma_C)}{\sigma_L+\sigma_C}. \quad (158)$$

[30]Totally differentiating (153a) leads to: $\hat{P} = \frac{-(\sigma_L+\sigma_C)\hat{\bar{\lambda}}+\alpha_L(\epsilon-\sigma_L)\hat{A}^H}{\Psi^N}$ with $\Psi^N = [\epsilon\alpha_L + \sigma_L(1-\alpha_L)] + [\alpha_C\phi + (1-\alpha_C)\sigma_C] > 0$. Totally differentiating (153b) and using the above equation to eliminate $\hat{P}$ yields (154).

[31]Totally differentiating (153a) and plugging (154) leads to (155).

When $\sigma_C = 1$, the rise in leisure triggered by the wealth effect following a technology shock is exactly offset by the fall in leisure resulting from the substitution effect caused by a higher wage. When $\sigma_C > 1$, the curvature of the utility function derived from consumption is less so that the marginal utility of consumption declines less rapidly. Therefore, the impact of the wealth effect on leisure is mitigated and the substitution effect dominates. Hence, a technology shock increases labor supply when $\sigma_C > 1$. It is worth noting that the elasticity of labor supply across sectors has no impact on the response of total hours worked as a rise in ϵ lowers the extent of the wealth and substitution effect by the same magnitude.

O.2 Model with Endogenous TOT

We now shed some light on the implications of endogenous TOT. We solve the model by assuming that workers do not experience a utility loss when shifting hours worked from one sector to another. When we let ϵ tend toward infinity into (9), we have:

$$L = L^H + L^N. \tag{159}$$

Because workers are devote their whole time to the sector that pays highest wages, both sectors must pay the same wage; thus eqs. (147) reduce to:

$$W = P^H A^H = P^N. \tag{160}$$

Totally differentiating (160) reveals that the price of non-traded goods in TOT goods, $\hat{P} = \hat{P}^N - \hat{P}^H$, appreciates by the same amount as $\hat{A}^H$, like in a model where TOT are exogenous. Differently, as long as home- and foreign-produced traded goods are imperfect substitutes, such an appreciation is achieved through a smaller appreciation in the relative price of non-tradables, $\hat{P}^N$, and a decline in the TOT. As we shall see below, the fall in the relative price of tradables plays a key role by mitigating the shift of labor toward the non-traded sector as the decrease in P^H encourages households to substitute home-produced traded goods for non-traded goods.

When the TOT are endogenous, two additional parameters determine the response of the open economy to a technology shock: the export price elasticity, ϕ_X, and the elasticity of substitution between home- and foreign- produced traded goods. We assume that both parameters are larger than one. The assumption of $\phi_X > 1$ is supported by evidence documented by Mejean and Imbs [2015] which indicates that $\phi_X > 1$ for the vast majority of the OECD countries.

Inserting first appropriate optimal decisions into (148), (150), (159), and (160), and differentiating leads to the response of the TOT to a technology shock biased toward the traded sector:[32]

$$\hat{P}^H = -\frac{\chi^H}{\left[(\phi_X - 1) + \alpha^H \rho\right](\sigma_L + \sigma_C) + (1 - \alpha^H)\chi^H} a < 0, \tag{161}$$

where

$$\chi^H = \sigma_C \alpha_C (\sigma_L + 1) + (1 - \alpha_C)\phi(\sigma_L + \sigma_C) > 0. \tag{162}$$

As shown in eq. (161), for the TOT to decline, the export price elasticity, ϕ_X, must be larger than one. Intuitively, a technology shock produces a positive wealth effect which encourages agents to consume more. Because imports increase, for trade to be balanced, the value of exports in terms of foreign-produced goods, i.e, $P^H X^H = \varphi_X \left(P^H\right)^{1-\phi_X}$, must increase; when $\phi_X > 1$, the fall in P^H improves the balance of trade.

Because the decline in TOT mitigates the rise in traded wages, W^H, the marginal utility of wealth declines less than that if the TOT were exogenous.[33] Inserting first (30) and (20a) together with (19a) into (150), differentiating and inserting (161) shows that the marginal utility of wealth

[32] Insert first (19b), (160) and the market clearing condition for non-tradables (148) into (159) and differentiate:

$$\alpha_L \hat{L}^H = \sigma_L \bar{\lambda} + \sigma_L \left(\hat{P}^H + \hat{A}^H\right) - (1 - \alpha_L)\hat{C}^N.$$

Then inserting first (20a) and (22) into the market clearing condition for home-produced traded goods (148), making use of the balanced trade condition to eliminate X^H and differentiating leads to:

$$\alpha_L \hat{A}^H + \sigma_L \hat{\bar{\lambda}} + \sigma_L \left(\hat{P}^H + \hat{A}^H\right) = \hat{C} - \omega_X \hat{P}^H,$$

where we eliminated $\alpha_L \hat{L}^H$ from the above equation by using the first equation. Totally differentiate (19a) and the market clearing condition for non-tradables by inserting first (21) and (22) in order to eliminate the $\hat{P}^N$ from the above equation; totally differentiating the balanced trade condition (150) to eliminate $\hat{\bar{\lambda}}$; collecting terms leads to (161).

[33] The change in the equilibrium value of the marginal utility of wealth can be rewritten in terms of

unambiguously declines:

$$\hat{\bar{\lambda}} = -\left\{\frac{\left[(\phi_X - 1) + \alpha^H(\rho - \sigma_C)\right]\left[\alpha_L + \sigma_L + (1-\alpha_C)\,\sigma_C\right] + (\sigma_C - \phi)\,(1-\alpha_C)\,\alpha^H(\sigma_L + \sigma_C)}{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \sigma_C) + (1-\alpha^H)\,\chi^H}\right\} a < 0. \tag{163}$$

Eq. (163) shows that the marginal utility of wealth unambiguously declines as long as export price elasticity, ϕ_X, is larger than one, and households are willing to substitute home- for foreign-produced traded goods, i.e., if $\rho > 1$. Intuitively, when the export price elasticity is larger than one, the TOT decline which provides incentives to substitute home- for foreign-produced traded goods. If $(\phi_X - 1) + \alpha^H(\rho - \sigma_C) > 0$, the fall in the relative price of tradables exerts a negative impact on imports. For trade to be balanced, the shadow value of wealth must decrease to increase imports of foreign-produced traded goods.

Because the positive wealth effect encourages households to consume more, the demand for non-traded goods increases. Since productivity of non-tradables remains unchanged, an excess demand shows up which appreciates the price of non-traded goods in terms of foreign-produced traded goods:[34]

$$\hat{P}^N = \frac{\left\{\left[(\phi_X - 1) + \alpha^H(\rho - \sigma_C) + \alpha^H(1-\alpha_C)(\sigma_C - \phi)\right](\sigma_L + \omega_C\sigma_C) + \alpha^H\alpha_C\omega_C\sigma_C(\sigma_C - 1)\right\}}{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \sigma_C) + (1-\alpha^H)\,\chi^H} a > 0. \tag{164}$$

It can be shown analytically that $\hat{P}^N < \hat{A}^H = a$ and thus the relative price of non-traded goods appreciates less than that if the TOT were exogenous. The reason is that the decline in TOT boosts consumption in home-produced traded goods which in turn mitigates the increase in demand for non-tradables. For labor to be shifted toward the non-traded sector, the elasticity of substitution between traded and non-traded goods must be smaller than 1.[35] As long as $\phi < 1$, the share of non-tradables in labor, $\nu^{N,L}$, increases. To show it formally, we totally differentiate the resource constraint for labor (159) and use the resulting expression to eliminate $\hat{L}$ from $\hat{\nu}^{L,N} = (1-\alpha_L)\left(\hat{L}^N - \hat{L}\right)$, i.e., $\hat{\nu}^{L,N} = (1-\alpha_L)\,\alpha_L\left(\hat{L}^N - \hat{L}^H\right)$. Computing responses in hours worked in the non-traded and the traded sector, the change in share of non-tradables in labor is:[36]

$$\hat{\nu}^{L,N} = (1-\alpha_L)\,\alpha_L \frac{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \sigma_C)(1-\phi)}{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \sigma_C) + (1-\alpha^H)\,\chi^H} a > 0. \tag{165}$$

While hours worked are reallocated toward the non-traded sector, the extent of the labor shifts are smaller than that if the TOT remained fixed. More precisely, by hampering the boom for non-tradables, the adjustment in the TOT curbs the rise in the labor share of non-tradables.[37] Because

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$\lim_{\rho\to\infty}\hat{\bar{\lambda}}$, i.e.,

$$\hat{\bar{\lambda}} = \left\{\frac{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \omega_C\sigma_C)}{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \sigma_C) + (1-\alpha^H)\,\chi^H}\lim_{\rho\to\infty}\hat{\bar{\lambda}} + \frac{\alpha^H\left[\alpha_C\sigma_C(\sigma_L + \omega_C) + (1-\alpha_C)\,\phi\,(\sigma_L + \omega_C\sigma_C)\right]}{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \sigma_C) + (1-\alpha^H)\,\chi^H} a\right\}.$$

Since the term in front of $\lim_{\rho\to\infty}\hat{\bar{\lambda}}$ is positive and smaller than one, while the second term on the RHS is positive, the marginal utility of wealth declines less when the TOT deteriorate.

[34] Totally differentiating (160) and substituting (161) and rearranging terms leads to (164).

[35] To see it formally, insert first (21) and (22) into the market clearing condition for non-traded goods (148), eliminate P^N by using (160), totally differentiate and insert (161); one obtains:

$$\hat{L}^N = \frac{\left[(\phi_X - 1) + \alpha^H\rho\right]\alpha_C\left[\sigma_L(\sigma_C - \phi) + \omega_C\sigma_C(1-\phi)\right]}{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \sigma_C) + (1-\alpha^H)\,\chi^H} a > 0,$$

where the positive sign of the above equation follows from assumption $\phi < 1$ and $\sigma_C \simeq 1$.

[36] To compute the change in hours worked in the traded sector, divide both sides of the market clearing condition of the home-produced traded good (148) by X^H and use the balanced trade condition (150) to eliminate X^H on the RHS of the equation, i.e., $\frac{Y^H}{X^H} = 1 + \frac{P^H C^H}{C^F}$. Inserting first (30) and (20a), and totally differentiating leads to: $\hat{Y}^H = -\left[\phi_X + \alpha^H(\rho - 1)\right]\hat{P}^H$ where we used the fact that $\omega_C\alpha_C = \alpha_L$. Using the fact that $\hat{L}^H = \hat{Y}^H - \hat{A}^H$, substituting (161) and rearranging terms leads to the percentage change in hours worked in the traded sector:

$$\hat{L}^H = -\frac{\left[(\phi_X - 1) + \alpha^H\rho\right]\left\{(\sigma_L + \omega_C\sigma_C)(1-\alpha_C)(\sigma_C - \phi) + (1-\sigma_C)\left[\sigma_L + \omega_C\sigma_C(1-\alpha_C)\right]\right\}}{\left[(\phi_X - 1) + \alpha^H\rho\right](\sigma_L + \omega_C\sigma_C) + (1-\alpha^H)\,\chi^H} a < 0,$$

where the negative sign of the above equation holds for $\phi < 1$ and as long as σ_C takes values close to one. Subtracting L^H from L^N and multiply by $(1-\alpha_L)\,\alpha_L$ leads to (165).

[37] To see it formally, let ρ tend toward infinity into (165) and apply l'Hôpital's rule; we get $\lim_{\rho\to\infty}\hat{\nu}^{L,N} = (1-\alpha_L)\,\alpha_L\,(1-\phi)\,a$; since $\frac{\left[(\phi_X-1)+\alpha^H\rho\right](\sigma_L+\sigma_C)}{\left[(\phi_X-1)+\alpha^H\rho\right](\sigma_L+\sigma_C)+\left(1-\alpha^H\right)\chi^H} < 1$, then eq. (165) is a scaled-down of $\lim_{\rho\to\infty}\hat{\nu}^{L,N}$.

less labor shifts toward the non-traded sector when the TOT decline, the share of tradables in real GDP, $\nu^{Y,H}$, increases by a larger amount. To compute the growth differential in GDP units between traded value added at constant prices and real GDP, use the fact that $\hat{Y}_R = \alpha_L \hat{Y}^H + (1-\alpha_L)\hat{Y}^N$ to eliminate $\hat{Y}_R$ from $\alpha_L\left(\hat{Y}^H - \hat{Y}_R\right)$, and substitute $\hat{Y}^N = \hat{C}^N$ and $\hat{Y}^H = \hat{C}^T - \left(1-\alpha^H\right)\hat{P}^H$, we get:[38]

$$\hat{\nu}^{Y,H} = (1-\alpha_L)\,\alpha_L\left[\phi a - \left(1-\alpha^H\right)(1-\phi)\,\hat{P}^H\right] > 0, \tag{166}$$

where $\hat{P}^H$ is given by eq. (161). Since $\lim_{\rho\to\infty}\hat{P}^H = 0$, we have $\lim_{\rho\to\infty}\hat{\nu}^{Y,H} = \phi a > 0$. As long as home- and foreign-produced traded goods are imperfect substitutes, i.e., $\rho < \infty$, the decline in the TOT increases exports and C^H which in turn mitigates the reallocation of labor toward the non-traded sector and thus amplifies the rise in the share of tradables in real GDP.

P Calibration Procedure

In this section, we provide more details about the calibration to a representative OECD economy and to data from 17 OECD countries. Appendix L presents the source and construction of data.

P.1 Initial Steady-State

Since we consider CES production functions and we compare the results with Cobb-Douglas production functions, we have to normalize the CES productions so that the steady-state is invariant when the elasticity of substitution σ^j is changed. Our strategy is to choose the **initial steady-state in a model with Cobb-Douglas production functions as the normalization point** and set parameters in the CES economy so as to target the ratios of the Cobb-Douglas economy. Because we consider the initial steady-state with Cobb-Douglas production functions as the normalization point, we have to calibrate the model with Cobb-Douglas production functions to the data. We denote the labor income share in a Cobb-Douglas economy by θ^j.

Normalizing total factor productivity (TFP henceforth) for the non-traded sector Z^N to 1, the calibration reduces to 24 parameters: $r^\star$, β, σ_C, σ_L, ϵ, ϑ, ϕ, ρ, φ, φ^H, ϕ_J, ρ_J, ι, ι^H, φ_X, ϕ_X, κ, δ_K, θ^H, θ^N, Z^H, ω_G $(=\frac{G}{Y})$, ω_{G^N} $(=\frac{P^N G^N}{G})$, ω_{G^H} $(=\frac{P^H G^H}{G^T})$, and initial conditions N_0, K_0.

Since we focus on the long-run equilibrium, the tilde is suppressed for the purposes of clarity.

[38]Eliminate X^H from $Y^H = C^H + X^H$ by using the fact that $X^H = C^F/P^H$, totally differentiate and make use of the fact that $\hat{C}^T = \alpha^H\hat{C}^H + \left(1-\alpha^H\right)\hat{C}^F$.

The steady-state of the open economy comprises 18 equations:

$$C = \left(P_C \bar{\lambda}\right)^{-\sigma_C}, \tag{167a}$$

$$L = \left(W \bar{\lambda}\right)^{\sigma_L}, \tag{167b}$$

$$C^N = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{-\phi} C, \tag{167c}$$

$$C^H = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi} \varphi_H \left(\frac{P^H}{P^T}\right)^{-\rho} C, \tag{167d}$$

$$C^F = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi} (1-\varphi_H) \left(\frac{1}{P^T}\right)^{-\rho} C, \tag{167e}$$

$$L^N = (1-\vartheta)\left(\frac{W^N}{W}\right)^{\epsilon} L, \tag{167f}$$

$$L^H = \vartheta\left(\frac{W^H}{W}\right)^{\epsilon} L \tag{167g}$$

$$I^N = (1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J} I, \tag{167h}$$

$$I^H = \iota\left(\frac{P_J^T}{P_J}\right)^{-\phi_J} \iota^H \left(\frac{P^H}{P_J^T}\right)^{-\rho_J} I, \tag{167i}$$

$$I^F = \iota\left(\frac{P_J^T}{P_J}\right)^{-\phi_J} \left(1-\iota^H\right) \left(\frac{1}{P_J^T}\right)^{-\rho_J} I, \tag{167j}$$

$$I = \delta_K K, \tag{167k}$$

$$\frac{G}{Y} = \omega_G, \tag{167l}$$

$$P^H Z^H \left(1-\theta^H\right) \left(k^H\right)^{-\theta^H} = P_J \left(r^\star + \delta_K\right), \tag{167m}$$

$$P^H Z^H \left(1-\theta^H\right) \left(k^H\right)^{-\theta^H} = P^N Z^N \left(1-\theta^N\right) \left(k^N\right)^{-\theta^N}, \tag{167n}$$

$$P^H Z^H \theta^H \left(k^H\right)^{1-\theta^H} = W^H, \tag{167o}$$

$$P^N Z^N \theta^N \left(k^N\right)^{1-\theta^N} = W^N, \tag{167p}$$

$$k^H L^H + k^N L^N = K, \tag{167q}$$

$$Z^N L^N \left(k^N\right)^{1-\theta^N} = C^N + G^N + I^N, \tag{167r}$$

$$X^H = \varphi_X \left(P^H\right)^{-\phi_X}, \tag{167s}$$

$$Z^H L^H \left(k^H\right)^{1-\theta^H} = C^H + X^H + I^H + G^H, \tag{167t}$$

$$r^\star N + P^H X^H - M^F = 0, \tag{167u}$$

and the intertemporal solvency condition

$$N - N_0 = \Psi_1 \left(K - K_0\right), \tag{167v}$$

where we used the fact that at the steady-state $I^g = J^g$ (with $g = H, F, N$), and we also have

$$G^N = \left(\omega_{G^N}/P^N\right) G, \tag{168a}$$

$$G^H = \left[(1-\omega_{G^N})\,\omega_{G^H}/P^H\right] G, \tag{168b}$$

$$G^F = (1-\omega_{G^N})\,(1-\omega_{G^H})\,G, \tag{168c}$$

$$P_C = \left[\varphi\left(P^T\right)^{1-\phi} + (1-\varphi)\left(P^N\right)^{1-\phi}\right]^{\frac{1}{1-\phi}}, , \tag{168d}$$

$$P^T = \left[\varphi_H\left(P^H\right)^{1-\rho} + (1-\varphi_H)\right]^{\frac{1}{1-\rho}}, \tag{168e}$$

$$P_J = \left[\iota\left(P_J^T\right)^{1-\phi_J} + (1-\iota)\left(P^N\right)^{1-\phi_J}\right]^{\frac{1}{1-\phi_J}}, \tag{168f}$$

$$P_J^T = \left[\iota_H\left(P^H\right)^{1-\rho_J} + (1-\iota_H)\right]^{\frac{1}{1-\rho_J}}, \tag{168g}$$

$$W = \left[\vartheta\left(W^H\right)^{\epsilon+1} + (1-\vartheta)\left(W^N\right)^{\epsilon+1}\right]^{\frac{1}{\epsilon+1}}, \tag{168h}$$

$$M^F = C^F + I^F + G^F, \tag{168i}$$

$$Y^H = Z^H L^H\left(k^H\right)^{1-\theta^H}, \tag{168j}$$

$$Y^N = Z^N L^N\left(k^N\right)^{1-\theta^N}, \tag{168k}$$

$$Y = P^H Y^H + P^N Y^N. \tag{168l}$$

Using (168), the system (167) jointly determines the following 22 variables C, L, C^N, C^H, C^F, L^N, L^H, I^N, I^H, I^F, I, G, k^H, k^N, W^H, W^N, K, P^N, X^H, P^H, N, $\bar{\lambda}$.

Before going any further, it is worth mentioning that in accordance with the empirical findings documented by Bems [2008] for OECD countries, we choose an elasticity of substitution between J^N and J^T of 1, i.e.,

$$J = \left(\frac{J^T}{\alpha_J}\right)^{\alpha_J}\left(\frac{J^N}{1-\alpha_J}\right)^{1-\alpha_J}, \tag{169}$$

where $\alpha_J = \frac{P_J^T J^T}{P_J J}$ and $1-\alpha_J = \frac{P^N J^N}{P_J J}$ are investment expenditure shares on tradables and non-tradables, respectively, which are fixed parameters. The investment price index, $P_J = P_J\left(P_J^T, P^N\right)$, associated with aggregator function (169) is:

$$P_J = \left(P_J^T\right)^{\alpha_J}\left(P^N\right)^{1-\alpha_J}. \tag{170}$$

Some of the values of parameters can be taken directly from data, but others need to be endogenously calibrated to fit a set of an average OECD economy features. Among the 24 parameters, 5 parameters, i.e., φ^H, ι^H, φ, ι, ϑ, δ_K together with initial conditions (N_0, K_0) must be set in order to match key properties of a typical OECD economy. More precisely, the parameters φ^H, ι^H, φ, ι, ϑ, δ_K together with the set of initial conditions are set to target α^H, α_J^H, α_C, α_L, ω_J, υ_N.

We denote by $\nu^{Y,H}$ the GDP share of home-produced traded goods, $\upsilon_{G^j} = G^j/P^jY^j$ and $\upsilon_{J^j} = P_J^j J^j/P^jY^j$ the ratio of government spending and investment expenditure on good j to output in sector j, respectively, $\upsilon_N = \frac{r^\star N}{P^H Y^H}$ the ratio of interest receipts from traded bonds holding to traded output, $\omega_X = \frac{P^H X^H}{Y}$ the ratio of exports to GDP, ω_G the ratio of government spending to GDP, and $\omega_J = \frac{P_J J}{Y}$ the ratio of investment expenditure to GDP. The steady-state can be reduced to the following five equations:

$$\frac{\nu^{Y,H}}{1-\nu^{Y,H}}\frac{\left(1+\upsilon_N-\upsilon_{J^H}+\upsilon_{G^H}\right)}{\left(1-\upsilon_{J^N}-\upsilon_{G^N}\right)} = \frac{\varphi}{1-\varphi}\left(\frac{P^T}{P^N}\right)^{\phi}, \tag{171a}$$

$$\frac{\nu^{Y,H}}{1-\nu^{Y,H}} = \frac{\left(P^H\right)^{\frac{1+\epsilon}{\theta^H}}}{\left(P^N\right)^{\frac{1+\epsilon}{\theta^N}}}\left(P_J\right)^{\left(\frac{\theta^H-\theta^N}{\theta^H\theta^N}\right)(1+\epsilon)}\Pi \tag{171b}$$

$$\nu^{Y,H} = \omega_C\alpha_C\alpha^H + \omega_J\alpha_J\alpha_J^H + \omega_{G^H}\left(1-\omega_{G^N}\right)\omega_G + \omega_X, \tag{171c}$$

$$\left(1-\theta^H\right)\nu^{Y,H} + \left(1-\theta^N\right)\left(1-\nu^{Y,H}\right) = P_J\left(r^\star+\delta_K\right)\frac{K}{Y}, \tag{171d}$$

$$\upsilon_N = \upsilon_{N_0} + \frac{r^\star\Psi_1}{\nu^{Y,H}}\left(\frac{K}{Y}-\upsilon_{K_0}\right), \tag{171e}$$

where $\upsilon_{K_0} = \frac{K_0}{Y}$ and Π is a term composed of parameters described by:

$$\begin{aligned}\Pi &\equiv \frac{\left(Z^H\right)^{\frac{1+\epsilon}{\theta^H}}}{\left(Z^N\right)^{\frac{1+\epsilon}{\theta^N}}} \frac{\vartheta}{1-\vartheta} \left(r^\star + \delta_K\right)^{\left(\frac{\theta^H - \theta^N}{\theta^H \theta^N}\right)(1+\epsilon)} \\ &\times \frac{\left[\left(\theta^H\right)^{\epsilon\theta^H} \left(1-\theta^H\right)^{\left(1-\theta^H\right)(1+\epsilon)}\right]^{1/\theta^H}}{\left[\left(\theta^N\right)^{\epsilon\theta^N} \left(1-\theta^N\right)^{\left(1-\theta^N\right)(1+\epsilon)}\right]^{1/\theta^N}}. \end{aligned} \tag{172}$$

The system (171) consisting of five equations determine $\nu^{Y,H}$, P^N, P^H, K/Y, and υ_N. The five equations (171a)-(171e) described the goods market equilibrium for tradables relative to non-tradables, the labor market equilibrium, the goods market equilibrium for the home-produced traded goods market equilibrium, the resource constraint for capital, the intertemporal solvency condition, respectively.

It is worth noting that φ_X is a free parameter which does not play any role in this calibration strategy since the ratio of exports to GDP is determined residually by υ_N, $\nu^{Y,H}$, ω_C, α_C, α^H, ω_J, α_J, α_J^H. To see it formally, use the current account equation in the long-run and divide both sides by GDP; one obtains:

$$\omega_X = -\upsilon_N \nu^{Y,H} + \omega_C \alpha_C \left(1-\alpha^H\right) + \omega_J \alpha_J \left(1-\alpha_J^H\right). \tag{173}$$

While φ_X does not play any role in the calibration strategy with Cobb-Douglas production functions, this parameter is necessary to target ω_X when we allow for CES production functions since the steady-state with Cobb-Douglas production functions is chosen as the normalization point.

Left-multiplying the home-produced traded goods market equilibrium (167t) by P^H, eliminating $P^H X^H$ by using the current account equation (167u), i.e., $P^H X^H = M^F - r^\star N$, leads to the goods market equilibrium for tradables:

$$P^H Y^H = P^T C^T + P_J^T J^T + G^T - r^\star N. \tag{174}$$

Let multiplying (167r) by P^N, dividing the market clearing condition for tradables (174) by the market clearing condition for the non-traded good (167r) and equating the resulting expression with the demand of tradables in terms of non-tradables for consumption obtained by calculating the ratio of $P^T C^T = P^H C^H + C^F$ using (167d)-(167e) to (167c), i.e., $\frac{P^T C^T}{P^N C^N} = \frac{\varphi}{1-\varphi}\left(\frac{P^N}{P^T}\right)^{\phi-1}$, leads to **the goods market equilibrium (171a)**. The derivation of the labor market equilibrium requires more steps. As mentioned below, we assume that the aggregator function for inputs of the investment good is Cobb-Douglas since data suggest that $\phi_J = 1$. In this case, the investment price index simplifies as (170). First, combining (167m) and (167n) leads to:

$$\frac{\left(k^H\right)^{1-\theta^H}}{\left(k^N\right)^{1-\theta^N}} = \frac{\left[P^H Z^H \left(1-\theta^H\right)\right]^{\frac{1-\theta^H}{\theta^H}}}{\left[P^N Z^N \left(1-\theta^N\right)\right]^{\frac{1-\theta^N}{\theta_N}}} \left[P_J \left(r^\star + \delta_K\right)\right]^{\frac{1-\theta^H}{\theta^H} - \frac{1-\theta^N}{\theta^N}}. \tag{175}$$

Dividing (167g) by (167f) leads to the supply of hours worked in the traded sector relative to the non-traded sector, i.e., $\frac{L^H}{L^N} = \frac{\vartheta}{1-\vartheta}\left(\frac{W^H}{W^N}\right)^{\epsilon}$. Dividing (167o) by (167p) leads to the relative wage of tradables, i.e., $\frac{W^H}{W^N} = \frac{P^H Z^H \theta^H \left(k^H\right)^{1-\theta^H}}{P^N Z^N \theta^N \left(k^N\right)^{1-\theta^N}}$. Inserting the latter expression into the former and using the production functions for the traded sector and non-traded sectors which imply $L^H = \frac{Y^H}{Z^H \left(k^H\right)^{1-\theta^H}}$ and $L^N = \frac{Y^N}{Z^N \left(k^N\right)^{1-\theta^N}}$, one obtains:

$$\frac{Y^H}{Y^N} = \frac{\vartheta}{1-\vartheta}\left(\frac{Z^H}{Z^N}\right)^{\epsilon+1}\left(\frac{P^H}{P^N}\right)^{\epsilon}\left(\frac{\theta^H}{\theta^N}\right)^{\epsilon}\left[\frac{\left(k^H\right)^{1-\theta^H}}{\left(k^N\right)^{1-\theta^N}}\right]^{1+\epsilon}.$$

Left-multiplying the above expression by $\frac{P^H Y}{P^N Y}$, inserting (175), and collecting terms leads to **the labor market equilibrium (171b)** while we set Π to eq. (172) in order to write the equation in compact form. To determine (171c), use the fact that $K^j = k^j L^j$, multiply both sides of (167q) by $\frac{R}{Y}$ where $R = P_J \left(r^\star + \delta_K\right)$ is the capital rental cost; we get:

$$\frac{RK^H}{P^H Y^H}\frac{P^H Y^H}{Y} + \frac{RK^N}{P^N Y^N}\frac{P^N Y^N}{Y} = \frac{RK}{Y}.$$

Using the fact that the capital income share $\frac{RK^j}{P^jY^j}$ in sector j is equal to $\left(1-\theta^j\right)$, one obtains **the resource constraint for capital described by eq. (171c)**. Multiplying both sides of (167t) by $\frac{P^H}{Y}$, and using (167d)-(167e) and (167i)-(167j) leads to (171c):

$$
\begin{aligned}
\nu^{Y,H} &= \frac{P^H C^H}{C^F}\frac{C^F}{Y} + \frac{P^H J^H}{J^F}\frac{J^F}{Y} + \frac{P^H G^H}{Y} + \frac{P^H X^H}{Y}, \\
&= \frac{\varphi^H}{1-\varphi^H}\left(P^H\right)^{1-\rho}\left(1-\alpha^H\right)\alpha_C\omega_C + \frac{\iota^H}{1-\iota^H}\left(P^H\right)^{1-\rho_J}\left(1-\alpha^H_J\right)\alpha_J\omega_J \\
&\quad +\omega_{G^H}\left(1-\omega_{G^N}\right)\omega_G + \omega_X.
\end{aligned}
$$

Finally, to get (171e), multiply both sides of (167v) by $\frac{r^\star}{P^HY^H}$, denote the ratio of interest receipts from the initial stock of traded bonds to traded output by $\upsilon_{N_0} = \frac{r^\star N_0}{P^HY^H}$ and the ratio of the initial capital stock to GDP by $\upsilon_{K_0} = \frac{K_0}{Y}$ leads to **eq. (171e) that describes the intertemporal solvency condition**.

Because the ratios we wish to target are different from the macroeconomic aggregates, i.e., $\nu^{Y,H}$, P^N, P^H, K/Y, υ_N, that are jointly determined by the system of equations (171), we have to relate the latter ratios to the former. First, the price of home-produced traded goods in terms of foreign-produced traded goods, P^H, determines the home content of consumption and investment expenditure in tradables by setting φ^H and φ^H_J:

$$
\alpha^H = \frac{\varphi^H\left(P^H\right)^{1-\rho}}{\varphi^H\left(P^H\right)^{1-\rho} + \left(1-\varphi^H\right)}, \qquad \text{and} \qquad \alpha^H_J = \frac{\iota^H\left(P^H\right)^{1-\rho_J}}{\iota^H\left(P^H\right)^{1-\rho_J} + \left(1-\iota^H\right)}. \tag{176}
$$

Second, the price of non-traded goods in terms of foreign-produced traded goods, P^N, determines the home tradable content of consumption expenditure by setting φ:

$$
\alpha_C = \frac{\varphi\left(P^H\right)^{1-\phi}}{\varphi^H\left(P^H\right)^{1-\phi} + \left(1-\varphi^H\right)\left(P^N\right)^{1-\phi}}. \tag{177}
$$

Third, the ratio K/Y along with the relative price of tradables, P^H, and the relative price of non-tradables, P^N (see (168g) and (170)), determine the investment-to-GDP ratio $P_J I/Y$ by setting δ_K (see eq. (167k)):

$$
\frac{P_J I}{Y} = P_J\frac{\delta_K K}{Y}. \tag{178}
$$

The ratio of net interest receipts from traded bonds holding to traded output, i.e., υ_N, determines the ratio of net exports to traded output, i.e. $\upsilon_{NX} = \frac{NX}{P^HY^H}$ with $NX = P^HX^H - M^F$; dividing both sides of the current account equation (167u) leads to:

$$
\upsilon_{NX} = -\upsilon_N. \tag{179}
$$

Finally, we show below that $\nu^{Y,H}$ is related to the share of tradables L^H/L which we target by setting ϑ. To do so, using the definition of the aggregate wage index (168h), the ratio of the aggregate wage to the non-traded wage can be rewritten as follows:

$$
\begin{aligned}
\left(\frac{W}{W^H}\right)^{\epsilon+1} &= \frac{\vartheta\left(W^H\right)^{\epsilon+1} + (1-\vartheta)\left(W^N\right)^{\epsilon+1}}{\left(W^H\right)^{\epsilon+1}}, \\
&= \vartheta + (1-\vartheta)\left(\frac{W^N}{W^H}\right)^{\epsilon+1},
\end{aligned}
$$

and by solving, we get

$$
\frac{W}{W^H} = \left[\vartheta + (1-\vartheta)\left(\frac{W^N}{W^H}\right)^{\epsilon+1}\right]^{\frac{1}{\epsilon+1}}. \tag{180}
$$

Since θ^j is the labor income share in sector j, the ratio of the non-traded wage to the traded wage can be written as follows:

$$
\frac{W^N}{W^H} = \frac{\theta^N}{\theta^N}\left(\frac{1-\nu^{Y,H}}{\nu^{Y,H}}\right)\frac{L^H}{L^N}. \tag{181}
$$

Dividing (167g) by (167f) leads to a positive relationship between the supply of hours worked to the traded sector relative to the non-traded sector and the traded wage relative to the non-traded wage, i.e., $\frac{L^H}{L^N} = \frac{\vartheta}{1-\vartheta}\left(\frac{W^H}{W^N}\right)^{\epsilon}$. Substituting the latter equation, eq. (181) can be solved for W^N/W^H, i.e.,

$$
\frac{W^N}{W^H} = \left[\frac{\vartheta}{1-\vartheta}\frac{\theta^N}{\theta^H}\left(\frac{1-\nu^{Y,H}}{\nu^{Y,H}}\right)\right]^{\frac{1}{\epsilon+1}}. \tag{182}
$$

Additionally, since $\alpha_L = \frac{W^H L^H}{WL} = \vartheta \left(\frac{W^H}{W}\right)^{\epsilon+1}$, the share of traded hours worked in total hours worked is governed by the following optimal rule:

$$\begin{aligned} \frac{L^H}{L} &= \vartheta \left(\frac{W^H}{W}\right)^{\epsilon}, \\ &= \vartheta \left(\frac{W}{W^H}\right)^{-\epsilon}. \end{aligned} \tag{183}$$

Inserting (182) into (180) and plugging the resulting expression into (183) gives us a relationship between the share of tradables in employment and the share of tradables in GDP, $\nu^{Y,H}$:

$$\begin{aligned} \frac{L^H}{L} &= \vartheta \left[\vartheta + (1-\vartheta)\left(\frac{W^N}{W^H}\right)^{\epsilon+1}\right]^{-\frac{\epsilon}{\epsilon+1}}, \\ &= \vartheta^{\frac{1}{\epsilon+1}} \left[1 + \frac{\theta^N}{\theta^H}\left(\frac{1-\nu^{Y,H}}{\nu^{Y,H}}\right)\right]^{-\frac{\epsilon}{\epsilon+1}}. \end{aligned} \tag{184}$$

According to (184), given $\nu^{Y,H}$, setting ϑ allows us to target the ratio L^H/L found in the data.

P.2 Calibration to a Representative OECD Economy

To calibrate our model, we estimated a set of parameters so that the initial steady state is consistent with the key empirical properties of a representative OECD economy. This section provides more details about how we calibrate the model to match the key empirical properties of a representative OECD economy. Because we consider an open economy setup with traded and non-traded goods, we calculate the non-tradable content of GDP, employment, consumption, gross fixed capital formation, government spending, labor compensation, for all countries in our sample, as summarized in Table 6. Since we assume that home- and foreign-produced traded goods are imperfect substitutes, we calculate the home content of consumption and investment expenditure in tradables on the one hand, and between purchases of home-produced goods from the home and the rest of the world (i.e., exports) on the other hand. To capture the key properties a typical OECD economy which is chosen as the baseline scenario, we take unweighted average values shown in the last line of Table 6. Columns 12-14 of Table 6 also report government spending and investment as a share of GDP along with the aggregate labor income share.

We first describe the parameters that are taken directly from the data; we start with the **preference parameters** shown in panel A of Table 7:

- One period in the model is a year.
- The world interest rate, $r^\star$, equal to the subjective time discount rate, β, is set to 4%.
- We set the intertemporal elasticity of substitution for consumption, σ_C, to 2 in line with estimates documented by Gruber [2013]. While this value is higher than that usually used in the international RBC literature (i.e., $\sigma_C = 1$), we choose this value to reduce the impact of the wealth effect on labor supply and generate a positive response of total hours worked.
- Next, we turn to the Frisch elasticity of labor supply. We set the intertemporal elasticity of substitution for labor supply σ_L to 1.6, in line with the evidence reported by Peterman [2016] who find a value for the macro Frisch elasticity of 1.5 and 1.75 for the population aged between 20 and 55, and between 20 and 60. This value of 1.6 enables us to generate an initial increase in total hours worked by 0.09% we estimate empirically following a 1% permanent increase in TFP of tradables relative to non-tradables, see Fig 15(a).
- The elasticity of labor supply across sectors, ϵ, which captures the degree of labor mobility is set to 1.6. Our estimates display a wide dispersion across countries as they range from a low of 0.01 for Norway to a high of 3.2 for the United States, see Table 9. This value of 1.6 is halfway between the lowest and highest estimate for the degree of labor mobility across sectors .[39]
- We set the elasticity of substitution between traded and non-traded goods, ϕ, to 0.44, in line with estimates by Stockman and Tesar [1995]. Because this parameter plays a key role in the quantitative analysis, we have estimated this parameter by running the regression of the share of non-tradables in consumption expenditure on the ratio of non-traded prices to CPI. We explore empirically two variants of the testable equation by including or not a country-specific

[39] Appendix M.3 presents the empirical strategy and contains the details of derivation of the relationship we explore empirically.

linear time trend which captures the fact that the preference for consumption in non-tradables may vary over time (see Appendix M.2). As can be seen in the last row for Table 10 which reports estimates for the whole sample, we find that ϕ stands at 0.66 or 0.33 depending on whether a country-specific linear time trend is included or not. A value of 0.44 falls in the range of these estimates.[40]

- We set the elasticity of substitution, ϕ_J, in investment between traded and non-traded inputs to 1, in line with the empirical findings documented by Bems [2008] for OECD countries.
- Following Backus, Kehoe and Kydland [1994], we set the elasticity of substitution, ρ (ρ_J), in consumption (investment) between home- and foreign-produced traded goods (inputs) to 1.5.

We carry on with the **non-tradable content** of consumption, investment and government expenditure, employment, along with sectoral labor income shares shown in the last line of Table 6 that reports the average of our estimates while panel B of Table 7 displays the value of parameters we choose to calibrate the model:

- The weight of consumption in non-tradables $1-\varphi$ is set to 0.49 to target a non-tradable content in total consumption expenditure (i.e. $1-\alpha_C$) of 53%.
- In order to target a non-tradable content of hours worked of 63% which corresponds to the 17 OECD countries' unweighted average shown in the last line of Table 6, we set the weight of labor supply to the traded sector in the labor index $L(.)$, $1-\vartheta$, to 0.6.
- We choose a value for the weight of non-traded inputs in the investment aggregator function $J(.)$, $1-\iota$, of 0.62 which allows us to obtain a non-tradable content of investment expenditure of 62%.
- In accordance with our estimate shown in the last line of Table 6, we choose a non-tradable content of government spending, $\omega_{G^N} = \frac{P^N G^N}{G}$, of 90%; by construction, we have a share of government consumption on tradables in total government spending, $\omega_{G^H} = 1-\omega_{G^N}$, of 10%.
- Columns 10 and 11 of Table 6 give the LIS of the traded and the non-traded sector for the seventeen OECD countries in our sample. LISs θ^H and θ^N average respectively to 0.63 and 0.68. These average values reveal that the non-traded sector is relatively more labor intensive than the traded sector. It is worth mentioning that our estimates of 0.63 and 0.68 for θ^H and θ^N, respectively, are consistent with an aggregate labor income share of 66%, as shown in column 12 of Table 6. Formally, the aggregate labor income share, denoted by s_L, is a value-weighted average of the sectoral labor income shares, i.e., $s_L = \frac{\theta^H P^H Y^H}{Y} + \frac{\theta^N P^N Y^N}{Y}$.
- We assume that initially, traded firms are as much productive as non-traded firms and thus normalize Z^j to 1.

We describe below the choice of parameters displayed in panel C of Table 7 which target the home content of expenditure in tradables:

- In order to target a home content of consumption expenditure in tradables of 77% which corresponds to the 17 OECD countries' unweighted average shown in the last line of Table 6, we set the weight of home-produced traded goods in the consumption aggregator function for tradables $C^T(.)$, φ^H, to 0.84.
- We choose a value for the weight of home-produced traded inputs in the traded investment aggregator function $J^T(.)$, ι^H, of 0.62 which allows us to obtain a home content of investment expenditure in tradables of 51%.
- Since data availability does not enable us to differentiate between government expenditure in home- and foreign-produced traded goods, we assume that the government does not import goods and services from abroad, and thus set $\omega_{G^H} = \frac{P^H G^H}{G^T}$ to 1 and $\omega_{G^F} = 0$.
- Building on structural estimates of the price elasticities of aggregate exports documented by Imbs and Mejean [2015], we set the export price elasticity, ϕ_X, to 1.7 in the baseline calibration.

We describe below the choice of parameters displayed in panel D of Table 7 characterizing macroeconomic variables such as investment, government spending and the balance of trade of a typical OECD economy:

- As shown in the last line of column 14 of Table 6, government spending as a percentage of GDP averages 20% and thus we set $\omega_G = \frac{G}{Y}$ to 0.2.

[40] We derive a testable equation by combining the demand for non-traded goods and the market clearing condition for non-tradables. Details of derivation of the equation we explore empirically can be found in section M.2.

- In order to target an investment-to-GDP ratio, $\omega_J = \frac{P_J I}{Y}$, of 24% as shown in the last line of column 13 of Table 6, we set the rate of physical capital depreciation, δ_K, to 9.3%.
- We choose the value of parameter κ so that the elasticity of I/K with respect to Tobin's q, i.e., Q/P_J, is equal to the value implied by estimates in Eberly, Rebelo, and Vincent [2008]. The resulting value of κ is equal to 17.[41]
- Finally, we choose initial values for N_0 and K_0 for the ratio of net exports to traded output to be nil at the initial steady-state, i.e., $\upsilon_{NX} \simeq 0$.

Investment- and government spending-to-GDP ratios along with balanced trade endogenously determine the consumption-to-GDP ratio. More precisely, since GDP is equal to the sum if its demand components, remembering that at the steady-state $I = J$, we thus have the following accounting identity, $Y = P_C C + P_J I + G + NX$. Dividing both sides by Y and remembering that net exports are nil, i.e., $NX = 0$, the consumption-to-GDP ratio denoted by $\omega_C = \frac{P_C C}{Y}$ is thus equal to 56%:

$$\omega_C = \frac{P_C C}{Y} = 1 - \left(\omega_J + \omega_G + \frac{NX}{Y}\right) = 56\%, \tag{185}$$

where $\omega_J = \frac{P_J I}{Y} = 24\%$, $\omega_G = \frac{G}{Y} = 20\%$, and $NX = 0$.

It is worth mentioning that the tradable content of GDP is endogenously determined by the tradable content of consumption, α_C, of investment, α_J, and of government expenditure, ω_{G^T}, along with the consumption-to-GDP ratio, ω_C, the investment-to-GDP ratio, ω_J, and government spending as a share of GDP, ω_G. More precisely, dividing the traded good market clearing condition (174) by GDP, Y, leads to an expression that allows us to calculate the tradable content of GDP:

$$\frac{P^H Y^H}{Y} = \omega_C \alpha_C + \omega_J \alpha_J + \omega_{G^T} \omega_G = 38\%, \tag{186}$$

where $\omega_C = 56\%$, $\alpha_C = 47\%$, $\omega_J = 24\%$, $\alpha_J = 38\%$, $\omega_{G^T} = 10\%$, and $\omega_G = 20\%$. According to (186), the values we target for the non-tradable content of consumption, investment and government spending along with the consumption-, investment-, and government spending-to-GDP ratios are roughly consistent with a tradable content of GDP of 39% found in the data, as reported in the last line of column 1 of Table 6. The cause of the slight discrepancy in the estimated tradable content of GDP is that nomenclatures for valued added by industry and for expenditure in consumption, investment, government expenditure by items are different. Reassuringly, the GDP share of tradables (39%) is close to that calculated by using demand components (38%).

Since we set initial conditions so that the economy starts with balanced trade, export as a share of GDP, ω_X, is endogenously determined by the import content of consumption, $1-\alpha^H$, of investment, $1-\alpha^H_J$, and of government expenditure in tradables, $1-\omega_{G^H}$, along with the consumption-to-GDP ratio, ω_C, and the investment-to-GDP ratio, ω_J, and government spending as a share of GDP, ω_G. More precisely, dividing the zero current account equation (167u) by GDP, Y, leads to an expression that allows us to calculate the GDP share of exports of final goods and services produced by the home country:

$$\frac{P^H X^H}{Y} = \omega_C \alpha_C \left(1-\alpha^H\right) + \omega_J \alpha_J \left(1-\alpha^H_J\right) + \left(1-\omega_{G^H}\right)\left(1-\omega_{G^N}\right)\omega_G = 10.4\%, \tag{187}$$

where $\omega_C = 56\%$, $1-\alpha^H = 23\%$, $\omega_J = 24\%$, $1-\alpha^H_J = 49\%$, $1-\omega_{G^H} = 0$; in line with our evidence reported in column 7 of Table 6, the ratios we target enable us to reproduce the imports to GDP ratio of 10%, keeping in mind that we consider trade on final goods.

In order to capture the dynamic adjustment of productivity in tradables relative to non-tradables, we assume that the response of sectoral TFP in percent is governed by the following dynamic equation:

$$\hat{Z}^j(t) = \hat{\tilde{Z}}^j + \bar{z}^j e^{-\xi^j t}, \tag{188}$$

where $\hat{\tilde{Z}}^j$ is the percentage steady-state change in sectoral TFP; $\bar{z}^j$ and $\xi^j > 0$ parametrize the initial increase in sectoral TFP and the speed at which Z^j reaches its new steady-state level, respectively. More precisely, $\bar{z}^j$ takes negative values when sectoral TFP undershoots its steady-state level. The 'true' measure of the technology bias toward tradables denoted by Z is given by $Z(t) = \frac{\left(Z^H(t)\right)^a}{\left(Z^H(t)\right)^b}$ with $a = \frac{1}{\left[(1-\alpha_J)+\alpha_J\frac{\theta^H}{\theta^N}\right]}$ and $b = a\frac{\theta^H}{\theta^N}$ (see (77)). We present below the parameters related to endogenous responses of sectoral TFPs to an exogenous shock to a productivity differential which are summarized in panel E of Table 7:

[41] Eberly, Rebelo, and Vincent [2008] run the regression $I/K = \alpha + \beta \,.\, \ln(q)$ and obtain a point estimate for β of 0.06. In our model, the steady-state elasticity of I/K with respect to Tobin's q is $1/\kappa$. Equating $1/\kappa$ to 0.06 gives a value for κ of 17.

- In the quantitative analysis, we consider permanent changes in sectoral TFP, $\tilde{Z}^j$, so that the labor share-adjusted TFP differential is 1% in the long run:

$$\hat{Z} = a\hat{\tilde{Z}}^H - b\hat{\tilde{Z}}^N = 1\%. \tag{189}$$

- We estimate a simple VAR model $[\epsilon^Z, \hat{Z}, \hat{Z}^H, Z^N]$ where ϵ^Z is the shock to a productivity differential which is identified by considering the baseline VAR model which includes aggregate variables. When we generate IRFs for traded and non-traded TFP, we find a slight discrepancy in the estimated technology shock biased toward the traded sector because $\hat{Z}(t)$ slightly differs from the weighted average $a\hat{\tilde{Z}}^H(t) - b\hat{\tilde{Z}}^N(t)$. We thus take the following route. We compute $\hat{Z}^N(t)$ at various horizons by using the following formula $\hat{Z}^N(t) = \frac{aZ^H(t) - \hat{Z}(t)}{b}$ (see eq. (189).
- To reproduce the initial response of sectoral TFP we estimate empirically, we choose $\bar{z}^j$ by setting $t = 0$ into (188):

$$\bar{z}^j = -\left(\hat{\tilde{Z}}^j - \hat{Z}^j(0)\right), \tag{190}$$

  where $\hat{\tilde{Z}}^j$ corresponds to steady-state change in percentage of TFP in sector $j = H, N$ and $\hat{Z}^j(0)$ is the initial response of TFP in sector j. Eq. (190) gives us $\bar{z}^H = -0.0936$ and $\bar{z}^N = 0.0002$.

- To reproduce the shape IRFs of sectoral TFPs, we first solve (188) for ξ^j:

$$\xi^j = -\frac{1}{t}\ln\left(\frac{\hat{Z}^j(t) - \hat{\tilde{Z}}^j}{\bar{z}^j}\right). \tag{191}$$

  We choose time t so that ξ^j gives us the best fit of the response of $\hat{Z}^j(t)$ estimated empirically. For both sectors, we take $t = 3$ which gives us $\xi^H = 0.5709$ and to $\xi^N = 1.1668$.

- Given values for $\bar{z}^j$, ξ^j and $\hat{\tilde{Z}}^j$, we can compute the transitional path for $\hat{Z}^j(t)$ by using (188) and thus the adjustment of the productivity of tradables relative to non-tradables by using (189), assuming that the weights a and b are constant over time.

P.3 Calibration Procedure with CES Production Functions

The production functions are assumed to take a CES form which we repeat for convenience:

$$Y^j(t) = \left[\gamma^j\left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)K^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{192}$$

where A^j and B^j are labor- and capital-augmenting productivity, and σ^j the elasticity of substitution between capital and labor in production.

Compared with a model imposing Cobb-Douglas production functions, the model assuming CES form for production technology has 8 additional parameters, i.e., σ^H, σ^N, γ^H, γ^N, A^H, B^H, A^N, B^N. Given that we assume Hicks-neutral technological change at the initial steady-state, i.e., $A^j = B^j = Z^j$, and sectoral TFP are set to one, it leaves us with 4 additional (compared with subsection P.1) parameters only. Among these four parameters, two can be taken from the data. Following Antràs [2004], we run the regression of (logged) valued added per hours worked on (logged) real wage over 1970-2013 in panel data while letting the coefficient in front of W^j/P^j vary across countries, see section M.4. We take unweighed average values shown in the last line of columns 17-18 of Table 6 and set $\sigma^H = 0.69$ and $\sigma^N = 0.72$. We normalize CES production functions because, as underlined by León-Ledesma et al. [2010], the normalization allows CES production functions featuring different elasticity of substitution to share the a common baseline point.

We assume Hicks-neutral technological change at the initial steady-state, i.e., $A_0^j = B_0^j = Z_0^j$, so that eq. (192) now reads as follows:

$$y_0^j = Z_0^j\left[\gamma^j + \left(1-\gamma^j\right)\left(k_0^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{193}$$

and the labor income share is given by

$$s_{L,0}^j = \gamma^j\left(\frac{Z_0^j}{y_0^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}. \tag{194}$$

The steady-state of a semi-small open economy with CES production functions is described by the following set of equations:

$$y^H = Z^H \left[\gamma^H + \left(1-\gamma^H\right)\left(k^H\right)^{\frac{\sigma^H-1}{\sigma^H}}\right]^{\frac{\sigma^H}{\sigma^H-1}}, \tag{195a}$$

$$y^N = Z^N \left[\gamma^N + \left(1-\gamma^N\right)\left(k^N\right)^{\frac{\sigma^N-1}{\sigma^N}}\right]^{\frac{\sigma^N}{\sigma^N-1}}, \tag{195b}$$

$$s_L^H = \gamma^H \left(\frac{Z^H}{y^H}\right)^{\frac{\sigma^H-1}{\sigma^H}}, \tag{195c}$$

$$s_L^N = \gamma^N \left(\frac{Z^N}{y^N}\right)^{\frac{\sigma^N-1}{\sigma^N}}, \tag{195d}$$

$$1-s_L^H = \left(1-\gamma^H\right)\left(\frac{Z^H k^H}{y^H}\right)^{\frac{\sigma^H-1}{\sigma^H}}, \tag{195e}$$

$$1-s_L^N = \left(1-\gamma^N\right)\left(\frac{Z^N k^N}{y^N}\right)^{\frac{\sigma^N-1}{\sigma^N}}, \tag{195f}$$

$$\frac{\nu^{Y,H}}{1-\nu^{Y,H}}\frac{\left(1+\upsilon_N-\upsilon_{J^H}+\upsilon_{G^H}\right)}{\left(1-\upsilon_{J^N}-\upsilon_{G^N}\right)} = \frac{\varphi}{1-\varphi}\left(\frac{P^T}{P^N}\right)^{\phi}, \tag{195g}$$

$$\frac{\nu^{Y,H}}{1-\nu^{Y,H}} = \frac{\vartheta}{1-\vartheta}\left(\frac{\gamma^H}{\gamma^N}\right)^{\epsilon}\left(\frac{P^H}{P^N}\right)^{1+\epsilon}\frac{\left(Z^H\right)^{\left(\frac{\sigma^H-1}{\sigma^H}\right)\epsilon}}{\left(Z^N\right)^{\left(\frac{\sigma^N-1}{\sigma^N}\right)\epsilon}}\frac{\left(y^H\right)^{\frac{\epsilon}{\sigma^H}+1}}{\left(y^N\right)^{\frac{\epsilon}{\sigma^N}+1}}, \tag{195h}$$

$$\nu^{Y,H} = \omega_C\alpha_C\alpha^H + \omega_J\alpha_J\alpha_J^H + \omega_{G^H}\left(1-\omega_{G^N}\right)\omega_G + \omega_X, \tag{195i}$$

$$\left(1-\theta^H\right)\nu^{Y,H} + \left(1-\theta^N\right)\left(1-\nu^{Y,H}\right) = P_J\left(r^\star+\delta_K\right)\frac{K}{Y}, \tag{195j}$$

$$\upsilon_N = \upsilon_{N_0} + \frac{r^\star\Psi_1}{\nu^{Y,H}}\left(\frac{K}{Y}-\upsilon_{K_0}\right), \tag{195k}$$

where $\upsilon_{N_0} = \frac{r^\star N_0}{Y}$, $\upsilon_{K_0} = \frac{K_0}{Y}$. The system (195) consisting of eleven equations determine y^H, y^N, s_L^H, s_L^N, k^H, k^N, $\nu^{Y,H}$, P^N, P^H, K/Y, and υ_N. The five equations (195g)-(195k) stand for the goods market equilibrium for tradables relative to non-tradables, the labor market equilibrium, the goods market equilibrium for the home-produced traded goods market equilibrium, the resource constraint for capital, the intertemporal solvency condition, respectively.

While these last five equations have been derived in subsection P.1, one equation deserves attention as the assumption of CES production functions modifies the derivation of the labor market equilibrium. Dividing (167g) by (167f) leads to the supply of hours worked in the traded sector relative to the non-traded sector, i.e., $\frac{L^H}{L^N} = \frac{\vartheta}{1-\vartheta}\left(\frac{W^H}{W^N}\right)^{\epsilon}$. Dividing (65b) by (65c) leads to the equilibrium relative wage of tradables, i.e.,

$$\frac{W^H}{W^N} = \frac{\gamma^H}{\gamma^N}\frac{\left(Z^H\right)^{\frac{\sigma^H-1}{\sigma^H}}}{\left(Z^N\right)^{\frac{\sigma^N-1}{\sigma^N}}}\frac{\left(y^H\right)^{\frac{1}{\sigma^H}}}{\left(y^N\right)^{\frac{1}{\sigma^N}}}.$$

Inserting the latter expression into the labor supply equation and using the fact that $L^H = \frac{Y^H}{y^H}$ and $L^N = \frac{Y^N}{y^N}$, one obtains:

$$\frac{Y^H}{Y^N} = \frac{\vartheta}{1-\vartheta}\left(\frac{\gamma^H}{\gamma^N}\right)^{\epsilon}\left(\frac{P^H}{P^N}\right)^{\epsilon}\frac{\left(Z^H\right)^{\left(\frac{\sigma^H-1}{\sigma^H}\right)\epsilon}}{\left(Z^N\right)^{\left(\frac{\sigma^N-1}{\sigma^N}\right)\epsilon}}\frac{\left(y^H\right)^{\frac{\epsilon}{\sigma^H}+1}}{\left(y^N\right)^{\frac{\epsilon}{\sigma^N}+1}}.$$

Left-multiplying the above expression by $\frac{P^H Y}{P^N Y}$, and collecting terms leads to **the labor market equilibrium (195h)**.

We choose the initial steady-state in a model with Cobb-Douglas production functions described in section P.1 as the normalization point; $\bar{k}^j$ and $\bar{y}^j$ are the steady-state quantities from the Cobb-Douglas case. The objective of the normalization is to choose γ^j in eq. (194), so as to maintain the steady-state sectoral labor income share at θ^j, and to choose Z^j in eq. (193) so as to maintain the sectoral steady-state output level equal to the Cobb-Douglas value $\bar{y}^j$. Let us remind that θ^j is the labor income share in the baseline model with Cobb-Douglas production functions; equating y_0^j and

k_0^j to $\bar{y}^j$ and $\bar{k}^j$, respectively, eqs. (193) and (194) can be solved for parameter γ^j

$$\gamma^j = \theta^j \left[\theta^j + \left(1-\theta^j\right)\left(\bar{k}^j\right)^{\frac{1-\sigma^j}{\sigma^j}}\right]^{-1}, \tag{196}$$

and parameter Z^j

$$Z^j = \bar{y}^j \left[\gamma^j + \left(1-\gamma^j\right)\left(\bar{k}^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{1-\sigma^j}}. \tag{197}$$

Making use of (176) and (177), we set φ^H, ι^H, and φ to target $\bar{\alpha}^H$, $\bar{\alpha}_J^H$, and $\bar{\alpha}_C$:

$$\varphi^H = \frac{\bar{\alpha}^H}{\bar{\alpha}^H + \left(1-\bar{\alpha}^H\right)\left(\bar{P}^H\right)^{1-\rho}}, \tag{198a}$$

$$\iota^H = \frac{\bar{\alpha}_J^H}{\bar{\alpha}_J^H + \left(1-\bar{\alpha}_J^H\right)\left(\bar{P}^H\right)^{1-\rho_J}}, \tag{198b}$$

$$\varphi = \frac{\bar{\alpha}_C}{\bar{\alpha}_C + \left(1-\bar{\alpha}_C\right)\left(\frac{\bar{P}^N}{\bar{P}^H}\right)^{\phi-1}}. \tag{198c}$$

We choose ϑ so as to target the tradable content of labor compensation $\bar{\alpha}_L$:

$$\vartheta = \frac{\bar{\alpha}_L}{\bar{\alpha}_L + \left(1-\bar{\alpha}_L\right)\left(\frac{\bar{W}^H}{\bar{W}^N}\right)^{1+\epsilon}}. \tag{199}$$

Using the fact that $\omega_X = \frac{P^H X^H}{Y}$ with $X^H = \varphi_X \left(P^H\right)^{-\phi_X}$, we set φ_X to target an export-to-GDP ratio $\bar{\omega}_X$:

$$\varphi_X = \bar{Y}\bar{\omega}_X \left(\bar{P}^H\right)^{\phi_X - 1}. \tag{200}$$

We choose δ_K so as to target an investment-to-GDP ratio $\bar{\omega}_J$:

$$\delta_K = \frac{\bar{\omega}_J \bar{Y}}{\bar{P}_J \bar{K}}. \tag{201}$$

We set N_0 so as to target $\bar{\omega}_C$ or alternatively balanced net exports (which imply $\upsilon_N = 0$) by using the accounting identity between GDP and the sum of demand components:

$$N_0 = \bar{Y}\left(\frac{\bar{\omega}_C + \bar{\omega}_J + \omega_G - 1}{r^\star}\right). \tag{202}$$

Finally, we choose K_0 to target $\bar{K}$ by using the intertemporal solvency condition:

$$K_0 = \bar{K} + \left(\frac{N_0 - \bar{N}}{\bar{\Psi}_1}\right) \tag{203}$$

P.4 Calibration Procedure with CES Production Functions and Factor Biased Technological Change

In this subsection, we provide more details about how we determine the direction and the magnitude of factor biased technological change. We begin with the approach adopted in the main text and then we contrast the results with those obtained by following an alternative method.

Estimating Empirically Factor Biased Technological Change

To calibrate the dynamic responses of A^j and B^j, we proceed as follows. To start with, we repeat the ratio of factor income share for convenience:

$$S^j = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j K^j}{A^j L^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{204}$$

Since we normalize CES production function (192) so that the relative weight of labor and capital is consistent with the labor and capital income share in the data, solving for γ^j leads to:

$$\gamma^j = \left(\frac{\tilde{A}_0^j}{\tilde{y}_0^j}\right)^{\frac{1-\sigma^j}{\sigma^j}} \tilde{s}_{L,0}^j, \tag{205a}$$

$$1-\gamma^j = \left(\frac{\tilde{B}_0^j \tilde{k}_0^j}{\tilde{y}_0^j}\right)^{\frac{1-\sigma^j}{\sigma^j}} (1-\tilde{s}_{L,0}^j). \tag{205b}$$

Dividing (205a) by (205b) leads to:

$$\tilde{S}_0^j = \frac{\gamma^j}{1-\gamma^j}\left(\frac{\tilde{B}_0^j \tilde{k}_0^j}{\tilde{A}_0^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{206}$$

Dividing (204) by (206) and solving for relative capital efficiency leads to:

$$\left(\frac{B^j(t)/\tilde{B}_0^j}{A^j(t)/\tilde{A}_0^j}\right) = \left(\frac{k^j(t)}{\tilde{k}_0^j}\right)^{-1}\left(\frac{S^j(t)}{\tilde{S}_0^j}\right)^{\frac{\sigma^j}{1-\sigma^j}}. \tag{207}$$

Since initially we assume Hicks-neutral technological change at the initial steady-state, we have $\tilde{A}_0^j = \tilde{B}_0^j = \tilde{Z}_0^j$. The technology frontier is described by

$$\frac{Z^j(t)}{\tilde{Z}_0^j} = \left(\frac{A^j(t)}{\tilde{A}_0^j}\right)^{s_L^j(t)}\left(\frac{B^j(t)}{\tilde{B}_0^j}\right)^{1-s_L^j(t)}. \tag{208}$$

Log-linearizing, the system (207)-(208) can be solved for labor and capital productivity:

$$\hat{A}^j(t) = \hat{Z}^j(t) - \left(1-\tilde{s}_{L,0}^j\right)\left[\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) - \hat{k}^j(t)\right], \tag{209a}$$

$$\hat{B}^j(t) = \hat{Z}^j(t) + \tilde{s}_{L,0}^j\left[\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) - \hat{k}^j(t)\right], \tag{209b}$$

where $\hat{S}^j(t) = \frac{\hat{s}^j(t)}{1-\tilde{s}_{L,0}^j}$. To recover the dynamics of A^j and B^j, we first estimate two VAR models; the first VAR model includes the productivity differential, Z, the labor income share in sector j, and the capital-labor ratio in sector j, i.e., $[\hat{Z}, \hat{s}_L^j, \hat{k}^j]$; the second VAR model includes the technology shock (identified from the estimation of the baseline VAR model including aggregate variables), sectoral TFPs, and the productivity differential. Next, we generate IRFs and plug estimated responses of Z^j, k^j, s_L^j into (209a)-(209b) which allows us to make inference on the underlying process of A^j and B^j in the data. As discussed below, four situations may emerge.

Differentiating (207) leads to:

$$\hat{B}^j(t) - \hat{A}^j(t) = \left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) - \hat{k}^j(t). \tag{210}$$

While eq. (210) gives us the excess of capital productivity growth over labor productivity growth, the system of equations which comprises (209a)-(209b) allows us to determine the changes in labor capital efficiency:

$$\hat{A}^j(t) = \hat{Z}^j(t) - \left(1-\tilde{s}_{L,0}^j\right)\left(\hat{B}^j(t) - \hat{A}^j(t)\right), \tag{211a}$$

$$\hat{B}^j(t) = \hat{Z}^j(t) + \tilde{s}_{L,0}^j\left(\hat{B}^j(t) - \hat{A}^j(t)\right). \tag{211b}$$

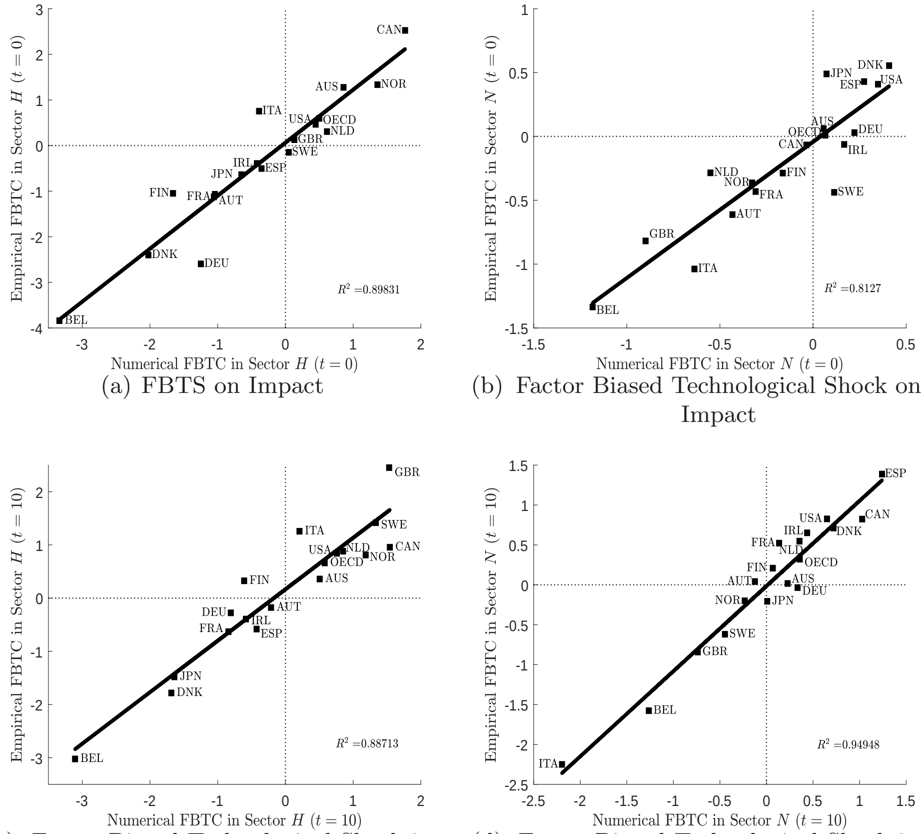
Eqs. (211a)-(211b) show that four situations can emerge:

- When the productivity differential between capital and labor $\left(\hat{B}^j - \hat{A}^j\right) > 0$ exceeds $\frac{\hat{Z}^j}{1-s_L^j} > 0$, we have $\hat{A}^j < 0$ (and $\hat{B}^j > 0$).
- When the decline in relative capital efficiency $-\left(\hat{B}^j - \hat{A}^j\right) > 0$ exceeds $\frac{\hat{Z}^j}{s_L^j} > 0$, we have $\hat{B}^j < 0$ (and $\hat{A}^j > 0$).
- When the productivity differential between capital and labor falls between $-\frac{\hat{Z}^j}{s_L^j}$ and $\frac{\hat{Z}^j}{1-s_L^j}$, we have $\hat{B}^j > 0$ and $\hat{A}^j > 0$:
  - if $\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) > \hat{k}^j(t)$, relative capital efficiency increases;
  - if $\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) < \hat{k}^j(t)$, relative capital efficiency declines.

We further specify a dynamic adjustment for $\hat{A}^j(t)$ and $\hat{B}^j(t)$ similar to that described by eq. (188), i.e.,

$$\hat{A}^j(t) = \hat{A}^j + \bar{a}^j e^{-\xi^j t}, \quad \hat{B}^j(t) = \hat{B}^j + \bar{b}^j e^{-\xi^j t}, \tag{212}$$

Traded Sector Non-Traded Sector



(a) FBTS on Impact (b) Factor Biased Technological Shock on Impact

(c) Factor Biased Technological Shock in the Long-Run (d) Factor Biased Technological Shock in the Long-Run

Figure 31: Empirically vs. Numerically Estimated FBTC in the Home-Produced Traded Goods and Non-Traded Goods Sector. Notes: Figure 31 plots impact (i.e., at time $t=0$) and long-run (i.e., at time $t=10$) responses of FBTC^j_{it} estimated numerically (by using (38a)-(38b)) on the horizontal axis against those estimated empirically (by using (80) to construct time series for FBTC and then estimating a VAR $[\hat{Z}_{it}, \text{FBTC}^j_{it}]$) on the vertical exis.

where we assume that the speed of adjustment ξ^j corresponds to the speed of adjustment of sectoral TFP, Z^j (i.e., $\xi^H = 0.5709$ and $\xi^N = 1.1668$, see subsection P.2). We choose $\bar{a}^j$, $\bar{b}^j$ by setting $t=0$ into (212), i.e., $\bar{a}^j = -\left(\hat{\tilde{A}}^j - \hat{A}^j(0)\right)$, and $\bar{b}^j = -\left(\hat{\tilde{B}}^j - \hat{B}^j(0)\right)$ which gives us $\bar{a}^H = -0.029840$, $\bar{b}^H = -0.202769$, $\bar{a}^N = 0.234035$, $\bar{b}^N = -0.500629$.

Contrasting Numerical vs. Empirical Estimates of FBTC

One alternative approach to that described above amounts to constructing time series for FBTC by using eq. (207), i.e.,

$$\begin{aligned} \text{FBTC}^j(t) &\equiv \left(\frac{B^j(t)/\tilde{B}^j_0}{A^j(t)/\tilde{A}^j_0}\right)^{\frac{1-\sigma^j}{\sigma^j}}, \\ &= \left(\frac{k^j(t)}{\tilde{k}^j_0}\right)^{-\frac{1-\sigma^j}{\sigma^j}} \left(\frac{S^j(t)}{\tilde{S}^j_0}\right). \end{aligned} \tag{213}$$

Using time series for sectoral capital ratios, k^j, labor income share, s^j_L, along with our estimates of σ^j, one can make inference on FBTC which we have denoted by FBTC^j_{it}. Then, we estimate a simple VAR model $[\hat{Z}_{it}, \text{FBTC}^j_{it}]$ by adopting the identification approach by Gali [1999]. Fig. 31 plots impact and long-run responses of FBTC estimated empirically on the vertical axis against FBTC computed numerically by using (38a)-(38b). Overall, differences between the two approaches are quantitatively small. While both methods should be identical, computation of FBTC by using (38a)-(38b) slightly improves the fit to the data.

Q Semi-Small Open Economy Model

This Appendix puts forward an open economy version of the neoclassical model with tradables and non-tradables, imperfect mobility of labor across sectors, capital adjustment costs and endogenous terms of trade. This section illustrates in detail the steps we follow in solving this model. We assume that production functions take a Cobb-Douglas form since this economy is the reference model for our calibration as we normalize CES productions by assuming that the initial steady state of the Cobb-Douglas economy is the normalization point.

Households supply labor, L, and must decide on the allocation of total hours worked between the traded sector, L^H, and the non-traded sector, L^N. They consume both traded, C^T, and non-traded goods, C^N. Traded goods are a composite of home-produced traded goods, C^H, and foreign-produced foreign (i.e., imported) goods, C^F. Households also choose investment which is produced using inputs of the traded, J^T, and the non-traded good, J^N. As for consumption, input of the traded good is a composite of home-produced traded goods, J^H, and foreign imported goods, J^F. The numeraire is the foreign good whose price, P^F, is thus normalized to one.

Q.1 Households

At each instant of time, the representative household consumes traded and non-traded goods denoted by C^T and C^N, respectively, which are aggregated by means of a CES function:

$$C = \left[\varphi^{\frac{1}{\phi}} \left(C^T\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} \left(C^N\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{214}$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The index C^T is defined as a CES aggregator of home-produced traded goods, C^H, and foreign-produced traded goods, C^F:

$$C^T = \left[\left(\varphi^H\right)^{\frac{1}{\rho}} \left(C^H\right)^{\frac{\rho-1}{\rho}} + (1-\varphi_H)^{\frac{1}{\rho}} \left(C^F\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{215}$$

where $0 < \varphi_H < 1$ is the weight of the home-produced traded good in the overall traded consumption bundle and ρ corresponds to the elasticity of substitution between home-produced traded goods goods and foreign-produced traded goods.

As in De Cordoba and Kehoe [2000], the investment good is produced using inputs of the traded good and the non-traded good according to a constant-returns-to-scale function which is assumed to take a CES form:

$$J = \left[\iota^{\frac{1}{\phi_J}} \left(J^T\right)^{\frac{\phi_J-1}{\phi_J}} + (1-\iota)^{\frac{1}{\phi_J}} \left(J^N\right)^{\frac{\phi_J-1}{\phi_J}}\right]^{\frac{\phi_J}{\phi_J-1}}, \tag{216}$$

where ι is the weight of the investment traded input ($0 < \iota < 1$) and ϕ_J corresponds to the elasticity of substitution in investment between traded and non-traded inputs. The index J^T is defined as a CES aggregator of home-produced traded inputs, J^H, and foreign-produced traded inputs, J^F:

$$J^T = \left[\left(\iota_H\right)^{\frac{1}{\rho_J}} \left(J^H\right)^{\frac{\rho_J-1}{\rho_J}} + (1-\iota_H)^{\frac{1}{\rho_J}} \left(J^F\right)^{\frac{\rho_J-1}{\rho_J}}\right]^{\frac{\rho_J}{\rho_J-1}}, \tag{217}$$

where $0 < \iota_H < 1$ is the weight of the home-produced traded in input in the overall traded investment bundle and ρ_J corresponds to the elasticity of substitution between home- and foreign-produced traded inputs.

Following Horvath [2000], we assume that hours worked in the traded and the non-traded sectors are aggregated by means of a CES function:

$$L = \left[\vartheta^{-1/\epsilon} \left(L^H\right)^{\frac{\epsilon+1}{\epsilon}} + (1-\vartheta)^{-1/\epsilon} \left(L^N\right)^{\frac{\epsilon+1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon+1}}, \tag{218}$$

where $0 < \vartheta < 1$ is the weight of labor supply to the traded sector in the labor index $L(.)$ and ϵ measures the ease with which hours worked can be substituted for each other and thereby captures the degree of labor mobility across sectors.

The representative household chooses consumption, decides on labor supply, and investment that maximizes his/her lifetime utility:

$$U = \int_0^\infty \left\{\frac{1}{1-\frac{1}{\sigma_C}} C(t)^{1-\frac{1}{\sigma_C}} - \frac{1}{1+\frac{1}{\sigma_L}} L(t)^{1+\frac{1}{\sigma_L}}\right\} e^{-\beta t} \mathrm{d}t, \tag{219}$$

subject to the flow budget constraint:

$$\dot{N}(t) = r^\star N(t) + R(t)K(t) + W(t)L(t) - T(t) - P_C\left(P^T(t), P^N(t)\right)C(t) - P_J\left(P^T(t), P^N(t)\right)J(t), \tag{220}$$

and capital accumulation which evolves as follows:

$$\dot{K}(t) = I(t) - \delta_K K(t), \tag{221}$$

where I is investment and $0 \leq \delta_K < 1$ is a fixed depreciation rate. The first term on the RHS of (220) $r^\star N(t) + R(t)K(t) + W(t)L(t) - T(t)$ is the representative household's real disposable income while the second term on the RHS, i.e., $P_C\left(P^T(t), P^N(t)\right)C(t) + P_J\left(P_J^T(t), P^N(t)\right)J(t)$, corresponds to consumption and investment expenditure including capital installation costs. More specifically, we assume that capital accumulation is subject to increasing and convex cost of net investment, $I(t) - \delta_K K(t)$:

$$J(t) = I(t) + \Psi\left(I(t), K(t)\right)K(t), \tag{222}$$

where $\Psi(.)$ is increasing (i.e., $\Psi'(.) > 0$), convex (i.e., $\Psi''(.) > 0$), is equal to zero at δ_K (i.e., $\Psi(\delta_K) = 0$), and has first partial derivative equal to zero as well at δ_K (i.e., $\Psi'(\delta_K) = 0$). We suppose the following functional form for the adjustment cost function:

$$\Psi\left(I(t), K(t)\right) = \frac{\kappa}{2}\left(\frac{I(t)}{K(t)} - \delta_K\right)^2. \tag{223}$$

Using (223), partial derivatives of total investment expenditure are:

$$\frac{\partial J(t)}{\partial I(t)} = 1 + \kappa\left(\frac{I(t)}{K(t)} - \delta_K\right), \tag{224a}$$

$$\frac{\partial J(t)}{\partial K(t)} = -\frac{\kappa}{2}\left(\frac{I(t)}{K(t)} - \delta_K\right)\left(\frac{I(t)}{K(t)} + \delta_K\right). \tag{224b}$$

Denoting the co-state variables associated with (220) and (221) by λ and Q', respectively, the first-order conditions characterizing the representative household's optimal plans are:

$$C(t) = \left(P_C(t)\lambda\right)^{-\sigma_C}, \tag{225a}$$

$$L(t) = \left(W(t)\lambda\right)^{\sigma_L}, \tag{225b}$$

$$Q(t) = P_J(t)\left[1 + \kappa\left(\frac{I(t)}{K(t)} - \delta_K\right)\right], \tag{225c}$$

$$\dot{\lambda}(t) = \lambda\left(\beta - r^\star\right), \tag{225d}$$

$$\dot{Q}(t) = \left(r^\star + \delta_K\right)Q(t) - \left\{R(t) + P_J(t)\frac{\kappa}{2}\left(\frac{I(t)}{K(t)} - \delta_K\right)\left(\frac{I(t)}{K(t)} + \delta_K\right)\right\}, \tag{225e}$$

and the transversality conditions $\lim_{t\to\infty} \bar{\lambda}N(t)e^{-\beta t} = 0$ and $\lim_{t\to\infty} Q(t)K(t)e^{-\beta t} = 0$; to derive (225c) and (225e), we used the fact that $Q(t) = Q'(t)/\lambda(t)$.

Given the above consumption indices, we can derive appropriate price indices. With respect to the general consumption index, we obtain the consumption-based price index P_C:

$$P_C = \left[\varphi\left(P^T\right)^{1-\phi} + (1-\varphi)\left(P^N\right)^{1-\phi}\right]^{\frac{1}{1-\phi}}, \tag{226}$$

where the price index for traded goods is:

$$P^T = \left[\varphi_H\left(P^H\right)^{1-\rho} + (1-\varphi_H)\right]^{\frac{1}{1-\rho}}. \tag{227}$$

Given the consumption-based price index (226), the representative household has the following demand of traded and non-traded goods:

$$C^T = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi} C, \tag{228a}$$

$$C^N = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{-\phi} C. \tag{228b}$$

Given the price indices (226) and (227), the representative household has the following demand of home-produced traded goods and foreign-produced traded goods:

$$C^H = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}\varphi_H\left(\frac{P^H}{P^T}\right)^{-\rho} C, \tag{229a}$$

$$C^F = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}(1-\varphi_H)\left(\frac{1}{P_T}\right)^{-\rho} C. \tag{229b}$$

As will be useful later, the percentage change in the consumption price index is a weighted average of percentage changes in the price of traded and non-traded goods in terms of foreign goods:

$$\hat{P}_C = \alpha_C \hat{P}^T + (1-\alpha_C)\,\hat{P}^N, \tag{230a}$$
$$\hat{P}^T = \alpha_H \hat{P}^H, \tag{230b}$$

where α_C is the tradable content of overall consumption expenditure and α^H is the home-produced goods content of consumption expenditure on traded goods:

$$\alpha_C = \varphi\left(\frac{P^T}{P_C}\right)^{1-\phi}, \tag{231a}$$
$$1-\alpha_C = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{1-\phi}, \tag{231b}$$
$$\alpha^H = \varphi_H\left(\frac{P^H}{P^T}\right)^{1-\rho}, \tag{231c}$$
$$1-\alpha^H = (1-\varphi_H)\left(\frac{1}{P^T}\right)^{1-\rho}. \tag{231d}$$

Given the CES aggregator functions above, we can derive the appropriate price indices for investment. With respect to the general investment index, we obtain the investment-based price index P_J:

$$P_J = \left[\iota\left(P_J^T\right)^{1-\phi_J} + (1-\iota)\left(P^N\right)^{1-\phi_J}\right]^{\frac{1}{1-\phi_J}}, \tag{232}$$

where the price index for traded goods is:

$$P_J^T = \left[\iota^H\left(P^H\right)^{1-\rho_J} + \left(1-\iota^H\right)\right]^{\frac{1}{1-\rho_J}}. \tag{233}$$

Given the investment-based price index (232), we can derive the demand for inputs of the traded good and the non-traded good:

$$J^T = \iota\left(\frac{P_J^T}{P_J}\right)^{-\phi_J} J, \tag{234a}$$
$$J^N = (1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J} J. \tag{234b}$$

Given the price indices (232) and (233), we can derive the demand for inputs of home-produced traded goods and foreign-produced traded goods:

$$J^H = \iota\left(\frac{P_J^T}{P_J}\right)^{-\phi_J}\iota^H\left(\frac{P^H}{P_J^T}\right)^{-\rho_J} J, \tag{235a}$$
$$J^F = \iota\left(\frac{P_J^T}{P_J}\right)^{-\phi_J}\left(1-\iota^H\right)\left(\frac{1}{P_J^T}\right)^{-\rho_J} J. \tag{235b}$$

As will be useful later, the percentage change in the investment price index is a weighted average of percentage changes in the price of traded and non-traded inputs in terms of foreign inputs:

$$\hat{P}_J = \alpha_J \hat{P}_J^T + (1-\alpha_J)\,\hat{P}^N, \tag{236a}$$
$$\hat{P}_J^T = \alpha_J^H \hat{P}^H, \tag{236b}$$

where α_J is the tradable content of overall investment expenditure and α_J^H is the home-produced goods content of investment expenditure on traded goods:

$$\alpha_J = \iota\left(\frac{P_J^T}{P_J}\right)^{1-\phi_J}, \tag{237a}$$
$$1-\alpha_J = (1-\iota)\left(\frac{P^N}{P_J}\right)^{1-\phi_J}, \tag{237b}$$
$$\alpha_J^H = \iota^H\left(\frac{P^H}{P_J^T}\right)^{1-\rho_J}, \tag{237c}$$
$$1-\alpha_J^H = \left(1-\iota^H\right)\left(\frac{1}{P_J^T}\right)^{1-\rho_J}. \tag{237d}$$

The aggregate wage index, $W(t)$, associated with the labor index defined above (218) is:

$$W = \left[\vartheta \left(W^H\right)^{\epsilon+1} + (1-\vartheta)\left(W^N\right)^{\epsilon+1}\right]^{\frac{1}{\epsilon+1}}, \tag{238}$$

where W^H and W^N are wages paid in the traded and the non-traded sectors, respectively.

Given the aggregate wage index, we can derive the allocation of aggregate labor supply to the traded and the non-traded sector:

$$L^H = \vartheta \left(\frac{W^H}{W}\right)^{\epsilon} L, \tag{239a}$$

$$L^N = (1-\vartheta)\left(\frac{W^N}{W}\right)^{\epsilon} L. \tag{239b}$$

As will be useful later, the percentage change in the aggregate wage index is a weighted average of percentage changes in sectoral wages:

$$\hat{W} = \alpha_L \hat{W}^H + (1-\alpha_L)\hat{W}^N, \tag{240}$$

where α_L is the tradable content of aggregate labor compensation:

$$\alpha_L = \vartheta \left(\frac{W^H}{W}\right)^{1+\epsilon}, \tag{241a}$$

$$1-\alpha_L = (1-\vartheta)\left(\frac{W^N}{W}\right)^{1+\epsilon}. \tag{241b}$$

Q.2 Firms

Both the traded and non-traded sectors use physical capital, K^j, and labor, L^j, according to constant returns to scale production functions $Y^j = Z^j F^j\left(K^j, L^j\right)$ which are assumed to take a Cobb-Douglas form:

$$Y^j = Z^j \left(L^j\right)^{\theta^j}\left(K^j\right)^{1-\theta^j}, \quad j = H, N \tag{242}$$

where θ^j is the labor income share in sector j and Z^j corresponds to the total factor productivity. Both sectors face two cost components: a capital rental cost equal to R, and a labor cost equal to the wage rate, i.e., W^H in the traded sector and W^N in the non-traded sector.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{K^j, L^j} \Pi^j = \max_{K^j, L^j} \left\{P^j Y^j - W^j L^j - RK^j\right\}. \tag{243}$$

Since capital can move freely between the two sectors, the value of marginal products in the traded and non-traded sectors equalizes while costly labor mobility implies a wage differential across sectors:

$$P^H Z^H \left(1-\theta^H\right)\left(k^H\right)^{-\theta^H} = P^N Z^N \left(1-\theta^N\right)\left(k^N\right)^{-\theta^N} \equiv R, \tag{244a}$$

$$P^H Z^H \theta^H \left(k^H\right)^{1-\theta^H} \equiv W^H, \tag{244b}$$

$$P^N Z^N \theta^N \left(k^N\right)^{1-\theta^N} \equiv W^N, \tag{244c}$$

where $k^j \equiv K^j/L^j$ denotes the capital-labor ratio for sector $j = H, N$.

The resource constraint for capital is:

$$K^H + K^N = K. \tag{245}$$

Q.3 Short-Run Solutions

Consumption and Labor

Before linearizing, we have to determine short-run solutions. First-order conditions (225a) and (225b) can be solved for consumption and aggregate labor supply which of course must hold at any point of time:

$$C = C\left(\bar{\lambda}, P^N, P^H\right), \quad L = L\left(\bar{\lambda}, W^H, W^N\right), \tag{246}$$

with partial derivatives given by

$$\hat{C} = -\sigma_C \hat{\bar{\lambda}} - \sigma_C \alpha_C \alpha^H \hat{P}^H - \sigma_C (1-\alpha_C)\hat{P}^N, \tag{247a}$$

$$\hat{L} = \sigma_L \hat{\bar{\lambda}} + \sigma_L (1-\alpha_L)\hat{W}^N + \sigma_L \alpha_L \hat{W}^H, \tag{247b}$$

where we used (240) and (230).

Inserting first the solution for consumption (246) into (228a)-(229b) allows us to solve for C^N, C^H, and C^F:

$$C^N = C^N\left(\bar{\lambda}, P^N, P^H\right), \quad C^H = C^H\left(\bar{\lambda}, P^N, P^H\right), \quad C^F = C^F\left(\bar{\lambda}, P^N, P^H\right), \tag{248}$$

with partial derivatives given by

$$\begin{aligned}
\hat{C}^N &= -\phi\hat{P}^N + (\phi - \sigma_C)\hat{P}_C - \sigma_C\hat{\bar{\lambda}}, \\
&= -\left[\alpha_C\phi + (1-\alpha_C)\sigma_C\right]\hat{P}^N + (\phi-\sigma_C)\alpha_C\alpha^H\hat{P}^H - \sigma_C\hat{\bar{\lambda}}, && (249a)\\
\hat{C}^H &= -\left[\rho\left(1-\alpha^H\right) + \phi(1-\alpha_C)\alpha^H + \sigma_C\alpha_C\alpha^H\right]\hat{P}^H + (1-\alpha_C)(\phi-\sigma_C)\hat{P}^N - \sigma_C\hat{\bar{\lambda}}, && (249b)\\
\hat{C}^F &= \alpha^H\left[\rho - \phi(1-\alpha_C) - \sigma_C\alpha_C\right]\hat{P}^H + (1-\alpha_C)(\phi-\sigma_C)\hat{P}^N - \sigma_C\hat{\bar{\lambda}}. && (249c)
\end{aligned}$$

Inserting first the solution for labor (246) into (239a)-(240) allows us to solve for L^H and L^N:

$$L^H = L^H\left(\bar{\lambda}, W^H, W^N\right), \quad L^N = L^N\left(\bar{\lambda}, W^H, W^N\right), \tag{250}$$

with partial derivatives given by:

$$\hat{L}^H = \left[\epsilon(1-\alpha_L) + \sigma_L\alpha_L\right]\hat{W}^H - (1-\alpha_L)(\epsilon-\sigma_L)\hat{W}^N + \sigma_L\hat{\bar{\lambda}}, \tag{251a}$$
$$\hat{L}^N = \left[\epsilon\alpha_L + \sigma_L(1-\alpha_L)\right]\hat{W}^N - \alpha_L(\epsilon-\sigma_L)\hat{W}^H + \sigma_L\hat{\bar{\lambda}}. \tag{251b}$$

Sectoral Wages and Capital-Labor Ratios

Plugging the short-run solutions for L^H and L^N given by (250) into the resource constraint for capital (245), the system of four equations consisting of (244a)-(244c) together with (245) can be solved for sectoral wages W^j and sectoral capital-labor ratios k^j. Denoting by $\xi^N \equiv K^N/K$ the share of non-traded capital in the aggregate stock of physical capital and log-differentiating (244a)-(244c) together with (245) yields in matrix form:

$$\begin{pmatrix} -\theta^H & \theta^N & 0 & 0 \\ \left(1-\theta^H\right) & 0 & -1 & 0 \\ 0 & \left(1-\theta^N\right) & 0 & -1 \\ \left(1-\xi^N\right) & \xi^N & \Psi_{W^H} & \Psi_{W^N} \end{pmatrix} \begin{pmatrix} \hat{k}^H \\ \hat{k}^N \\ \hat{W}^H \\ \hat{W}^N \end{pmatrix}$$
$$= \begin{pmatrix} \hat{P}^N - \hat{P}^H - \hat{Z}^H + \hat{Z}^N \\ -\hat{P}^H - \hat{Z}^H \\ -\hat{P}^N - \hat{Z}^N \\ \hat{K} - \Psi_{\bar{\lambda}}\hat{\bar{\lambda}} \end{pmatrix}, \tag{252}$$

where we set:

$$\begin{aligned}
\Psi_{W^j} &= \left(1-\xi^N\right)\frac{L^H_{W^j}W^j}{L^H} + \xi^N\frac{L^N_{W^j}W^j}{L^N}, && (253a)\\
\xi^N &\equiv \frac{k^N L^N}{K}, && (253b)\\
\Psi_{\bar{\lambda}} &= \left(1-\xi^N\right)\sigma_L + \xi^N\sigma_L = \sigma_L. && (253c)
\end{aligned}$$

The short-run solutions for sectoral wages and capital-labor ratios are:

$$W^j = W^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right), \quad k^j = k^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right). \tag{254}$$

Inserting first sectoral wages (254), sectoral hours worked (250) can be solved as functions of the shadow value of wealth, the capital stock, the price of non-traded goods in terms of foreign goods, P^N, and the terms of trade:

$$L^j = L^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right). \tag{255}$$

Finally, plugging solutions for sectoral labor (255) and sector capital-labor ratios (254), production functions (242) can be solved for sectoral value added:

$$Y^j = Y^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right), \tag{256}$$

where

$$\hat{Y}^j = \hat{Z}^j + \sum_X \frac{\partial L^j}{\partial X}\frac{X}{L^j} + \left(1-\theta^j\right)\frac{\partial k^j}{\partial X}\frac{X}{k^j}, \tag{257}$$

where $X = \bar{\lambda}, K, P^N, P^H, Z^H, Z^N$.

The Return on Domestic Capital, R

The return on domestic capital is:

$$R = P^H Z^H \left(1 - \theta^H\right) \left(k^H\right)^{-\theta^H}. \tag{258}$$

Inserting first the short-run static solution for the capital-labor ratio k^H given by (254), eq. (258) can be solved for the return on domestic capital:

$$R = R\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right), \tag{259}$$

where partial derivatives are

$$\hat{R} = \hat{Z}^j + \sum_X \frac{\partial k^H}{\partial X} \frac{X}{k^H}, \tag{260}$$

where $X = \bar{\lambda}, K, P^N, P^H, Z^H, Z^N$.

Optimal Investment Decision, I/K

Eq. (225c) can be solved for the investment rate:

$$\frac{I}{K} = v\left(\frac{Q}{P_I\left(P^T, P^N\right)}\right) + \delta_K, \tag{261}$$

where

$$v\left(.\right) = \frac{1}{\kappa}\left(\frac{Q}{P_J} - 1\right), \tag{262}$$

with

$$v_Q = \frac{\partial v(.)}{\partial Q} = \frac{1}{\kappa}\frac{1}{P_J} > 0, \tag{263a}$$

$$v_{P^H} = \frac{\partial v(.)}{\partial P^H} = -\frac{1}{\kappa}\frac{Q}{P_J}\frac{\alpha_J \alpha_J^H}{P^H} < 0, \tag{263b}$$

$$v_{P^N} = \frac{\partial v(.)}{\partial P^N} = -\frac{1}{\kappa}\frac{Q}{P_J}\frac{(1-\alpha_J)}{P^N} < 0. \tag{263c}$$

Inserting (261) into (222), investment including capital installation costs can be rewritten as follows:

$$\begin{aligned} J &= K\left[\frac{I}{K} + \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2\right], \\ &= K\left[v(.) + \delta_K + \frac{\kappa}{2}\left(v(.)\right)^2\right]. \end{aligned} \tag{264}$$

Eq. (264) can be solved for investment including capital installation costs:

$$J = J\left(K, Q, P^N, P^H\right), \tag{265}$$

where

$$J_K = \frac{\partial J}{\partial K} = \frac{J}{K}, \tag{266a}$$

$$J_X = \frac{\partial J}{\partial X} = \kappa v_X \left(1 + \kappa v(.)\right) > 0, \tag{266b}$$

with $X = Q, P^H, P^N$.

Substituting (266) into (234b), (235a), and (235b) allows us to solve for the demand of non-traded, home-produced traded, and foreign inputs:

$$J^N = J^N\left(K, Q, P^N, P^H\right), \quad J^H = J^H\left(K, Q, P^N, P^H\right), \quad J^F = J^F\left(K, Q, P^N, P^H\right), \tag{267}$$

with partial derivatives given by

$$\begin{aligned}
\hat{J}^N &= -\alpha_J \phi_J \hat{P}^N + \phi_J \alpha_J \alpha_J^H \hat{P}^H + \hat{J}, \\
&= \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \hat{Q} - \left[\alpha_J \phi_J + \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} (1-\alpha_J) \right] \hat{P}^N \\
&+ \alpha_J \alpha_J^H \left[\phi_J - \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \right] \hat{P}^H + \hat{K}, \qquad (268a) \\
\hat{J}^H &= -\left[\rho_J \left(1-\alpha_J^H\right) + \alpha_J^H \phi_J (1-\alpha_J) \right] \hat{P}^H + \phi_J (1-\alpha_J) \hat{P}^N + \hat{J}, \\
&= -\left\{ \left[\rho_J \left(1-\alpha_J^H\right) + \alpha_J^H \phi_J (1-\alpha_J) \right] + \alpha_J \alpha_J^H \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \right\} \hat{P}^H \\
&+ (1-\alpha_J) \left[\phi_J - \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \right] \hat{P}^N + \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \hat{Q} + \hat{K}, \qquad (268b) \\
\hat{J}^F &= \alpha_J^H \left[\rho_J - \phi_J (1-\alpha_J) \right] \hat{P}^H + \phi_J (1-\alpha_J) \hat{P}^N + \hat{J}, \\
&= \alpha_J^H \left\{ \left[\rho_J - \phi_J (1-\alpha_J) \right] - \alpha_J \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \right\} \hat{P}^H \\
&+ (1-\alpha_J) \left[\phi_J - \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \right] \hat{P}^N + \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \hat{Q} + \hat{K}, \qquad (268c)
\end{aligned}$$

where use has been made of (266), i.e.,

$$\begin{aligned}
\hat{J} &= \hat{K} + \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \hat{Q} - \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} (1-\alpha_J) \hat{P}^N \\
&\quad - \alpha_J \alpha_J^H \frac{Q}{P_J} \frac{(1+\kappa v(.))}{J} \hat{P}^H.
\end{aligned}$$

Q.4 Market Clearing Conditions

Finally, we have to solve for the relative price of non-traded goods and the terms of trade.

Market Clearing Condition for Non-Tradables

The role of the price of non-tradables in terms of foreign goods is to clear the non-traded goods market:

$$Y^N = C^N + G^N + J^N. \qquad (269)$$

Inserting solutions for C^N, J^N, Y^N given by (248), (267), (256), respectively, the non-traded goods market clearing condition (269) can be rewritten as follows:

$$Y^N \left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right) = C^N \left(\bar{\lambda}, P^N, P^H\right) + G^N + J^N \left(K, Q, P^N, P^H\right). \qquad (270)$$

Eq. (270) can be solved for the relative price of non-tradables:

$$P^N = \Psi^N \left(K, Q, P^H, Z^H, Z^N, \bar{\lambda}\right), \qquad (271)$$

with partial derivatives given by:

$$\begin{aligned}
\Psi_K^N &= \frac{\partial \Psi^N}{\partial K} = -\frac{\left(Y_K^N - J_K^N\right)}{\Delta^N} < 0, \qquad (272a) \\
\Psi_Q^N &= \frac{\partial \Psi^N}{\partial Q} = \frac{J_Q^N}{\Delta^N} > 0, \qquad (272b) \\
\Psi_{P^H}^N &= \frac{\partial \Psi^N}{\partial P^H} = -\frac{\left(Y_{P^H}^N - C_{P^H}^N - J_{P^H}^N\right)}{\Delta^N} > 0, \qquad (272c) \\
\Psi_{Z^H}^N &= \frac{\partial \Psi^N}{\partial Z^H} = -\frac{Y_{Z^H}^N}{\Delta^N} > 0, \qquad (272d) \\
\Psi_{Z^N}^N &= \frac{\partial \Psi^N}{\partial Z^N} = -\frac{Y_{Z^N}^N}{\Delta^N} < 0, \qquad (272e)
\end{aligned}$$

where we set

$$\Delta^N = \left(Y_{P^N}^N - C_{P^N}^N - J_{P^N}^N\right) > 0. \qquad (273)$$

Market Clearing Condition for Home-Produced Traded Goods

The role of the price of home-produced goods in terms of foreign-produced goods or the terms of trade is to clear the home-produced traded goods market:

$$Y^H = C^H + G^H + J^H + X^H, \qquad (274)$$

where X^H stands for exports which are negatively related to the terms of trade:

$$X^H = \varphi_X \left(P^H\right)^{-\phi_X}, \tag{275}$$

where ϕ_X is the elasticity of exports with respect to the terms of trade. The rationale behind (275) comes from the fact that exports are the sum of foreign demand for the domestically produced tradable consumption goods and investment inputs denoted by $C^{F,\star}$ and $J^{F,\star}$, respectively:

$$\begin{aligned} X^H(t) &= C^{F,\star}(t) + J^{F,\star}(t), \\ &= \varphi \left(\frac{P^{T,\star}}{P^\star_C}\right)^{-\phi} (1-\varphi^\star_H) \left(\frac{P^H(t)}{P^\star_T}\right)^{-\rho^\star} C^\star + \iota \left(\frac{P^{T,\star}_J}{P^\star_J}\right)^{-\phi_J} (1-\iota^\star_H) \left(\frac{P^H(t)}{P^{T,\star}_J}\right)^{-\rho^\star_J} J^\star, \end{aligned}$$

where we assume that the rest of the world have similar preferences with potentially different elasticities (i..e, $\rho^\star \neq \rho$ and $\rho^\star_J \neq \rho_J$) between foreign and domestic tradable goods. To keep things simple, we assume that the rest of the world has already completed the convergence of technological change in the traded sector toward technological change in the non-traded sector so that $Z^{H,\star} = Z^{N,\star}$. Therefore foreign prices denoted with a star remain constant and thus domestic exports are decreasing in the terms of trade, $P^H(t)$.

Inserting solutions for C^H, J^H, Y^H given by (248), (267), (256), respectively, the traded goods market clearing condition (274) can be rewritten as follows:

$$Y^H\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right) = C^H\left(\bar{\lambda}, P^N, P^H\right) + G^H + J^H + X^H\left(P^H\right). \tag{276}$$

Eq. (276) can be solved for the terms of trade:

$$P^H = \Psi^H\left(K, Q, P^N, Z^H, Z^N, \bar{\lambda}\right), \tag{277}$$

with partial derivatives given by:

$$\Psi^H_K = \frac{\partial \Psi^H}{\partial K} = -\frac{\left(Y^H_K - J^H_K\right)}{\Delta^H} < 0, \tag{278a}$$

$$\Psi^H_Q = \frac{\partial \Psi^H}{\partial Q} = \frac{J^H_Q}{\Delta^H} > 0, \tag{278b}$$

$$\Psi^H_{P^N} = \frac{\partial \Psi^H}{\partial P^N} = -\frac{\left(Y^H_{P^N} - C^H_{P^N} - J^H_{P^N}\right)}{\Psi^N} > 0, \tag{278c}$$

$$\Psi^H_{Z^H} = \frac{\partial \Psi^H}{\partial Z^H} = -\frac{Y^H_{Z^H}}{\Delta^H} < 0, \tag{278d}$$

$$\Psi^H_{Z^N} = \frac{\partial \Psi^H}{\partial Z^N} = -\frac{Y^H_{Z^N}}{\Delta^H} > 0, \tag{278e}$$

where we set

$$\Delta^H = \left(Y^H_{P^H} - C^H_{P^H} - J^H_{P^H} - X^H_{P^H}\right) > 0, \tag{279}$$

where $X^H_{P^H} = \frac{\partial X^H}{\partial P^H} < 0$.

Q.5 Solving the Model

In our model, there are three state variables, namely K, Z^H, Z^N, and one control variable, Q. To solve the model, we have to express all variables in terms of state and control variables. Plugging first eq. (277) into (271) allows us to solve for the relative price of non-tradables:

$$P^N = P^N\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{280}$$

where partial derivatives (with respect to $X = K, Q, Z^H, Z^N$) are given by

$$P^N_X = \frac{\partial P^N}{\partial X} = \frac{\Psi^N_X + \Psi^N_{P^H}\Psi^H_X}{\Delta^N + \Psi^N_{P^H}\Psi^H_{P^N}}, \tag{281}$$

with $P^N_K < 0$, $P^N_Q > 0$, $P^N_{Z^H} \gtrless 0$, $P^N_{Z^N} < 0$.

Plugging first eq. (280) into (277) allows us to solve for the terms of trade:

$$P^H = P^H\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{282}$$

where partial derivatives (with respect to $X = K, Q, Z^H, Z^N$) are given by

$$P^H_X = \frac{\partial P^H}{\partial X} = \Psi^H_X + \Psi^H_{P^N} P^N_X, \tag{283}$$

with $P^H_K < 0$, $P^H_Q > 0$, $P^H_{Z^H} < 0$, $P^H_{Z^N} \lessgtr 0$.

Substituting solutions for the relative price of non-tradables (280) and the terms of trade (282) into solutions for consumption (248), sectoral output (256), the return on domestic capital (259), and the optimal investment decision (261) yields:

$$C^j = C^j\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{284a}$$

$$Y^j = Y^j\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{284b}$$

$$R = R\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{284c}$$

$$v = v\left(K, Q, Z^H, Z^N, \bar{\lambda}\right). \tag{284d}$$

Remembering that the non-traded input J^N used to produce the capital good is equal to $(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J} J$ (see eq. (234b)) with $J = I + \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K$, using the fact that $J^N = Y^N - C^N - G^N$ and inserting $I = \dot{K} + \delta_K$, the capital accumulation equation reads as follows:

$$\dot{K} = \frac{Y^N - C^N - G^N}{(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J}} - \delta_K K - \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K. \tag{285}$$

Inserting short-run solutions for non-traded output (284b) and for consumption in non-tradables (284a), substituting optimal investment decision (284d) into the physical capital accumulation equation (285), and plugging the short-run solution for the return on domestic capital (284c) into the dynamic equation for the shadow value of capital stock (225e), the dynamic system reads as follows:[42]

$$\begin{aligned}
\dot{K} \equiv \Upsilon\left(K, Q, Z^H, Z^N\right) &= \frac{Y^N\left(K, Q, Z^H, Z^N\right) - C^N\left(K, Q, Z^H, Z^N\right) - G^N}{(1-\iota)\left\{\frac{P^N(.)}{P_J[P^H(.), P^N(.)]}\right\}^{-\phi_J}} \\
&\quad -\delta_K K - \frac{K}{2\kappa}\left\{\frac{Q}{P_J\left[P^H(.), P^N(.)\right]} - 1\right\}^2, \qquad (286a) \\
\dot{Q} \equiv \Sigma\left(K, Q, Z^H, Z^N\right) &= (r^\star + \delta_K) Q - \Big[R\left(K, Q, Z^H, Z^N\right) \\
&\quad + P_J\left[P^H(.), P^N(.)\right] \frac{\kappa}{2} v(.) \left(v(.) + 2\delta_K\right)\Big], \qquad (286b)
\end{aligned}$$

where $P^N(.)$ and $P^H(.)$ are given by (280) and (282).

To facilitate the linearization, it is useful to break down the capital accumulation into two components:

$$\hat{K} = J - \delta_K K - \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K. \tag{287}$$

The first component is J. Using the fact that $J = \frac{J^N}{(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J}}$ and log-linearizing gives:

$$\hat{J} = \hat{J}^N + \phi_J \alpha_J \hat{P}^N - \phi_J \alpha_J \alpha^H_J \hat{P}^H \tag{288}$$

where we used the fact that $\hat{P}_J = \alpha_J \alpha^H_J \hat{P}^H + (1-\alpha_J)\hat{P}^N$. Using (287) and the fact that $J^N = Y^N - C^N - G^N$, linearizing (287) in the neighborhood of the steady-state gives:

$$\begin{aligned}
\dot{K} &= \frac{J}{J^N}\left[dY^N(t) - dC^N(t)\right] + \phi_J \frac{J}{P^N}\alpha_J dP^N(t) \\
&- \phi_J \frac{J}{P^H}\alpha_J \alpha^H_J dP^H(t) - \delta_K dK(t), \qquad (289)
\end{aligned}$$

where $J = I = \delta_K K$ in the long-run.

As will be useful, let us denote by Υ_K, Υ_Q, and Υ_{Z^j} the partial derivatives evaluated at the steady-state of the capital accumulation equation w.r.t. K, Q, and Z^j, respectively. Using (284) and (289), these elements of the Jacobian matrix are given by:

$$\Upsilon_K \equiv \frac{\partial \dot{K}}{\partial K} = \frac{J}{J^N}\left(Y^N_K - C^N_K\right) + \alpha_J \phi_J J\left(\frac{P^N_K}{P^N} - \alpha^H_J \frac{P^H_K}{P^H}\right) - \delta_K \gtrless 0, \tag{290a}$$

$$\Upsilon_Q \equiv \frac{\partial \dot{K}}{\partial Q} = \frac{J}{J^N}\left(Y^N_Q - C^N_Q\right) + \alpha_J \phi_J J\left(\frac{P^N_Q}{P^N} - \alpha^H_J \frac{P^H_Q}{P^H}\right) > 0, \tag{290b}$$

$$\Upsilon_{Z^j} \equiv \frac{\partial \dot{K}}{\partial Z^j} = \frac{J}{J^N}\left(Y^N_{Z^j} - C^N_{Z^j}\right) + \alpha_J \phi_J J\left(\frac{P^N_{Z^j}}{P^N} - \alpha^H_J \frac{P^H_{Z^j}}{P^H}\right), \tag{290c}$$

[42] We omit the shadow value of wealth from short-run solutions for clarity purposes as λ remains constant over time.

where $J = \delta_K K$ in the long run.

Let us denote by Σ_K, Σ_Q, and Σ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the marginal value of an additional unit of capital w.r.t. K, Q, and Z^j, respectively:

$$\Sigma_K \equiv \frac{\partial \dot{Q}}{\partial K} = -R_K - P_J \kappa v_K \delta_K > 0, \tag{291a}$$

$$\Sigma_Q \equiv \frac{\partial \dot{Q}}{\partial Q} = (r^\star + \delta_K) - P_J \kappa v_Q \delta_K = r^\star > 0, \tag{291b}$$

$$\Sigma_{Z^j} \equiv \frac{\partial \dot{Q}}{\partial Z^j} = -R_{Z^j} - P_J \kappa v_{Z^j} \delta_K. \tag{291c}$$

Assuming that the saddle-path stability condition is fulfilled, and denoting the negative eigenvalue by ν_1 and the positive eigenvalue by ν_2, the general solutions for K and Q are:

$$K(t) - \tilde{K} = D_1 e^{\nu_1 t} + D_2 e^{\nu_2 t}, \quad Q(t) - \tilde{Q} = \omega_2^1 D_1 e^{\nu_1 t} + \omega_2^2 D_2 e^{\nu_2 t}, \tag{292}$$

where K_0 is the initial capital stock and $\left(1, \omega_2^i\right)'$ is the eigenvector associated with eigenvalue ν_i:

$$\omega_2^i = \frac{\nu_i - \Upsilon_K}{\Upsilon_Q}. \tag{293}$$

Because $\nu_1 < 0$, $\Upsilon_K > 0$ and $\Upsilon_Q > 0$, we have $\omega_2^1 < 0$, regardless of sectoral capital intensities, which implies that the shadow value of investment and the stock physical capital move in opposite direction along a stable path (i.e., $D_2 = 0$).

Q.6 Current Account Equation and Intertemporal Solvency Condition

To determine the current account equation, we use the following identities and properties:

$$P_C C = P^H C^H + C^F + P^N C^N, \tag{294a}$$

$$P_J J = P^H J^H + J^F + P^N J^N, \tag{294b}$$

$$T = G = P^H G^H + G^F + P^N G^N, \tag{294c}$$

$$WL + RK = \left(W^H L^H + RK^H\right) + \left(W^N L^N + RK^N\right) = P^H Y^H + P^N Y^N, \tag{294d}$$

where (294d) follows from Euler theorem. Using (294d), inserting (294a)-(294c) into (220) and invoking market clearing conditions for non-traded goods (269) and home-produced traded goods (274) yields:

$$\begin{aligned} \dot{N} &= r^\star N + P^H \left(Y^H - C^H - G^H - J^H\right) - \left(C^F + J^F + G^F\right), \\ &= r^\star N + P^H X^H - M^F, \end{aligned} \tag{295}$$

where $X^H = Y^H - C^H - G^H - J^H$ stands for exports of home goods and we denote by M^F imports of foreign consumption and investment goods:

$$M^F = C^F + G^F + J^F. \tag{296}$$

Substituting first solutions for P^N and P^H given by (280) and (282), respectively, into (267) and (275) allows us to express the demand for input of foreign-produced traded goods, J^F, and exports of home goods, X^H:

$$J^F = J^F\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{297a}$$

$$X^H = X^H\left(K, Q, Z^H, Z^N, \bar{\lambda}\right). \tag{297b}$$

Inserting (297a)-(297b) into(295) allows us to write the current account equation as follows:

$$\begin{aligned} \dot{N} &\equiv r^\star N + \Xi\left(K, Q, Z^H, Z^N\right), \\ &= r^\star N + P^H\left(K, Q, Z^H, Z^N\right) X^H\left(K, Q, Z^H, Z^N\right) - M^F\left(K, Q, Z^H, Z^N\right). \end{aligned} \tag{298}$$

Let us denote by Ξ_K, Ξ_Q, and Ξ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the current account w.r.t. K, Q, and Z^j, respectively:

$$\Xi_K \equiv \frac{\partial \dot{N}}{\partial K} = (1 - \phi_X) X^H P_K^H - M_K^F, \tag{299a}$$

$$\Xi_Q \equiv \frac{\partial \dot{N}}{\partial Q} = (1 - \phi_X) X^H P_Q^H - M_Q^F, \tag{299b}$$

$$\Xi_{Z^j} \equiv \frac{\partial \dot{N}}{\partial Z^j} = (1 - \phi_X) X^H P_{Z^j}^H - M_{Z^j}^F. \tag{299c}$$

where we used the fact that $P^H X^H = \varphi_X \left(P^H\right)^{1-\phi_X}$ (see eq. (275)).

Linearizing (298) in the neighborhood of the steady-state, making use of (299a) and (299b), inserting solutions for $K(t)$ and $Q(t)$ given by (292) and solving yields the general solution for the net foreign asset position:

$$N(t) = \tilde{N} + \left[\left(N_0 - \tilde{N}\right) - \Psi_1 D_1 - \Psi_2 D_2\right] e^{r^\star t} + \Psi_1 D_1 e^{\nu_1 t} + \Psi_2 D_2 e^{\nu_2 t}, \tag{300}$$

where N_0 is the initial stock of traded bonds and we set

$$E_i = \Xi_K + \Xi_Q \omega_2^i, \tag{301a}$$

$$\Psi_i = \frac{E_i}{\nu_i - r^\star}. \tag{301b}$$

Invoking the transversality condition leads to the linearized version of the nations's intertemporal solvency condition:

$$\tilde{N} - N_0 = \Psi_1 \left(\tilde{K} - K_0\right), \tag{302}$$

where K_0 is the initial stock of physical capital.

Q.7 Derivation of the Accumulation Equation of Non Human Wealth

Remembering that the stock of financial wealth $A(t)$ is equal to $N(t) + Q(t)K(t)$, differentiating w.r.t. time, i.e., $\dot{A}(t) = \dot{N}(t) + \dot{Q}(t)K(t) + Q(t)\dot{K}(t)$, plugging the dynamic equation for the marginal value of capital (225e), inserting the accumulation equations for physical capital (221) and traded bonds (220), yields the accumulation equation for the stock of financial wealth or the dynamic equation for private savings:

$$\dot{A}(t) = r^\star A(t) + W(t)L(t) - T(t) - P_C(t)C(t). \tag{303}$$

where we assume that the government levies lump-sum taxes, T, to finance purchases of foreign-produced, home-produced and non-traded goods, i.e., $T = G = \left(G^F + P^H(.)G^H + P^N(.)G^N\right)$.

We first determine short-run solutions for aggregate labor supply and aggregate wage index. Inserting first short-run solutions for the relative price of non-tradables (280) and the terms of trade (282) into (238) allows us to solve for sectoral wages, $W^j = W^j\left(K, Q, Z^H, Z^N, \bar{\lambda}\right)$. Then inserting sectoral wages into (238) and (246) allows us to solve for aggregate wage, aggregate labor supply and consumption:

$$W = W\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{304a}$$

$$L = L\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{304b}$$

$$C = C\left(K, Q, Z^H, Z^N, \bar{\lambda}\right). \tag{304c}$$

Inserting short-run solutions for the relative price of non-tradables (280) and the terms of trade (282) into (238) into (226) and (294c) allows us to solve for the consumption price index and government spending:

$$G = G\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{305a}$$

$$P_C = P_C\left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{305b}$$

where partial derivatives are $G_X = P_X^H G^H + P_X^N G^N$ with $X = K, Q, Z^j$ $(j = H, N)$ and

$$\frac{\partial P_C}{\partial X} = \alpha_C \alpha^H \frac{P_C}{P^H} P_X^H + (1 - \alpha_C)\frac{P_C}{P^N} P_X^N, \tag{306}$$

with $X = K, Q, Z^j$

Inserting (304a)-(304c) into (295) allows us to write the current account equation as follows:

$$\begin{aligned}
\dot{A} &\equiv r^\star A + \Lambda\left(K, Q, Z^H, Z^N\right), \\
&= r^\star A + W\left(K, Q, Z^H, Z^N\right) L\left(K, Q, Z^H, Z^N\right) - G\left(K, Q, Z^H, Z^N\right) \\
&- P_C\left[P^H(.), P^N(.)\right] C\left(K, Q, Z^H, Z^N\right),
\end{aligned} \tag{307}$$

where P^N and P^H are given by (280) and (282), respectively.

Let us denote by Λ_K, Λ_Q, and Λ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the non human wealth w.r.t. K, Q, and Z^j, respectively:

$$\Lambda_K \equiv \frac{\partial \dot{A}}{\partial K} = \left(W_K L + W L_K\right) - G_K - \left(\frac{\partial P_C}{\partial K} C + P_C C_K\right), \tag{308a}$$

$$\Lambda_Q \equiv \frac{\partial \dot{A}}{\partial Q} = \left(W_Q L + W L_Q\right) - G_Q - \left(\frac{\partial P_C}{\partial Q} C + P_C C_Q\right), \tag{308b}$$

$$\Lambda_{Z^j} \equiv \frac{\partial \dot{A}}{\partial Z^j} = \left(W_{Z^j} L + W L_{Z^j}\right) - G_{Z^j} - \left(\frac{\partial P_C}{\partial Z^j} C + P_C C_{Z^j}\right). \tag{308c}$$

Linearizing (307) in the neighborhood of the steady-state, making use of (308a) and (308b), inserting solutions for $K(t)$ and $Q(t)$ given by (292) and solving yields the general solution for the stock of non human wealth:

$$A(t) = \tilde{A} + \left[\left(A_0 - \tilde{A}\right) - \Delta_1 D_1 - \Delta_2 D_2\right] e^{r^\star t} + \Delta_1 D_1 e^{\nu_1 t} + \Delta_2 D_2 e^{\nu_2 t}, \tag{309}$$

where A_0 is the initial stock of financial wealth and we set

$$M_i = A_K + A_Q \omega_2^i, \tag{310a}$$

$$\Delta_i = \frac{M_i}{\nu_i - r^\star}. \tag{310b}$$

The linearized version of the representative household's intertemporal solvency condition is:

$$\tilde{A} - A_0 = \Delta_1 \left(\tilde{K} - K_0\right), \tag{311}$$

where A_0 is the initial stock of non human wealth.

Q.8 The Steady-State

Below, we characterize the whole steady-state and use tilde to denote long-run values. Setting $\dot{N} = \dot{K} = \dot{Q} = 0$ into (220), (221) and (225e), and inserting short-run static solutions for k^N, Y^N and Y^H, C^j derived above, the steady-state can be summarized by four equations:

$$Z^H\left(1-\theta^H\right)\left[k^H\left(\tilde{K}, \tilde{P}^H, \tilde{P}^N, Z^H, Z^N, \bar{\lambda}\right)\right]^{-\theta^H} = P_J\left(\tilde{P}^H, \tilde{P}^N\right)\left(r^\star + \delta_K\right), \tag{312a}$$

$$Y^N\left(\tilde{K}, \tilde{P}^H, \tilde{P}^N, Z^H, Z^N, \bar{\lambda}\right) = C^N\left(\tilde{P}^H, \tilde{P}^N, \bar{\lambda}\right) + \left(1-\alpha_J\right) P_J\left(\tilde{P}^H, \tilde{P}^N\right)\delta_K \tilde{K} + G^N, \tag{312b}$$

$$Y^H\left(\tilde{K}, \tilde{P}^H, \tilde{P}^N, Z^H, Z^N, \bar{\lambda}\right) = C^H\left(\tilde{K}, \tilde{Q}, Z^H, Z^N \bar{\lambda}\right) + \alpha_J \alpha_J^H P_J\left(\tilde{P}^H, \tilde{P}^N\right)\delta_K \tilde{K} + G^H + X^H\left(\tilde{P}^H\right), \tag{312c}$$

$$r^\star \tilde{N} + \tilde{P}^H X^H\left(\tilde{P}^H\right) - M^F\left(\tilde{K}, \tilde{P}^H, \tilde{P}^N, \bar{\lambda}\right) \tag{312d}$$

$$\tilde{N} - N_0 = \Psi_1\left(\tilde{K} - K_0\right). \tag{312e}$$

These five equations jointly determine $\tilde{P}^N$, $\tilde{P}^H$, $\tilde{K}$, $\tilde{N}$ and $\bar{\lambda}$.

R Solving for Permanent Technology Shocks

In this section, we provide the main steps for the derivation of formal solutions following a permanent technology shock biased toward the traded sector.

R.1 Sectoral Technology Shocks

In line with our empirical findings, we assume that total factor productivity in sector j, $Z^j(t)$, evolves according to the following dynamic equation:

$$Z^j(t) = \tilde{Z}^j + z^j e^{-\xi^j t} \tag{313}$$

where $\tilde{Z}^j$ and $\tilde{Z}^j_0$ are the new and initial steady-state values of TFP in sector j; $z^j = \tilde{Z}^j_0 \bar{z}^j$ is a parameter whose significance will be detailed below; ξ^j is a positive parameter which governs the speed at which sector j' TFP converges toward its new long-run level. To be consistent with our VAR specification, we express (313) in percentage deviation from initial steady-state:

$$\begin{aligned}\hat{Z}^j(t) &= \frac{Z^j(t) - \tilde{Z}^j_0}{\tilde{Z}^j_0}, \\ &= \hat{\tilde{Z}}^j + \bar{z}^j e^{-\xi^j t}, \end{aligned} \tag{314}$$

where $\hat{\tilde{Z}}^j$ is the percentage deviation of sector j' TFP relative to its initial value:

$$\hat{\tilde{Z}}^j = \frac{\tilde{Z}^j_1 - \tilde{Z}^j_0}{\tilde{Z}^j_0}. \tag{315}$$

Setting $t = 0$ into (314) yields:

$$\hat{Z}^j(0) = \hat{\tilde{Z}}^j + \bar{z}^j. \tag{316}$$

Since our VAR evidence indicates that TFP in both sectors rise initially and increase monotonically toward their long-run levels, the parameter $\bar{z}^j$ will take negative values as Z^j undershoots its state-state value on impact. Differentiating (313) with respect to time leads to:

$$\begin{aligned}\dot{Z}^j(t) &= -\xi^j z^j e^{-\xi^j t}, \\ &= -\xi^j \left(Z^j(t) - \tilde{Z}^j\right),\end{aligned} \tag{317}$$

where ξ^j measures the speed at which Z^j closes the gap with its long-run level.

As shown in section E, the 'true' measure of the technology bias toward tradables is given by $\frac{(Z^H(t))^a}{(Z^H(t))^b}$. In the quantitative analysis, we consider permanent changes in sectoral TFP, $\tilde{Z}^j$, so that the labor share-adjusted TFP differential is 1% in the long run:

$$a\hat{\tilde{Z}}^H - b\hat{\tilde{Z}}^N = 1\%. \tag{318}$$

R.2 Formal Solutions for $K(t)$ and $Q(t)$

Using (286a), (286b), and (317), the adjustment of the open economy towards the steady-state is described by a dynamic system which comprises four equations:

$$\dot{K} = \Upsilon\left(K(t), Q(t), Z^H(t), Z^N(t)\right), \tag{319a}$$
$$\dot{Q} = \Sigma\left(K(t), Q(t), Z^H(t), Z^N(t)\right), \tag{319b}$$
$$\dot{Z}^H(t) = -\xi^H\left(Z^H(t) - \tilde{Z}^H\right), \tag{319c}$$
$$\dot{Z}^N(t) = -\xi^N\left(Z^N(t) - \tilde{Z}^N\right). \tag{319d}$$

The linearized system can be written in a matrix form:

$$\begin{pmatrix} \dot{K}(t) \\ \dot{Q}(t) \\ \dot{Z}^H(t) \\ \dot{Z}^N(t) \end{pmatrix} = \begin{pmatrix} \Upsilon_K & \Upsilon_Q & \Upsilon_{Z^H} & \Upsilon_{Z^N} \\ \Sigma_K & \Sigma_Q & \Sigma_{Z^H} & \Sigma_{Z^N} \\ 0 & 0 & -\xi^H & 0 \\ 0 & 0 & 0 & -\xi^N \end{pmatrix} \begin{pmatrix} K(t) - \tilde{K} \\ Q(t) - \tilde{Q} \\ Z^H(t) - \tilde{Z}^H \\ Z^N(t) - \tilde{Z}^N \end{pmatrix} \tag{320}$$

where the coefficients of the Jacobian matrix, Υ_X and Σ_X with $X = K, Q, Z^H, Z^N$, are given by (290) and (291).

Denoting by ν_i the eigenvalue (with $i = 1, 2, 3, 4$), the characteristic polynomial is:

$$\left(\xi^N + \nu_i\right)\left(\xi^H + \nu_i\right)\left[(\nu_i)^2 - \nu_i\left(\Upsilon_K + \Sigma_K\right) - \left(\Upsilon_Q\Sigma_K + \Upsilon_K\Sigma_Q\right)\right] = 0, \tag{321}$$

where $\Upsilon_K + \Sigma_K = r^\star$. The characteristic polynomial has three negative roots and one postive root:

$$\nu_4 = -\xi^N < \nu_3 = -\xi^H < \nu_1 < 0 < r^\star < \nu_2, \tag{322}$$

where inequality $\xi^N > \xi^H$ follows from the calibration.

We denote by ω^i_j the jth element of eigenvector ω^i related to eigenvalue ν_i, calculated as $(\nu_i I_{4\times 4} - J)\,\omega^i = 0$ (where J is the Jacobian matrix given by (320)). The general solution that characterize the adjustment toward the new steady-state can be written as follows:

$$K(t) - \tilde{K} = \sum_{i=1}^{4} \omega^i_1 D_i e^{\nu_i t}, \tag{323a}$$
$$Q(t) - \tilde{Q} = \sum_{i=1}^{4} \omega^i_2 D_i e^{\nu_i t}, \tag{323b}$$
$$Z^H(t) - \tilde{Z}^H = D_3 e^{\nu_3 t}, \tag{323c}$$
$$Z^N(t) - \tilde{Z}^N = D_4 e^{\nu_4 t}, \tag{323d}$$

where we normalized ω^1_1, ω^2_1, ω^3_3, and ω^4_4 to 1. To allow the dynamic system to converge toward the new long-run equilibrium, we eliminate explosive paths and set $D_2 = 0$. D_i is an arbitrary constant which is determined by initial conditions:

$$K(0) - \tilde{K} = D_1 + \omega^3_1 D_3 + \omega^4_1 D_4, \tag{324a}$$
$$Z^H(0) - \tilde{Z}^H = D_3 = z^H, \tag{324b}$$
$$Z^N(0) - \tilde{Z}^N = D_4 = z^N, \tag{324c}$$

where $K(0) = K_0$ is the initial capital stock, $Z^H(0) = \tilde{Z}_0^H$ and $Z^N(0) = \tilde{Z}_0^N$ are initial sectoral TFP; setting $t = 0$ into (313) and using (324a), we thus have

$$D_1 = K_0 - \tilde{K} - \omega_1^3 z^H - \omega_1^4 z^N, \tag{325a}$$
$$D_3 = z^H, \tag{325b}$$
$$D_4 = z^N. \tag{325c}$$

R.3 Formal Solution for the Net Foreign Asset Position, $N(t)$

To determine the formal solution for the net foreign asset position, we first linearize the current account equation (298) in the neighborhood of the steady-state

$$\dot{N}(t) = r^\star \left(N(t) - \tilde{N}\right) + \sum_X \Xi_X \left(X(t) - \tilde{X}\right), \tag{326}$$

where $X = K, Q, Z^H, Z^N$, and substitute the solutions for $K(t)$ and $Q(t)$ along with dynamic equations of sectoral TFP described by (323), remembering that $D_2 = 0$:

$$\dot{N}(t) = r^\star \left(N(t) - \tilde{N}\right) + \sum_{i=1,3,4} E_i D_i e^{\nu_i t}, \tag{327}$$

where

$$E_1 = \Xi_K + \Xi_Q \omega_2^1, \tag{328a}$$
$$E_3 = \Xi_K \omega_1^3 + \Xi_Q \omega_2^3 + \Xi_{Z^H}, \tag{328b}$$
$$E_4 = \Xi_K \omega_1^4 + \Xi_Q \omega_2^4 + \Xi_{Z^N}. \tag{328c}$$

Solving the differential equation (328) for $N(t)$ yields the general solution for the net foreign asset position:

$$N(t) - \tilde{N} = \left[\left(N_0 - \tilde{N}\right) + \sum_{i=1,3,4} \Phi_N^i\right] e^{r^\star t} - \sum_{i=1,3,4} \Phi_N^i e^{\nu_i t}. \tag{329}$$

where we set $\Phi_N^i = \frac{E_i D_i}{r^\star - \nu_i}$.

Invoking the transversality condition, one obtains the 'stable' solution for the stock of net foreign assets so that $N(t)$ converges toward its steady-state value $\tilde{N}$:

$$N(t) - \tilde{N} = \sum_{i=1,3,4} \Phi_N^i e^{\nu_i t}, \tag{330}$$

Eq. (330) gives the trajectory for $N(t)$ consistent with the intertemporal solvency condition:

$$\tilde{N} - N_0 = \sum_{i=1,3,4} \Phi_N^i. \tag{331}$$

Differentiating (330) w.r.t. time gives the trajectory for the current account along the transitional path when sectoral TFP follows the temporal path given by eq. (317):

$$\dot{N}(t) = \nu_i \sum_{i=1,3,4} \Phi_N^i e^{\nu_i t}. \tag{332}$$

R.4 Formal Solution for the Stock of Non Human Wealth, $A(t)$

To determine the formal solution for the stock of non human wealth, we first linearize the current account equation (307) in the neighborhood of the steady-state

$$\dot{A}(t) = r^\star \left(A(t) - \tilde{A}\right) + \sum_X \Lambda_X \left(X(t) - \tilde{X}\right), \tag{333}$$

where $X = K, Q, Z^H, Z^N$, and substitute the solutions for $K(t)$ and $Q(t)$ along with dynamic equations of sectoral TFP described by (323), remembering that $D_2 = 0$:

$$\dot{A}(t) = r^\star \left(A(t) - \tilde{A}\right) + \sum_{i=1,3,4} M_i D_i e^{\nu_i t}, \tag{334}$$

where

$$M_1 = \Lambda_K + \Lambda_Q \omega_2^1, \tag{335a}$$

$$M_3 = \Lambda_K \omega_1^3 + \Lambda_Q \omega_2^3 + \Lambda_{Z^H}, \tag{335b}$$

$$M_4 = \Lambda_K \omega_1^4 + \Lambda_Q \omega_2^4 + \Lambda_{Z^N}. \tag{335c}$$

Solving the differential equation (334) for $A(t)$ yields the general solution for the stock of non human wealth:

$$A(t) - \tilde{A} = \left[\left(A_0 - \tilde{A} \right) + \sum_{i=1,3,4} \Phi_A^i \right] e^{r^\star t} - \sum_{i=1,3,4} \Phi_A^i e^{\nu_i t}. \tag{336}$$

where we set $\Phi_A^i = \frac{M_i D_i}{r^\star - \nu_i}$.

Invoking the transversality condition, one obtains the 'stable' solution for the stock of non human wealth so that $A(t)$ converges toward its steady-state value $\tilde{A}$:

$$A(t) - \tilde{A} = \sum_{i=1,3,4} \Phi_A^i e^{\nu_i t}, \tag{337}$$

Eq. (337) gives the trajectory for $A(t)$ consistent with the intertemporal solvency condition:

$$\tilde{A} - A_0 = \sum_{i=1,3,4} \Phi_A^i. \tag{338}$$

Differentiating (338) w.r.t. time gives the trajectory for private savings (equal to national savings as we abstract from public debet) along the transitional path when sectoral TFP follows the temporal path given by eq. (317):

$$\dot{A}(t) = \nu_i \sum_{i=1,3,4} \Phi_A^i e^{\nu_i t}. \tag{339}$$

R.5 Formal Solution for $Q(t)K(t)$

To determine the dynamics of investment, we first derive the formal solution for the shadow value of the capital stock, $Q(t)K(t)$. We thus linearize $Q(t)K(t)$ in the neighborhood of the steady-state:

$$Q(t)K(t) - P_J \tilde{K} = P_J \left(K(t) - \tilde{K} \right) + \tilde{K} \left(Q(t) - \tilde{K} \right), \tag{340}$$

where we used the fact that $\tilde{Q} = P_J$ in the long-run. Substitute the solutions for $K(t)$ and $Q(t)$ along with dynamic equations of sectoral TFP described by (323), remembering that $D_2 = 0$:

$$Q(t)K(t) - P_J \tilde{K} = \sum_{i=1,3,4} S_i D_i e^{\nu_i t}, \tag{341}$$

where $S_1 = P_J \omega_1^i + \tilde{K} \omega_2^i$. Totally differentiating (341) w.r.t. time gives the trajectory for private investment along the transitional path when sectoral TFP follows the temporal path given by eq. (317):

$$Q(t)\dot{K}(t) = \nu_i \sum_{i=1,3,4} S_i D_i e^{\nu_i t}. \tag{342}$$

Since $N(t) = A(t) - Q(t)K(t)$, we thus have:

$$\dot{N}(t) = \dot{A}(t) - Q(t)\dot{K}(t); \tag{343}$$

where expressions for the current account, national savings and private investment are given by (332), (339), and (342), respectively.

S Semi-Small Open Economy Model with CES Production Functions

This section extends the model laid out in section Q to CES production functions and factor biased technological change. Since first order conditions from households' maximization problem detailed in subsection Q.1 remain identical, we do not repeat them and emphasize the main changes caused by the assumption of CES production functions.

S.1 Firms

Both the traded and non-traded sectors use physical capital, K^j, and labor, L^j, according to constant returns to scale production functions which are assumed to take a CES form:

$$Y^j = \left[\gamma^j \left(A^j L^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j K^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{344}$$

where γ^j and $1-\gamma^j$ are the weight of labor and capital in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, A^j and B^j are labor- and capital-augmenting efficiency. Both sectors face two cost components: a capital rental cost equal to R, and a labor cost equal to the wage rate, i.e., W^H in the traded sector and W^N in the non-traded sector.

First-Order Conditions

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{K^j,L^j} \Pi^j = \max_{K^j,L^j} \left\{P^j Y^j - W^j L^j - RK^j\right\}. \tag{345}$$

Since capital can move freely between the two sectors, the value of marginal products in the traded and non-traded sectors equalizes while costly labor mobility implies a wage differential across sectors:

$$P^H\left(1-\gamma^H\right)\left(B^H\right)^{\frac{\sigma^H-1}{\sigma^H}}\left(k^H\right)^{-\frac{1}{\sigma^H}}\left(y^H\right)^{\frac{1}{\sigma^H}} = P^N\left(1-\gamma^N\right)\left(B^N\right)^{\frac{\sigma^N-1}{\sigma^N}}\left(k^N\right)^{-\frac{1}{\sigma^N}}\left(y^N\right)^{\frac{1}{\sigma^N}} \equiv R, \tag{346a}$$

$$P^H\gamma^H\left(A^H\right)^{\frac{\sigma^H-1}{\sigma^H}}\left(L^H\right)^{-\frac{1}{\sigma^H}}\left(Y^H\right)^{\frac{1}{\sigma^H}} \equiv W^H, \tag{346b}$$

$$P^N\gamma^N\left(A^N\right)^{\frac{\sigma^N-1}{\sigma^N}}\left(L^N\right)^{-\frac{1}{\sigma^N}}\left(Y^N\right)^{\frac{1}{\sigma^N}} \equiv W^N, \tag{346c}$$

where we denote by $k^j \equiv K^j/L^j$ the capital-labor ratio for sector $j = H, N$, and $y^j \equiv Y^j/L^j$ value added per hours worked described by

$$y^j = \left[\gamma^j\left(A^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j k^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}. \tag{347}$$

The resource constraint for capital is:

$$K^H + K^N = K. \tag{348}$$

Some Useful Results

Multiplying both sides of (346b)-(346c) by L^j and dividing by sectoral value added leads to the labor income share:

$$s_L^j = \gamma^j\left(\frac{A^j}{y^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}. \tag{349}$$

Multiplying both sides of (346a) by K^j and dividing by sectoral value added leads to the capital income share:

$$1 - s_L^j = \left(1-\gamma^j\right)\left(\frac{B^j k^j}{y^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}. \tag{350}$$

Dividing eq. (349) by eq. (350), the ratio of the labor to the capital income share denoted by $S^j = \frac{s_L^j}{1-s_L^j}$ reads as follows:

$$S^j = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j K^j}{A^j L^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{351}$$

Dividing (346b)-(346c) by (346a) leads to a positive relationship between the relative cost of labor and the capital-labor ratio in sector j:

$$\frac{W^j}{R} = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j}{A^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}\left(\frac{K^j}{L^j}\right)^{\frac{1}{\sigma^j}}. \tag{352}$$

To determine the conditional demands for both inputs, we make use of (352) which leads to:

$$L^j = K^j\left(\frac{\gamma^j}{1-\gamma^j}\right)^{\sigma^j}\left(\frac{B^j}{A^j}\right)^{1-\sigma^j}\left(\frac{W^j}{R}\right)^{-\sigma^j}, \tag{353a}$$

$$K^j = L^j\left(\frac{1-\gamma^j}{\gamma^j}\right)^{\sigma^j}\left(\frac{B^j}{A^j}\right)^{\sigma^j-1}\left(\frac{W^j}{R}\right)^{\sigma^j}. \tag{353b}$$

Inserting eq. (353b) (eq. (353a) resp.) in the CES production function and solving for L^j (K^j resp.) leads to the conditional demand for labor (capital resp.):

$$L^j = Y^j \left(A^j\right)^{\sigma^j - 1} \left(\frac{\gamma^j}{W^j}\right)^{\sigma} \left(X^j\right)^{\frac{\sigma^j}{1-\sigma^j}}, \quad K^j = Y^j \left(B^j\right)^{\sigma^j - 1} \left(\frac{1-\gamma^j}{R}\right)^{\sigma^j} \left(X^j\right)^{\frac{\sigma^j}{1-\sigma^j}}, \tag{354}$$

where X^j is given by:

$$X^j = \left(\gamma^j\right)^{\sigma^j} \left(A^j\right)^{\sigma^j-1} \left(W^j\right)^{1-\sigma^j} + \left(1-\gamma^j\right)^{\sigma^j} \left(B^j\right)^{\sigma^j-1} R^{1-\sigma^j}. \tag{355}$$

Total cost is equal to the sum of the labor and capital cost:

$$C^j = W^j L^j + R K^j. \tag{356}$$

Inserting conditional demand for inputs (353) into total cost (356), we find C^j is homogenous of degree one with respect to the level of production

$$C^j = c^j Y^j, \quad \text{with} \quad c^j = \left(X^j\right)^{\frac{1}{1-\sigma^j}}. \tag{357}$$

Using the fact that $\left(c^j\right)^{1-\sigma^j} = X^j$, conditional demand for labor (353a) can be rewritten as $L^j = Y^j \left(A^j\right)^{\sigma^j-1} \left(\frac{\gamma^j}{W^j}\right) \left(c^j\right)^{\sigma^j}$ which gives the labor share denoted by s_L^j:

$$s_L^j = \frac{W^j L^j}{P^j Y^j} = \left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j}{A^j}\right)^{1-\sigma^j} \left(c^j\right)^{\sigma^j-1}, \tag{358a}$$

$$1 - s_L^j = \frac{R K^j}{P^j Y^j} = \left(1-\gamma^j\right)^{\sigma^j} \left(\frac{R}{B^j}\right)^{1-\sigma^j} \left(c^j\right)^{\sigma^j-1}. \tag{358b}$$

S.2 Short-Run Solutions

Sectoral Wages and Capital-Labor Ratios

Plugging the short-run solutions for L^H and L^N given by (250) into the resource constraint for capital (348), the system of four equations consisting of (346a)-(346c) together with (348) can be solved for sectoral wages W^j and sectoral capital-labor ratios k^j. Log-differentiating (346a)-(346c) together with (348) yields in matrix form:

$$\begin{pmatrix} -\left(\frac{s_L^H}{\sigma^H}\right) & \left(\frac{s_L^N}{\sigma^N}\right) & 0 & 0 \\ \left(\frac{1-s_L^H}{\sigma^H}\right) & 0 & -1 & 0 \\ 0 & \left(\frac{1-s_L^N}{\sigma^N}\right) & 0 & -1 \\ \frac{K^H}{K} & \frac{K^N}{K} & \Psi_{W^H} & \Psi_{W^N} \end{pmatrix} \begin{pmatrix} \hat{k}^H \\ \hat{k}^N \\ \hat{W}^H \\ \hat{W}^N \end{pmatrix}$$
$$= \begin{pmatrix} \hat{P}^N - \hat{P}^H - \left(\frac{\sigma^H - s_L^H}{\sigma^H}\right)\hat{B}^H + \left(\frac{\sigma^N - s_L^N}{\sigma^N}\right)\hat{B}^N - \left(\frac{s_L^H}{\sigma^H}\right)\hat{A}^H + \left(\frac{s_L^N}{\sigma^N}\right)\hat{A}^N \\ -\hat{P}^H - \left[\frac{\left(\sigma^H-1\right)+s_L^H}{\sigma^H}\right]\hat{A}^H - \left(\frac{1-s_L^H}{\sigma^H}\right)\hat{B}^H \\ -\hat{P}^N - \left[\frac{\left(\sigma^N-1\right)+s_L^N}{\sigma^N}\right]\hat{A}^N - \left(\frac{1-s_L^N}{\sigma^N}\right)\hat{B}^N \\ \hat{K} - \Psi_{\bar{\lambda}}\hat{\bar{\lambda}} \end{pmatrix}, \tag{359}$$

where we set:

$$\Psi_{W^j} = \frac{K^H}{K}\frac{L^H_{W^j} W^j}{L^H} + \frac{K^N}{K}\frac{L^N_{W^j} W^j}{L^N}, \tag{360a}$$

$$\Psi_{\bar{\lambda}} = \frac{K^H}{K}\sigma_L + \frac{K^N}{K}\sigma_L = \sigma_L. \tag{360b}$$

The short-run solutions for sectoral wages and capital-labor ratios are:

$$W^j = W^j\left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right), \quad k^j = k^j\left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right). \tag{361}$$

Inserting first sectoral wages (361), sectoral hours worked (358a) can be solved as functions of the shadow value of wealth, the capital stock, the price of non-traded goods in terms of foreign goods, P^N, and the terms of trade:

$$L^j = L^j\left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right). \tag{362}$$

Totally differentiating output per hours worked (347) leads to:

$$\hat{y}^j = s_L^j \hat{A}^j + \left(1 - s_L^j\right) \hat{B}^j + \left(1 - s_L^j\right) \hat{k}^j, \tag{363}$$

where s_L^j and $1 - s_L^j$ are the labor and capital income share, respectively, described by eqs. (349)-(350). Plugging solutions for sectoral capital-labor ratios (361) into (363) allows us to solve for sectoral value added per hours worked:

$$y^j = y^j \left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right), \tag{364}$$

Using the fact that $Y^j = y^j L^j$, differentiating, inserting (364) and solutions for sectoral labor (362) and sectoral capital-labor ratios (361), one obtains the solutions for sectoral value added:

$$Y^j = Y^j \left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right). \tag{365}$$

The Return on Domestic Capital, R

The return on domestic capital is:

$$R = P^N \left(1 - \gamma^N\right) \left(B^N\right)^{\frac{\sigma^N - 1}{\sigma^N}} \left(k^N\right)^{-\frac{1}{\sigma^N}} \left(y^N\right)^{\frac{1}{\sigma^N}}. \tag{366}$$

Differentiating (366) and making use of (363) leads to:

$$\hat{R} = \hat{P}^N - \frac{s_L^N}{\sigma^N} \hat{k}^N + \frac{s_L^N}{\sigma^N} \hat{A}^N + \left(\frac{\sigma^N - s_L^N}{\sigma^N}\right) \hat{B}^N. \tag{367}$$

Inserting the short-run static solution for the capital-labor ratio k^N given by (361), eq. (366) can be solved for the return on domestic capital:

$$R = R\left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right). \tag{368}$$

Market Clearing Condition for Non-Tradables

The role of the price of non-tradables in terms of foreign goods is to clear the non-traded goods market:

$$Y^N = C^N + G^N + J^N. \tag{369}$$

Inserting solutions for C^N, J^N, Y^N given by (248), (265), (365), respectively, the non-traded goods market clearing condition (369) can be rewritten as follows:

$$Y^N\left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right) = C^N\left(\bar{\lambda}, P^N, P^H\right) + G^N + J^N\left(K, Q, P^N, P^H\right). \tag{370}$$

Eq. (370) can be solved for the relative price of non-tradables:

$$P^N = \Psi^N\left(K, Q, P^H, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \tag{371}$$

with partial derivatives given by:

$$\Psi_K^N = \frac{\partial \Psi^N}{\partial K} = -\frac{\left(Y_K^N - J_K^N\right)}{\Delta^N} < 0, \tag{372a}$$

$$\Psi_Q^N = \frac{\partial \Psi^N}{\partial Q} = \frac{J_Q^N}{\Delta^N} > 0, \tag{372b}$$

$$\Psi_{P^H}^N = \frac{\partial \Psi^N}{\partial P^H} = -\frac{\left(Y_{P^H}^N - C_{P^H}^N - J_{P^H}^N\right)}{\Delta^N} > 0, \tag{372c}$$

$$\Psi_{Z^H}^N = \frac{\partial \Psi^N}{\partial A^j} = -\frac{Y_{A^j}^N}{\Delta^N} > 0, \tag{372d}$$

$$\Psi_{Z^N}^N = \frac{\partial \Psi^N}{\partial B^j} = -\frac{Y_{B^j}^N}{\Delta^N} < 0, \tag{372e}$$

where we set

$$\Delta^N = \left(Y_{P^N}^N - C_{P^N}^N - J_{P^N}^N\right) > 0. \tag{373}$$

Market Clearing Condition for Home-Produced Traded Goods

The role of the price of home-produced traded goods in terms of foreign-produced goods or the terms of trade is to clear the home-produced traded goods market:

$$Y^H = C^H + G^H + J^H + X^H, \tag{374}$$

where X^H stands for exports which are negatively related to the terms of trade:

$$X^H = \varphi_X \left(P^H\right)^{-\phi_X}, \tag{375}$$

where ϕ_X is the elasticity of exports with respect to the terms of trade.

Inserting solutions for C^H, J^H, Y^H given by (248), (265), (365), respectively, the traded goods market clearing condition (374) can be rewritten as follows:

$$Y^H\left(\bar{\lambda}, K, P^N, P^H, A^H, A^N, B^H, B^N\right) = C^H\left(\bar{\lambda}, P^N, P^H\right) + G^H + J^H\left(K, Q, P^N, P^H\right) + X^H\left(P^H\right). \tag{376}$$

Eq. (376) can be solved for the terms of trade:

$$P^H = \Psi^H\left(K, Q, P^N, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \tag{377}$$

with partial derivatives given by:

$$\Psi^H_K = \frac{\partial \Psi^H}{\partial K} = -\frac{\left(Y^H_K - J^H_K\right)}{\Delta^H} < 0, \tag{378a}$$

$$\Psi^H_Q = \frac{\partial \Psi^H}{\partial Q} = \frac{J^H_Q}{\Delta^H} > 0, \tag{378b}$$

$$\Psi^N_{P^H} = \frac{\partial \Psi^H}{\partial P^N} = -\frac{\left(Y^H_{P^N} - C^H_{P^N} - J^H_{P^N}\right)}{\Psi^N} > 0, \tag{378c}$$

$$\Psi^H_{A^j} = \frac{\partial \Psi^H}{\partial A^j} = -\frac{Y^H_{A^j}}{\Delta^H} < 0, \tag{378d}$$

$$\Psi^H_{B^j} = \frac{\partial \Psi^H}{\partial B^j} = -\frac{Y^H_{B^j}}{\Delta^H} > 0, \tag{378e}$$

where we set

$$\Delta^H = \left(Y^H_{P^H} - C^H_{P^H} - J^H_{P^H} - X^H_{P^H}\right) > 0, \tag{379}$$

where $X^H_{P^H} = \frac{\partial X^H}{\partial P^H} < 0$.

S.3 Solving the Model

In our model, there are five state variables, namely K, A^H, A^N, B^H, B^N, and one control variable, Q. To solve the model, we have to express all variables in terms of state and control variables. Plugging first eq. (377) into (371) allows us to solve for the relative price of non-tradables:

$$P^N = P^N\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \tag{380}$$

where partial derivatives (with respect to $X = K, Q, Z^H, Z^N$) are given by

$$P^N_X = \frac{\partial P^N}{\partial X} = \frac{\Psi^N_X + \Psi^N_{P^H}\Psi^H_X}{\Delta^N + \Psi^N_{P^H}\Psi^H_{P^N}}, \tag{381}$$

with $P^N_K < 0$, $P^N_Q > 0$, $P^N_{Z^H} \gtrless 0$, $P^N_{Z^N} < 0$.

Plugging first eq. (380) into (377) allows us to solve for the terms of trade:

$$P^H = P^H\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \tag{382}$$

where partial derivatives (with respect to $X = K, Q, Z^H, Z^N$) are given by

$$P^H_X = \frac{\partial P^H}{\partial X} = \Psi^H_X + \Psi^H_{P^N} P^N_X, \tag{383}$$

with $P^H_K < 0$, $P^H_Q > 0$, $P^H_{A^H} < 0$, $P^H_{B^H} < 0$ $P^H_{A^N} \lesseqgtr 0$, $P^H_{B^N} \lesseqgtr 0$.

Substituting solutions for the relative price of non-tradables (380) and the terms of trade (382) into solutions for consumption (248), sectoral value added (365), the return on domestic capital (368), and the optimal investment decision (261) yields:

$$C^j = C^j\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \tag{384a}$$

$$Y^j = Y^j\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \tag{384b}$$

$$R = R\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \tag{384c}$$

$$v = v\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right). \tag{384d}$$

Remembering that the non-traded input J^N used to produce the capital good is equal to $(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J} J$ (see eq. (234b)) with $J = I + \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K$, using the fact that $J^N = Y^N - C^N - G^N$ and inserting $I = \dot{K} + \delta_K$, the capital accumulation equation reads as follows:

$$\dot{K} = \frac{Y^N - C^N - G^N}{(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J}} - \delta_K K - \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K. \tag{385}$$

Inserting short-run solutions for non-traded output (384b) and for consumption in non-tradables (384a), substituting optimal investment decision (384d) into the physical capital accumulation equation (385), and plugging the short-run solution for the return on domestic capital (384c) into the dynamic equation for the shadow value of capital stock (225e), the dynamic system reads as follows:[43]

$$\begin{aligned}
\dot{K} \equiv \Upsilon\left(K, Q, A^H, A^N, B^H, B^N\right) &= \frac{Y^N\left(K, Q, A^H, A^N, B^H, B^N\right) - C^N\left(K, Q, A^H, A^N, B^H, B^N\right) - G^N}{(1-\iota)\left\{\frac{P^N(.)}{P_J[P^H(.),P^N(.)]}\right\}^{-\phi_J}} \\
&\quad -\delta_K K - \frac{K}{2\kappa}\left\{\frac{Q}{P_J\left[P^H(.), P^N(.)\right]} - 1\right\}^2, \qquad (386a) \\
\dot{Q} \equiv \Sigma\left(K, Q, A^H, A^N, B^H, B^N\right) &= \left(r^\star + \delta_K\right) Q - \Big[R\left(K, Q, A^H, A^N, B^H, B^N\right) \\
&\quad + P_J\left[P^H(.), P^N(.)\right] \frac{\kappa}{2} v(.)\left(v(.) 2\delta_K\right)\Big], \qquad (386b)
\end{aligned}$$

where $P^N(.)$ and $P^H(.)$ are given by (380) and (382).

S.4 Current Account Equation and Intertemporal Solvency Condition

Following the same steps as in subsection Q.6, the current account reads as:

$$\dot{N} = r^\star N + P^H X^H - M^F, \qquad (387)$$

where $X^H = Y^H - C^H - G^H - J^H$ stands for exports of home goods and we denote by M^F imports of foreign consumption and investment goods:

$$M^F = C^F + G^F + J^F. \qquad (388)$$

Substituting first solutions for P^N and P^H given by (380) and (382), respectively, into (267) and (375) allows us to express the demand for input of foreign-produced traded goods, J^F, and exports of home goods, X^H:

$$J^F = J^F\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right), \qquad (389a)$$

$$X^H = X^H\left(K, Q, A^H, A^N, B^H, B^N, \bar{\lambda}\right). \qquad (389b)$$

Inserting (389a)-(389b) into(387) allows us to write the current account equation as follows:

$$\begin{aligned}
\dot{N} &\equiv r^\star N + \Xi\left(K, Q, A^H, A^N, B^H, B^N\right), \\
&= r^\star N + P^H\left(K, Q, A^H, A^N, B^H, B^N\right) X^H\left(K, Q, A^H, A^N, B^H, B^N\right) \\
&\quad - M^F\left(K, Q, A^H, A^N, B^H, B^N\right). \qquad (390)
\end{aligned}$$

S.5 Dynamics of Factor-Augmenting Efficiency

We further specify a dynamic adjustment for $\hat{A}^j(t)$ and $\hat{B}^j(t)$ similar to that described by eq. (314), i.e.,

$$A^j(t) = \tilde{A}^j + a^j e^{-\xi^j t}, \qquad (391a)$$

$$B^j(t) = \tilde{B}^j + b^j e^{-\xi^j t}, \qquad (391b)$$

where a^j (b^j) will take negative values as A^j (B^j) undershoots its state-state value on impact., parameter ξ^j measures the speed at which A^j and B^j close the gap with its respective long-run level; we assume that the speed of adjustment ξ^j corresponds to the speed of adjustment of sectoral TFP, Z^j; since the paths of factor biased technological change are expressed in percentage deviation relative to initial steady-state, we have:

$$\hat{A}^j = \frac{\tilde{A}^j - \tilde{A}^j_0}{\tilde{A}^j_0}, \qquad \hat{B}^j = \frac{\tilde{B}^j - \tilde{B}^j_0}{\tilde{B}^j_0}, \qquad (392a)$$

$$\hat{A}^j(t) = \frac{A^j(t) - \tilde{A}^j_0}{\tilde{A}^j_0}, \qquad \hat{B}^j(t) = \frac{B^j(t) - \tilde{B}^j_0}{\tilde{B}^j_0}, \qquad (392b)$$

where $\tilde{A}^j$ and $\tilde{B}^j$ are the final steady-state levels of labor and capital efficiency.

[43] We omit the shadow value of wealth from short-run solutions for clarity purposes as λ remains constant over time.

In percentage deviation relative to initial steady-state, the adjustment in factor-biased technological change is assumed to be described by the following set of dynamic equations

$$\hat{A}^j(t) = \hat{A}^j + \bar{a}^j e^{-\xi^j t}, \tag{393a}$$

$$\hat{B}^j(t) = \hat{B}^j + \bar{b}^j e^{-\xi^j t}, \tag{393b}$$

where $\bar{a}^j = a^j/\tilde{A}^j_0$ and $\bar{b}^j = b^j/\tilde{B}^j_0$. Differentiating (393) with respect to time leads to:

$$\dot{A}^j(t) = -\xi^j \left(A^j(t) - \tilde{A}^j\right), \tag{394a}$$

$$\dot{B}^j(t) = -\xi^j \left(B^j(t) - \tilde{B}^j\right). \tag{394b}$$

S.6 The Technology Frontier

While we relax the assumption of Hicks-neutral technological change, we have to relate the changes in labor and capital efficiency, i.e., $\hat{A}^j(t)$ and $\hat{B}^j(t)$, respectively, to the percentage deviation of TFP in sector j, i.e., $\hat{Z}^j(t)$, in order to be consistent with our empirical strategy. A natural way to map A^j and B^j into Z^j is to assume that besides optimally choosing factor inputs, firms also optimally choose the production function. Following Caselli and Coleman [2006] and Caselli [2016], the menu of possible choices of production functions is represented by a set of possible (A^j, B^j) pairs. These pairs are chosen along the technology frontier which is assumed to take a Cobb-Douglas form:

$$\left(A^j(t)\right)^{\alpha^j(t)} \left(B^j(t)\right)^{1-\alpha^j(t)} \leq Z^j(t) \tag{395}$$

where $Z^j > 0$ is the height of the technology frontier and $\alpha^j(t)$ is a time-varying positive parameter which determines the weight of labor-augmenting technological change.

Firms choose A^j and B^j along the technology frontier described by eq. (395) that minimizes the cost function (see (355)-(357)) described by:

$$c^j(t) \equiv \left[\left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)}\right)^{1-\sigma^j} + \left(1-\gamma^j\right)^{\sigma^j} \left(\frac{R(t)}{B^j(t)}\right)^{1-\sigma^j}\right]^{\frac{1}{1-\sigma^j}}, \tag{396}$$

subject to (395) which holds as an equality. Differentiating (396) and next (395) to eliminate $\hat{B}^j(t)$ (keeping $\hat{Z}^j$ fixed) leads to:

$$\begin{aligned}
\hat{c}^j(t) &= -\left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)}\right)^{1-\sigma^j} \left(c^j(t)\right)^{\sigma^j-1} \hat{A}^j(t) - \left(1-\gamma^j\right)^{\sigma^j} \left(\frac{R(t)}{B^j(t)}\right)^{1-\sigma^j} \left(c^j(t)\right)^{\sigma^j-1} \hat{B}^j(t), \\
&= -s^j_L(t)\hat{A}^j(t) - \left(1 - s^j_L(t)\right) \hat{B}^j(t, \\
&= -s^j_L(t)\hat{A}^j(t) + \left(1 - s^j_L\right) \frac{\alpha^j(t)}{1-\alpha^j(t)} \hat{A}^j(t),
\end{aligned} \tag{397}$$

where we used the fact that $\left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)}\right)^{1-\sigma^j} \left(c^j(t)\right)^{\sigma^j-1} = s^j_L(t)$ (see eq. (358a)), and $\left(1-\gamma^j\right)^{\sigma^j} \left(\frac{R(t)}{B^j(t)}\right)^{1-\sigma^j} \left(c^j(t)\right)^{\sigma^j-1} = 1 - s^j_L(t)$ (see eq. (358b)), together with $\hat{B}^j(t) = -\frac{\alpha^j}{1-\alpha^j}\hat{A}^j(t)$. Setting the above equation to zero to perform the cost minimization and solving leads to:

$$\alpha^j(t) = s^j_L(t), \tag{398}$$

where s^j_L is described by (349). The intuition behind equality (398) is straightforward. Firms choose parameters A^j and B^j along the technology frontier described by eq. (395) that minimizes the unit cost function (396). More specifically, firms intend to choose the optimal trade-off between A^j and B^j that minimizes c^j. Variations in A^j and B^j modify the unit cost for producing in proportion to the share of labor and capital cost in value added, i.e., $\hat{c}^j = -s^j_L\hat{A}^j - \left(1 - s^j_L\right)\hat{B}^j$. The unit cost for producing is minimized when the contribution of higher capital efficiency exactly offsets lower labor efficiency, i.e., $\left(1 - s^j_L\right)\hat{B}^j = -s^j_L\hat{A}^j$. Since along the same technology frontier, a fall in $\alpha^j\hat{A}^j$ must be compensated by a rise by $\left(1-\alpha^j\right)\hat{B}^j$ to keep Z^j constant, the optimal trade-off that minimizes the unit cost is that the weight of capital efficiency $1-\alpha^j$ is equivalent to its contribution to the decline in the unit cost, $1 - s^j_L$. The weight of labor and capital efficiency into the technology frontier which minimizes the unit cost for producing are thus strictly equal to the shares of labor and capital cost in value added.

Inserting the optimal choice of (A^j, B^j) pair along the technology frontier and assuming that $D^j = Z^j$, one obtains a relationship between total factor productivity and labor- and capital-augmenting productivity:

$$Z^j(t) = \left(A^j(t)\right)^{s_L^j(t)} \left(B^j(t)\right)^{1-s_L^j(t)}. \tag{399}$$

We assume Hicks-neutral technological change at the initial steady-state, i.e., $A^j = B^j = Z^j$. Log-linearizing eq. (399) in the neighborhood of the initial steady-state leads to:

$$\begin{aligned}
\ln Z^j(t) - \ln \tilde{Z}_0^j &= \tilde{s}_{L,0}^j \left(\ln A^j(t) - \ln \tilde{A}_0^j\right) + \left(1 - \tilde{s}_{L,0}^j\right)\left(\ln B^j(t) - \ln \tilde{B}_0^j\right) \\
&\quad + \ln \tilde{A}_0^j \left(s_L^j(t) - \tilde{s}_{L,0}^j\right) + \ln \tilde{B}_0^j \left[\left(1 - s_L^j(t)\right) - \left(1 - \tilde{s}_{L,0}^j\right)\right], \\
&= \tilde{s}_{L,0}^j \left(\ln A^j(t) - \ln \tilde{A}_0^j\right) + \left(1 - \tilde{s}_{L,0}^j\right)\left(\ln B^j(t) - \ln \tilde{B}_0^j\right),
\end{aligned}$$

where the last two terms cancel out as a result of our assumption that initially $\tilde{A}_0^j = \tilde{B}_0^j = \tilde{Z}_0^j$. Denoting by a hat the deviation in percentage from initial steady-state, the above equation simply reads as follows:

$$\hat{Z}^j(t) = \tilde{s}_{L,0}^j \hat{A}^j(t) + \left(1 - \tilde{s}_{L,0}^j\right)\hat{B}^j(t). \tag{400}$$

Log-linearizing (351) in the neighborhood of the initial steady-state leads to:

$$\hat{B}j(t) - \hat{A}^j(t) = \left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) - \hat{k}^j(t). \tag{401}$$

The system consisting of the technology frontier (400) and the demand for factors of production (401) can be solved for $\hat{A}^j(t)$ and $\hat{B}^j(t)$ which leads to (38a)-(38b) in the main text.

As shown in section E, the 'true' measure of the technology bias toward tradables is given by $\frac{\left(Z^H(t)\right)^a}{\left(Z^H(t)\right)^b}$. In the quantitative analysis, we consider permanent changes in sectoral TFP, $\tilde{Z}^j$, so that the labor share-adjusted TFP differential is 1% in the long run:

$$a\hat{\tilde{Z}}^H - b\hat{\tilde{Z}}^N = 1\%, \tag{402}$$

where $\hat{Z}^j$ is given by eq. (400).

Graphical Representation of the Technology Frontier

The technology frontier plots the set of labor and capital efficiency in $(\ln A^j, \ln B^j)$-space for given Z^j. Log-linearizing eq. (395) leads to:

$$\frac{\partial \ln B^j(t)}{\partial \ln A^j(t)} = -\frac{\alpha^j(t)}{1-\alpha^j(t)} < 0. \tag{403}$$

Raising the weight of labor-augmenting technological change leads to a steeper technology frontier. The technology frontier has an intercept along the vertical axis of $\frac{\ln Z^j}{1-s_L^j}$ while an intercept along the horizontal axis of $\frac{\ln Z^j}{s_L^j}$.

Totally differentiating the unit cost function leads to:

$$\frac{\partial \ln B^j(t)}{\partial \ln A^j(t)} = -\left(\frac{\gamma^j}{1-\gamma^j}\right)^{\sigma^j}\left(\frac{W^j}{R}\frac{B^j}{A^j}\right)^{1-\sigma^j} < 0. \tag{404}$$

The unit cost function is downward-sloping in the $(\ln A^j, \ln B^j)$-space; the unit cost function is convex as long as $\sigma^j < 1$. From the differentiation of the unit cost function, we have:

$$\begin{aligned}
\hat{c}^j &= \left(\gamma^j\right)^{\sigma^j}\left(\frac{W^j}{A^j}\right)^{1-\sigma^j}\left(c^j\right)^{\sigma^j-1}\left(\hat{W}^j - \hat{A}^j\right) \\
&\quad + \left(1-\gamma^j\right)^{\sigma^j}\left(\frac{R}{B^j}\right)^{1-\sigma^j}\left(c^j\right)^{\sigma^j-1}\left(\hat{R} - \hat{B}^j\right), && (405) \\
&= s_L^j\left(\hat{W}^j - \hat{A}^j\right) + \left(1 - s_L^j\right)\left(\hat{R} - \hat{B}^j\right), && (406)
\end{aligned}$$

it is straightforward to see that the when $\sigma^j < 1$, a rise in W^j or in R causes the cost function to shift downward in the $(\ln A^j, \ln B^j)$-space. In deriving (406), we made use of (358a)-(358b).

Firms will choose a $(\ln A^j, \ln B^j)$ pair by equating the slope of the unit cost function to the slope of the technology frontier, i.e.,

$$\begin{aligned}
\left(\frac{\gamma^j}{1-\gamma^j}\right)^{\sigma^j}\left(\frac{W^j(t)}{R(t)}\frac{B^j(t)}{A^j(t)}\right)^{1-\sigma^j} &= \frac{\alpha^j(t)}{1-\alpha^j(t)}, \\
\left(\frac{\gamma^j}{1-\gamma^j}\right)^{\sigma^j}\left(\frac{W^j(t)}{R(t)}\frac{B^j(t)}{A^j(t)}\right)^{1-\sigma^j} &= \frac{\alpha^j(t)}{1-\alpha^j(t)}, \\
S^j(t) &= \frac{\alpha^j(t)}{1-\alpha^j(t)},
\end{aligned} \tag{407}$$

where $S^j = \frac{s^j_L}{1-s^j_L}$; we have inserted (352) to get the second line of (407), and we have substituted (351) to get the last line. According to (407), as production becomes more labor intensive, i.e., S^j increases, the economy moves along the steeper part of the unit cost for producing, and it is optimal for firms to increase the weight of labor-augmenting technological change. Graphically, as the economy , the technology frontier rotates clockwise and thus firms choose to reduce A^j and increase B^j, for given Z^j. If we consider an increase in Z^j associated with a rise in S^j, the technology frontier shifts upward and becomes steeper.

S.7 CES Technology Frontier

In this subsection, we investigate the implications of assuming a more general form for the technology frontier. As we shall see it, a CES or a Cobb-Douglas form for the technology frontier leads to the same results for our analysis. We assume that firms in sector j choose labor and capital efficiency along the technology frontier which is assumed to take a CES form:

$$\left[\gamma^j_Z\left(A^j(t)\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}} + \left(1-\gamma^j_Z\right)\left(B^j(t)\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}}\right]^{\frac{\sigma^j_Z}{\sigma^j_Z-1}} \leq Z^j(t), \tag{408}$$

where $Z^j > 0$ is the height of the technology frontier, $0 < \gamma^j_Z < 1$ is the weight of labor efficiency in TFP and $\sigma^j_Z > 0$ corresponds to the elasticity of substitution between labor and capital efficiency. Performing the minimization of the unit cost for producing (396) subject to the technology frontier (408) leads to:

$$\frac{\gamma^j_Z}{1-\gamma^j_Z}\left(\frac{A^j}{B^j}\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}} = \frac{s^j_L}{1-s^j_L}, \tag{409}$$

where we used the fact that $\left(\gamma^j\right)^{\sigma^j}\left(\frac{W^j(t)}{A^j(t)}\right)^{1-\sigma^j}\left(c^j(t)\right)^{\sigma^j-1} = s^j_L(t)$ (see eq. (358a)), and $\left(1-\gamma^j\right)^{\sigma^j}$ $\left(\frac{R(t)}{B^j(t)}\right)^{1-\sigma^j}\left(c^j(t)\right)^{\sigma^j-1} = 1-s^j_L(t)$ (see eq. (358b)). When $\sigma^j_Z = 1$, eq. (409) collapses to (398), i.e., $\gamma^j = \alpha^j = s^j_L$. We explore below the implications of $\sigma^j_Z \neq 1$. As shall be useful later, we solve eq. (409) for s^j_L:

$$\begin{aligned}
s^j_L &= \frac{\gamma^j_Z\left(A^j\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}}}{\gamma^j_Z\left(A^j\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}} + \left(1-\gamma^j_Z\right)\left(B^j\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}}}, \\
&= \gamma^j_Z\left(\frac{A^j}{Z^j}\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}},
\end{aligned} \tag{410}$$

where we made use of (408) to obtain the last line.

Log-linearizing (408) in the neighborhood of the initial steady-state and making use of eq. (410) leads to:

$$\begin{aligned}
\hat{Z}^j(t) &= \gamma^j_Z\left(\frac{A^j_0}{Z^j_0}\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}}\hat{A}^j(t) + \left(1-\gamma^j_Z\right)\left(\frac{B^j_0}{Z^j_0}\right)^{\frac{\sigma^j_Z-1}{\sigma^j_Z}}\hat{B}^j(t), \\
&= s^j_{L,0}\hat{A}^j(t) + \left(1-s^j_{L,0}\right)\hat{B}^j(t).
\end{aligned} \tag{411}$$

Eq. (411) is identical to (400) obtained in the Cobb-Douglas case. Solving eq. (411) and the log-linearized version of the demand for factors of production (401) leads to the solutions for $\hat{A}^j(t)$ and $\hat{B}^j(t)$ described by (38a)-(38b) in the main text obtained by assuming a Cobb-Douglas for the technology frontier.

T Addressing the SVAR Critique

In this section, we address the SVAR critique. In section T.1, we detail the different points of the SVAR critique which has emerged after Galì's [1999] paper. In section T.2, we evaluate the importance of technology shocks for economic fluctuations. In section T.3, we investigate if our identification of asymmetric technology shocks across sectors is contaminated by non-technology shocks. In section T.4, we conduct a robustness check w.r.t. to the number of lags. In section T.5, we adjust sectoral TFPs with sectoral capital utilization rates and identify shocks to traded relative to non-traded utilization-adjusted-TFP. In section T.6, we replace the country-level traded relative to non-traded TFP with its world counterpart. In section T.7, we employ the Max Share approach.

T.1 Short Review of the Debate about SVAR Identification of Technology Shocks

The SVAR methodology allows researchers to estimate the adjustment of macroeconomic variables conditional on a shock. We run VARs on the actual data and impose identification assumptions to identify a specific shock and trace out the dynamic responses of variables to this shock. Then we calibrate the macroeconomic model and compare the theoretical responses with empirical responses in order to determine which model is more suited to rationalize the SVAR evidence.

The identification of technology shocks by adopting the SVAR methodology has been subject to criticism. As summarized by Dupaigne, Fève, and Matheron [2007], the distortions in a DSVAR may originate from several sources: (i) hours are over-differenced (Erceg, Gust and Guerrieri [2005]) (ii) average labor productivity is a poor proxy for total factor productivity at business cycle frequencies (Chang and Hong [2006]); (iii) the estimation of DSVARs is subject to small-sample biases, especially with long-run restrictions (see Faust and Leeper [1997]); (iv) a structural VAR with a finite number of lags may poorly approximate the dynamics of DSGE models (Chari, Kehoe and McGrattan [2008]).

Whilst SVAR models might be subject to potential biases, nevertheless, the information they produce can effectively complement analyses conducted with dynamic macroeconomic models, help to point out the dimensions where these models fail, and provide stylized facts and predictions which can improve the realism of macroeconomic models.

Because we focus on the reallocation effects of technology shocks biased toward tradables by using panel data, our identification of asymmetric technology shocks and the dynamic adjustment of sectoral variables are not, as shown below, subject to the biases aforementioned. We first summarize the biases, explain why they should be strongly mitigated, if not eliminated, and we will go into further details in the subsections below.

Sectoral shares display a trend in the data. First, as mentioned in the main text, most of the literature focuses on total hours worked and there has been an unsettled debate about whether they should enter the VAR model in log level or in first difference. The problem is obvious. In the long-run, total hours worked divided by population should be constant (as assumed by the RBC model) but data horizon is too short so that hours worked display a unit root, in line with our panel unit root tests (see Appendix N.1). In contrast, in our paper, we do not focus on total hours but instead on the traded-goods-share of total hours worked and the value added share of tradables at constant prices. As surveyed by Herrendorf, Rogerson and Valentinyi [2014], both the value added and the labor share of tradables display a clear trend in all OECD countries as a result of the productivity growth differential between tradables and non-tradables and thus both variables must enter the VAR model in growth rates. Fig. 32 plots the share of traded hours worked in total hours worked. As it stands out, all OECD countries experience a secular decline in the labor share of tradables. This variable must enter the VAR model in growth rate.

TFP is a better proxy of technological change than labor productivity. Most of the literature investigating the effects of technology shocks uses labor productivity to approximate technological change. The use of average labor productivity (i.e., $y^j = \text{tfp}^j + s_L^j k^j$) as a proxy for technology imposes a long-run identification which implies that any shock which has a persistent effect on the capital-labor ratio might contaminate the estimated responses to technology shocks which explains why Chari, Kehoe and McGrattan [2008] find that an economy without capital will not be subject to the bias identified by the authors. On the contrary, the use of TFP is less prone to be influenced by persistent non-technology shocks.

Chang and Hong [2006] have shown that labor productivity is the correct measure from which to identify technology shocks. The reason to this is that labor productivity reflects both improved efficiency and changes in the input mix (i.e., in the capital-labor ratio). In support of their argument, the authors show that labor productivity and TFP are not cointegrated, therefore the long-run component of labor productivity does not truly identify technology shocks. Chaudourne, Fève and Guay [2014] estimate the short-run responses of hours worked in various (bivariate) SVARs estimated on (actual) U.S. data by using three different measures of productivity (used for long-run identifica-

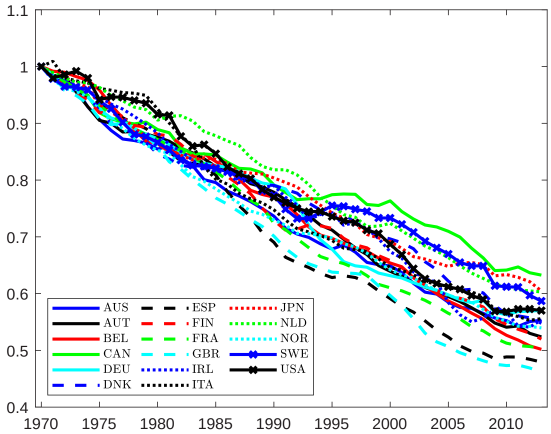


Figure 32: Traded-Goods-Share of Total Hours Worked in (Seventeen) OECD Countries. Notes: We plot the traded-goods-share of total hours worked for the seventeen OECD countries. Source: EU KLEMS [2011] and OECD [2011]. Sample: 17 OECD countries, 1970-2013, annual data.

tion): labor productivity, TFP, adjusted-TFP. When the Solow residual and the adjusted measure of TFP are considered, the specification of hours (in level or in first difference) does not matter. On impact, the authors find that hours worked decrease and after two years the response becomes persistently positive. This finding means that when technological change is properly measured, i.e., by using TFP or adjusted-TFP, consistent VAR estimates are obtained. In contrast, VAR estimates are significantly biased when labor productivity is used to approximate technological change. The reason why labor productivity might lead the SVAR identification to be subject to biases is that as claimed by Erceg, Gust and Guerrieri [2005], the slow adjustment of capital makes it hard to gauge the long-run impact of a technology shock on labor productivity, contributing to downward bias in the estimated impulse responses.

Small sample bias. Faust and Leeper [1997] argue that structural VARs with long-run restriction do not enable precise inference due to small sample bias. Erceg, Gust and Guerrieri [2005] find that most of the small-sample bias is attributable to the difficulty in precisely estimating the long-run response of variables to the structural shocks in the VAR model. Such a difficulty is caused by the slow adjustment of capital which complicates the estimation of the long-run impact of the technology shock on labor productivity and also makes it hard to disentangle technology shocks from highly persistent non-technology shocks. By using TFP, we overcome this difficulty. Chari, Kehoe and McGrattan [2008] have shown that the small sample bias remains limited and that the lag truncation bias might cause a more significant bias. Our Panel SVAR estimates very accurately the responses of variables as it circumvents the small sample bias at a country level by considering 17 countries. The confidence bands are tight enough to allow us to discriminate between competing flexible price models. Christiano, Eichenbaum, and Vigfusson [2006] make the case that even if the VAR point estimates of the structural impulse responses are inaccurate in small samples, after accounting for sampling uncertainty, researchers would rarely reject a DSGE model incorrectly. Although the confidence bands may be wide, they are not so wide as to be consistent with any possible DSGE model.

Finite number of lags: lag-truncation bias. Whilst estimation of VAR models necessitates only a small number of lags (commonly 4 lags on quarterly data and 2 lags on annual data), the VAR representation of many theoretical models includes an infinite number of lags. Chari, Kehoe and McGrattan [2008], Erceg, Guerrieri and Gust [2005]) and Dupaigne, Fève and Matheron [2007] show that persistent non-technology shocks disturb the identification of permanent technology shocks. When non-technology shocks are persistent and they account for a large share of GDP fluctuations, the SVAR estimations are biased. Conversely, when demand shocks are not too persistent or if they account for a trivial fraction of output fluctuations, the means of the SVAR impulse responses are close to the model's theoretical impulse responses.

Their common intuition is that, under decreasing returns to labor input, every shock with long-lasting negative effects on labor input stimulates average labor productivity, even in the medium-run. Such shocks contaminate the estimated response of labor input to permanent productivity shocks. CKM argue that the need for a large number of lags when running the VAR stems from the presence of capital. As shown by Chaudourne, Fève and Guay [2014], the use of average labor productivity as a proxy for technology is responsible for the lag-truncation bias as persistent non-technology shocks have long-lasting effects on the capital stock which contaminates the identification of true technology shocks. In addition, shocks to labor tax or capital tax have permanent effects on labor productivity.

T.2 Forecast Error Variance Decomposition

As demonstrated by Chari et al. [2008], when the non-technology shock generates over 50% of the variance of output in the model in the DSVAR long-run specification, empirical IRFs could be biased. We conduct a forecast error variance decomposition (FEVD) for the whole panel of seventeen countries in Table 25, and for one country at a time in Table 26. In both cases, we split the whole period into two sub-periods, i.e, 1970-1992 and 1993-2013, respectively. Each cell reports the FEV attributable to technology shocks. Whilst in Table 25, we exclusively focus on the share of FEV of value added/value added share growth attributable to technology shocks, in Table 26, we also provide the share of FEV of hours worked/labor growth attributable to technology shocks.

Before discussing the results from the FEVD below, it is worth mentioning that the evidence documented by Galì an Gambetti [2009] who use a time-varying SVAR, reveals that the contribution of non-technology shocks to the variance of output has declined dramatically during the great moderation whilst the contribution of technology shocks to output volatility has significantly increased in relative terms. Our results below confirm these findings.

Overall, Table 25 and Table 26 show that asymmetric technology shocks play a large role in explaining sectoral movements. Let us start with Table 25:

- Contrary to the conventional wisdom, as shown in the first row, technology (measured by labor productivity) does not explain a small fraction of total hours worked growth in OECD countries, see e.g., Christiano, Eichenbaum and Vigfusson [2006]. The reason is that most of the literature computes the share of FEV of total hours worked on U.S. data and like the existing literature, we find that labor productivity growth explains a small fraction of total hours worked growth, i.e., 8.1% over 1970-2013. The U.S. is the OECD country where the fraction of $\hat{L}_t$ explained by labor productivity is the lowest. As shown in the first row of Table 25, the share of the FEV of $\hat{L}_t$ attributable to labor productivity growth averages about 40% and increases up to 60% in the Netherlands.
- The second and the third row show the fraction of FEV of traded and non-traded value added at constant prices attributable to traded and non-traded labor productivity growth. Whilst sectoral productivity growth explains a small fraction of sectoral value added growth before 1992 in OECD countries, shocks to traded labor productivity account for a much larger fraction of traded value added growth, i.e., about 45%, during the Great Moderation.
- The fourth and fifth row reveal that shocks to traded relative to non-traded labor productivity (i.e., shocks to A^H/A^N) explain between 57% and 59% of the value added share of tradables and non-tradables, respectively.
- From the sixth to the last row, we replace labor productivity with total factor productivity. As can be seen in the sixth row, whilst asymmetric technology shocks account for a negligible fraction of real GDP growth before 1992, it explains 41% of its variance over the period 1993-2013. This finding is in line with the rising importance of asymmetric technology shocks across sectors we uncover in the main text, as also documented by Foerster et al. [2011], Garìn et al. [2018] on U.S. data.
- Rows 7-8 confirm the rising importance of asymmetric technology shocks for the variations of sectoral value added shares as the share of FEV of $\nu^{Y,H}$ and $\nu^{H,N}$ attributable to a shock to traded relative to TFP has doubled when we move from 1970-1992 to 1993-2013.
- Interestingly, the last two rows show that the fraction of FEV of traded value added attributable to traded TFP has tripled during the Great Moderation while the the FEV of non-traded value added explained by non-traded TFP has also considerably increased.

We go on with Table 26 which shows the contribution of asymmetric technology shocks to real GDP growth (column 1), variations of value added shares at constant prices (columns 2,4,10,12), variations of labor shares (columns 3,5,11,13), variations of sectoral value added at constant prices (columns 6,8), variations of sectoral hours worked (columns 7,9). To compute the fraction of FEV of each variable explained by asymmetric technology shocks, we have estimated each VAR model for one country at a time and then we have calculated the cross-country mean, the minimum and the maximum. The conclusion that emerges from Table 26 is that technology shocks account for a large share of variations of sectoral shares and this contribution displays a wide dispersion across time and space:

- In line with the conclusion in the main text, the importance of asymmetric technology shocks for real GDP growth and variations in the sectoral composition has increased over time.
- Whilst the contribution of asymmetric technology shocks vary considerable across time, its importance for economic fluctuations also varies across space. For each sub-period, there is a huge discrepancy between the minimum and the maximum of the fraction of the FEV of variables attributable to asymmetric technology shocks across sectors.

- To be more concrete, let us take some examples. During the period 1970-1992, only four countries display a fraction of the FEV of the value added share of tradables at constant prices explained by shocks to traded to non-traded TFP lower than 10% (Australia, Germany, Italy, Sweden). Conversely, the fraction of the variation of $\nu^{Y,H}$ attributable to changes in relative productivity of tradables amounts to 40% in the US, 48% in Ireland, 67% in Japan, 82% in Finland. When we turn to the period 1993-2013, only one country displays a fraction of FEV of $\nu^{Y,H}$ explained by shocks to traded relative to non-traded TFP lower than 10% (say Germany). Whilst 48% of $d\nu_t^{Y,H}$ is explained by variations in relative productivity of tradables in the U.S., it amounts to 66% in the U.K., 72% in Belgium, 77% in Denmark, 80% in Norway.
- Whilst column 3 of Table 26 shows that on average, 29% of the FEV of the labor share of tradables in 1970-1992 and about 31% in 1993-2013 is attributable to shocks to traded relative to non-traded TFP, the share of the FEV of $d\nu_t^{L,H}$ varies from 1% in the Netherlands to 71% in Austria over 1970-1992, and from 6% in Sweden to 56% in Spain over 1993-2003.
- As displayed by columns 4-5, the two aforementioned conclusions also hold for the non-traded sector.
- Columns 6-9 show that on average, the contribution of asymmetric technology shocks across sectors to the FEV of sectoral value at constant prices and sectoral hours worked is more stable over time. The cross-country dispersion is very pronounced for both sectors as it ranges between 6% and 84% for traded value added and between 1% and 76% for non-traded hours worked.

In conclusion, likewise Holly and Petrella [2012], technology and non-technology shocks seem to be equally important for explaining aggregate fluctuations after 1992. Whilst so far the literature has focused its attention on the share of FEV of total hours worked explained by shocks to aggregate labor productivity, we have conducted a FEVD across countries before and after 1992. The contribution of asymmetric technology shocks to the FEV of sectoral value added and sectoral hours worked varies considerably across time and space. For example, the contribution of shocks to traded to non-traded TFP to the variation in the value added share of tradables is higher than 50% in seven OECD countries and is lower than 10% in only one country.

Table 25: The Share of the FEV of Aggregate TFP Growth Attributable to Asymmetric Technology Shocks across Sectors in %: Panel Dimension

VAR Model	1970-2013 (1)	1970-1992 (2)	1993-2013 (3)
$[A, L]$	38.4	41.7	39.7
$[A^H, Y^H]$	28.2	9.9	44.9
$[A^N, Y^N]$	4.6	7.5	7.5
$[A^H/A^N, \nu^{Y,H}, \nu^{L,H}]$	54.9	50.5	56.9
$[A^H/A^N, \nu^{Y,N}, \nu^{L,N}]$	54.9	53.4	58.7
$[Z, Y_R, L, W_C]$	15.9	2.6	41.0
$[Z, \nu^{Y,H}, \nu^{L,H}]$	31.6	20.6	34.5
$[Z, \nu^{Y,N}, \nu^{L,N}]$	32.3	19.0	35.4
$[Z^H, \nu^{Y,H}, \nu^{L,H}]$	33.4	16.4	45.6
$[Z^N, \nu^{Y,N}, \nu^{L,N}]$	2.6	0.3	13.0

Notes: FEVD: Forecast Error Variance Decomposition of VAR Models over Two-Subperiods. The number in columns 1-3 denotes the fraction of the total forecast error variance of value added/value added share attributable to identified technology shock. $A = Y_R/L$ refers to aggregate labor productivity; $A^H = Y^H/L^H$ and $A^N = Y^N/L^N$ refer to traded and non-traded labor productivity, respectively; a rise in $Z_t = (Z_t^H)^a/(Z_t^N)^b)$ refers to an asymmetric technology shock across sectors. Note that we do not report the share of hours worked/labor share attributable to technology as we focus on the contribution of technology shocks to the variance of value added growth. We consider a forecast horizon of 10 years because considering earlier forecast horizon gives similar results. We consider a two- or three-variable VAR model which includes alternative measures of productivity, ordered first, and all variables are in growth rate. We estimate in panel format on annual data over 1970-2013 and in columns 2 and 3, we split the entire period into 1970-1992 and 1993-2013. Sample: 17 OECD countries, 1970-2013, annual data.

T.3 Are our Asymmetric Technology Shocks across Sectors Contaminated by Non-Technology Shocks?

In the lines of Francis and Ramey [2005], we assess below the validity of the technology shocks identified using long-run restrictions by subjecting the model to a series of test. These tests include

i) exogeneity tests, ii) controlling for the effects of changes in labor tax rates and government spending, iii) sensitivity to assumptions about the hours process.

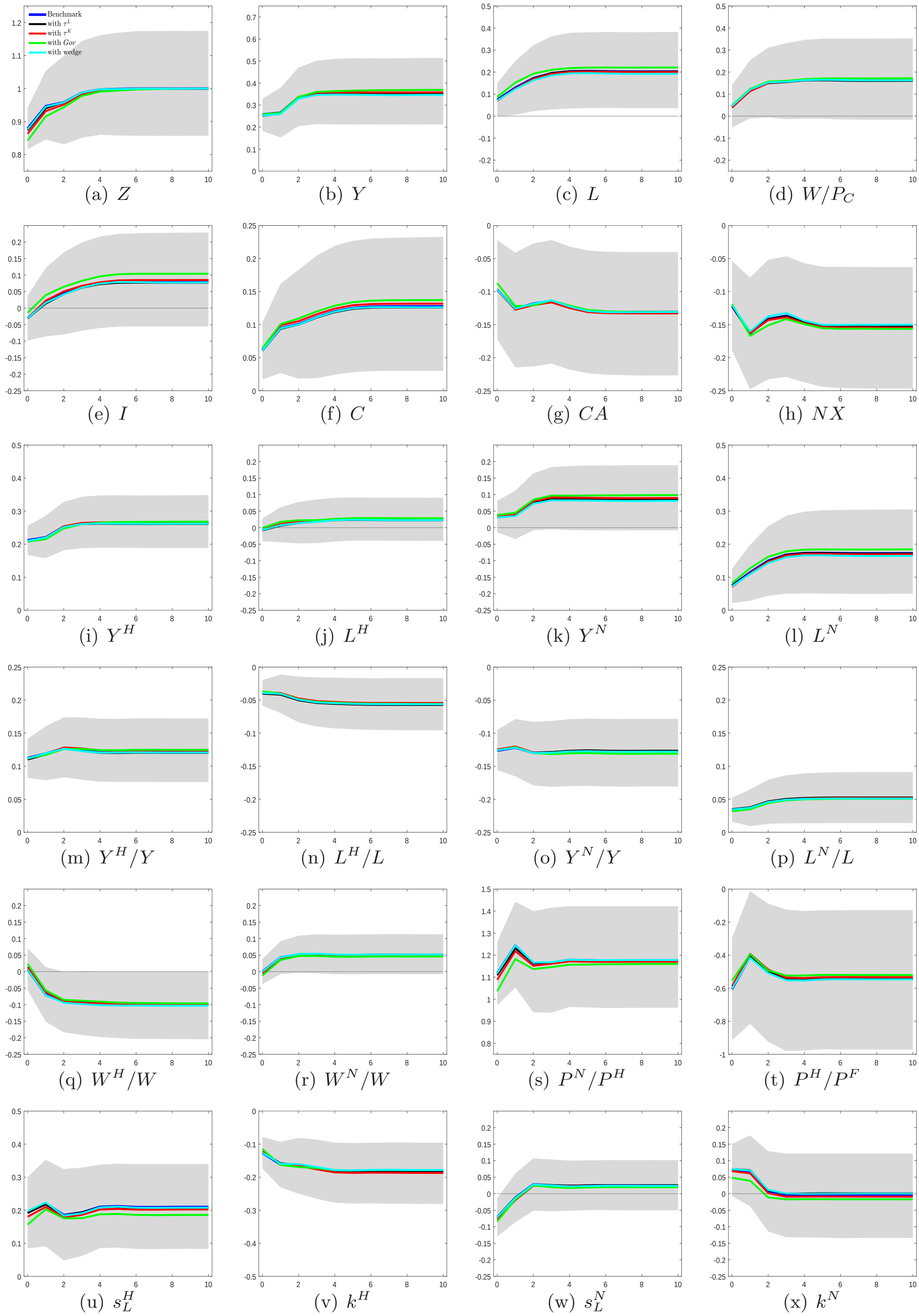
Mertens and Ravn [2011] find that permanent changes in income tax rates induce permanent changes in hours worked as well as in labor productivity which leads to a violation of the standard long-run identification strategy for technology shocks. The importance of controlling for tax changes was raised earlier by Uhlig [2004] who points out that changes in capital income tax rates may give rise to long-lasting changes in labor productivity, thus leading to a violation of the identifying assumption for technology shocks. Because Gali [1999] uses labor productivity, the shocks identified could include capital income tax rate shocks. As stressed by Francis and Ramey [2005], permanent shifts in government spending have permanent effects on wages, and hours, but not on labor productivity (because the capital-labor ratio remains unaffected). However, as shown by Chaudourne, Fève and Guay [2014], permanent or long-lasting non-technology shocks can contaminate the SVAR identification of technology shocks as they impinge on hours worked and thus on labor productivity.

Because our measure of productivity is total factor productivity, the technology shocks we identified in the main text should not be contaminated by non-technology shocks. The reason is twofold. One advantage of using TFP is that labor productivity is presumably affected in more important ways by business cycle fluctuations than TFP. More specifically, total factor productivity is a measure of technological change purified from changes in the capital labor-ratio. Second, asymmetric technology shocks across sectors are less likely to be contaminated by non-technology shocks, such as permanent or persistent changes in tax rates or in monetary policy which affect both sectors symmetrically whilst we identify permanent changes in traded relative to non-traded TFP. To confirm this assumption, we closely follow Francis and Ramey [2005].

Estimating VAR models by controlling for labor and capital taxation, government spending, and the labor wedge. To overcome the limitations of the ability of the SVAR approach to identify technology shocks, one recommendation is to consider a larger VAR specification to reduce biases that may arise due to omitted variables, i.e., by controlling for the shifts in non-technology variables. Since labor tax and capital income tax rates along with government spending are observable, we control for them when running the VAR models we estimate in the main text. We provide details about the source and construction of data in the next paragraph (i.e., in exogeneity tests). In Fig. 33, the blue line displays estimated dynamic adjustment of variables to a 1% permanent increase in traded relative to non-traded TFP in the long-run and we contrast empirical IRFs in the baseline model with these estimated empirically when we add the labor tax rate, the capital income, government spending, or the labor wedge, ordered second in the VAR model. Dynamic adjustment of variables when we control for the labor tax rate and the capital income tax rate is displayed by the black and the red line, respectively, while empirical IRFs when we control for government spending and the labor wedge are shown in the green and the cyan line, respectively.

Shaded areas are 90% confidence bounds associated with the baseline VAR model. The figure makes very clear that controlling for tax rates, government spending, or the labor wedge has little or no effect on the results. All of our conclusions hold qualitatively and also quantitatively. Most importantly, a permanent increase in traded relative to non-traded TFP lowers the labor share of tradables (i.e., $\nu_{it}^{L,H}$) and increases the value added share of tradables at constant prices (i.e., $\nu_{it}^{Y,H}$). Note that the results for the baseline VAR model are not exactly those shown in the main text because the control variables, especially the labor wedge, are available over a smaller sample of OECD countries and over a shorter period of time: AUS (1986-2008), AUT (1977-2010), CAN (1972-2010), DEU (1993-2010), ESP (1996-2010), FIN (1976-2010), FRA (1971-2010), GBR (1972-2010), IRL (2000-2010), ITA (1972-2010), JPN (1974-2008), NOR (1979-2010), SWE (1975-2010) and USA (1971-2010). To compare consistently the results of the baseline VAR model without control variables with those when we add control variables, we have re-estimated all VAR models for the fourteen OECD countries and the period where the control variables are available.

Exogeneity tests. The identified technology shock should not in principle be correlated with other exogenous non-technology shifts nor with lagged endogenous variables. An additional means to test whether the identified shows are really technology shocks is to test whether non-technology variables are correlated with the shocks. We consider four types of non-technology variables: changes in labor and capital tax rates, shocks government spending, and shifts in the labor wedge. Following Francis and Ramey [2005], we estimate in panel format on annual data the baseline VAR model which includes the ratio of traded to non-traded TFP, real GDP, total hours worked, and the real consumption wage, all variables entering the VAR model in growth rates. We identify asymmetric technology shocks across sectors as shocks that increase permanent traded relative to non-traded TFP and we run the regression of the identified structural technology shocks, denoted by $\epsilon_{Z,it}$, on the variations of the labor income tax rate, $d\tau_{it}^{L}$, the capital income tax rates, τ_{it}^{K}. Source: Both labor and capital income tax are provided by Mc Daniel [2007] who average labor tax for all OECD countries of our sample. Time series for labor tax rates cover the period 1970-2013. The labor tax is the average tax rate on household income plus average payroll tax rate paid by employer and employee. We also run the regression of identified shocks to traded relative to



(a) Z (b) Y (c) L (d) W/P_C

(e) I (f) C (g) CA (h) NX

(i) Y^H (j) L^H (k) Y^N (l) L^N

(m) Y^H/Y (n) L^H/L (o) Y^N/Y (p) L^N/L

(q) W^H/W (r) W^N/W (s) P^N/P^H (t) P^H/P^F

(u) s_L^H (v) k^H (w) s_L^N (x) k^N

Figure 33: Effects of a Permanent Increase in Traded relative to Non-Traded TFP: Controlling for Taxation, Government Spending, and the Labor Wedge. Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for baseline VAR models while the black line, the red line, the green line, and the cyan line show the dynamic adjustment when we control for the labor tax rate, the capital income tax, government spending, and the labor wedge, respectively. Sample: AUS (1986-2008), AUT (1977-2010), CAN (1972-2010), DEU (1993-2010), ESP (1996-2010), FIN (1976-2010), FRA (1971-2010), GBR (1972-2010), IRL (2000-2010), ITA (1972-2010), JPN (1974-2008), NOR (1979-2010), SWE (1975-2010) and USA (1971-2010).

non-traded TFP on exogenous shocks to government spending. To identify exogenous shocks to government consumption, we estimate a VAR model in panel format on annual data which includes government consumption (ordered first), real GDP, total hours worked and the real consumption wage; all quantities are divided by the working age population and enter the VAR model in log level; we adopt a standard Cholesky decomposition. Source: government final consumption expenditure (CGV), OECD Economic Outlook Database [2017]. Finally, Chari et al. [2007] find that that the efficiency and labor wedges together account for essentially all of the fluctuations on US data. Time-varying labor wedges account for all frictions which generate a deviation from tax-adjusted marginal rate of substitution between leisure and consumption (MRS) and the marginal product of labor (MPN). Chari et al. [2007] show that shocks to the labor wedge in a model with flexible prices are equivalent to monetary policy shocks in a model with sticky wages sticky wages. The labor wedge should encompass most of the fluctuations due to the effects of non-technology shocks and thus it is crucial to investigate whether they contaminate our identification of technology shocks. Source: Time series for the labor wedge are taken from Karabarbounis [2014] who has computed the labor wedge for 15 OECD countries over the period 1970-2010. Data are not available for three countries of our sample, including Belgium, Denmark, the Netherlands.

Sample. AUS (1986-2008), AUT (1977-2010), CAN (1972-2010), DEU (1993-2010), ESP (1996-2010), FIN (1976-2010), FRA (1971-2010), GBR (1972-2010), IRL (2000-2010), ITA (1972-2010), JPN (1974-2008), NOR (1979-2010), SWE (1975-2010) and USA (1971-2010).

Empirical strategy and results. We run the regression, in panel format on annual data, of identified asymmetric technology shocks across sectors, $\epsilon_{Z,it}$, on the deviation of tax rates and labor wedge relative to trend in percentage, exogenous shocks to government spending, and variations in the labor wedge:

$$\epsilon_{Z,it} = d_i + d_t + \beta \hat{x}_{it} + \eta^j_{i,t}, \tag{412}$$

where $\eta^j_{i,t}$ is an i.i.d. error term; country fixed effects are captured by country dummies, d_i, and common macroeconomic shocks by year dummies, d_t. We have logged tax rates, the labor wedge, and government spending, (i.e., $\tau^L_{it}, \tau^K_{it}, G_{it}$) and estimated their trend, $\bar{x}_{it}$, by applying a Hodrick-Prescott filter with a smoothing parameter of $\lambda = 100$ (as we use annual data), and calculated $\hat{x}_{it} = x_{it} - \bar{x}_{it}$. Panel data estimations are shown in Table 27. Odd columns show results when we run the regression on the current values of the shift in the non-technology variable whilst even columns displays estimates when we run the regression on current and lagged values of variations in non-technology variables (i.e., in $t-1$, $t-2$). Adding lagged values on non-technology shifts allow us to take into account for the persistence of variations in non-technology variables. The p-values for the F-tests show that none of the variables is significant in explaining our identified asymmetric technology shock across sectors, except for exogenous shocks to government spending. Cardi and Restout [2021] find empirically that shocks to government spending leads traded firms to increase traded TFP. Because fiscal shocks are temporary, they should not contaminate our identification of technology shocks. When we run Granger causality tests, we find that exogenous government shocks do not cause technology shocks. Hence, there is no evidence that the technology shock identified using long-run restrictions is correlated with any of the shifts of non-technology variables.

In contrast, we expect non-technology shocks we identify by estimating the VAR model with long-run restrictions to be correlated with the set of non-technology variables. To test this assumption, we run the same regression as above, i.e., eq. (412) where $\epsilon_{Z,it}$ is replaced with the shocks which increase permanently real GDP but have no permanent effect on the ratio of traded relative to non-traded TFP denoted by $\epsilon_{Y,it}$. Table 28 shows that all but shifts in the capital income tax have significant predictive power for the non-technology shock. Table 29 summarizes the main results for exogeneity tests for both technology and non-technology shocks.

T.4 Robustness Check w.r.t. lags

Erceg, Gust and Guerrieri [2005] find that a four-variable SVAR with four lags (as the authors use quarterly data) performs well in recovering the true responses from DGP. More specifically, the SVAR predicts correctly the sign and the pattern of responses but some empirical IRFs are biased as the SVAR tends to understate the rise in labor productivity and real GDP. The source of bias, called the lag-truncation bias arises because the VAR allows for a limited number of lags which provides an approximation of the true dynamics implied by the model which considers an infinite number of lags. Erceg, Gust and Guerrieri [2005] find that the truncation bias appears negligible for each variable considered by the authors. Thus a short-ordered VAR provides a goods approximation of the true dynamics.

Because Chari et al. [2008] find that increasing the number of lags implies that empirical IRF is a good approximation of theoretical IRF, as a robustness check, we increase the number of lags from 2 to 8 to estimate all VAR models.[44] Chaudourne, Fève and Gay [2014] also indicate that the

[44] The simulations in Chari et al. [2008] (see Figure 3), which represent the least favorable DSGE model example discussed in this literature, show that with four autoregressive lags, the approximation to the true

bias can be reduced by increasing the number of lags in the DSVAR. In the baseline VAR model, we consider 2 lags.

In Fig. 34, we re-estimate all VAR models of the main text. The baseline VAR model which allows for two lags as we use annual data is displayed by the solid blue line. Whilst in the red line we allow for one lag, in the green line, we allow for three lags; in the cyan line, we allow for four lags; in the magenta line, we allow for five lags and in the yellow line, we allow for six lags; in the solid black line, we allow for seven lags and in the dashed black line, we allow for eight lags. Overall, all responses lie within the 90% confidence bounds of the original VAR model. We may notice some quantitative differences. First, as we increase the number of lags, the rise in the relative productivity of tradables is softened in the short-run but quantitatively, the difference with the baseline is small. Second, with regard to aggregate variables, whilst the rise in hours worked is somewhat amplified, the rise in GDP demand components are strongly mitigated, including investment, consumption, and next exports. Most importantly, the dynamic adjustment of sectoral variables remains little sensitive to the increase in the number of lags. The permanent increase in traded relative to non-traded TFP raises the value added share of tradables (at constant prices), regardless of the number of lags. Because the rise in non-traded hours worked remains unchanged and the response of traded hours worked is slightly amplified, the decline in the labor share of tradables is mitigated. The smaller decline in $\nu^{L,H}$ could suggest the presence of larger mobility costs and/or technological change biased toward labor more pronounced in the traded than in the non-traded sector. However, none of these explanations seem to be in line with the results since relative sectoral wages change less as lags are increased and FBTC^H increases by a smaller amount. One potential explanation is that we understate the deterioration in the terms of trade. If we lowered the values for the elasticity of substitution between home-produced and foreign-produced traded goods, ρ, and the price-elasticity of exports, ϕ_X, in the model, the relative price of home-produced traded goods should decline more which would further increase the demand for labor in the traded sector and would mitigate the fall in the labor share of tradables. However, our own estimates for ρ indicate indicate that this parameter is larger than one.

T.5 'Purified' Sectoral TFPs: Shock to Traded relative to Non-Traded Utilization-Adjusted-TFP

'Purified' TFP eliminates biases in estimating the effects of technology shocks. Chaudourne, Fève and Guay [2014] analyze the properties of estimators and IRF to a permanent technology shock when technological change is measured by means of labor productivity, TFP, 'purified' TFP. The authors show that the estimated responses from the DSVAR model are biased in a finite sample if technological change is measured by labor productivity. This bias comes from the fact that both the technology and the non-technology shocks have a permanent effect on labor productivity when hours worked follow a persistent process. The authors also demonstrate that the bias is considerably reduced when the econometrician uses the TFP to measure technological change and the bias is completely eliminated when TFP is purified, i.e., adjusted with factor utilization rate. In addition to eliminating the potential bias in empirical IRFs, Basu, Fernald and Kimball [2006] show that correcting for unobserved input utilization can avoid understate TFP changes when technology improves because utilization falls.

We adjust below the annual Solow residual with capital utilization. We construct our own time series for the capital utilization rate for the seventeen OECD countries because such time series are available only for a few countries and a limited period of time and they are not available at a sectoral level. In addition, in constructing our own time series for the capital utilization rate, we adapt the methodology proposed by Imbs [1999] to a sectoral level where production functions are of the CES type.

Methodology of construction of time series for sectoral capital-utilization rate. We construct time-varying capital utilization series by adapting the procedure proposed in Imbs [1999] to construct our own series of utilization-adjusted TFP in sector $j = H, N$. We assume perfectly competitive factor markets and a technology which is constant returns to scale in effective capital and labor. Both the traded and non-traded sectors use physical capital, K^j, and labor, L^j, according to constant returns to scale production functions which are assumed to take a CES form:

$$Y^j = \left[\gamma^j \left(A^j L^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j u^{K,j} K^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}. \tag{413}$$

Denoting the capital rental cost by $R^j(t) = P_J(t)\left(\delta^j(t) + r^\star\right)$, the profit reads as follows:

$$\Pi^j = P^j Y^j - W^j L^j - R^j K^j. \tag{414}$$

impulse response is poor, but with 40 lags the bias appears reasonably small.

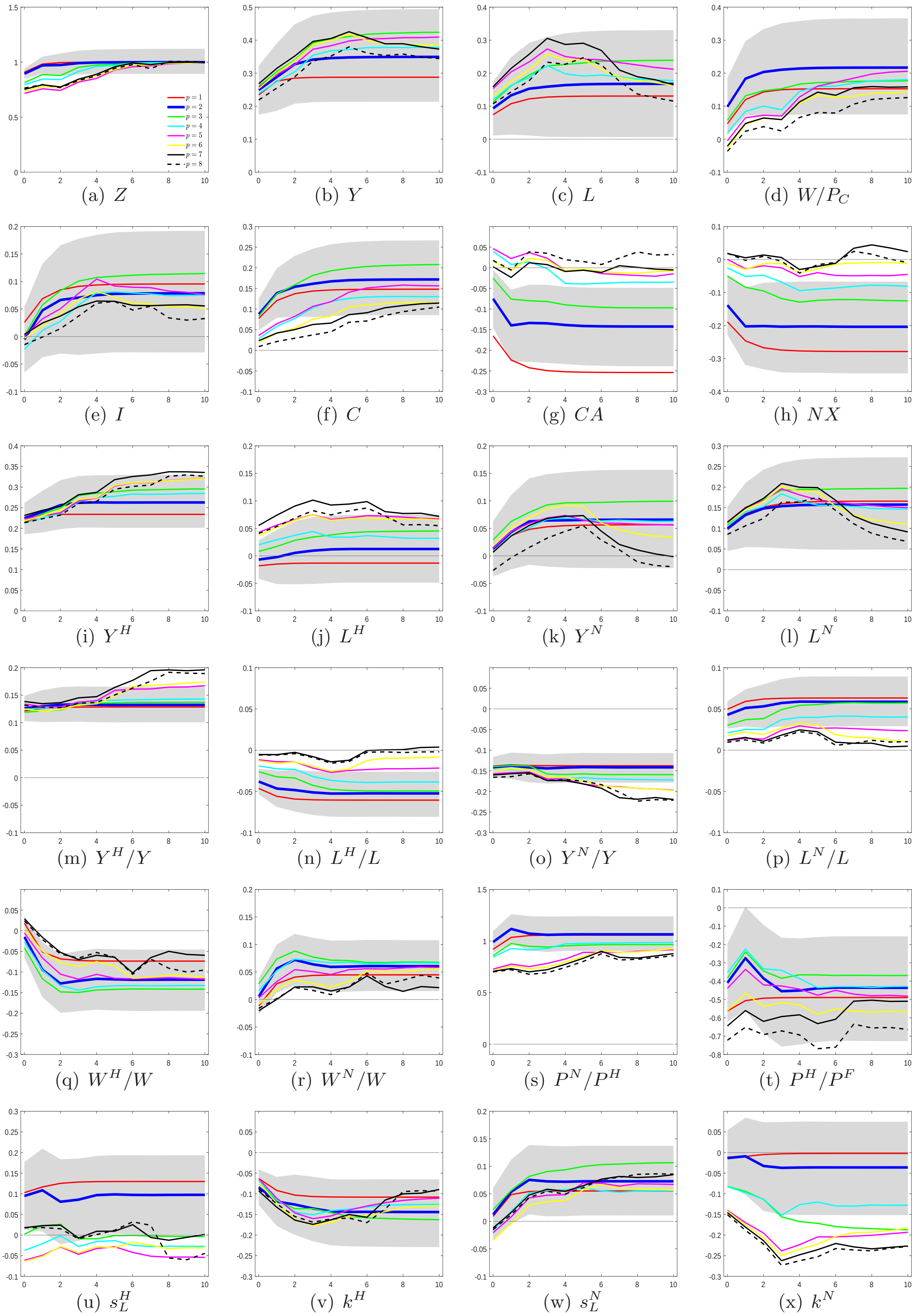


Figure 34: Robustness Check: Increasing the Number of Lags of SVAR Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Shaded areas indicate the 90 percent confidence associated with the baseline VAR model allowing for 2 lags. The baseline VAR model which allows for two lags is displayed by the solid blue line. Whilst in the red line we allow for one lag, in the green line we allow for three lags; in the cyan line, we allow for four lags; in the magenta line, we allow for five lags and in the yellow line, we allow for six lags; in the solid black line, we allow for seven lags and in the dashed black line, we allow for eight lags. Sample: 17 OECD countries, 1970-2013, annual data.

We denote the capital utilization rate by $u^{K,j}(t)$. Because more intensive capital use depreciates the capital more rapidly, we assume the following relationship between capital use and depreciation:

$$\delta^j(t) = \delta\left(u^{K,j}(t)\right)^{\phi^j}, \tag{415}$$

where $\delta = 9.3\%$ and ϕ is the parameter which must determined. At the steady-state, we have $u^{K,j} = 1$ and thus capital depreciation collapses to δ which is symmetric across sectors.

Profit maximization leads to first order conditions on K^j, $u^{K,j}$, L^j:

$$P^j\left(1-\gamma^j\right)\left(B^j u^{K,j}\right)^{\frac{\sigma^j-1}{\sigma^j}}\left(K^j\right)^{-\frac{1}{\sigma^j}}\left(Y^j\right)^{\frac{1}{\sigma^j}} = R^j, \tag{416a}$$

$$P^j\left(1-\gamma^j\right)\left(B^j K^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\left(u^{K,j}\right)^{-\frac{1}{\sigma^j}}\left(Y^j\right)^{\frac{1}{\sigma^j}} = P_J\delta\phi\left(u^{K,j}\right)^{\phi-1}K^j. \tag{416b}$$

$$P^j\gamma^j\left(A^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\left(L^j\right)^{-\frac{1}{\sigma^j}}\left(Y^j\right)^{\frac{1}{\sigma^j}} = W^j, \tag{416c}$$

Multiplying both sides of the first equality and third equality by K^j and L^j, resp., and dividing by sectoral value added leads to the labor and capital income share, resp.:

$$s_L^j = \gamma^j\left(\frac{A^j L^j}{Y^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}. \tag{417a}$$

$$1-s_L^j = \left(1-\gamma^j\right)\left(\frac{B^j u^{K,j} K^j}{Y^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}. \tag{417b}$$

By using the definition of the LIS above and inserting the expression for the capital rental cost, FOC can be rewritten as follows:

$$\left(1-s_L^j\right)\frac{P^j(t)Y^j(t)}{P_J(t)K^j(t)} = \left(\delta^j(t)+r^\star\right), \tag{418a}$$

$$\left(1-s_L^j\right)\frac{P^j(t)Y^j(t)}{P_J(t)K^j(t)} = \delta^j(t)\phi^j, \tag{418b}$$

$$s_L^j = \frac{W^j L^j}{P^j Y^j}. \tag{418c}$$

By combining the FOCs (418a)-(418b) evaluated at the steady-state, we have:

$$\left(r^\star + \delta^j\right) = \delta^j\phi^j, \tag{419}$$

which allows us to pin down ϕ^j. We set $\delta = 0.093$ and $r^\star = 0.04$ for a representative OECD; note that $\phi^j = \phi$ is determined by (419). We let δ (obtained from calibrating the model to the data when we target the investment to GEP ratio) and $r^\star$ (long-run interest rate minus CPI inflation rate) vary across countries to compute ϕ.

We use the value added share in sector j to allocate the aggregate capital stock across sectors:

$$K^j(t) = \frac{P^j(t)Y^j(t)}{P(t)Y_R(t)}K(t), \tag{420}$$

where $K(t)$ is the capital stock at constant prices and $\frac{P^j(t)Y^j(t)}{P(t)Y_R(t)}$ is the value added share of sector $j = H, N$ at nominal prices. Inserting (420) into (418a)-(419), first order conditions on K^j and $u^{K,j}$ now read as follows:

$$\left(1-s_L^j(t)\right)\frac{P(t)Y_R(t)}{P_J(t)K(t)} = \left(\delta^j(t)+r^\star\right), \tag{421a}$$

$$\left(1-s_L^j(t)\right)\frac{P(t)Y_R(t)}{P_J(t)K(t)} = \delta^j(t)\phi^j. \tag{421b}$$

Solving (421b) for $u^{K,j}(t)$ leads to:

$$u^{K,j}(t) = \left[\frac{\left(1-s_L^j(t)\right)}{\delta\phi^j}\frac{P(t)Y_R(t)}{P_J(t)K(t)}\right]^{\frac{1}{\phi^j}}, \tag{422}$$

Dropping the time index to denote the steady-state value, the capital utilization rate is:

$$u^{K,j} = \left[\frac{\left(1-s_L^j\right)}{\delta\phi^j}\frac{PY_R}{P_J K}\right]^{\frac{1}{\phi^j}}. \tag{423}$$

Dividing (422) by (423) leads to the capital utilization rate relative to its steady-state:

$$\frac{u^{K,j}(t)}{u^{K,j}} = \left[\left(\frac{1-s_L^j(t)}{1-s_L^j}\right)\frac{P(t)Y_R(t)}{PY_R}\frac{P_J(t)K(t)}{P_JK}\right]^{\frac{1}{\phi^j}}. \tag{424}$$

The factor-utilization TFP in sector $j = H, N$ is denoted by Z^j:

$$\hat{Z}^j(t) = \hat{Y}^j(t) - s_L^j\hat{L}^j(t) + \left(1-s_L^j\right)\hat{K}^j(t) + \left(1-s_L^j\right)\hat{u}^j(t). \tag{425}$$

TFP series or Solow residual are:

$$T\hat{F}P^j(t) = \hat{Y}^j(t) - s_L^j\hat{L}^j(t) - \left(1-s_L^j\right)\hat{K}^j(t) \tag{426}$$

Normalizing the initial value for sectoral TFP to 100, the growth rate of the Solow residual allows us to recover the time series in level for $\text{TFP}^j(t)$.

Then we construct time series series of utilization-adjusted sectoral TFP which takes into account for the deviation of factor utilization rate relative to the initial steady-state:

$$\begin{aligned}\hat{Z}^j(t) &= T\hat{F}P^j(t) - \left(1-s_L^j\right)\hat{u}^{K,j}(t), \\ \ln Z^j(t) - \ln Z^j &= \left(\ln \text{TFP}^j(t) - \ln \text{TFP}^j\right) - \left(1-s_L^j\right)\left(\ln u^{K,j}(t) - \ln u^{K,j}\right).\end{aligned} \tag{427}$$

where $\hat{Z}^j(t)$ is the percentage deviation of utilization-adjusted TFP relative to the initial steady-state. The percentage deviation of variable $X(t)$ from initial steady-state is denoted by $\hat{X}(t) = \ln X(t) - \ln \bar{X}(t)$ where $\ln \bar{X}(t)$ is obtained by applying a HP filter with a smoothing parameter of 100. To compute $T\hat{F}P^j(t)$, we take the log of $\text{TFP}^j(t)$ and subtract the trend component extracted from a HP filter applied to the log of $\text{TFP}^j(t)$, i.e., $\ln \text{TFP}^j(t) - \ln \bar{\text{TFP}}^j(t)$. The same logic applies to $u^{K,j}(t)$.

Data for real interest rate, $r^\star$. The real interest rate is computed as the real long-term interest rate which is the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index (CPI). Sources: OECD Economic Outlook Database [2017] for the long-term interest rate on government bonds and OECD Prices and Purchasing Power Parities Database [2017] for the CPI. Data coverage: 1970-2013 except for IRL (1990-2013) and KOR (1983-2013). The first column of Table 30 shows the value of the real interest rate which averages 3.1% over the period 1970-2013.

Data for capital depreciation rate. The value of δ_K is chosen to be consistent with the ratio of capital depreciation to GDP observed in the data and averaged over 1970-2015:

$$\frac{1}{46}\sum_{t=1970}^{2015}\frac{\delta_K P_{J,t}K_t}{Y_t} = \frac{CFC}{Y}, \tag{428}$$

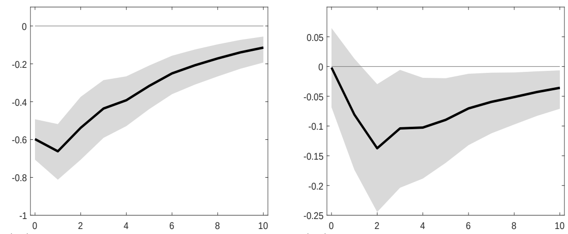
where $P_{J,t}$ is the deflator of gross capital formation series, Y_t is GDP at current prices, and CFC/Y is the ratio of consumption of fixed capital at current prices to nominal GDP averaged over 1970-2013. Deflator of gross capital formation, GDP at current prices and consumption of fixed capital are taken from the OECD National Account Database [2017]. The second column of Table 30 shows the value of the capital depreciation rate obtained by using the formula (428). The capital depreciation rate averages to 5%.

Construction of time series for capital utilization, $u_t^{K,j}$. To construct time series for the capital utilization rate, $u_t^{K,j}$, we proceed as follows. We use time series for the real interest rate, $r^\star$ and for the capital depreciation rate, δ_K to compute $\phi = \frac{r^\star+\delta_K}{\delta_K}$ (see eq. (419)). Once we have calculated ϕ for each country, we use time series for the LIS in sector j, $s_{L,t}^j$, GDP at current prices, $P_tY_{R,t} = Y_t$, the deflator for investment, $P_{J,t}$, and times series for the aggregate capital stock, K_t to compute time series for $u_t^{K,j}$ by using the formula (422).

Empirical strategy, responses of unadjusted, adjusted technology variables and responses of capital utilization rate. Once we have adjusted sectoral TFP with capital utilization, see eq. (427), we construct the utilization-adjusted-TFP differential index between tradables and non-tradables, as in eq. (4), i.e., $\hat{Z}_{it} = a_i\hat{Z}_{it}^H - b_i\hat{Z}_{it}^N$. Then we replace the ratio of traded to non-traded TFP with the ratio of utilization-adjusted-traded-TFP to the utilization-adjusted-non-traded-TFP within each VAR model and identify technology shocks as shocks which increase permanently the relative utilization-adjusted-TFP of tradables. As demonstrated by Chaudourne, Fève and Guay [2014], in doing this, we ensure that technology shocks are not contaminated by non-technology shocks.

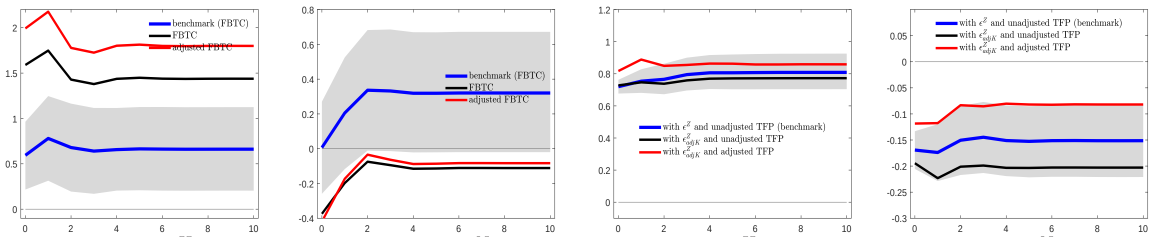
The black line in Fig. 35 shows the dynamic adjustment of capital utilization rates in the traded and the non-traded sector following a permanent increase in utilization-adjusted-TFP of tradables relative to non-tradables. We find empirically that the permanent increase in the relative productivity of tradables, once sectoral TFPs are purified, leads to a fall in the capital utilization rate in the traded sector and a slight increase on impact in the non-traded sector followed by a rapid decline. Intuitively, because technological change is strongly biased toward labor in the traded sector, the demand for capital declines which leads traded firms to use less intensively the capital stock. With regard to the non-traded sector, as we shall see below, technological change is biased toward capital on impact and converges toward Hicks neutral technological change as time passes.

Fig. 36 plots empirical responses of FBTC and TFP, either adjusted (in red lines) or unadjusted with capital utilization rate (in blue line if technology shocks are based on Solow residuals, or in black line if technology shocks are based on utilization-adjusted-TFP). The responses of sectoral TFPs lie within the confidence bounds of the baseline VAR model shown in the blue line. The rise in traded FBTC is more pronounced and non-traded FBTC declines instead of increasing when technology shocks are identified from 'purified' sectoral TFPs.



(a) Traded Capital Utilization Rate, $u^{K,H}$ (b) Non-Traded Capital Utilization Rate, $u^{K,N}$

Figure 35: Responses of Sectoral Capital Utilization Rate following a Permanent Increase in Utilization-Adjusted-TFP of Tradables relative to Non-Tradables Notes: Exogenous 1% permanent increase of utilization-TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The black line shows the responses we estimate empirically following a permanent increase in capital-utilization-adjusted-TFP of tradables relative to non-tradables. We adjusted sectoral TFPs with sectoral capital utilization rates which have been constructed by adapting the methodology proposed by Imbs [1999]. Sample: 17 OECD countries, 1970-2013, annual data.



(a) $FBTC^H$ (b) $FBTC^N$ (c) Z^H (d) Z^N

Figure 36: Responses of Capital-Utilization Adjusted Sectoral TFP and FBTC following a Permanent Increase in Utilization-Adjusted-TFP of Tradables relative to Non-Tradables Notes: Exogenous 1% permanent increase of utilization-TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the responses when technology shocks are identified by using sectoral TPFs measured as Solow residuals whilst the solid black and red lines show results when technology shocks are shocks to capital-utilization-adjusted-traded-TFP relative to capital-utilization-adjusted-non-traded-TFP. The black line shows the responses of technology variables unadjusted with capital utilization whilst the red line shows the responses of capital-utilization adjusted TFP and FBTC in sector $j = H, N$. Sample: 17 OECD countries, 1970-2013, annual data.

Effects of Asymmetric Technology Shocks across Sectors depending on whether Sectoral TFPs are Adjusted or Not with Capital Utilization Rate. Fig. 37 shows the dynamic effects of a shock to capital-utilization-adjusted-TFP of tradables relative to non-tradables. As can be seen in Fig. 37(a), whether sectoral TFPs are adjusted or not with the capital utilization rate, the rise in the relative productivity of tradables is quite similar. As displayed by 37(b), real GDP increases less than in the baseline scenario. The reason to this discrepancy is obvious from the inspection of Fig. 37(i) and Fig. 37(k). As shown in these two figures, the response of non-traded value added at constant prices remains mostly unchanged compared with the baseline case whilst traded value added at constant prices increases less. Because Y^H depends on $u^{K,H}$ (see the CES production function in eq. (413)), the decline in $u^{K,H}$ caused by technological change biased toward labor softens the rise in traded value added and thus in real GDP. As displayed by Fig. 37(c), hours worked increase less than in the baseline case. As shown in Fig. 37(j), the response of traded hours is still not significant whilst Fig. 37(l) reveals that non-traded hours worked increase less than if sectoral TFPs were unadjusted because technological change is biased toward capital on impact in the non-traded sector, see Fig. 36(b), which explains why the rise in total hours worked is mitigated.

T.6 Shock to World TFP of Tradables relative to Non-Tradables

World TFP shocks are independent from persistent country-specific non-technology shocks and ensures the robustness of the identification of technology shocks. In this subsection, we conduct a third empirical test of the robustness of our SVAR results. As reviewed in subsection T.1, Erceg, Gust and Guerrieri [2005], Chari, Kehoe and McGrattan [2008] have shown that persistent non-technology shocks can disturb the identification of permanent technology shocks if they account for a large fraction of output fluctuations. Because the SVAR allows for a limited number of lags, the SVAR model faces some difficulties to disentangle pure technology shocks from other shocks which have long-lasting (or even permanent) effects on labor productivity. As mentioned above, because we use the TFP, our analysis is less subject to this bias but to ascertain the absence of bias, we conduct a new experiment where we identify a technology shock which is by construction purified from country specific non-technology shocks which could potentially contaminate the identification of technology shocks. As stressed by Dupaigne and Fève [2009], on the top of persistent domestic non-technology shocks, the problem becomes more stringent in an international context because foreign non-permanent shocks contaminate the permanent technology shock as identified from a country-level SVAR model. Using labor productivity growth to measure technological change, the authors show that SVARs estimated on country-level data deliver biased estimates of the response of labor input. Because labor productivity growth depends on adjustment of the capital stock which adjusts sluggishly and through this channel non-technology shocks can contaminate the 'true' identification of technology shocks, the authors find that each country's average productivity of labor reflect all the shocks in the model, including those which materialize in the other countries.

Because SVARs on country-level data fail to properly disentangle the permanent technology shock common to all countries from the country-specific stationary shocks, Dupaigne and Fève propose to replace the country-level measure of productivity with an aggregate measure of country-level productivity. Because world permanent productivity shocks are not affected by country-specific persistent non-technology shocks, identifying technology shocks by using productivity growth common to all countries can eliminate the problem of identification raised by Erceg, Gust and Guerrieri [2005], Chari, Kehoe and McGrattan [2008]. Dupaigne and Fève [2009] find empirically that when they use the G7 labor productivity instead of country-level labor productivities, there is almost no discrepancy between the responses of employment evaluated at the country and G7 level.

Construction of the world TFP growth differential between tradables and non-tradables. Building on the ingenious idea of Dupaigne and Fève [2009], we replace the country-level ratio of traded to non-traded TFP with the 'world' ratio of traded to non-traded TFP. To construct the world productivity growth differential between tradables and non-tradables, we proceed as follows. Because TFP is an index, we could calculate the seventeen OECD countries unweighed average of the country-level sectoral TFP. To ensure that our measure of world sectoral TFP reflects the common component of each sectoral TFP to the seventeen OECD countries, we run the regression of the growth rate of TFP in sector j at time t in country i on country and year effects:

$$\hat{Z}^j_{it} = d_i + d_t + \eta_{it}, \tag{429}$$

where d_i captures the country fixed effects, d_t are time dummies, and η_{it} are the i.i.d. error terms. We interpret estimates of time dummies as the growth rate of TFP which is common to the seventeen OECD countries. Denoting the world component of sectoral TFP in sector j by $Z^{W,j}_{it}$, we construct a weighted world productivity differential index between tradables and non-tradables by augmenting sectoral world TFPs with weights a and b (see eq. (4)), i.e., $\hat{Z}^W_t = a\hat{Z}^{W,H}_{it} - b\hat{Z}^{W,N}_{it}$. Fig. 38 plots in the blue line with circles the rate of growth of the world productivity growth differential between tradables and non-tradables. In the black line with triangles, we plot the productivity growth differential between tradables and non-tradables where (logged) sectoral TFP are averaged across countries. Because the blue and the black line are hardly distinguishable, we can conclude that estimating the world component of sectoral productivity gives very similar results to averaging TFP.

Contribution of world TFP component to rate of growth of domestic TFP. One interesting question to ask is to what extent the world component of TFP contributes to the rate of growth of the country-level TFP. Column 1 of Table 31 shows the variance of the growth rate of TFP. We consider four measures: aggregate TFP, traded TFP, non-traded TFP and the ratio of traded to non-traded TFP (weighted by a and b respectively). Column 2 of Table 31 shows the variance of the rate of growth of world TFP. Column 3 gives the contribution of the world component to

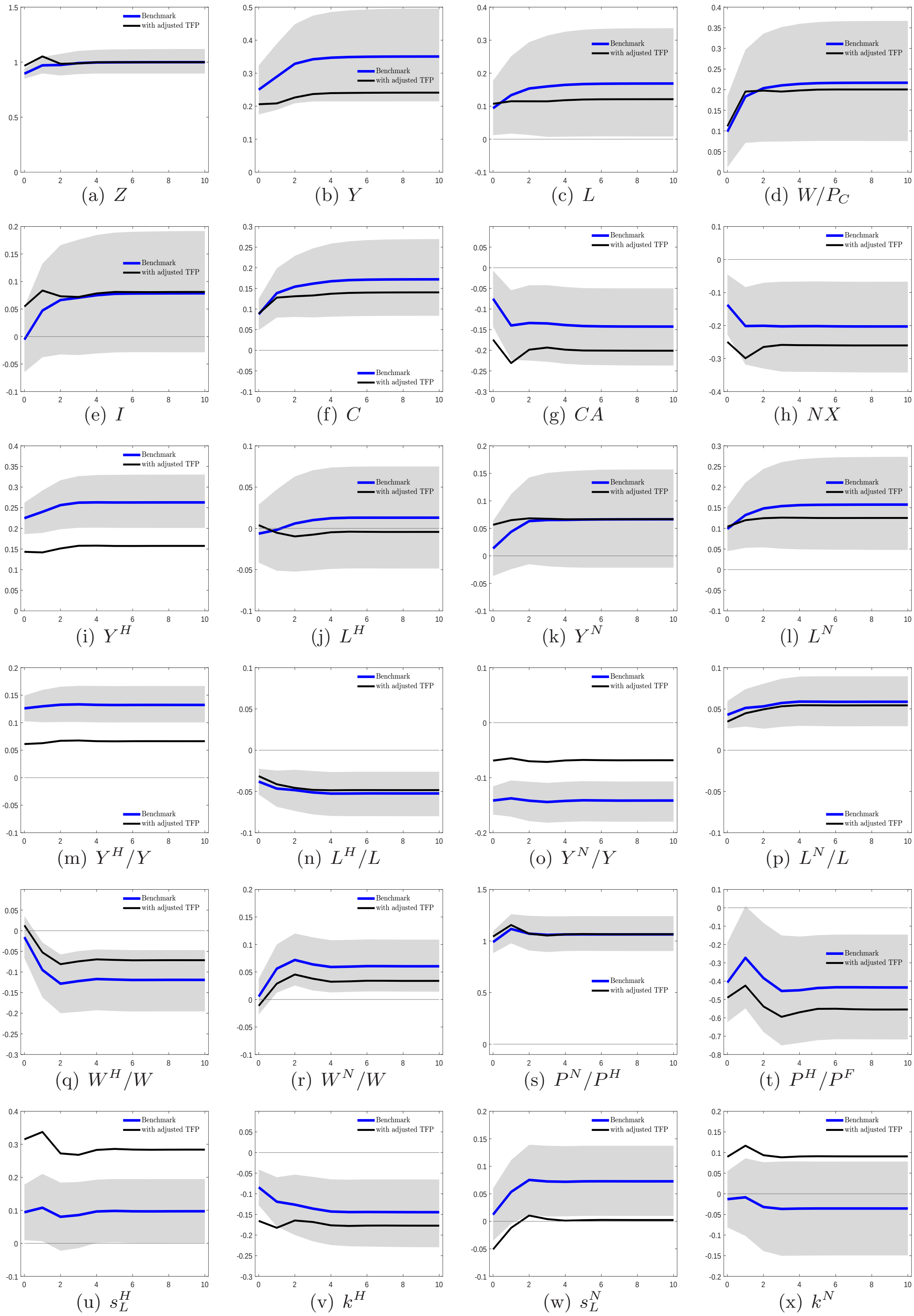


Figure 37: Effects of a Permanent Increase in Utilization-Adjusted-TFP of Tradables relative to Non-Tradables Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added, sectoral value added share), percentage deviation from trend in total hours worked units (sectoral hours worked, sectoral hours worked share), percentage deviation from trend (sectoral TFPs, relative price of non-tradables, terms of trade, relative wage). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for the baseline VAR model where sectoral TPFs are Solow residuals whilst the solid black lines show results when we adjust sectoral TFPs with sectoral capital utilization rates which have been constructed by adapting the methodology proposed by Imbs [1999]. Sample: 17 OECD countries, 1970-2013, annual data.

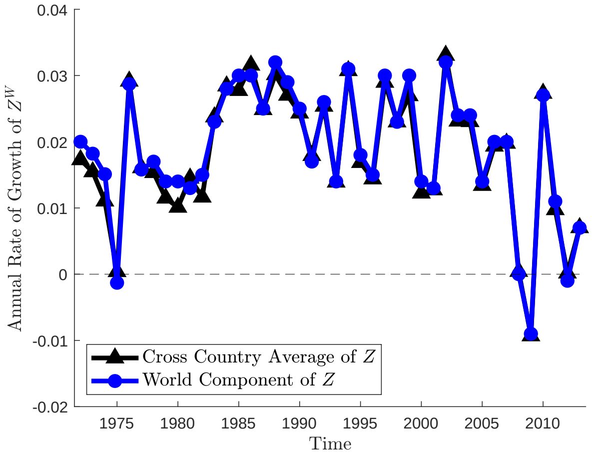


Figure 38: Rate of Growth of the Ratio of World TFP of Tradables Relative to Non-Tradable Notes: We run the regression of the growth rate of TFP in sector j at time t in country i on country and year effects, see eq. (429), and interpret estimated coefficients for time dummies as the rate of growth of sectoral TFP which is common to the seventeen OECD countries of our sample. Denoting the world component of TFP in sector j by $Z_{it}^{W,j}$, we construct a weighted world productivity differential index between tradables and non-tradables by augmenting sectoral world TFPs with weights a and b (see eq. (4)), i.e., $\hat{Z}_t^W = a\hat{Z}_{it}^{W,H} - b\hat{Z}_{it}^{W,N}$. The solid blue line with circles plots the world productivity growth differential between tradables and non-tradables against time. Alternatively, we calculate a weighted world productivity growth differential by averaging logged sectoral TFP across countries which is displayed by the black line with triangles. The two measures give similar results. Sample: 17 OECD countries, 1970-2013, annual data.

the rate of growth of the country-level TFP. The first row reveals that over the period 1970-2013, the common component to the seventeen OECD countries of the rate of growth of aggregate TFP contributes to 45% of the rate of growth of the country-level aggregate TFP. As can be seen in the second and third row, as expected, the world component of traded TFP is much larger than the wold component of non-traded TFP since traded firms are more prone to benefit from international innovations as they are more open to trade and investment more in R&D.

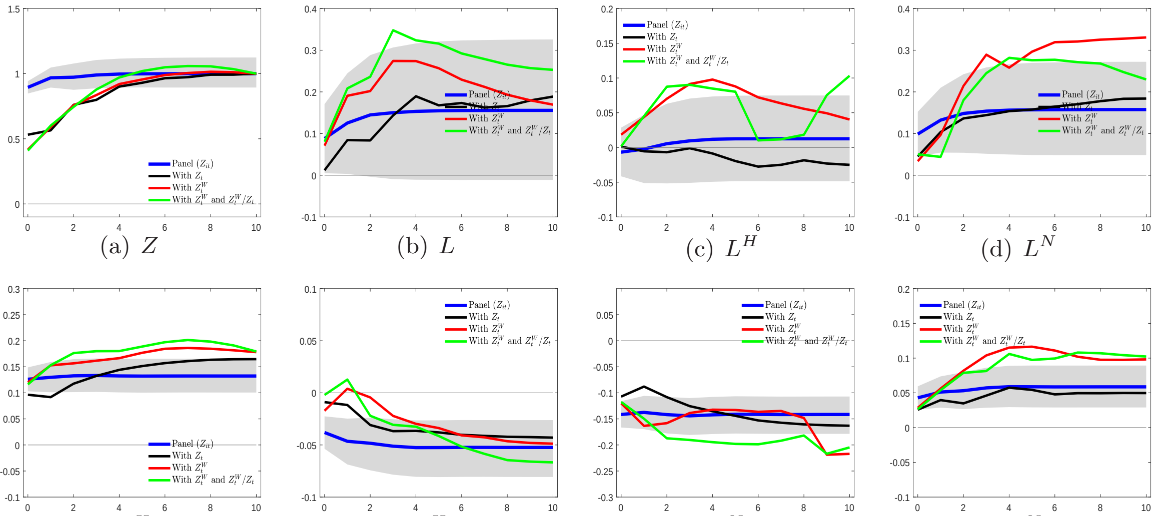
Empirical strategy and results. In the main text, to estimate the sectoral composition effects of a technology shock biased toward tradables, we consider VAR models which include the ratio of traded to non-traded TFP, Z_{it}, and a vector of sectoral variables such as value added at constant prices, Y_{it}^j, hours worked, L_{it}^j, and the real consumption wage, $W_{C,it}^j$ in sector j or alternatively the value added share, $\nu_{it}^{Y,j}$, the labor share, $\nu_{it}^{L,j}$, and the relative wage, W_{it}^j/W_{it}, in sector j. We also consider a VAR model which includes relative prices to inspect the transmission mechanism. The blue line in Fig. 39 plots the responses of the relative productivity of tradables, total and sectoral hours worked, and the dynamic adjustment of the sectoral value added and labor shares when we estimate the VAR model in panel format where we consider the country-level TFP growth differential between tradables and non-tradables ordered first in the VAR model.

To show that our identification of asymmetric permanent technology shocks across sectors are not contaminated by persistent non-technology shocks, we re-estimate each VAR model by replacing the ratio of traded to non-traded TFP with the world TFP of tradables relative to non-tradables denoted by Z_t^W, i.e., we estimate $[\hat{Z}_t^W, \hat{V}_{it}^j]$ where V^j is a set of sectoral variables detailed above. Since the productivity growth differential between tradables and non-tradables is symmetric across the seventeen OECD countries of our sample, we re-estimate each VAR model for one country at a time. The red line in Fig. 39 shows the median of the responses when the country-level productivity growth differential between tradables and non-tradables is replaced with the world productivity growth differential between tradables and non-tradables, ordered first.

Because the blue line shows results when we estimate the VAR model in panel format, to have consistent baseline empirical results which can be compared with, we re-estimate the VAR models where country-level productivity growth differential between tradables and non-tradables is ordered first for one country at a time. The black line in Fig. 39 shows the median of the responses. To check whether the identification of asymmetric technology shocks across sectors is contaminated by persistent country-specific non-technology shocks, we augment each VAR model with the difference between the country-level productivity growth differential between tradables and non-tradables and the world productivity growth differential between tradables and non-tradables, i.e., $[\hat{Z}_t^W, \hat{V}_{it}^j, \hat{Z}_{it} - \hat{Z}_t^W]$. This difference measures the country-specific productivity growth differential between tradables and non-tradables. The median of responses in the augmented VAR model is shown in the green line in Fig. 39.

When we estimate each VAR model for one country at a time and plot the median of the responses, the rise in the relative productivity of tradables is mitigated, as shown in the black line.

Importantly, as displayed by the red line, a permanent increase in world TFP of tradables relative to non-tradables generates an endogenous adjustment of traded TFP relative to non-traded TFP which is identical to that when we use the country-level productivity growth differential between tradables and non-tradables. Therefore, our identification of asymmetric technology shocks across sectors is not contaminated by non-technology shocks. Inspection of all panels in Fig. 39 reveals that the dynamic adjustment of variables following a permanent increase in world TFP of tradables relative to non-tradables shown in the red line lies within the confidence bounds of the baseline VAR model where we use the country-level productivity differential. The responses shown in the red line are also very close to the dynamic adjustment of variables when the VAR model is augmented with the country-specific productivity growth differential between tradables and non-tradables which further confirms that the responses are not subject to bias and therefore are not contaminated by persistent non-technology shocks.



(a) Z (b) L (c) L^H (d) L^N

(e) Y^H/Y (f) L^H/L (g) Y^N/Y (h) L^N/L

Figure 39: Labor Market Effects of a Permanent Increase in World Traded TFP relative to World Non-Traded TFP Notes: Exogenous 1% permanent increase of world TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added share), percentage deviation from trend in total hours worked units (sectoral hours worked, sectoral hours worked share), percentage deviation from trend (sectoral TFPs). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for the baseline VAR model where sectoral TPFs are country-level Solow residuals. The solid black line shows the median of the responses when we estimate the same VAR model as in the baseline case but for one country at a time. The red line shows the median of the responses when the country-level productivity growth differential between tradables and non-tradables is replaced with the world productivity growth differential between tradables and non-tradables, ordered first. The green line shows the median of the responses when we augment the latter VAR model with the country-specific TFP growth differential between tradables and non-tradables (ordered last) calculated as the difference between the country-level TFP growth differential between tradables and non-tradables and the world TFP growth differential. Sample: 17 OECD countries, 1970-2013, annual data.

Table 26: The Share of the FEV of Value Added or Hours Worked Attributable to Asymmetric Technology Shocks across Sectors in %: Cross-Country

	$[Z, Y_R, L, W_C]$	$[Z, \nu^{Y,H}, \nu^{L,H}]$		$[Z, \nu^{Y,N}, \nu^{L,N}]$		$[Z, Y^H, L^H]$		$[Z, Y^N, L^N]$		$[Z^H, \nu^{Y,H}, \nu^{L,H}]$		$[Z^N, \nu^{Y,N}, \nu^{L,N}]$	
Panel A.1970-1992	Y_R	$\nu^{Y,H}$	$\nu^{L,H}$	$\nu^{Y,N}$	$\nu^{L,N}$	Y^H	L^H	Y^N	L^N	$\nu^{Y,H}$	$\nu^{L,H}$	$\nu^{Y,N}$	$\nu^{L,N}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Mean	27.5	35.8	28.8	36.7	28.6	30.0	29.2	28.6	30.6	31.0	20.1	22.1	28.6
Min	3.3	4.9	1.1	2.4	1.2	7.8	3.6	3.3	1.3	3.1	4.0	2.8	4.7
Max	64.6	82.4	70.8	75.9	71.8	83.7	66.7	76.8	64.1	58.8	73.2	38.8	50.4
Panel B.1993-2013	Y_R	$\nu^{Y,H}$	$\nu^{L,H}$	$\nu^{Y,N}$	$\nu^{L,N}$	Y^H	L^H	Y^N	L^N	$\nu^{Y,H}$	$\nu^{L,H}$	$\nu^{Y,N}$	$\nu^{L,N}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Mean	39.7	44.3	30.7	42.8	31.6	44.2	29.1	36.8	33.8	50.4	25.9	33.5	22.2
Min	7.3	8.3	6.0	13.0	5.4	5.7	2.1	5.0	2.8	12.2	1.2	5.1	4.4
Max	73.0	80.0	56.2	82.2	63.5	83.4	60.7	77.1	75.9	82.5	62.6	59.9	57.2

Notes: FEVD: Forecast Error Variance Decomposition of VAR Models over Two-Subperiods. The number in columns 1-13 denotes the fraction of the total forecast error variance of value added/value added share or hours worked/labor share growth, attributable to identified asymmetric technology shocks across sectors (i.e., shock to $Z_t = (Z_t^H)^a/(Z_t^N)^b$). We consider a forecast horizon of 10 years because considering earlier forecast horizon gives similar results. We consider an aggregate four-variable VAR in column 1 and six three-variable VAR model which includes Z^H/Z^N, Z^H, or Z^N, ordered first, and all variables are in growth rate. We estimate the VAR model for one country at a time over 1970-1992 (see Panel A) and 1993-2013 (see Panel B). In the row 'Mean', we average the fraction of the total FEV of the corresponding variable across countries. Whilst the row 'Min' gives the minimum fraction among the seventeen OECD countries, 'Max' gives the maximum of the fraction of FEV explained by a permanent increase in Z. Sample: 17 OECD countries, 1970-2013, annual data.

Table 27: Identified Permanent Technology Shocks: Exogeneity Test

	Dependent Variable: ε_{it}^{Z}							
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathrm{d}\tau_{it}^{L}$	-0.002	0.030						
	(-0.119)	(0.959)						
$\mathrm{d}\tau_{it}^{K}$			-0.006	-0.009				
			(-0.679)	(-0.846)				
ε_{it}^{G}					0.166^{b}	0.176^{b}		
					(2.456)	(2.638)		
dwedge_{it}							-0.001	-0.004
							(-0.150)	(-0.631)
P-value for Exogeneity Test	0.911	0.544	0.528	0.575	0.008	0.044	0.869	0.769
R^2	0.041	0.047	0.042	0.047	0.059	0.059	0.041	0.044
Controls (2 lags on the explanatory variable)	yes	no	yes	no	yes	no	yes	no
Country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Countries	14	14	14	14	14	14	14	14
Observations	427	408	427	408	427	408	427	408

Notes: Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Explanatory variables $\mathrm{d}x_{it}$ for $\mathrm{d}x_{it} = \mathrm{d}\tau_{it}^{L}, \mathrm{d}\tau_{it}^{K}, \mathrm{dwedge}_{it}$ enter in regression as deviations from trend. The trend component is extracted by using an Hodrick-Prescott (HP) filter to the variables in logs. The parameter λ of the HP filter takes the value of 100. x_{it} also includes exogenous shocks to government spending we have estimated by adopting a Cholesly decomposition. The exogeneity F-test is based on a regression of the identified technology shock ε_{it}^{Z} on fixed effects, time dummies and (i) $\mathrm{d}x_{it}$ or (ii) $\mathrm{d}x_{it}$ and two lags of $\mathrm{d}x_{it}$. The null hypothesis is that all of the coefficients on explanatory variable are jointly equal to zero. If p-value ≥ 0.05 at a 5% significance level, the variable is not significant in explaining the identified technology shock ε_{it}^{Z}.

Table 28: Identified Permanent Non-Technology Shocks: Exogeneity Test

	Dependent Variable: $\varepsilon_{it}^{Y_R}$							
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathrm{d}\tau_{it}^{L}$	-0.055^{a}	-0.046^{c}						
	(-2.851)	(-1.892)						
$\mathrm{d}\tau_{it}^{K}$			-0.017^{c}	-0.015				
			(-1.848)	(-1.533)				
ε_{it}^{G}					0.162^{a}	0.150^{b}		
					(2.743)	(2.491)		
dwedge_{it}							0.025^{a}	0.026^{a}
							(5.585)	(4.282)
P-value for Exogeneity Test	0.001	0.045	0.033	0.239	0.003	0.053	0.000	0.000
R^2	0.080	0.091	0.064	0.081	0.074	0.093	0.134	0.189
Controls (2 lags on the explanatory variable)	yes	no	yes	no	yes	no	yes	no
Country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Countries	14	14	14	14	14	14	14	14
Observations	427	408	427	408	427	408	427	408

Notes: Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Explanatory variables $\mathrm{d}x_{it}$ for $\mathrm{d}x_{it} = \mathrm{d}\tau_{it}^{L}, \mathrm{d}\tau_{it}^{K}, \mathrm{dwedge}_{it}$ enter in regression as deviations from trend. The trend component is extracted by using an Hodrick-Prescott (HP) filter to the variables in logs. The parameter λ of the HP filter takes the value of 100. x_{it} also includes exogenous shocks to government spending we have estimated by adopting a Cholesly decomposition. The exogeneity F-test is based on a regression of the identified technology shock $\varepsilon_{it}^{Y_R}$ on fixed effects, time dummies and (i) $\mathrm{d}x_{it}$ or (ii) $\mathrm{d}x_{it}$ and two lags of $\mathrm{d}x_{it}$. The null hypothesis is that all of the coefficients on explanatory variable are jointly equal to zero. If p-value ≥ 0.05 at a 5% significance level, the variable is not significant in explaining the identified technology shock $\varepsilon_{it}^{Y_R}$.

Table 29: Summary Table: P-values for Exogeneity Tests for Identified Technology (ε_{it}^{Z}) and Non-Technology ($\varepsilon_{it}^{Y_R}$) Shocks

	$\mathrm{d}\tau_{it}^{L}$		$\mathrm{d}\tau_{it}^{K}$		ε_{it}^{G}		dwedge_{it}	
Technology shock	0.911	0.544	0.528	0.575	0.008	0.044	0.869	0.769
Non-technology shock	0.001	0.045	0.033	0.239	0.003	0.053	0.000	0.000

Notes: Variables $\mathrm{d}x_{it}$ for $\mathrm{d}x_{it} = \mathrm{d}\tau_{it}^{L}, \mathrm{d}\tau_{it}^{K}, \epsilon_{it}^{G}, \mathrm{dwedge}_{it}$ enter in regression as deviations from trend. The exogeneity F-test is based on a regression of the shock ε_{it}^{Z} or $\varepsilon_{it}^{Y_R}$ on fixed effects, time dummies and (i) $\mathrm{d}x_{it}$ or (ii) $\mathrm{d}x_{it}$ and two lags of $\mathrm{d}x_{it}$. The null hypothesis is that all of the coefficients on explanatory variable are jointly equal to zero. If p-value ≥ 0.05 at a 5% significance level, the variable is not significant in explaining the identified ε_{it}^{Z} or $\varepsilon_{it}^{Y_R}$.

Table 30: Data on Real Interest Rate ($r^{\star}$) and Fixed Capital Depreciation Rate (δ_K)

Country	$r^{\star}$	δ_K
AUS	0.030	0.058
AUT	0.032	0.040
BEL	0.034	0.041
CAN	0.033	0.100
DEU	0.027	0.033
DNK	0.048	0.062
ESP	0.020	0.036
FIN	0.026	0.048
FRA	0.033	0.043
GBR	0.025	0.031
IRL	0.036	0.042
ITA	0.025	0.029
JPN	0.019	0.050
NLD	0.031	0.035
NOR	0.028	0.102
SWE	0.032	0.026
USA	0.027	0.069
OECD	0.031	0.050

Table 31: The Share of Variance of TFP Growth Attributable to World TFP Growth (in %)

VAR Model	Total Variance (1)	Variance World (2)	Contribution in % World (3)	Country-level (4)
Aggregate TFP	0.0050	0.0022	45.0	55.0
Traded TFP	0.0115	0.0049	42.2	57.8
Non-Traded TFP	0.0044	0.0012	26.3	73.7
Ratio of Traded to Non-Traded TFP	0.0112	0.0035	31.3	68.7

Notes: The left-hand side of the table specifies the measure of productivity. The figures in column 1 are the variance of the corresponding measure of TFP. We run the regression of the growth rate of TFP in sector j at time t in country i on country and year effects, see eq. (429), and interpret estimated coefficients for time dummies as the rate of growth of TFP which is common to the seventeen OECD countries of our sample. Column 2 shows the variance of the growth rate of world component of TFP. The figure in columns 3-4 denotes the fraction of the variance of country-level TFP growth attributable to the world component and country-specific component, respectively. Sample: 17 OECD countries, 1970-2013, annual data.

T.7 Max Share Identification

Advantages of Max share over LR identification of technology shocks. One key difference between the empirical and the theoretical model is that the former imposes a small number of lags whilst the latter allows for an infinite number of lags. Erceg, Gust and Guerrieri [2005], Chari et al. [2008] argue that it causes a lag-truncation bias which lead estimated IRFs to be biased, in magnitude for the former and in sign for the latter. Francis et al. [2014] offer an alternative approach to identification with the intent of addressing the aforementioned shortcoming associated with long-run restriction in small-sample estimation. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. This method has two major advantages over the standard long-run identification which assumes that the technology shock is the sole contributor of long-run productivity shifts, all other structural innovations having transitory effects on productivity. First, in place of the restriction that the unit root in productivity is driven exclusively by technology, their approach imposes a weaker restriction that the forecast-error variance in productivity at long horizons is dominated by the technology shock. This allows other shocks to influence productivity at finite horizon. Second, the max share approach considers a finite horizon which is more suited to estimate $B_k A_0$ (see section B, eq. (42)). Intuitively, as shown by Uhlig [2004], there is no horizon, at which technology shocks alone explain productivity. Thus, neither short-run, medium-run, nor long-run identification will exactly identify the technology shock. He finds however that medium-run identification works better than the other two.

Using data simulated from a RBC model and a standard medium-scale DSGE model with sticky prices, Francis et al. [2014] find that the Max Share approach exhibits less bias (measured by the deviation between the median response and the theoretical response) and less uncertainty (measured by the width of the 68 percent error bands) than the LR approach. In addition to the responses to the shocks, when the authors compare the model-generated and the estimated technology shocks, they find a high correlation (of 0.81) for the Max share shocks with the true shocks generated by RBC and NK models whilst the correlation is lower for technology shocks from the LR model.

Empirical strategy and comparison of the effects of estimated technology shocks from the LR model with those obtained from the max share identification. As mentioned in Section B where we detail formally the long-run identification of asymmetric technology shocks across sectors, we consider a specification where all variables enter the VAR model in growth rate, we order the ratio of traded to non-traded TFP first, and identify asymmetric technology shocks across sectors as shocks that increase permanently the TFP of tradables relative to the TFP of non-tradables (at an infinite horizon). Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including labor productivity enter the VAR in log levels. As mentioned above, instead of estimating the long-run cumulative matrix $B(1)A_0$, the max share approach amounts to estimating $B_k A_0$ at a finite horizon. The Maximum Forecast Error Variance approach extracts the shock that best explains the FEV at a long but finite horizon of the ratio of traded to non-traded TFP.

LR model vs. Max share: One country at a time. Since one key contribution of our paper is to show that a technology shock that increases permanently traded relative to non-traded TFP raises the value added share of tradables at constant prices and lowers the labor share of tradable, we focus on the VAR model which includes the TFP of tradables relative to non-tradables (ordered first), Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. In Fig. 40-43, we generate the empirical responses from the VAR model estimated for one country at at time. We have estimated the same VAR model for the sixteen OECD countries of our sample. The blue line shows responses obtained by imposing LR restrictions to identify asymmetric technology shocks across sectors. The black line shows results when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run. As it stands out, for all countries and all variables, the LR model generates empirical responses which have the same sign and the same magnitude as the max share identification, thus confirming the robustness of the long-run identification of a permanent increase in traded relative to non-traded TFP. More specifically, all responses generated by applying the max share identification lie within the confidence bounds associated with the LR model. We may notice some quantitative differences however. The max share produces a larger increase of the value added share of tradables at constant prices $\nu_t^{Y,H}$ than that predicted by the LR model for Denmark and for Italy the first two years only. Most importantly, the response of the traded-goods share of tradables from the LR model shown in the blue line can hardly be differentiated from the response of the same model generated by applying the max share approach as shown in the black line.

LR model vs. Max share: Scatter-plot. Whilst it is clear from empirical IRFs shown in

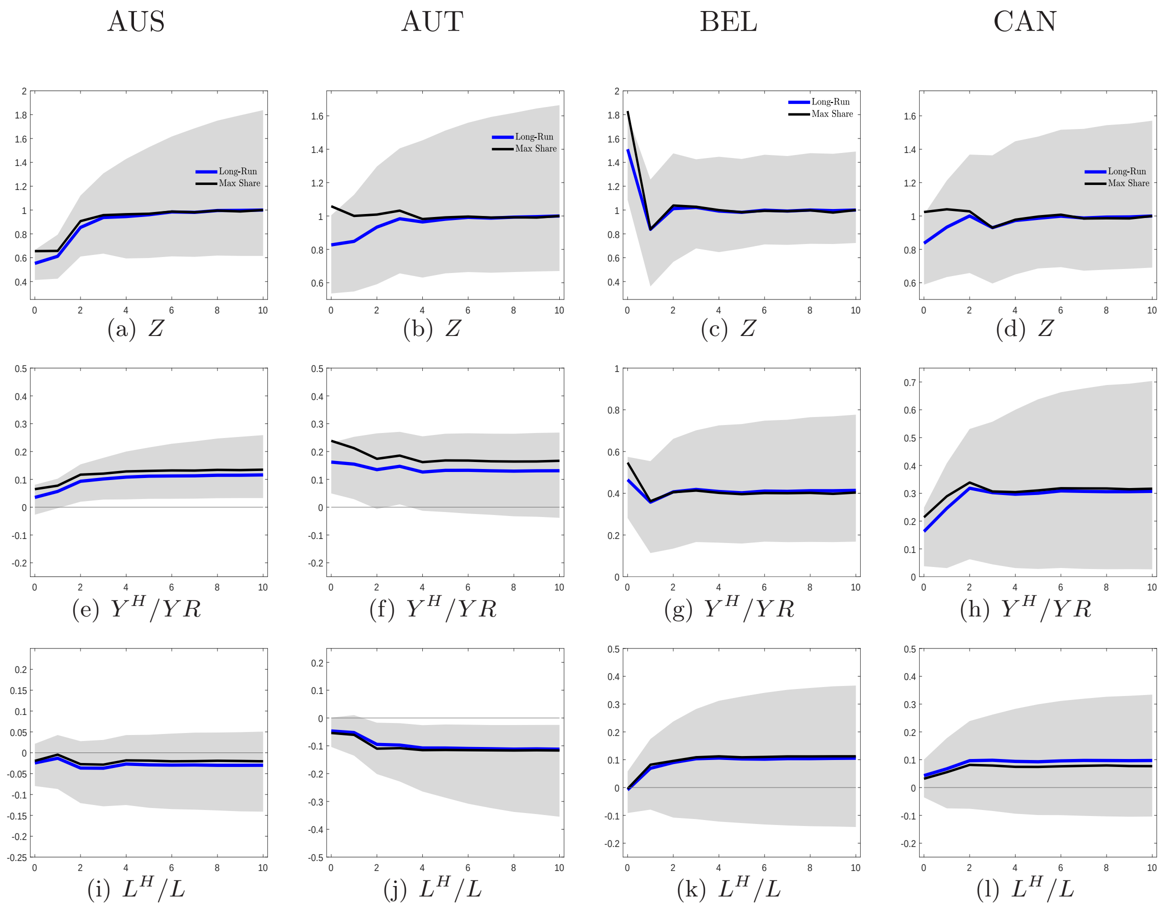
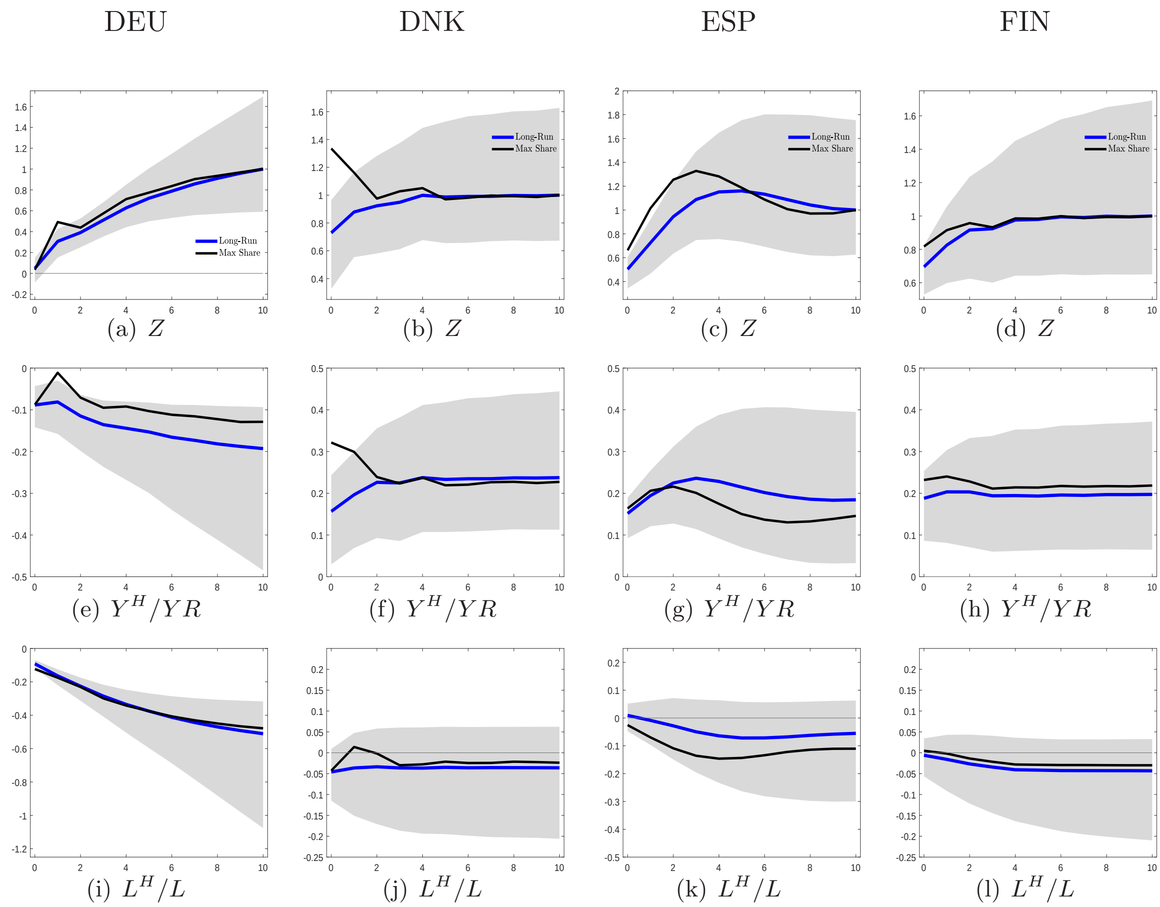


Figure 40: Impulse Responses to an Asymmetric Technology Shock across Sectors in the Max Share (solid black line) and LR (solid blue line) Models for Australia, Austria, Belgium, Canada. Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (value added share of tradables), percentage deviation from trend in total hours worked units (traded-goods-share of total hours worked), percentage deviation from trend (TFP of tradables relative to TFP of non-tradables). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for the VAR model which includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. The blue line shows responses for the LR model, i.e., when the VAR model is estimated for one country at a time and asymmetric technology shocks are identified by imposing long-run restrictions. The black line shows results when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run. Sample: Australia, Austria, Belgium, Canada, 1970-2013, annual data.

Fig. 40-43 that the LR model generates similar empirical IRFs to those obtained by applying the Max share, we quantify the discrepancy in the impact and long-run responses between the LR and Max share approaches in Fig. 44. In each panel, we contrast the responses from a VAR model imposing long-run restrictions shown in the horizontal axis with the responses by using the max share identification developed by Francis et al. [2014] shown in the vertical axis. We estimate for one country at a time the VAR model which includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. Each square shows impact (first row of Fig. 44) and long-run (second row of Fig. 44) responses of the value added share at constant prices (first column) and the traded-goods-share of total hours worked (second column). To assess the extent of the discrepancy in the responses between the LR model and the max share identification, we plot a black trend line and gives its equation and the R^2.

Since the IRFs generated by applying the Max share identification are subject to a small bias, if any, if the LR model generates responses with the same sign of the responses to max share shocks, then we can conclude that empirical IRFs from the LR identification of asymmetric technology shocks across sectors are also unbiased or at least the bias is mitigated. Inspection of the first column of Fig. 44 reveals that the sign of the responses of the value added share of tradables from the LR model is identical to those from the max share approach for all countries and both on impact and in the long-run. When we turn to the second column of Fig. 44 which shows impact and long-run responses of the labor share of tradables, we find that the sign is identical between the two approaches in the long-run whilst the sign is reversed for three countries on impact including,



(a) Z (b) Z (c) Z (d) Z

(e) Y^H/YR (f) Y^H/YR (g) Y^H/YR (h) Y^H/YR

(i) L^H/L (j) L^H/L (k) L^H/L (l) L^H/L

Figure 41: Impulse Responses to an Asymmetric Technology Shock across Sectors in the Max Share (solid black line) and LR (solid blue line) Models for Germany, Denmark, Spain, Finland. Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (value added share of tradables), percentage deviation from trend in total hours worked units (traded-goods-share of total hours worked), percentage deviation from trend (TFP of tradables relative to TFP of non-tradables). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for the VAR model which includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. The blue line shows responses for the LR model, i.e., when the VAR model is estimated for one country at a time and asymmetric technology shocks are identified by imposing long-run restrictions. The black line shows results when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run. Sample: Germany, Denmark, Spain, Finland, 1970-2013, annual data.

Finland, Japan and Spain. However, the change in the labor share of tradables is small for these three countries and the response from the max share shock lies within the confidence bounds of the shock from the LR model. Overall, we can conclude that the responses of the value added share and the labor share of tradables following a permanent increase in traded relative to non-traded TFP have the same sign whether the technology shock is identified by imposing LR restrictions or by applying the Max share approach. In addition, it is worth noting that the R^2 is high both in the short-run and in the long-run, thus confirming that responses for the LR model are highly correlated with responses for Max share approach.

If the trend line had a slope equal to one, then we could conclude that both the Max share identification and the LR model generate responses which have the same magnitude. Because we plot responses to the Max share shocks on the vertical axis against the responses to the technology shocks identified by imposing LR restrictions, if the slope of the trend line has a slope larger than one, then it reveals that the LR model understates the 'true' responses whilst if the slope is smaller than one, it means that the LR model overstates the 'true' responses. With regard to impact responses, inspection of the equation of the trend line reveals that the coefficient of the slope is larger than one on impact for both the value added share of tradables and the traded-goods-share of total hours worked, thus suggesting that imposing LR restrictions tend to somewhat understate the 'true' responses on impact. More specifically, the impact response of the value added share of tradables at constant prices averages 0.114 ppt of GDP for the long-run model and 0.166 ppt of GDP for the max share identification. The impact response of the labor share of tradables averages -0.023 ppt of GDP for the long-run model and -0.027 ppt of GDP for the max share identification.

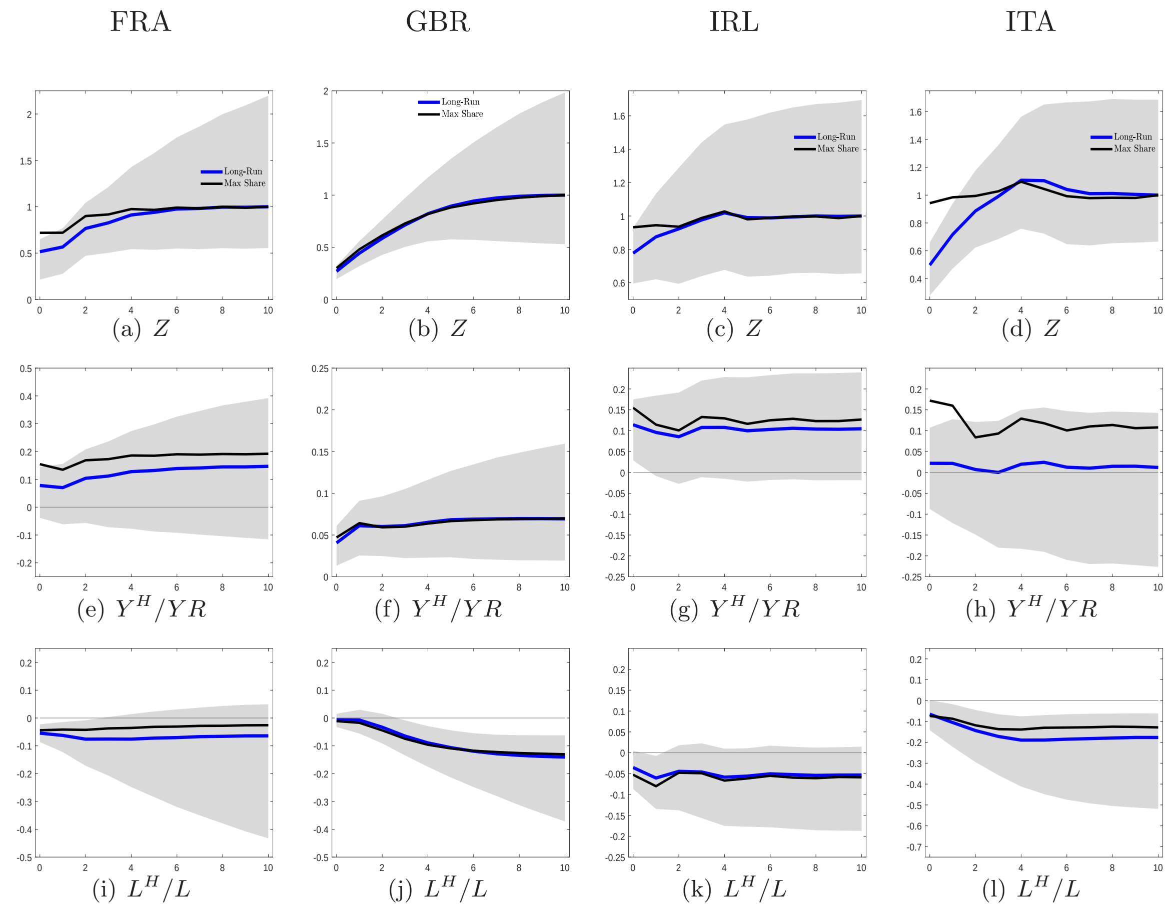


Figure 42: Impulse Responses to an Asymmetric Technology Shock across Sectors in the Max Share (solid black line) and LR (solid blue line) Models for France, the United Kingdom, Ireland, Italy. Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (value added share of tradables), percentage deviation from trend in total hours worked units (traded-goods-share of total hours worked), percentage deviation from trend (TFP of tradables relative to TFP of non-tradables). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for the VAR model which includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. The blue line shows responses for the LR model, i.e., when the VAR model is estimated for one country at a time and asymmetric technology shocks are identified by imposing long-run restrictions. The black line shows results when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run. Sample: France, the United Kingdom, Ireland, Italy, 1970-2013, annual data.

When we turn to long-run responses shown in the second row of Fig. 44, the slope of trend line becomes smaller than one for the long-run response of the labor share of tradables which implies that the long-run model tends to somewhat overstate the decline in the labor share of tradables at a long horizon. More specifically, the impact response of the labor share of tradables averages -0.064 ppt of GDP for the long-run model and -0.057 ppt of GDP for the max share identification. Whilst the slope of the trend line is smaller than one for the long-run responses of $\nu_t^{Y,H}$, the intercept is positive so that the LR model slightly understates the rise in the value added share of tradables at a long horizon. More specifically, the long-run response of the value added share of tradables at constant prices averages 0.154 ppt of GDP for the long-run model and 0.171 ppt of GDP for the max share identification.

Overall, the sign and the magnitude of responses of the value added share and the labor share of tradables are identical for all countries whether we adopt a long-run identification or the max share approach.

LR model vs. Max share: Panel. So far, we have compared the responses to technology shocks across countries by considering the max share approach and the LR model. To ease the comparison between the two approaches, it is convenient to compare one single IRF of one variable between the LR model and the Max share identification. Fig. 45 shows the responses for the VAR model which includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. The blue line shows responses for the LR model, i.e., when the VAR model is estimated in panel format and asymmetric technology shocks are identified by imposing long-run

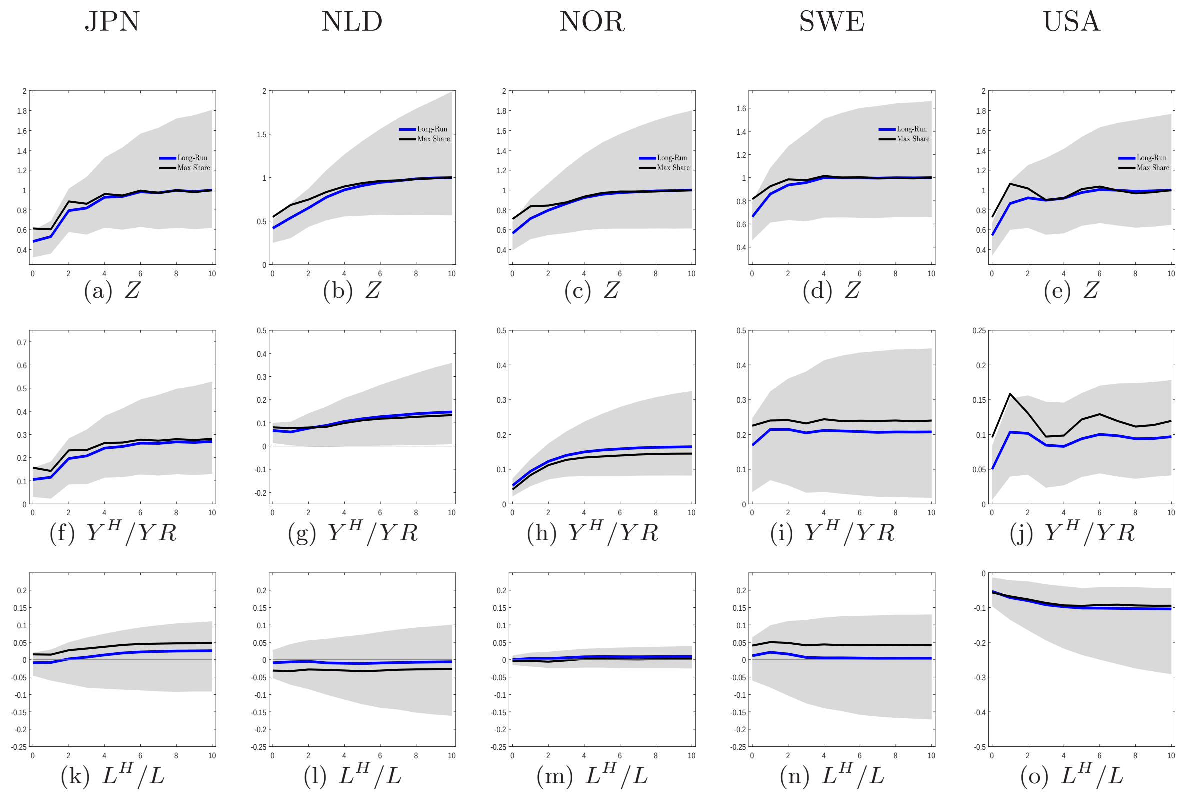


Figure 43: Impulse Responses to an Asymmetric Technology Shock across Sectors in the Max Share (solid black line) and LR (solid blue line) Models for Japan, the Netherlands, Norway, Sweden, the United States. Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (value added share of tradables), percentage deviation from trend in total hours worked units (traded-goods-share of total hours worked), percentage deviation from trend (TFP of tradables relative to TFP of non-tradables). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The blue line shows the response for the VAR model which includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. The blue line shows responses for the LR model, i.e., when the VAR model is estimated for one country at a time and asymmetric technology shocks are identified by imposing long-run restrictions. The black line shows results when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run. Sample: Japan, the Netherlands, Norway, Sweden, the United States, 1970-2013, annual data.

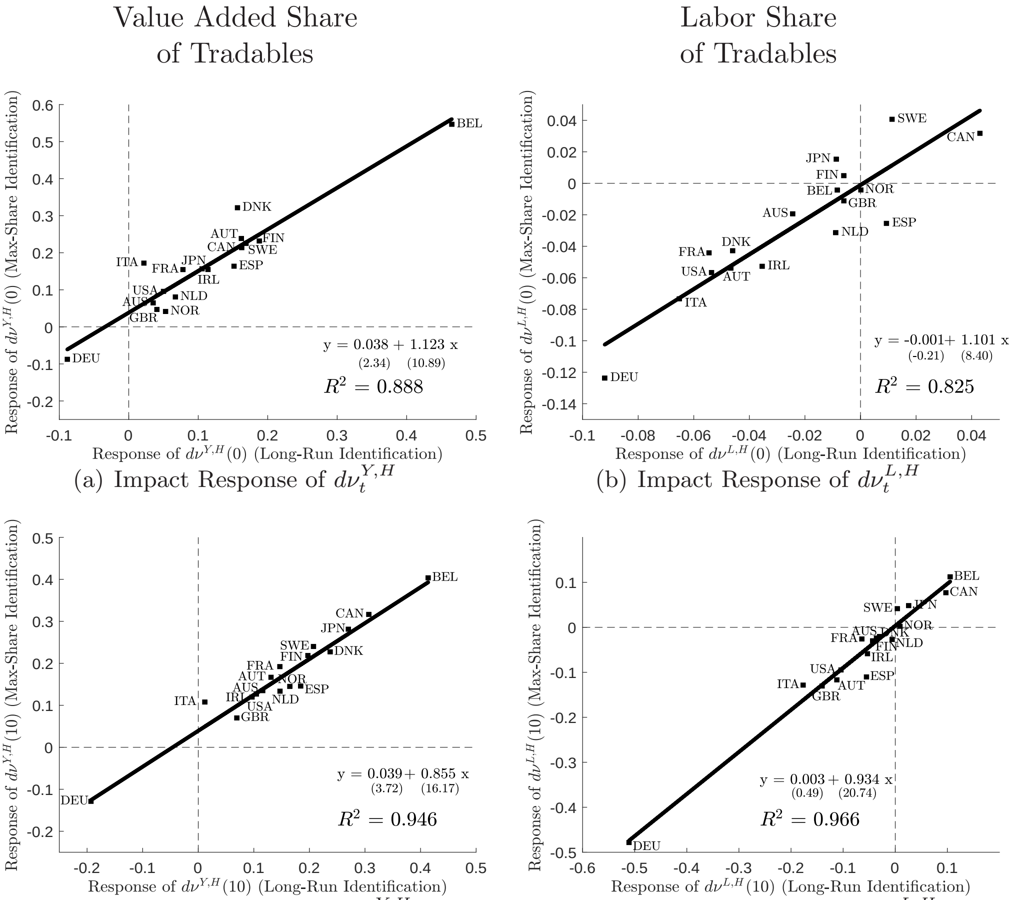
restrictions. To make our results comparable, we estimate the same VAR model (and impose long-run restrictions) but for one country at at time. The black line shows the median of the responses. The red line shows median responses when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run.

Contrasting the black line for LR model and the red line for the Max share approach, we find that the LR model tends to somewhat understate the 'true' response of the value added share of tradables. In contrast, the LR model tends to overstate the decline in the labor share of tradables in the long-run. However, the responses to the max shocks lie within the confidence bounds of the baseline VAR model estimated in panel format. To conclude, the LR model generates responses which are consistent and unbiased as imposing long-run restrictions lead to responses which are almost identical in terms of sign and magnitude to those obtained when applying the max share approach.

U Robustness to Model's Assumptions

The objection of this section is to test the robustness of the theoretical (and empirical) results with respect to the baseline model's assumptions. More specifically, we re-assess numerically the effects of technology shocks

- by introducing capital-utilization rate and investigating the effects of a permanent increase in capital-utilization-adjusted-TFP of tradables relative to non-tradables;
- by assuming preferences between consumption and leisure so as to eliminate the wealth effect as proposed by Greenwood, Hercowitz, and Huffman [1988] (GHH thereafter);



(a) Impact Response of $d\nu_t^{Y,H}$ (b) Impact Response of $d\nu_t^{L,H}$

(c) Long-Run Response of $d\nu_t^{Y,H}$ (d) Long-Run Response of $d\nu_t^{L,H}$

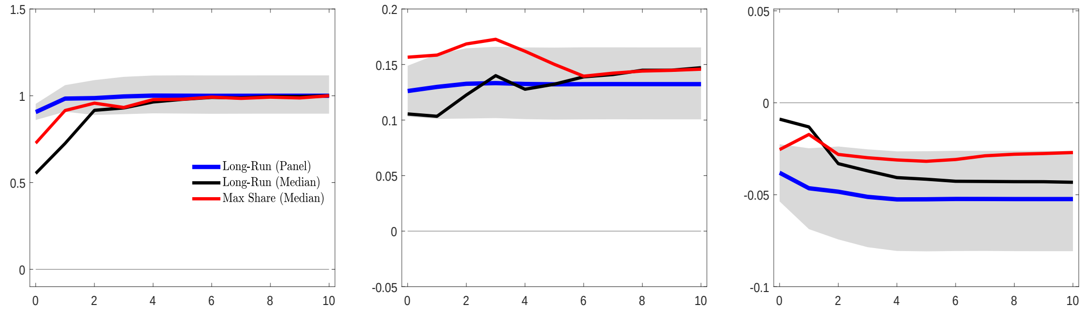
Figure 44: Impact and Long-Run Responses to an Asymmetric Technology Shock across Sectors in the Max Share Identification (Vertical Axis) Against LR Identification (Horizontal Axis) Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal/Vertical axes measure percentage deviation from trend in GDP units (value added share of tradables), percentage deviation from trend in total hours worked units (traded-goods-share of total hours worked). In each panel, we contrast (impact or long-run) responses from a VAR model imposing long-run restrictions shown in the horizontal axis with the (impact or long-run) responses by using the max share identification developed by Francis et al. [2014] shown in the vertical axis. The VAR model includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^{H}/W_{it}. Each square shows impact (first row of Fig. 44) and long-run (second row of Fig. 44) responses when we estimate the VAR model for one country at a time. To assess the extent of the discrepancy in the responses between the LR model and the max share identification, we plot a black trend line and gives its equation and the R^2. Sample: 17 OECD countries, 1970-2013, annual data.

- by assuming non-separable preferences between consumption and leisure in the lines of Shimer [2009];
- by augmenting non-separable preferences between consumption and leisure with time non-separability by introducing outward-looking consumption habits (i.e., external habits or 'catching-up' with the Joneses), see e.g., Carroll, Overland and Weil [2000];
- by assessing the ability of the baseline model (for the baseline calibration) to account for the effects of a temporary shock to aggregate TFP;
- by computing the effects of both a permanent and temporary shock to aggregate TFP and by assessing the ability of the model to account for the standard stylized facts for open economies.

U.1 Extension to Capital Utilization Rate

Introducing the capital utilization rate into the model. We consider a semi-small open economy with CES production functions which is identical to that laid out in section S, except that we allow for endogenous capital utilization. We do not repeat the main elements of the model and emphasize the main changes caused by the assumption of endogenous capital utilization.

In line with the current practice, we assume that households decide about the intensity of capital utilization. We let the function $C^{K,j}(t)$ denote the adjustment costs associated with the choice of capital utilization rate which are increasing and convex functions of the capital utilization rate



(a) Z (b) Y^H/YR (c) L^H/L

Figure 45: Impulse Responses to an Asymmetric Technology Shock across Sectors in the Max Share (solid red line) and LR (solid blue line for panel/black line for median responses) Models in Panel Format. Notes: Exogenous 1% permanent increase of TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (value added share of tradables), percentage deviation from trend in total hours worked units (traded-goods-share of total hours worked), percentage deviation from trend (TFP of tradables relative to TFP of non-tradables). Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. The VAR model includes TFP of tradables relative to non-tradables, Z_{it}, the value added share of tradables at constant prices, $\nu_{it}^{Y,H}$, the labor share of tradables, $\nu_{it}^{L,H}$, and the relative wage of tradables, W_{it}^H/W_{it}. The blue line shows responses for the LR model, i.e., when the VAR model is estimated in panel format and asymmetric technology shocks are identified by imposing long-run restrictions. To make our results comparable, we estimate the same VAR model (and impose long-run restrictions) but for one country at at time. The black line shows the median of the responses. The red line shows median responses when we estimate the aforementioned VAR model for each country and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run. Sample: 17 OECD countries, 1970-2013, annual data.

$u^{K,j}(t)$:

$$C^{K,j}(t) = \xi_1^j \left(u^{K,j}(t) - 1\right) + \frac{\xi_2^j}{2}\left(u^{K,j}(t) - 1\right)^2, \tag{430}$$

where $\xi_2^j > 0$, $\chi_2^j > 0$ are free parameters; as $\xi_2 \to \infty$, $\chi_2 \to \infty$, utilization is fixed at unity.

Households can accumulate internationally traded bonds (expressed in foreign good units), $N(t)$, that yield net interest rate earnings of $r^\star N(t)$. Denoting lump-sum taxes by $T(t)$, household's flow budget constraint states that real disposable income (on the RHS of the equation below) can be saved by accumulating traded bonds, consumed, $P_C(t)C(t)$, or invested, $P_J(t)J(t)$:

$$\begin{aligned} & \dot{N}(t) + P_C(t)C(t) + P_J(t)J(t) + P^H(t)C^{K,H}(t)\alpha_K(t)K(t) + P^N(t)C^{K,N}(t)\left(1-\alpha_K(t)\right)K(t) \\ = \; & r^\star N(t) + W(t)L(t) - T(t) + \left[\alpha_K(t)u^{K,H}(t) + \left(1-\alpha_K(t)\right)u^{K,N}(t)\right]R(t)K(t), \end{aligned} \tag{431}$$

where we denote the share of traded capital in the aggregate capital stock by $\alpha_K(t) = K^H(t)/K(t)$.

While FOC (19a)-(19b) remain unchanged, the rest of first-order conditions are modified as follows:

$$\begin{aligned} \dot{Q}(t) = \left(r^\star + \delta_K\right)Q(t) - \Big\{ & \left[\alpha_K(t)u^{K,H}(t) + \left(1-\alpha_K(t)\right)u^{K,N}(t)\right]R(t) \\ -P^H(t)C^{K,H}(t)\alpha_K(t) - P^N(t)C^{K,N}(t)\left(1-\alpha_K(t)\right) & + P_J(t)\frac{\kappa}{2}\left(\frac{I(t)}{K(t)} - \delta_K\right)\left(\frac{I(t)}{K(t)} + \delta_K\right)\Big\}, \end{aligned} \tag{432a}$$

$$R(t) = P^H(t)\left[\xi_1^H + \xi_2^H\left(u^{K,H}(t) - 1\right)\right], \tag{432b}$$

$$R(t) = P^N(t)\left[\xi_1^N + \xi_2^N\left(u^{K,N}(t) - 1\right)\right], \tag{432c}$$

where we denote the share of traded capital in the aggregate capital stock by $\alpha_K(t) = K^H(t)/K(t)$.

Both the traded and non-traded sectors use physical capital (inclusive of capital utilization), denoted by $\tilde{K}^j(t) = u^{K,j}(t)K^j(t)$, and labor, L^j, according to a constant returns to scale technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j\left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)\tilde{K}^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{433}$$

where $0 < \gamma^j < 1$ and $0 < 1-\gamma^j < 1$ are the weight of labor and capital in the production technology, respectively, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$. We allow for labor- and capital-augmenting efficiency denoted by $A^j(t)$ and $B^j(t)$.

Firms lease the capital from households and hire workers. They face two cost components: a capital rental cost equal to $R(t)$, and a labor cost equal to the wage rate $W^j(t)$. Both sectors are assumed to be perfectly competitive and thus choose capital services and labor by taking prices as given. While capital can move freely between the two sectors, costly labor mobility implies a wage differential across sectors:

$$P^j(t)\gamma^j \left(A^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(y^j(t)\right)^{\frac{1}{\sigma^j}} = W^j(t), \tag{434a}$$

$$P^j(t)\left(1-\gamma^j\right)\left(B^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(u^{K,j}(t)k^j(t)\right)^{-\frac{1}{\sigma^j}} \left(y^j(t)\right)^{\frac{1}{\sigma^j}} = R(t), \tag{434b}$$

where we denote by $k^j(t) \equiv K^j(t)/L^j(t)$ the capital-labor ratio for sector $j = H, N$, and $y^j(t) \equiv Y^j(t)/L^j(t)$ refers to value added per hours worked. Dividing eq. (434a) by eq. (434b), denoting the labor income share by s_L^j and rearranging terms leads to the demand

$$S^j(t) \equiv \frac{s_L^j(t)}{1-s_L^j(t)} = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j(t)u^{K,j}(t)k^j(t)}{A^j(t)}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{435}$$

Inserting solutions (250) for L^H and L^N into the resource constraint for capital:

$$k^H L^H + k^N L^N = K, \tag{436}$$

and solving for (434a)-(434b) together with (436) leads to $k^j, L^j, Y^j\left(\lambda, K, P^N, P^H, A^j, B^j, u^{K,H}, u^{K,N}\right)$. Next, using the fact that R is given by eq. (434b), insert these solutions into (432b)-(432c) and solve for $u^{K,j}\left(\lambda, K, P^N, P^H, A^j, B^j\right)$. The market clearing conditions read

$$Y^N(t) = C^N(t) + J^N(t) + G^N(t) + C^{K,N}(t)K^N(t), \tag{437a}$$

$$Y^H(t) = C^H(t) + J^H(t) + G^H(t) + X^H(t) + C^{K,H}(t)K^H(t). \tag{437b}$$

Eq. (437a)-(437b) can be solved for $P^H, P^N\left(\lambda, K, Q, A^j, B^j\right)$. Plug back these solutions into k^j, L^j, Y^j.

Calibration of parameters governing the law of motion of sectoral capital utilization rate. We turn to the calibration of parameters which govern the capital adjustment cost functions described by (432b)-(432c). Evaluating first-order conditions (432b)-(432c) at the steady-state leads to $\xi_1^j = \frac{R}{P^j}$ and thus ξ_1^j is endogenously pinned down by the initial steady-state value of the ratio of the capital rental rate to the value added deflator, P^j. It gives us $\xi_1^H = 0.124$ and $\xi_1^N = 0.111$. Log-linearizing (432b)-(432c) leads to:

$$\hat{u}^{K,j}(t) = \frac{\xi_1^j}{\xi_2^j}\left(\hat{R}^j(t) - \hat{P}^j(t)\right). \tag{438}$$

According to eq. (438), it is profitable to increase the capital utilization rate when the real capital cost goes up while the parameter ξ_2^j determines the magnitude of the adjustment in $u^{K,j}(t)$. We choose a value for the parameter ξ_2^j so as to account for the empirical response of the capital utilization rate to government shock found in the data. We choose a value for ξ_2^H of 0.000001 and a value for ξ_2^N of 0.05.

The first two rows Fig. 46 show the dynamic adjustment of sectoral TFPs whether they are adjusted or not with capital utilization rates. The blue line shows the empirical IRFs while the black line with squares shows the dynamic adjustment computed numerically. As shown in Fig. 46(e), our model can generate a fall in the capital utilization rate of tradables and reproduces well the decreasing path of the capital utilization rate of non-tradables as can be seen in Fig. 46(f). Adopting the same methodology as in the main text, log-linearizing 437 and the technology frontier (27), and solving for labor and capital-augmenting efficiency leads to:

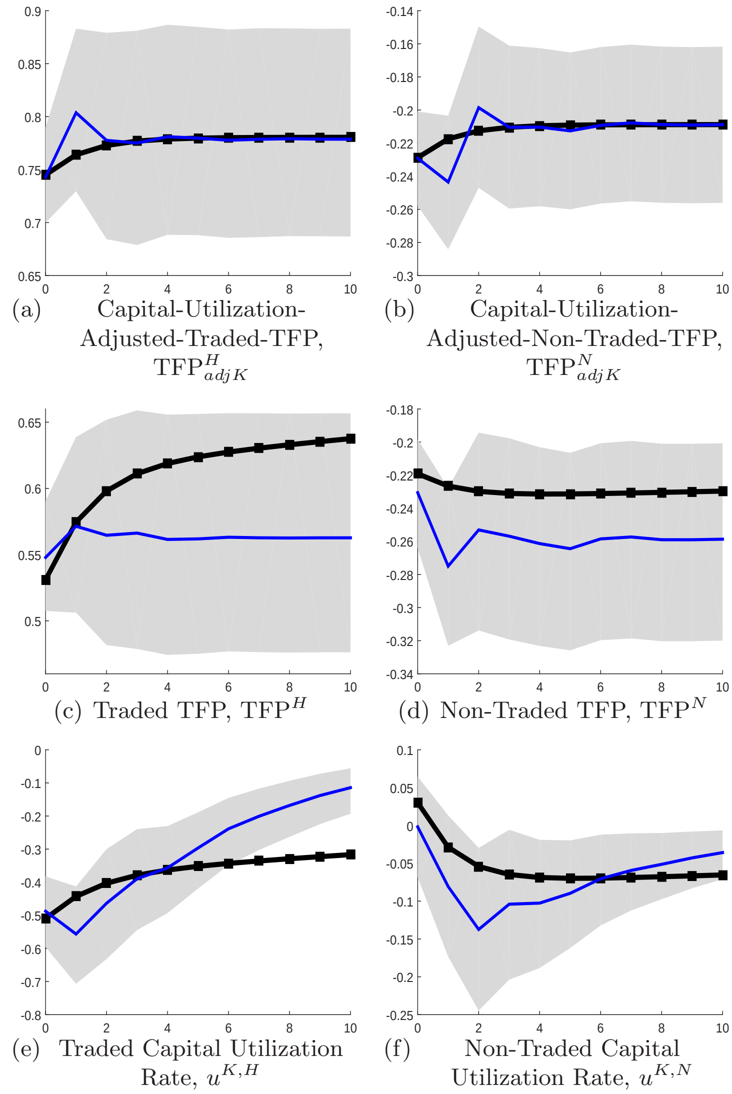
$$\hat{A}^j(t) = \hat{Z}^j(t) - \left(1-s_L^j\right)\left[\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) - \hat{k}^j(t) - \hat{u}^{K,j}(t)\right], \tag{439a}$$

$$\hat{B}^j(t) = \hat{Z}^j(t) + s_L^j\left[\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j(t) - \hat{k}^j(t) - \hat{u}^{K,j}(t)\right], \tag{439b}$$

where $\hat{Z}^j(t)$ now denotes the capital-utilization-adjusted-TFP in sector j expressed in percentage deviation relative to initial steady-state. Once we have inferred the dynamics of $\hat{A}^j(t)$ and $\hat{B}^j(t)$ from (439a)-(439b), we assume

$$\hat{A}^j(t) = \hat{A}^j + \bar{a}^j e^{-\xi^j t}, \quad \hat{B}^j(t) = \hat{B}^j + \bar{b}^j e^{-\xi^j t}, \tag{440}$$

and set $\bar{a}^j$, $\bar{b}^j$ so as to replicate the initial responses of A^j and B^j, i.e., $\bar{a}^j = -\left(\hat{A}^j - \hat{A}^j(0)\right)$, and $\bar{b}^j = -\left(\hat{B}^j - \hat{B}^j(0)\right)$, and choose ξ^j so as to reproduce the dynamics of $Z^j(t)$. We normalize $\hat{Z}(\infty) = a\hat{Z}^H(\infty) - b\hat{Z}^N(\infty) = 1\%$, see Fig. 47(a).



(a) Capital-Utilization-Adjusted-Traded-TFP, TFP^{H}_{adjK}

(b) Capital-Utilization-Adjusted-Non-Traded-TFP, TFP^{N}_{adjK}

(c) Traded TFP, TFP^{H}

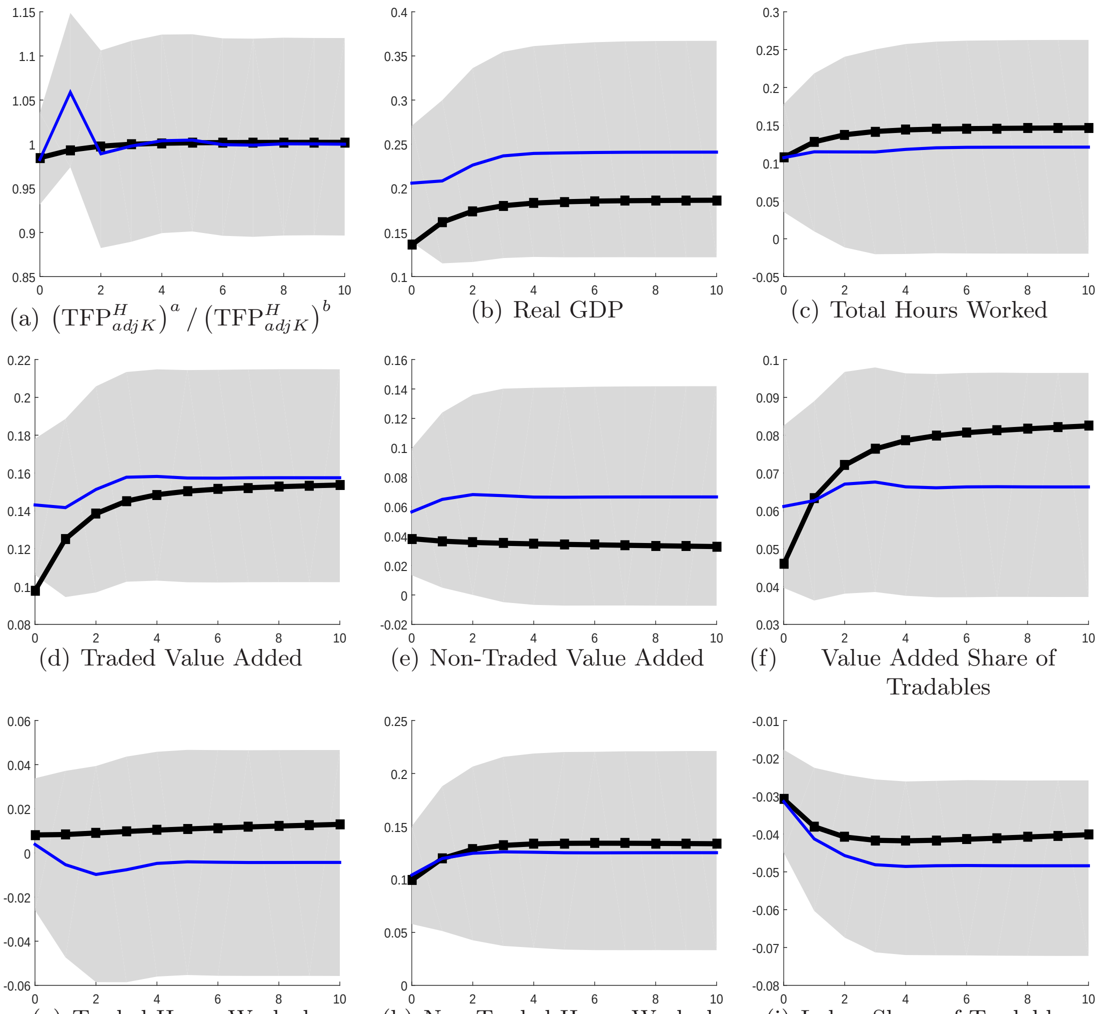
(d) Non-Traded TFP, TFP^{N}

(e) Traded Capital Utilization Rate, $u^{K,H}$

(f) Non-Traded Capital Utilization Rate, $u^{K,N}$

Figure 46: Responses of Sectoral TFPs and Capital Utilization Rates following a Permanent Increase in Utilization-Adjusted-TFP of Tradables relative to Non-Tradables: Model vs. Data Notes: Exogenous 1% permanent increase of utilization-TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Solid blue lines display point estimates of VAR model with shaded area indicating 90% confidence bounds; the blue line shows the responses when technology shocks are identified by using sectoral capital-utilization-adjusted-TPFs whilst solid black lines with squares display baseline model predictions, i.e., when we allow for IML ($\epsilon = 1.6$), endogenous terms of trade ($\rho = \rho_J = 1.5$), gross complementarity between capital and labor in production (i.e., $\sigma^H = 0.687$, $\sigma^N = 0.716$), and technological change biased toward labor. Sample: 17 OECD countries, 1970-2013, annual data.

Model vs. Data. Fig. 47 and Fig. 48 contrast theoretical responses shows in black line with squares with empirical responses shown in blue line. Overall, our model with endogenous capital utilization rate reproduces well our VAR evidence. The first row of Fig. 47 shows that our model with capital utilization rate can account for the dynamics of real GDP and total hours worked whilst it somewhat understates the rise in real GDP. The second and the third row show that the model understate the increase in sectoral value added because the fall in traded capital utilization rate exerts a negative impact on Y^H whilst it reproduces very well the dynamics of traded and non-traded hours worked. Importantly, as shown in Fig. 47(f) and Fig. 47(i), the model augmented with endogenous capital utilization also reproduces well the rise in the value added share of tradables and the decline in the labor share of tradables. As displayed by Fig. 48(a), the strong appreciation in the relative price of non-tradables (upper part) provides some incentives to reallocate labor toward the non-traded sector while the terms of trade deterioration (lower part) mitigates the labor reallocation. As can be seen in Fig. 48(b), we replicate well the sectoral wage differential. Finally, as shown in Fig. Fig. 48(c) and Fig. 48(d), technology change in strongly biased toward the traded sector which increases labor demand in the traded sector and thus hampers the shift of labor toward the non-traded sector. It is worth mentioning that if we shut down endogenous capital utilization, the labor share of tradables slightly increases instead of decreasing as a result of technological change biased toward labor in the traded sector.

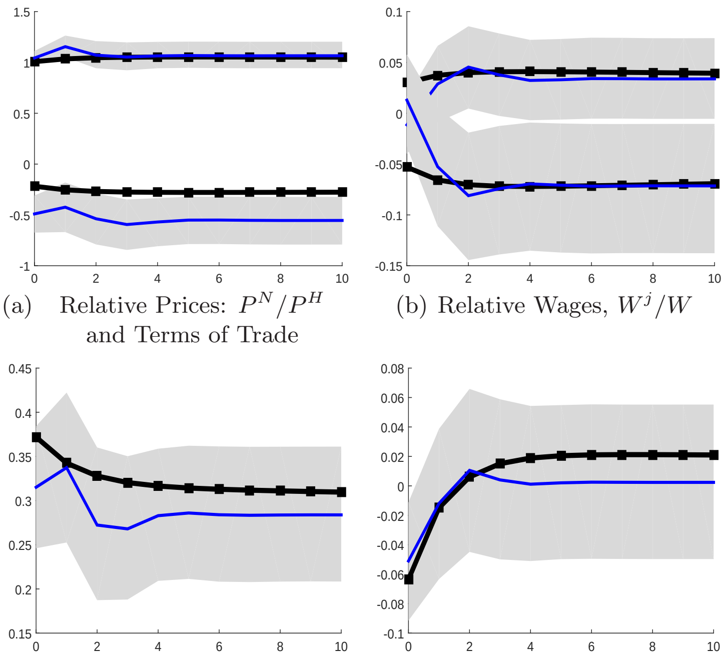


(a) $(\mathrm{TFP}^H_{adjK})^a$ / $(\mathrm{TFP}^H_{adjK})^b$ (b) Real GDP (c) Total Hours Worked

(d) Traded Value Added (e) Non-Traded Value Added (f) Value Added Share of Tradables

(g) Traded Hours Worked (h) Non-Traded Hours Worked (i) Labor Share of Tradables

Figure 47: Sectoral Composition Effects of a Permanent Increase in Utilization-Adjusted-TFP of Tradables relative to Non-Tradables: Model vs. Data Notes: Exogenous 1% permanent increase of utilization-TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. Solid blue lines display point estimates of VAR model with shaded area indicating 90% confidence bounds; the blue line shows the responses when technology shocks are identified by using sectoral capital-utilization-adjusted-TPFs whilst solid black lines with squares display baseline model predictions, i.e., when we allow for IML ($\epsilon = 1.6$), endogenous terms of trade ($\rho = \rho_J = 1.5$), gross complementarity between capital and labor in production (i.e., $\sigma^H = 0.687$, $\sigma^N = 0.716$), and technological change biased toward labor. Sample: 17 OECD countries, 1970-2013, annual data.



(a) Relative Prices: P^N/P^H and Terms of Trade

(b) Relative Wages, W^j/W

(c) Traded LIS

(d) Non-Traded LIS

Figure 48: Dynamic Adjustment of Prices, Wages and LISs to a Permanent Increase in Utilization-Adjusted-TFP of Tradables relative to Non-Tradables: Model vs. Data Notes: Exogenous 1% permanent increase of utilization-TFP in tradables relative to non-tradables. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. Solid blue lines display point estimates of VAR model with shaded area indicating 90% confidence bounds; the blue line shows the responses when technology shocks are identified by using sectoral capital-utilization-adjusted-TPFs whilst solid black lines with squares display baseline model predictions, i.e., when we allow for IML ($\epsilon = 1.6$), endogenous terms of trade ($\rho = \rho_J = 1.5$), gross complementarity between capital and labor in production (i.e., $\sigma^H = 0.687$, $\sigma^N = 0.716$), and technological change biased toward labor. Sample: 17 OECD countries, 1970-2013, annual data.

U.2 MaCurdy [1981] vs. GHH [1988] Preferences

MaCurdy [1981] vs. GHH [1988] Preferences. In our model, we consider a representative household setup where we allow for the familiar isoelastic intensive-margin MaCurdy [1981] preferences which are separable in consumption and labor:

$$\Lambda(t) \equiv \frac{C(t)^{1-\frac{1}{\sigma_C}}}{1-\frac{1}{\sigma_C}} - \frac{L(t)^{1+\frac{1}{\sigma_L}}}{1+\frac{1}{\sigma_L}}, \tag{441}$$

where $L(t)$ is the total hours worked and σ_L is the Frisch elasticity of labor. To generate a rise in total hours worked in accordance with what we estimate empirically in the short-run, we set $\sigma_C = 2$ as it significantly reduces the negative impact of the wealth effect on labor supply and to produce the magnitude of the increase in total hours worked on impact, we choose $\sigma_L = 1.6$ based on estimates of the macro Frisch elasticity of labor supply documented by Peterman [2016].

To check the robustness of our results, we investigate the dynamic effects of a permanent increase in traded relative to non-traded TFP by considering Greenwood, Hercowitz, and Huffman [1988] (GHH thereafter) preferences where the functional form is specified so as to eliminate the wealth effect in the household's labor supply decision. The representative household chooses the time path of consumption and hours worked to maximize the following objective function:

$$\Upsilon(t) = \int_0^\infty X(t) e^{-\beta t} \mathrm{d}t, \quad X(t) \equiv \ln C(t) - \frac{L(t)^{1+1/\sigma_L}}{1+1/\sigma_L}, \tag{442}$$

where σ_L is the Frisch elasticity of labor supply (at the intensive margin).

Main changes. We consider a semi-small open economy with CES production functions which is identical to that laid out in Online Appendix S, except that we allow for GHH [1988] preferences. We do not repeat the main elements of the model and emphasize the main changes caused by the assumption of GHH preferences. The first order conditions for firms are not modified and thus we focus on FOC for the representative household. The representative household chooses $C(t)$ and $L(t)$

so as to maximize his/her lifetime utility (442) subject to (12) and (18) together with (17):

$$\frac{1}{X(t)} = P_C(t)\lambda, \tag{443a}$$

$$\frac{1}{X(t)} L(t)^{\frac{1}{\sigma_L}} = \lambda W(t), \tag{443b}$$

while FOC (19c)-(19e) remain unchanged. Plugging (443a) into (443b) leads to:

$$L(t)^{\frac{1}{\sigma_L}} = \frac{W(t)}{P_C(t)}. \tag{444}$$

From (444), it is obvious that the decision on labor supply no longer depends on the wealth effect (which is captured by λ) and is only influenced by the substitution effect as captured by the real consumption wage, $W(t)/P_C(t)$. Log-linearizing (444), i.e., $\hat{L}(t) = \sigma_L \hat{W}(t) - \sigma_L \hat{P}_C(t)$, confirms that the Frisch elasticity of labor supply collapses to σ_L. Totally differentiating (443a) and eliminating $\hat{L}(t)$ by inserting (443b) leads to:

$$\hat{C}(t) = -X\hat{\lambda} - \hat{P}_C(t)\left[\frac{X}{C} + \frac{\sigma_L}{C} L^{1+\frac{1}{\sigma_L}}\right] - \frac{\sigma_L}{C} L^{1+\frac{1}{\sigma_L}} \hat{W}(t). \tag{445}$$

According to (445), the IES is $\frac{X}{C}$ since it measures by ho much future consumption increases relative present consumption in % when the interest rate increases by one percentage point.

First-order conditions (443a) and (443b) can be solved for consumption and labor as follows:

$$C = C\left(\bar{\lambda}, W, P^H, P^N\right), \quad L = L\left(\bar{\lambda}, W, P^H, P^N\right). \tag{446}$$

To derive the partial derivatives, we take logarithm and totally differentiate the system which yields in matrix form:

$$\begin{pmatrix} -1 & L^{\frac{1}{\sigma_L}} \\ 0 & \frac{1}{\sigma_L L} \end{pmatrix} \begin{pmatrix} \hat{C}(t) \\ \hat{L}(t) \end{pmatrix} \begin{pmatrix} X\hat{\bar{\lambda}} + X\alpha_C \alpha^H \hat{P}^H(t) + X(1-\alpha_C)\hat{P}^N(t) \\ \hat{W} - \alpha_C \alpha^H \hat{P}^H(t) - (1-\alpha_C)\hat{P}^N(t) \end{pmatrix}, \tag{447}$$

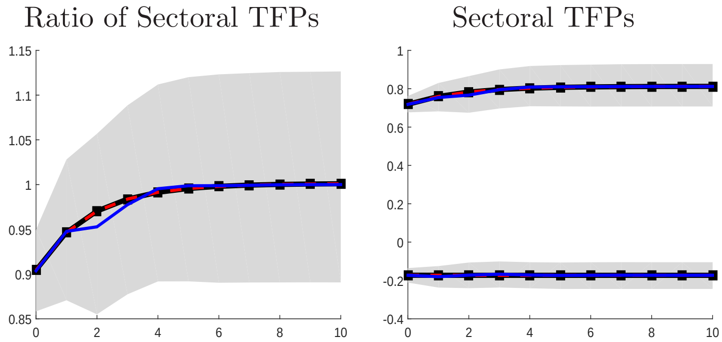
where we denote by a hat the deviation in percentage. The procedure to solve the model is identical to that detailed in Online Appendix S.

Calibration. Empirical studies based on micro data generally report lower values for the Frisch elasticity of labor supply than those chosen to calibrate macroeconomic models. Microeconometric estimates fall in the range of 0.1 to 0.5. In our baseline parametrization, we set the intertemporal elasticity of substitution for labor supply σ_L to 0.4, in line with evidence reported by Fiorito and Zanella [2012]. We choose σ_L to be 0.4 in our baseline setting which allows us to replicate the rise in total hours worked on impact. The remaining parameters remain mostly unchanged. We slightly adjust φ, φ^H, and ι^H so as the model targets the non-tradable content of consumption expenditure, the home-content of expenditure on tradables for both consumption and investment, respectively. For our calibration, the IES which is measured by X/C is equal to 0.67 which corresponds to a standard value chosen by the RBC literature.

Numerical results and discussion. In Fig. 49, we show the dynamic paths for traded relative to non-traded, traded TFP, and non-traded TFP. The technology shock is identical to that in the main text. The blue line in Fig. 50 and Fig. 51 contrasts empirical IRFs shown in the blue line with baseline model's predictions shown in the solid black line with squares. We also contrast the model predictions with the predictions of a model assuming GHH preferences. Overall, whether we consider MaCurdy [1981] or GHH [1988] preferences, the results are almost identical. The difference is that the Frisch elasticity of labor supply chosen to calibrate the model with GHH preferences collapses to microeconometric estimates (as we choose a value of 0.4) while we choose a value of 1.6 for MaCurdy [1981] preferences which is in line with recent estimates of the macro Frisch elasticity of labor supply documented by Peterman [2016]. As shall be clear later when exploring the effects of a temporary increase in aggregate TFP, GHH preferences are too restrictive to allow the model to replicate both permanent and temporary effects of technology shocks. The main issue is that GHH preferences shut down the wealth effect which is helpful to match the data following certain shocks.

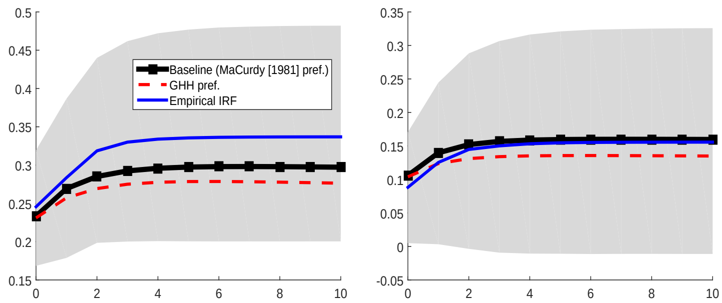
U.3 MaCurdy [1981] vs. Shimer [2009] Preferences

In subsection U.2, we contrast preferences separable in consumption and leisure with a particular class of non-separable preferences proposed by GHH [1988] which shut down the wealth effect from labor supply decision. We have seen that as long as we allow for a Frisch elasticity of labor supply which is low enough, i.e., in accordance with microeconometric estimates of σ_L, GHH preferences



(a) $Z \equiv \left(Z^H\right)^a / \left(Z^N\right)^b$ (b) Sectoral TFPs, Z^H and Z^N

Figure 49: Dynamic Adjustment of Sectoral TFPs following a 1% Permanent Increase in Traded relative to Non-Traded TFP: Empirical vs. Theoretical IRF. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds; solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Fig. 49(a) shows the dynamic adjustment of the ratio of traded to non-traded TFP. Fig. 49(b) shows the dynamic adjustment of traded as well as non-traded TFP.



(a) Real GDP Y_R (b) Total Hours Worked, L

Figure 50: Dynamic Adjustment of Real GDP and Total Hours Worked following a 1% Permanent Increase in Traded relative to Non-Traded TFP: MaCurdy [1981] vs. GHH [1988] Preferences. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences in the baseline model, we contrast baseline model's predictions with those from the same model assuming Greenwood, Hercowitz, and Huffman [1988] (GHH) preferences shown in dashed red lines.

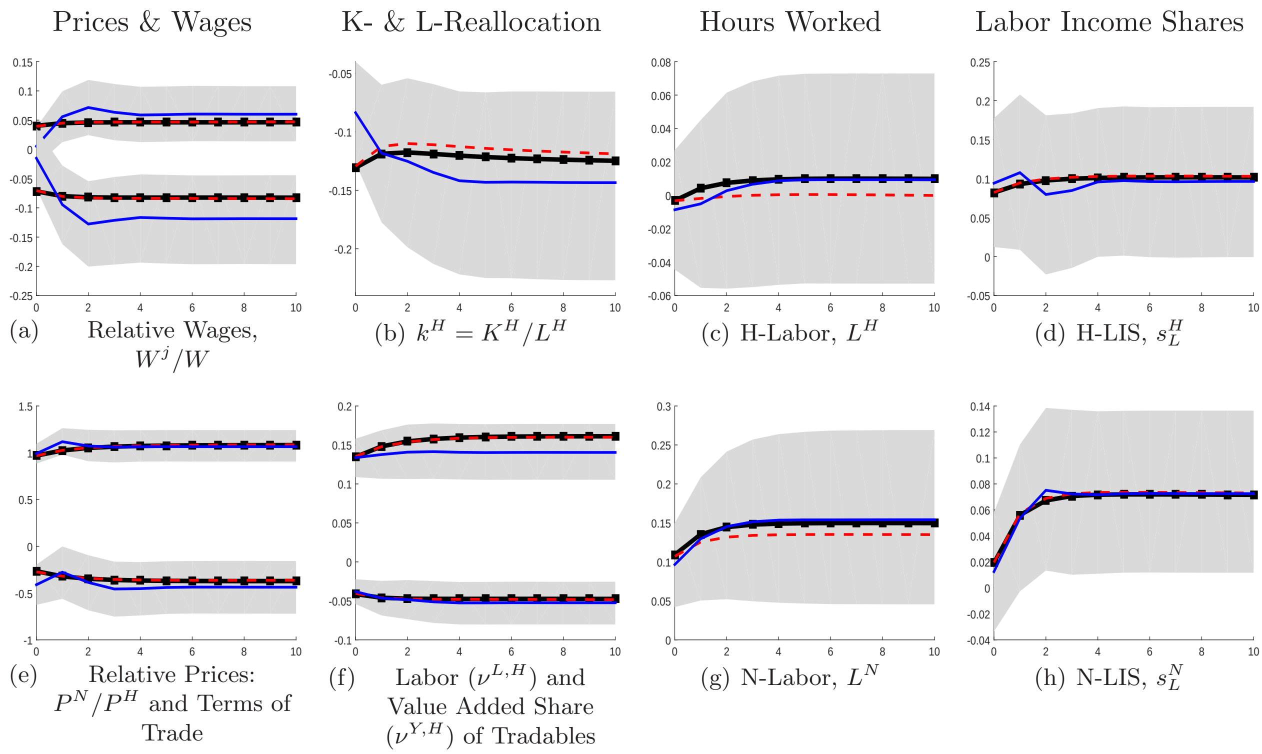


Figure 51: Sectoral Composition Effects a 1% Permanent Increase in Traded relative to Non-Traded TFP: MaCurdy [1981] vs. GHH [1988] Preferences. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences in the baseline model, we contrast baseline model's predictions with those from the same model assuming Greenwood, Hercowitz, and Huffman [1988] (GHH) preferences shown in dashed red lines.

lead exactly to the same results as in the main text. In this subsection, we consider a more general class of preferences which has been proposed by Shimer [2009].

Main changes. We consider a semi-small open economy with CES production functions which is identical to that laid out in section S, except that we allow for non-separability in consumption and leisure in preferences. We do not repeat the main elements of the model and emphasize the main changes caused by the assumption of non-separable preferences. In the main text, we assume that preferences are separable in consumption and leisure. We relax this assumption and allow for consumption and leisure to be substitutes. In particular, this more general specification implies that consumption can be affected by the aggregate wage rate while labor supply can now be influenced by relative prices. As previously, the household's period utility function is increasing in his/her consumption C and decreasing in his/her labor supply L, with functional form (see Shimer [2009]):

$$\Lambda \equiv \frac{C^{1-\sigma}V(L)^{\sigma}-1}{1-\sigma}, \quad \text{if} \quad \sigma \neq 1, \quad V(L) \equiv \left(1+(\sigma-1)\gamma\frac{\sigma_L}{1+\sigma_L}L^{\frac{1+\sigma_L}{\sigma_L}}\right) \tag{448}$$

and

$$\Lambda \equiv \log C - \gamma\frac{\sigma_L}{1+\sigma_L}L^{\frac{1+\sigma_L}{\sigma_L}}, \quad \text{if} \quad \sigma = 1. \tag{449}$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure; it is worthwhile noticing that if $\sigma > 1$, the marginal utility of consumption is increasing in hours worked. Importantly, such preferences imply that the Frisch elasticity of labor supply is constant.

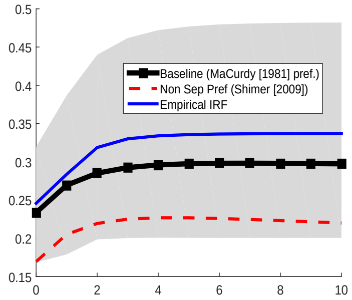
As shall be useful below, we write down the partial derivatives of (448):

$$\Lambda_C = C^{-\sigma}V(L)^{\sigma}, \tag{450a}$$

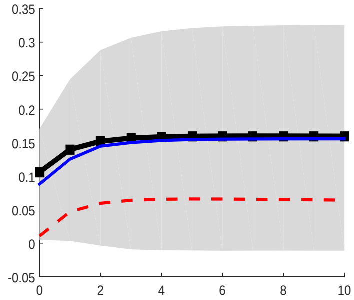
$$\Lambda_L = -C^{1-\sigma}\sigma V(L)^{\sigma-1}\gamma L^{\frac{1}{\sigma_L}}, \tag{450b}$$

$$\Lambda_{CL} = -\frac{\Lambda_L(\sigma-1)}{C}, \tag{450c}$$

where $\Lambda_C = \frac{\partial \Lambda}{\partial C}$. According to eq. (450c), the marginal utility of consumption is increasing in labor supply as long as $\sigma > 1$, i.e., if consumption and leisure are gross substitutes.



(a) Real GDP Y_R



(b) Total Hours Worked, L

Figure 52: Dynamic Adjustment of Real GDP and Total Hours Worked following a 1% Permanent Increase in Traded relative to Non-Traded TFP: MaCurdy [1981] vs. Shimer[2009] Preferences. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences in the baseline model, we contrast baseline model's predictions with those from the same model considering a more general class of preferences by allowing consumption and leisure to be non-separable, as suggested by Shimer [2009], shown in dashed red lines.

The first order conditions for firms are not modified and thus we focus on FOC for the representative household. The representative household chooses $C(t)$ and $L(t)$ so as to maximize his/her lifetime utility with an instantaneous utility given by (448) subject to (12) and (18) together with (17). While FOC (19c)-(19e) remain unchanged, the remaining first-order conditions characterizing the representative household's optimal plans read:

$$C^{-\sigma} V(L)^{\sigma} = P_C \lambda, \tag{451a}$$

$$C^{1-\sigma} \sigma \gamma L^{1/\sigma_L} V(L)^{\sigma-1} = W \lambda. \tag{451b}$$

First-order conditions (451a) and (451b) can be solved for consumption and labor as follows:

$$C = C\left(\bar{\lambda}, W, P^H, P^N\right), \quad L = L\left(\bar{\lambda}, W, P^H, P^N\right). \tag{452}$$

To derive the partial derivatives, we take logarithm and totally differentiate the system which yields in matrix form:

$$\begin{pmatrix} -\sigma & \sigma\left(\frac{1+\sigma_L}{\sigma_L}\right)\left[\frac{V(L)-1}{V(L)}\right] \\ (1-\sigma) & \left\{\frac{1}{\sigma_L} + (\sigma-1)\left(\frac{1+\sigma_L}{\sigma_L}\right)\left[\frac{V(L)-1}{V(L)}\right]\right\} \end{pmatrix} \begin{pmatrix} \hat{C} \\ \hat{L} \end{pmatrix} = \begin{pmatrix} \hat{\bar{\lambda}} + \alpha_C \alpha^H \hat{P}^H + (1-\alpha_C)\hat{P}^N \\ \hat{\bar{\lambda}} + \hat{W} \end{pmatrix}, \tag{453}$$

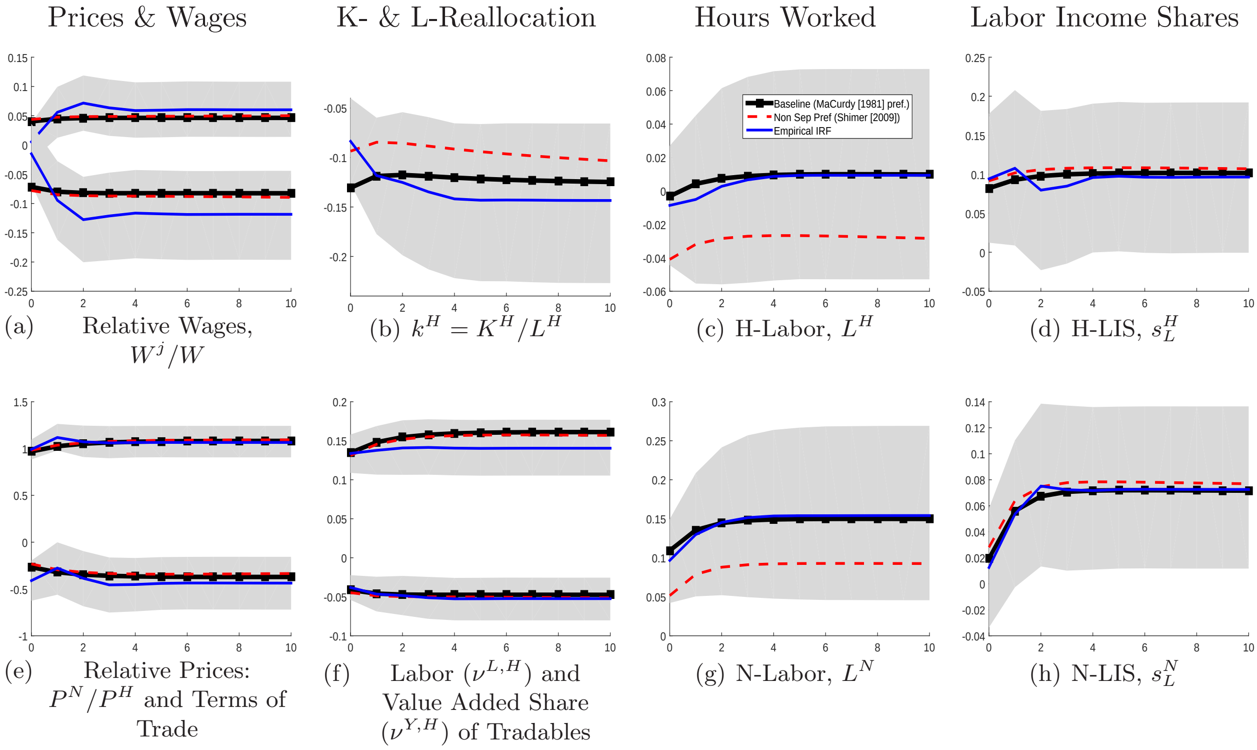
where we denote by a hat the deviation in percentage.

Calibration. When numerically exploring the implications of non-separability in preferences between consumption and leisure, we set the substitutability between consumption and leisure captured by σ to 2, which is a standard value when adopting this class of preferences, see e.g., Shimer [2009], keeping unchanged the baseline calibration discussed in section 4.1, in particular we maintain $\sigma_L = 1.6$. It is worth mentioning with the class of preferences shown in eq. (448), the IES reduces to $\frac{1}{\sigma} = 0.5$.

Numerical results and discussion. We contrast the effects of a permanent increase in traded relative to non-traded TFP in a model assuming MaCurdy preferences, shown in the black line with squares, with the predictions of a model assuming a general class of preferences which allows for non-separability between consumption and leisure shown in dashed red lines. We generate dynamic paths for sectoral TFPs as those shown in Fig. 49 and thus we do not repeat these IRFs. The blue lines display empirical IRFs. Inspection of Fig. 52 reveals that assuming non-separability in preferences between consumption and leisure somewhat fails to generate a sufficient increase in labor supply (see the dashed red lines). As can be seen in Fig. 53(g) and 53(c), non-separable preferences leads the model to substantially understate the rise in sectoral hours worked. The reason is that setting $\sigma = 2$ implies that the wealth effect is strong which tends to completely neutralize the substitution effect. Except for missing the rise in hours worked, the model assuming non-separability in consumption and leisure can account for the evidence related to prices, wages, the labor share and the value added share of tradables, and the LISs.

U.4 Time Separable Preferences vs. Consumption Habits

In this subsection, we add time non separability to the general class of preferences proposed by Shimer [2009].



(a) Relative Wages, W^j/W (b) $k^H = K^H/L^H$ (c) H-Labor, L^H (d) H-LIS, s_L^H

(e) Relative Prices: P^N/P^H and Terms of Trade (f) Labor ($\nu^{L,H}$) and Value Added Share ($\nu^{Y,H}$) of Tradables (g) N-Labor, L^N (h) N-LIS, s_L^N

Figure 53: Sectoral Composition Effects a 1% Permanent Increase in Traded relative to Non-Traded TFP: MaCurdy [1981] vs. Shimer[2009] Preferences. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences in the baseline model, we contrast baseline model's predictions with those from the same model considering a more general class of preferences by allowing consumption and leisure to be non-separable, as suggested by Shimer [2009], shown in dashed red lines.

Main changes. We consider a semi-small open economy with CES production functions which is identical to that laid out in section S, except that we allow for non-separability in preferences between consumption and leisure and time non-separability generated by the introduction of consumption habits. We do not repeat the main elements of the model and emphasize the main changes caused by the assumption of non-separable preferences. In the main text, we assume that consumption and leisure are separable and we impose time separable preferences because the marginal utility of current consumption depends on current consumption only and not on consumption at the other dates. We relax these two assumptions and allow for consumption and leisure to be substitutes and the marginal utility of current consumption to be influenced by consumption habits. In the lines of Shimer [2009], the household's period utility function is increasing in his/her consumption C and decreasing in his/her labor supply L, with functional form described by (448)-(449).

At any instant of time, households derive utility, not only from their current consumption $C(t)$, but also from their current level of habits denoted by $S(t)$. Hence, the representative household maximizes the following objective function:

$$\int_0^\infty \left\{ \frac{U\left[C(t), S(t)\right]^{1-\sigma} V(L(t))^{\sigma} - 1}{1-\sigma} \right\} e^{-\beta t} \mathrm{d}t, \tag{454}$$

where $V(L)$ is given by (448) and β is the consumer's discount rate. The habitual standard of living is defined as a distributed lag over past consumption:

$$S(t) = \delta \int_{-\infty}^{t} C(\tau) \, e^{-\delta(t-\tau)} \mathrm{d}\tau, \qquad \delta > 0. \tag{455}$$

where the parameter δ indexes the relative weight of recent consumption in determining the reference stock $S(t)$. Differentiating equation (455) with respect to time gives the law of motion of the stock of habits:

$$\dot{S}(t) = \delta \left[C(t) - S(t) \right], \tag{456}$$

where the parameter $\delta \geq 0$ determines the relative weight of consumption at different times. According to this specification, the reference stock is defined as an exponentially declining weighted average of past economy-wide levels of consumption. Intuitively, the larger δ, the greater the weight of consumption in the recent past in determining the stock of habits, and the faster the reference stock S adjusts to current consumption.

In line with Carroll, Overland, and Weil [2000], we assume that the utility derived from current and past consumption takes an iso-elastic form. The felicity function for current and past consumption can be rewritten as

$$U\left(C,S\right)=\frac{1}{1-\sigma}\left[\frac{C}{S^{\gamma}}\right]^{1-\sigma}=\frac{1}{1-\sigma}\left[C^{1-\gamma}\left(\frac{C}{S}\right)^{\gamma}\right]^{1-\sigma}, \tag{457}$$

where $\sigma > 0$ corresponds to the coefficient of relative risk aversion, and $0<\gamma<1$ is the weight of habits S in utility. The instantaneous utility function (457) is increasing in consumption, $U_C\left(C,S\right) > 0$, decreases with the stock of habits, $U_S\left(C,S\right)\leq 0$ as long as $\gamma > 0$; an increase in a uniformly maintained consumption level raises utility, i.e. $U_C\left(C,C\right)+U_S\left(C,C\right) > 0$, as long as $0\leq\gamma<1$. Since $\sigma>0$, $U(C,S)$ is concave w.r.t. C, i.e., $U_{CC}<0$. We assume $\sigma>\frac{1+\gamma}{\gamma}$ so that $U_{SS}<0$.

According to (457), agents derive utility from a geometric weighted average of absolute and relative consumption where γ is the weight of relative consumption. If $\gamma=0$, the case of time separability in preferences obtains. Hence, the intertemporal marginal rate of substitution between consumption at date $t+1$ and consumption at date t does not depend on consumption at other dates, which implies a fixed rate of time preference along a constant consumption path outside the steady-state. Faced with a positive income shock, habit-forming agents find it optimal to increase their consumption only moderately in the short-run, and thereby to save to sustain their ne higher standard of living.

As shall be useful below, we write down the partial derivatives of (448):

$$\Lambda_C = C^{-\sigma}S^{-\gamma(1-\sigma)}V(L)^{\sigma} > 0, \tag{458a}$$

$$\Lambda_S = -\gamma C^{1-\sigma}S^{-[\gamma(1-\sigma)+1]}V(L)^{\sigma} < 0, \tag{458b}$$

$$\Lambda_{CC} = -\frac{\sigma\Lambda_C}{C} < 0, \tag{458c}$$

$$\Lambda_{SS} = -\frac{\Lambda_S\left[\gamma\left(1-\sigma\right)+1\right]}{S} < 0, \quad \text{iff} \quad \sigma > \frac{1+\gamma}{\gamma}, \tag{458d}$$

$$\Lambda_{CS} = \frac{\gamma\left(\sigma-1\right)\Lambda_C}{S} > 0, \quad \text{iff} \quad \sigma > 1, \tag{458e}$$

$$\Lambda_L = -C^{1-\sigma}\sigma V(L)^{\sigma-1}\gamma L^{\frac{1}{\sigma_L}} < 0, \tag{458f}$$

$$\Lambda_{LL} = \frac{\Lambda_L}{L}\left\{\frac{1}{\sigma_L}+\left(\sigma-1\right)\left(\frac{1+\sigma_L}{\sigma_L}\right)\left[\frac{V(L)-1}{V(L)}\right]\right\} < 0, \tag{458g}$$

$$\Lambda_{LC} = -\frac{\Lambda_L\left(\sigma-1\right)}{C} > 0, \quad \text{iff} \quad \sigma > 1, \tag{458h}$$

$$\Lambda_{LS} = \frac{\Lambda_L\gamma\left(\sigma-1\right)}{S} < 0, \quad \text{iff} \quad \sigma > 1, \tag{458i}$$

where $\Lambda_C=\frac{\partial\Lambda}{\partial C}$. To ensure that first-order conditions yield a maximum, we assume $\sigma>\frac{1+\gamma}{\gamma}>1$, $0<\gamma<1$.

As stressed by Carroll et al. [2000], Alvarez-Cuadrado et al. [2004]), there exists two versions of consumers' behavior, depending on wether or not they internalize the impact of their current consumption decisions on the future evolution of the reference stock and thus on future utility. In the latter case, agents behave as *outward-looking* consumers; since the economy is composed of a large number of agents, each single agent is to small to influence the reference stock, thus the representative agent will take it as exogenous. In the former case, the reference stock is an exponentially declining weighted average of the household's own past levels of real expense. Therefore, each household takes the effect of his current consumption decisions on his future habit stock into account. To keep things simple, we consider the case of external habits which implies that *outward-looking* consumers do not take into account the impact of their consumption decisions on the aggregate stock of habits. Since individuals are identical, the average values of real consumption, stock of habits, and traded bonds holding are equal to values prevailing for each individual. In eq. (455), the reference stock is thus formed as an exponentially declining weighted average of past economy-wide average levels of consumption C.

The first order conditions for firms are not modified and thus we focus on FOC for the representative household. The representative household chooses $C(t)$ and $L(t)$ so as to maximize his/her lifetime utility with an instantaneous utility given by (454) subject to (12) and (18) together with (17). While FOC (19c)-(19e) remain unchanged, the remaining first-order conditions characterizing the representative household's optimal plans read:

$$\Lambda_C = P_C \lambda, \tag{459a}$$
$$\Lambda_L = W \lambda, \tag{459b}$$

where Λ_C and Λ_L are given by eq. (458a) and (458f).

First-order conditions (459a) and (459b) can be solved for consumption and labor as follows:

$$C = C\left(\bar{\lambda}, W, P^H, P^N, S\right), \quad L = L\left(\bar{\lambda}, W, P^H, P^N, S\right). \tag{460}$$

To derive the partial derivatives, we take logarithm and totally differentiate the system which yields in matrix form:

$$\begin{pmatrix} \frac{\Lambda_{CC}}{\Lambda_C} & \frac{\Lambda_{CL}}{\Lambda_C} \\ \frac{\Lambda_{LC}}{\Lambda_L} & \frac{\Lambda_{LL}}{\Lambda_L} \end{pmatrix} \begin{pmatrix} dC \\ dL \end{pmatrix} = \begin{pmatrix} \hat{\bar{\lambda}} + \alpha_C \alpha^H \hat{P}^H + (1-\alpha_C)\hat{P}^N - \frac{\Lambda_{CS}}{\Lambda_C} dS \\ \hat{\bar{\lambda}} + \hat{W} - \frac{\Lambda_{LS}}{\Lambda_L} dS \end{pmatrix}, \tag{461}$$

where we denote by a hat the deviation in percentage; Λ_{CS} and Λ_{LS} are given by (458e) and (458i). Inserting first $C = C\left(\bar{\lambda}, W, P^H, P^N, W^H, W^N, S\right)$ into (228a)-(229b) allows us to solve for C^N, C^H, and C^F, i.e., $C^g\left(\bar{\lambda}, P^N, P^H, W^H, W^N, S\right)$. Inserting first the solution for labor $L = L\left(\bar{\lambda}, W, P^H, P^N, W^H, W^N, S\right)$ into (239a)-(240) allows us to solve for L^H and L^N: $L^j\left(\bar{\lambda}, P^N, P^H, W^H, W^N, S\right)$ Inserting for L^H and L^N into the resource constraint for capital (436), i.e., $k^H L^H + k^N L^N = K$, and solving the system of four equations consisting of (346a)-(346c) together with (436) leads to $k^j, W^j, L^j, Y^j\left(\lambda, K, P^N, P^H, S, A^j, B^j\right)$. Inserting solutions into the market clearing conditions (29) for non-tradables and tradables and solving leads to $P^H, P^N\left(\lambda, K, Q, S, A^j, B^j\right)$. Plug back these solutions into k^j, L^j, Y^j.

The adjustment of the open economy toward the steady state is described by a dynamic system which comprises seven equations that are functions of $K(t)$, $Q(t)$, $S(t)$, $A^j(t)$, $B^j(t)$:

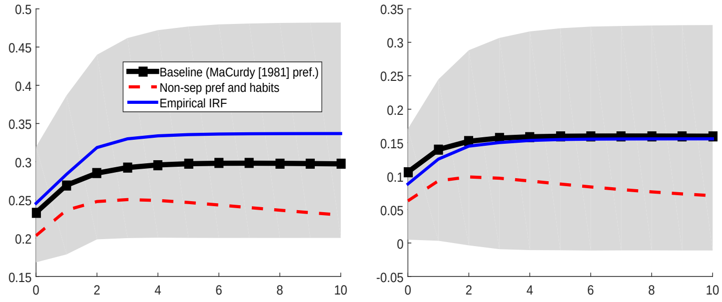
$$\dot{K}(t) = \Upsilon\left(K(t), Q(t), S(t), A^H(t), B^H(t), A^N(t), B^N(t)\right), \tag{462a}$$
$$\dot{Q}(t) = \Sigma\left(K(t), Q(t), S(t), A^H(t), B^H(t), A^N(t), B^N(t)\right), \tag{462b}$$
$$\dot{S}(t) = \Pi\left(K(t), Q(t), S(t), A^H(t), B^H(t), A^N(t), B^N(t)\right), \tag{462c}$$
$$\dot{A}^j(t) = -\xi^j\left(A^j(t) - \tilde{A}^j\right), \qquad \dot{B}^j(t) = -\xi^j\left(B^j(t) - \tilde{B}^j\right), \tag{462d}$$

where $j = H, N$. The first dynamic equation corresponds to the non-traded goods market clearing condition (29) and the second dynamic equation corresponds to (19e) which equalizes the rates of return on domestic equities and foreign bonds, $r^\star$, once we have substituted appropriate first-order conditions. Equations (462d) are the law of motion of labor- and capital-augmenting efficiency, respectively, in sector j. Eq. (462c) is the law of motion for consumption habits stock. We linearize (462a)-(462c) around the steady-state. Denoting by ω_k^i the kth element of eigenvector ω^i related to eigenvalue ν_i, the general solution that characterizes the adjustment toward the new steady-state can be written as follows: $V(t) - V = \sum_{i=1}^{7} \omega^i D_i e^{\nu_i t}$ where V is the vector of state and control variables. Denoting the positive eigenvalue by $\nu_3 > 0$, we set $D_3 = 0$ to eliminate explosive paths and determine the five arbitrary constants D_i (with $i = 1, ..., 7$, $i \neq 2$) by using the five initial conditions, i.e., $K(0) = K_0$, $S(0) = S_0$, $A^j(0) = A_0^j$, and $B^j(0) = B_0^j$ for $j = H, N$. Setting $t = 0$ into the solutions for the stock of capital and the stock of habits, i.e., $K_0 - K = D_1 + D_2$ and $S_0 - S = \omega_3^1 D_1 + \omega_3^2 D_2$, and solving for arbitrary constants:

$$D_1 = \frac{(K_0 - K)\,\omega_3^2 - (S_0 - S)}{\omega_3^2 - \omega_3^1}, \tag{463a}$$
$$D_2 = \frac{(S_0 - S) - (K_0 - K)\,\omega_3^1}{\omega_3^2 - \omega_3^1}. \tag{463b}$$

Calibration. We keep the same calibration as in the main text. The new parameters pertain to the weight of habits in utility, γ, and the speed of adjustment, δ, in the determination of the reference stock. We set γ at 0.8 in line with empirical estimates documented by Gruber [2002] and Sommer [2007]. We follow Carroll et al. [2000] and set $\delta = 0.2$. The relative-risk aversion parameter σ is set at 2.3 so as to satisfy the condition $\sigma > \frac{1+\gamma}{\gamma} > 1$.

Numerical results and discussion. We contrast the effects of a permanent increase in traded relative to non-traded TFP in a model assuming MaCurdy preferences, shown in the black line with squares, with the predictions of a model assuming a general class of preferences which allows for non-separability between consumption and leisure together with external habits. The consumers do not internalize the impact of their current consumption decisions on the future evolution of the reference stock and thus on future utility. In Carroll et al. [2000] terminology, agents behave



(a) Real GDP Y_R (b) Total Hours Worked, L

Figure 54: Dynamic Adjustment of Real GDP and Total Hours Worked following a 1% Permanent Increase in Traded relative to Non-Traded TFP: MaCurdy [1981] vs. Shimer[2009] Preferences with External Habits. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences in the baseline model, we contrast baseline model's predictions with those from the same model considering a more general class of preferences by allowing consumption and leisure to be non-separable, as suggested by Shimer [2009], and by allowing for consumption habits which generate time non separability, in the lines of Carroll, Overland and Weil [2000] shown in dashed red lines.

as outward-looking consumers; since the economy is composed of a large number of agents, each single agent is to small to influence the reference stock, thus the representative agent will take it as exogenous. The implications of the combination of intra- and inter- non-separability in preferences, as captured by lifetime utility (454) are shown in dashed red lines. We generate dynamic paths for sectoral TFPs as those shown in Fig. 49 and thus we do not repeat these IRFs. The blue lines display empirical IRFs. Inspection of Fig. 54 reveals that augmenting non-separable preferences in consumption and leisure with catchup-up with the Joneses consumption behavior improves the ability of the model to account for the evidence, although the baseline model is doing better across all dimensions. First, adding habits to the model improves the ability of a model allowing for consumption and leisure being gross substitutes, laid out in subsection U.3, because habits mitigate the wealth effect. Intuitively, in the baseline model with MaCurdy preferences and $\sigma_C = 2$, because the IES is larger, the marginal utility of wealth must decline less, i.e., by 0.465%. When we consider non-separable preferences in the lines of Shimer [2009] with $\sigma = 2$, the IES is low at 0.5 which requires a large decline in the marginal utility of wealth, i.e., by 0.916%. When we augment the class of non-separable preferences proposed by Shimer [2009] with habits in the lines of Carroll et al. [2000], the long-run IES increases compared with a model abstracting from habits. As a result, the marginal utility of wealth falls by 0.689%. Intuitively, in a model with habits, when agents experience a positive income shock, they accumulate savings which amplifies the long-run increase in consumption. However, the decline in the marginal utility of wealth is still too large which results in an increase in total hours worked (and therefore in real GDP, see Fig. 54(a)) shown in dashed red lines in Fig. 54(b) whose magnitude is lower than what we estimate empirically shown in the blue line. As a result, the model with non-separability in preferences between consumption and leisure and habits understates the rise in non-traded hours worked, see Fig. 55(g), and generates a decline in L^H, see Fig. 55(c), in contradiction with our evidence. Except for missing the rise in total and sectoral hours worked, the model assuming non-separability in consumption and leisure and habits can account for the evidence related to prices, wages, and the LISs., although the model understates the decline in the labor share of tradables (see the lower part of Fig. 55(f).

U.5 MaCurdy [1981] Preferences and IES for Consumption

In our model, we consider a representative household setup where we allow for the familiar isoelastic intensive-margin MaCurdy [1981] preferences which are separable in consumption and labor:

$$\Lambda(t) \equiv \frac{C(t)^{1-\frac{1}{\sigma_C}}}{1-\frac{1}{\sigma_C}} - \frac{L(t)^{1+\frac{1}{\sigma_L}}}{1+\frac{1}{\sigma_L}}, \tag{464}$$

where $\sigma_C > 0$ is the intertemporal elasticity of substitution for consumption, and $\sigma_L > 0$ the Frisch elasticity of (aggregate) labor supply.

Calibration and discussion. As mentioned in the main text in section 4.1, we choose a value of two for σ_C in line with estimates documented by Crossley and Low [2011], Gourinchas and Parker [2002], Gruber [2013]. While we are aware that an elasticity of intertemporal substitution around one is a typical choice in the business cycle literature, this value of two for the IES allows the

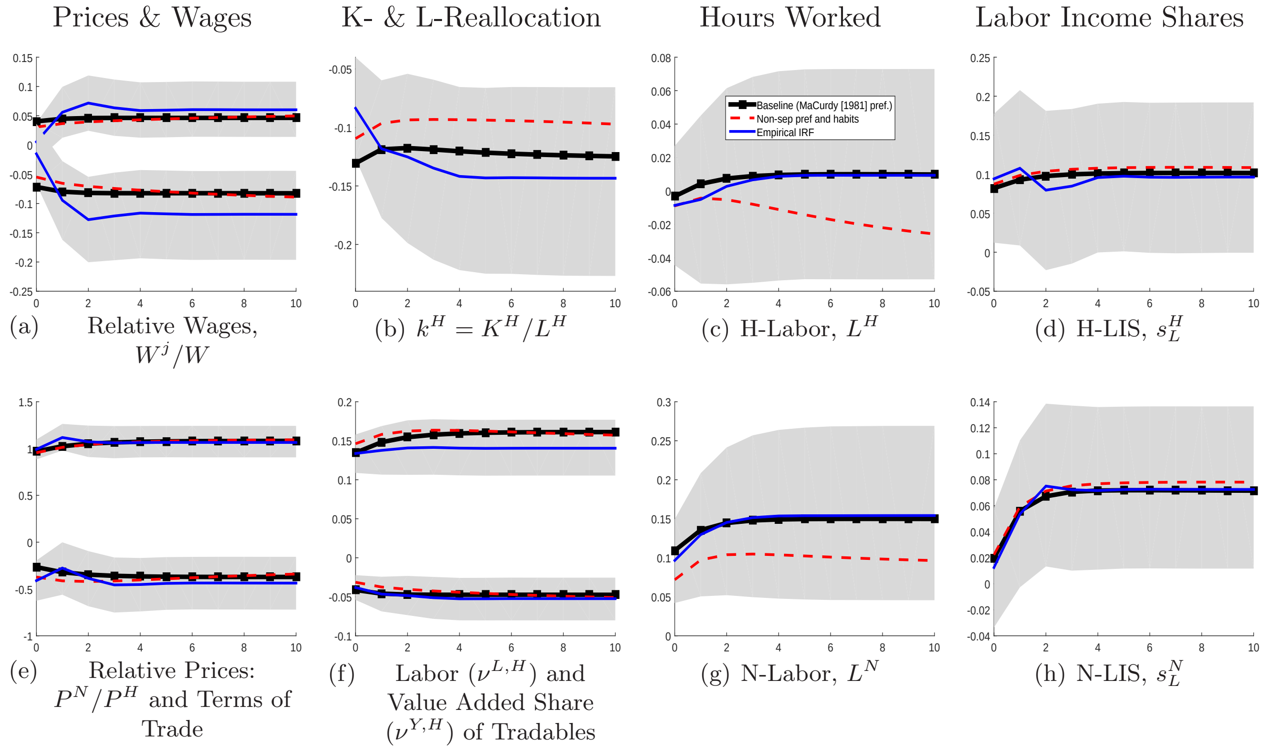
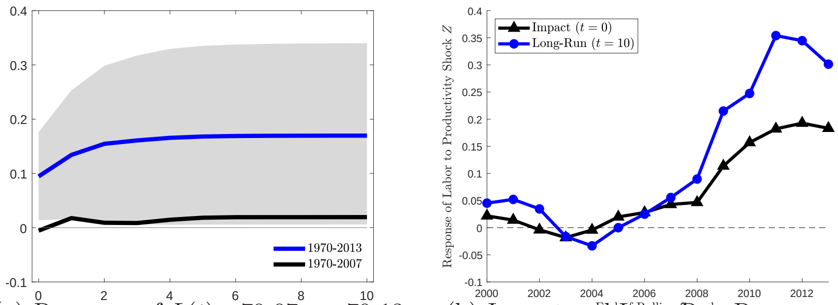


Figure 55: Sectoral Composition Effects a 1% Permanent Increase in Traded relative to Non-Traded TFP: MaCurdy [1981] vs. Shimer[2009] Preferences with External Habits. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences in the baseline model, we contrast baseline model's predictions with those from the same model considering a more general class of preferences by allowing consumption and leisure to be non-separable, as suggested by Shimer [2009], and by allowing for consumption habits which generate time non separability, in the lines of Carroll, Overland and Weil [2000] shown in dashed red lines.

semi-small open economy to match the evidence along all dimensions, in particular it enables us to generate a rise in labor supply by the same magnitude than that estimated empirically. Intuitively, a technology shock produces two opposite effects on labor supply. On the one hand, a rise in TFP raises the aggregate wage rate which encourages agents to lower leisure and supply more labor through a substitution effect. On the other hand, a rise in TFP lowers the marginal utility of wealth which leads agents to consumption more goods (and services) and leisure. The strength of the wealth effect depends on the value of the IES. Where preferences are time separable, the IES σ_C collapses to the inverse of the the coefficient of relative risk aversion σ. The coefficient σ parametrizes the curvature of the utility function derived from consumption as it measures the speed at which marginal utility declines (in %) when consumption increases by one %. As σ takes lower values, the marginal utility of consumption declines less rapidly as the curvature of the utility function is less pronounced. Therefore, following a positive wealth effect, the representative household will increase more consumption and less leisure as σ takes lower values and thus as σ_C gets larger. Because leisure time increases less when σ_C takes higher values, the negative impact of the wealth effect on labor supply is mitigated and thus agents are encouraged to significantly increase total hours worked.

Response of total hour worked to asymmetric technology shock across sectors; 1970-2007 vs. 1970-2013. Fig. 56 plots the dynamic response of total hours worked to a 1% permanent increase in traded relative to non-traded TFP when we estimate the VAR model which includes the relative productivity of tradables, Z_{it}, real GDP, $Y_{R,it}$, total hours worked, L_{it}, the real consumption wage, $W_{C,it}$, i.e., $x_{it}^A = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$. Fig. 56(a) contrasts the dynamic response of $L(t)$ shown in solid blue line when we estimate the VAR model over 1970-2013 with the response of $L(t)$ shown in the solid black line when we estimate the VAR model over 1970-2007. As it stands out, total hours worked are not responsive to the permanent increase in traded to non-traded TFP when the VAR model is estimated over 1970-2007 which suggests that over this period, the IES for consumption is equal to one so that the wealth effect (as reflected in the fall in $\bar{\lambda}$) and the substitution effect (as reflected in the rise in $W(t)$) cancel out, see eq. (465) below. Differently, when we estimate the same VAR model over 1970-2013, it appears that hours worked now increase significantly although the confidence interval is wide. As long as the IES for consumption is set to one, the wealth effect and the substitution effect cancel out and $L(t)$ cannot increase. To generate a positive and significant response of total hours worked to the rise in the relative productivity of



(a) Response of $L(t)$: 70-07 vs. 70-13

(b) Impact and Long-Run Response of $L(t)$ in Rolling Sub-Samples ($T = 30$)

Figure 56: Time-Increasing Response of Total Hours Worked to a Permanent Increase in Traded relative to Non-Traded TFP: Notes: Fig. 56(a) plots the dynamic response of total hours worked to a 1% permanent increase in traded relative to non-traded TFP. The blue line shows the dynamic response of L_t when we estimate the VAR model which includes the relative productivity of tradables, Z_{it}, real GDP, $Y_{R,it}$, total hours worked, L_{it}, the real consumption wage, $W_{C,it}$, i.e., $x^A_{it} = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$., over 1970-2013. The black line displays the response of $L(t)$ when we estimate the same VAR model over the period 1970-2007. In Fig. 56(b), we estimate the same VAR model including aggregate variables but in rolling sub-samples with a window of fixed length of thirty tears ($T = 30$), i.e., over 1970-2000, 1971-2001, ..., 1983-2013. The black line with triangles shows the impact response of L_t whilst the blue line with circles displays the response of $L(t)$ in the long-run Sample: 17 OECD countries, 1970-2013, annual data.

tradables, we have to choose a value for the IES for consumption which is larger than one. Whilst assuming Greenwood, Hercowitz, and Huffman [1988] preferences allows the model to account for the dynamic response of total hours worked we estimate empirically shown in Fig. 56(a), we show in subsection U.8 that a model assuming GHH [1988] preferences cannot account for the dynamic response of total hours worked following a temporary increase in aggregate TFP. In Fig. 56(b), we estimate the same VAR model including aggregate variables, i.e., $x^A_{it} = \left[\hat{Z}_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}\right]$, over rolling sub-samples of the same length of time of 30 years and we plot the impact response of total hours worked in the black line with triangles and the long-run response of total hours worked in the blue line with circles against the end date of the rolling window. As is clear form Fig. 56(b), total hours worked start to respond positively to an increase in the relative productivity of tradables during the great recession and afterwards which suggests that the negative impact of the wealth effect on $L(t)$ has declined. This hypothesis is supported by the evidence documented by Cundy [2018] who reports a value of 2.8 for the IES between 2009 and 2014.

Literature and values for IES. Attanasio and Weber [2010] have reviewed the literature studying intertemporal substitution in consumption and estimates fall in the range between 0.5 and 1. For example, Attanasio and Weber [1995] estimate the IES to be 0.67. There also exists a vast literature which reports values for the IES larger than one, especially close to a value of two. Crossley and Low [2011] estimate an elasticity of 1.7. Gourinchas and Parker [2002] report values for the intertemporal elasticity of substitution (equal to the inverse of the coefficient of risk aversion) ranging from 0.7 to 2 based on their structural estimation strategy, i.e., the coefficient of relative risk aversion varies between 1.4 and 0.5. There exists a wide dispersion in the estimated coefficients of relative risk aversion, from a low of 0.282 (Some High School) to a high value of 2.290 (Graduate School). Cundy [2018] reports a value of 2.8 for the IES between 2009 and 2014. Gruber [2013] estimates an IES of 2. In a recent paper, Bansal and Yaron [2004] show that an IES larger one is necessary to reconcile many asset prices. Bansal et al. [2010] find that small values of IES fail to account for the observed dynamics of the risk-free rate and choose a value of 1.5 for the IES to replicate the dynamics of the price-dividend ratio. The estimate obtained by Hansen and Singleton [1982],[1983], lies between 0.5 and 2, while the estimate obtained by Eichenbaum, Hansen, and Singleton [1988] can be as high as 10 depending on the data set used. By generating some artificial data from a standard RBC model, Mao [1989] explores the reliability of estimates of the intertemporal substitution effect and reports a value of 2.5 for the IES.

Numerical results and discussion. Before discussing numerical results, it is worth mentioning that in subsection U.3, we contrast the predictions of the baseline model where we consider MaCurdy preferences with an IES for consumption of two with the predictions of a model assuming non-separability in preferences between consumption and leisure by adopting a class of preferences as proposed by Shimer [2009]. The class of Shimer preferences implies that the coefficient of relative risk aversion collapses to the parameter σ that determines the gross substitutability between consumption and leisure. When we assume that consumption and leisure are gross substitutes by setting $\sigma = 2$, the IES for consumption is equal to 0.5. We have seen that a value of 0.5 considerably understates the rise in total hours worked as the wealth effect exerts a strong negative impact on labor supply. Below, we keep the same (i.e., MaCurdy) preferences across all scenarios and let the IES for consumption vary between 0.7, 1, and 2. The value of 0.7 is motivated by the evidence documented by Attanasio and Weber [1995] who estimate the IES to be 0.67.

In Fig. 57 and Fig. 58, we contrast the results for the baseline model shown in the solid black line with squares where we set the IES for consumption to two with the predictions of the same model when we set the IES to one, as displayed by dashed red lines, or when we allow IES for consumption to be smaller than one (i.e., $\sigma_C = 0.7$), as shown in the dash-dot black line with diamonds. Whilst the semi-small open economy model performs well in reproducing the VAR evidence when we set the IES for consumption to two, the performance declines when we set $\sigma_C = 1$ although all IRFs lie within the confidence bounds. In contrast, when we set $\sigma_C = 0.7$, the model predicts a fall in total hours worked instead of an increase, in contradiction with our evidence, and therefore understates the rise in non-traded hours worked and generates a significant decline in traded hours worked. As mentioned above, as we lower the value for the IES for consumption, the wealth effect further discourages labor supply. To be more concrete, in section O.1, we derive analytical results by abstracting from capital accumulation. When we allow for imperfect mobility of labor across sectors and assume exogenous terms of trade, we can show analytically that the response of total hours worked to an increase in traded productivity depends on the value of the IES for consumption (see eq. (158):

$$\hat{L} = -\frac{\sigma_L \alpha_L (1 - \sigma_C)}{\sigma_L + \sigma_C}. \tag{465}$$

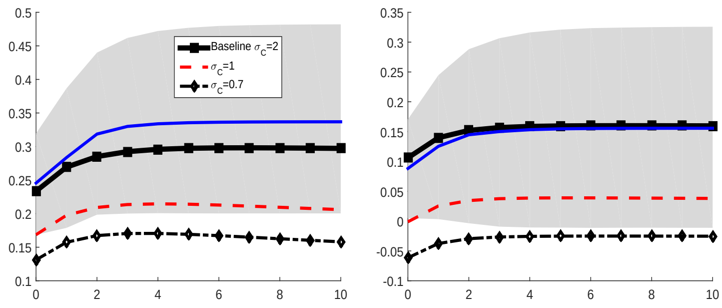
Because we abstract from physical capital accumulation to derive eq. (465), this equation can be viewed as the response of total hours worked on impact (because K is predetermined at K_0 at time $t = 0$). When $\sigma_C = 1$, the rise in leisure triggered by the wealth effect following a technology shock is exactly offset by the fall in leisure resulting from the substitution effect caused by a higher wage. Total hours worked thus remain unresponsive to the rise in relative traded productivity, as shown in the dashed red line in Fig. 57(b). When $\sigma_C < 1$, the wealth effect more than offsets the substitution effect so that total hours worked decline as displayed by the dash-dot black line with diamonds in Fig. 57(b). Conversely, when $\sigma_C > 1$, the curvature of the utility function derived from consumption is less so that the marginal utility of consumption declines less rapidly. Therefore, the impact of the wealth effect on leisure is mitigated and the substitution effect dominates. Hence, a technology shock increases labor supply when $\sigma_C > 1$, as can be seen in the solid black line with squares.

In Fig. 58, we show the responses of the same variables as in the main text and contrast the predictions of the baseline model (black line with squares) with those produced by the same model assuming an IES of one (dashed red line) or an IES of 0.7 (dash-dot black line). Overall, a model assuming values for the IES of consumption equal or lower than one leads the model to understate the responses of sectoral hours worked as such values mitigate the rise in total hours worked. The IES for consumption merely influences the responses of relative prices, labor share of tradables, value added share of tradables, and sectoral LISs. When we set the value for the IES for consumption to one, the responses of L^H and L^N lie within the confidence bounds of the baseline VAR model whilst it is only when we choose value lower than one that the dynamic adjustment of sectoral hours worked no longer lies within the confidence bounds.

U.6 Temporary Shock to Aggregate TFP

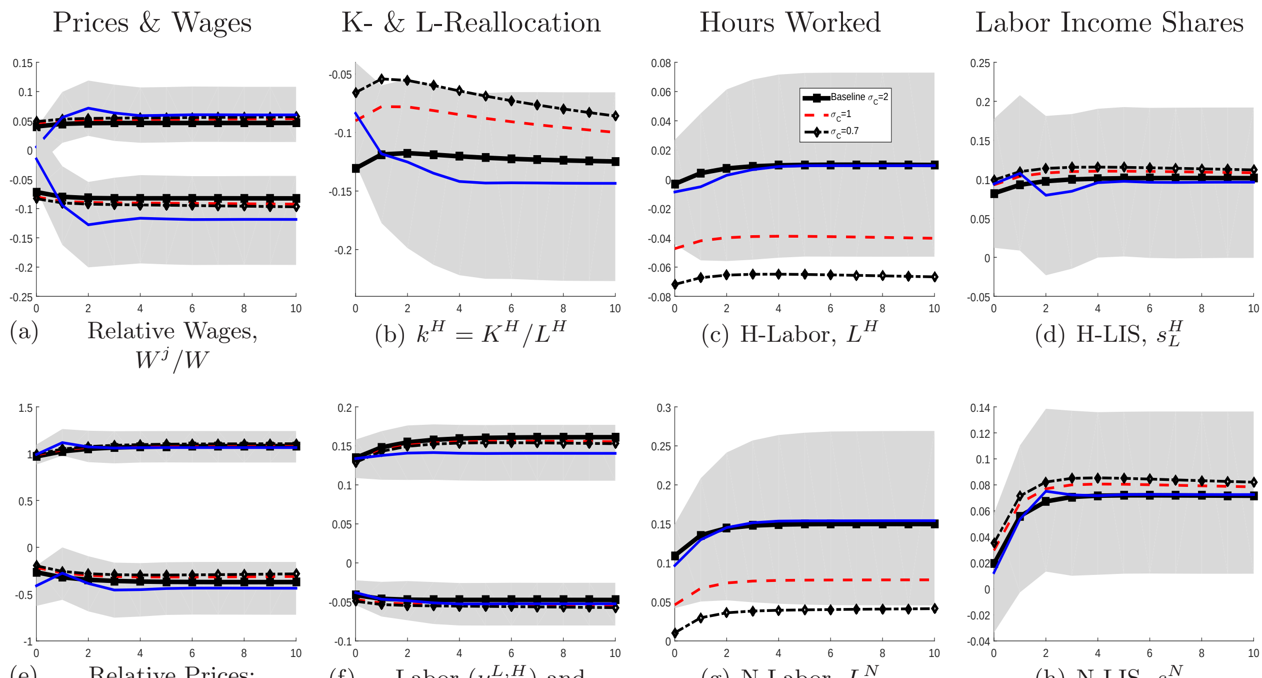
So far, we have explored variants of our baseline model by introducing endogenous capital utilization rate and by exploring the impact of considering different class of preferences. In this subsection, our objective is the following. We want to assess the ability of our model to account for the effects of a temporary increase in aggregate TFP. The reason is that a temporary technology shock is a standard shock in the RBC literature and in addition the identification of temporary shocks through Cholesky decomposition is not subject to identification biases, as stressed by Christian, Eichenbaum and Vigfusson [2006]. More specifically, the authors find that structural VARs perform remarkably well when identification is based on short-run restrictions. Because empirical IRFs following a temporary technology shock are accurately estimated, if our baseline model with the same calibration can account for the VAR evidence following a temporary increase in aggregate TFP, then the model is validated by the data and if the same model can also account for the empirical IRFs following a permanent increase in traded relative to non-traded TFP, then the identification of asymmetric technology shocks is validated by the model.

Identification of temporary aggregate TFP shocks: Empirical strategy. To investigate the effects of a temporary increase in aggregate TFP, we estimate a VAR model where variables are in log-level. We order (logged) aggregate TFP first and adopt a Cholesky decomposition which amounts to assuming that aggregate TFP is exogenous within the year (i.e., aggregate TFP does not respond within the year to the variables included in the VAR model). We re-estimate all VAR models



(a) Real GDP Y_R (b) Total Hours Worked, L

Figure 57: Dynamic Adjustment of Real GDP and Total Hours Worked following a 1% Permanent Increase in Traded relative to Non-Traded TFP: Quantitative Implications of IES. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences across all scenarios, we set the IES for consumption to two in the baseline calibration. To explore the quantitative implications of the values for IES, we show results for $\sigma_C = 1$ in the dashed red lines and we show results for $\sigma_C = 0.7$ in the dash-dot black line with diamonds.



(a) Relative Wages, W^j/W (b) $k^H = K^H/L^H$ (c) H-Labor, L^H (d) H-LIS, s_L^H

(e) Relative Prices: P^N/P^H and Terms of Trade (f) Labor ($\nu^{L,H}$) and Value Added Share ($\nu^{Y,H}$) of Tradables (g) N-Labor, L^N (h) N-LIS, s_L^N

Figure 58: Sectoral Composition Effects a 1% Permanent Increase in Traded relative to Non-Traded TFP: : Quantitative Implications of IES. Notes: Solid blue lines display point estimate of VAR model with shaded area indicating 90% confidence bounds. Solid black lines with squares display baseline model predictions, i.e., when we allow for imperfect mobility of labor, endogenous terms of trade, gross complementarity between capital and labor in production, and technological change biased toward labor. Whilst we consider MaCurdy [1981] preferences across all scenarios, we set the IES for consumption to two in the baseline calibration. To explore the quantitative implications of the values for IES, we show results for $\sigma_C = 1$ in the dashed red lines and we show results for $\sigma_C = 0.7$ in the dash-dot line.

considered in the main text by replacing the ratio of traded to non-traded TFP with aggregate TFP, denoted by Z^A. More specifically, to estimate the sectoral composition effects, we consider VAR models which include aggregate TFP, Z^A_{it}, and a vector of sectoral variables such as value added at constant prices, Y^j_{it}, hours worked, L^j_{it}, and the real consumption wage, $W^j_{C,it}$ in sector j or alternatively the value added share, $\nu^{Y,j}_{it}$, the labor share, $\nu^{L,j}_{it}$, and the relative wage, W^j_{it}/W_{it}, in sector j. We consider a VAR model which includes relative prices to inspect the transmission mechanism. We also consider a VAR model which includes aggregate variables, i.e., aggregate TFP, real GDP, total hours worked, the real consumption wage, and we replace the real consumption wage with the current account. All variables enter the VAR model in log-level. We estimate the reduced form of VAR models by panel OLS regression with country and time fixed effects.

We generated impulse response functions which summarize the responses of variables to an increase in aggregate TFP by 1% on impact. As displayed by the solid blue line in Fig. 59(a), the response of aggregate TFP is hump-shaped, peaking after one year and then gradually declining; it shows a high level of persistence over time as it is about 10 years before the shock dies out. In line with our discussion in the main text where we consider a permanent shock to aggregate TFP (in section 2.2 where we decompose aggregate TFP in symmetric and asymmetric technology shocks) instead of a temporary technology shock, the transitory shock to aggregate TFP is associated with an increase in sectoral TFPs, the magnitude of the rise in traded TFP being larger than the increase in non-traded TFP.

Calibration. The calibration is identical to that described in section 4.1 in the main text. In order to account for the non-monotonic pattern of the dynamic adjustment of aggregate TFP $Z^A(t)$ in line with our evidence (see Fig. 59(a)), we proceed as follows. To achieve a perfect match with the data, we specify the law of motion for labor- and capital-augmenting efficiency:

$$\hat{A}^j(t) = e^{-\xi^j t} - \left(1 - a^j\right) e^{-\chi^j t}, \tag{466a}$$

$$\hat{B}^j(t) = e^{-\xi^j t} - \left(1 - b^j\right) e^{-\chi^j t}, \tag{466b}$$

and choose a^j (b^j) to reproduce the impact response of labor- (capital-) augmenting technological change while $\xi^j > 0$ and $\chi^j > 0$ are chosen to reproduce the shape of factor-augmenting productivity together with their cumulative change following a shock to aggregate TFP. To infer the dynamics of A^j and B^j in the data, we solve the log-linearized version of technological frontier, i.e., $\hat{Z}^j(t) = s^j_L \hat{A}^j(t) + \left(1 - s^j_L\right) \hat{B}^j(t)$, and the log-linearized version of the demand of factors of production, i.e., $\left(\hat{B}^j(t) - \hat{A}^j(t)\right) = \frac{\sigma^j}{1-\sigma^j} \hat{S}^j(t) - \hat{k}^j(t)$, for labor and capital-augmenting efficiency which leads to (38a)-(38b). We plug estimated values for σ^j and empirically estimated responses for $s^j_L(t)$ and $k^j(t)$ into (38a)-(38b) to recover the dynamics for $A^j(t)$ and $B^j(t)$. Inserting (466a) and (466b) into the log-linearized version of the technology frontier allows us to recover the dynamics of TFP in sector j:

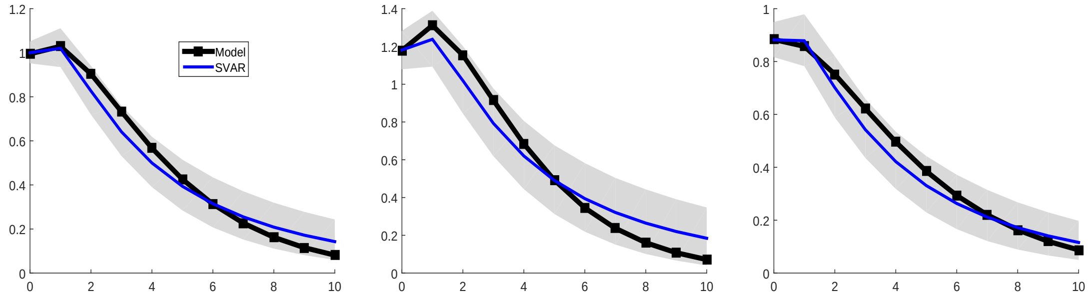
$$\hat{Z}^j(t) = e^{-\xi^j t} - \left(1 - z^j\right) e^{-\chi^j t}, \tag{467}$$

where $\bar{z}^j = s^j_L \bar{a}^j + \left(1 - s^j_L\right) \bar{b}^j$. Inserting (467) into the sectoral decomposition of aggregate TFP growth described by eq. (2) allows us to recover the dynamics of aggregate TFP

$$\hat{Z}^A(t) = \nu^{Y,H} \hat{Z}^H(t) + \left(1 - \nu^{Y,H}\right) \hat{Z}^N(t). \tag{468}$$

In Fig. 59, we contrast the empirical response functions (shown in blue lines) of aggregate and sectoral TFPs with the theoretical response functions (shown in black lines with squares) generated by the law of motion (467) together with ((468). As can be seen in Fig. 59(a)-59(c), the theoretical responses perform well in reproducing the evidence and thus the dynamic equations (466a)-(466b) which govern the adjustment of factor-augmenting efficiency and the log-linearized version of technology frontier are consistent with data.

Dynamic effects of a temporary increase in aggregate TFP. Fig. 60, 61 show the sectoral composition effects of a temporary increase in aggregate TFP. The horizontal axis measures time after the shock in years and the vertical axis measures percentage deviations from trend. In each case, the solid line represents the point estimate, while the shaded area indicates the 90% confidence bounds obtained by bootstrap sampling. As shown in the first row of Fig. 60, a temporary shock to aggregate TFP increases real GDP and the real consumption wage but lowers total hours worked the first three years. Whilst the baseline model described in the main text and chosen parameters performs very well in reproducing the sectoral effects of a permanent increase in traded relative to non-traded TFP, the same model with the same values of parameters also performs well in reproducing both the aggregate and sectoral effects of a temporary technology shock. More specifically, the model can account for the decline in total hours worked. While setting $\sigma_C = 2$ mitigates the negative impact of the wealth effect on labor supply, a shock to aggregate TFP leads firms to bias technological change toward capital, as reflected in the decline in sectoral LISs, as



(a) Aggregate TFP (b) Traded TFP (c) Non-Traded TFP

Figure 59: Dynamic Responses of Aggregate and Sectoral TFPs to an Unanticipated Temporary Shock to Aggregate TFP. Notes: Effects of a 1% temporary increase in aggregate TFP. Solid blue line displays point estimate of VAR with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario where we consider a semi-small open economy with tradables and non-tradables, CES production functions, imperfect mobility of labor across sectors, endogenous terms of trade, and FBTC. The set of parameters is identical to the set of values chosen in the main text.

displayed by Fig. 61(g) and Fig. 61(h). The rise in the demand for capital lowers the demand for labor which therefor drives down total hours worked. As shown below, allowing non separable preferences with an IES lower than one (i.e., equal to 0.5) decreases the performance of the model in reproducing VAR evidence.

Although the technology shock leads agents to consume more traded and non-traded goods, because the temporary aggregate TFP is associated with a significant increase in both traded and non-traded TFP, an excess supply shows up in both the non-traded and the traded goods market which lowers their prices. Fig. 61(b) shows that the model tends to overstate the decline in the terms of trade. In the blue line, we construct the terms of trade as the ratio of the value added deflator of tradables to the deflator of imports of goods and services. In the red line, we construct the terms of trade as the ratio of the traded value added deflator to the weighted sum of the traded value added deflator of the sixteen trade partners of the corresponding country i, the weight being equal to the share $\alpha^{M,i,k}$ of imports from the trade partner k, i.e, $\text{TOT}_t = P_t^H / P_t^{H,\star}$ where $P_{it}^{H,\star} = \Pi_{k \neq i} \alpha^{M,i,k} P_t^{H,k}$. Source: Direction of Trade Statistics [2017]. Both measures lead to similar results. Since traded TFP increases by a larger amount than non-traded TFP, the traded value added deflator falls more than the non-traded value added deflator thus appreciating the relative price of non-tradables, as shown in Fig. 61(a). As can be seen in Fig. 61(c), the decline in the terms of trade improves the current account, in line with our evidence, because the fall in the relative price of home-produced traded goods raises exports in volume disproportionately since $\rho > 1$, as evidence suggests.

Because non-traded and traded goods are gross complements, the fall in non-traded good prices lowers the demand for labor in the non-traded sector. Conversely, since home-produced and foreign-produced traded goods are gross substitutes, the fall in relative price of home-produced traded goods stimulates the demand for labor in the traded sector which thus leads to a reallocation of labor toward the traded sector as shown in Fig. 60(i). Labor shifts toward the traded sector although technological change is more biased toward capital in the traded than in the non-traded sector. As displayed by Fig. 61(d) and Fig. 61(e), the shift of labor toward the traded sector is associated with an increase in the relative wage of tradables and a decline in the relative wage of non-tradables. Because technological change is biased toward capital in both sectors, hours worked fall both in the traded and in the non-traded sector, as shown in Fig. 60(g) and Fig. 60(h). Whilst sectoral hours worked decline, Fig. 60(d) and Fig. 60(e) show that the increase in sectoral TFPs has an expansionary effect on sectoral value added at constant prices.

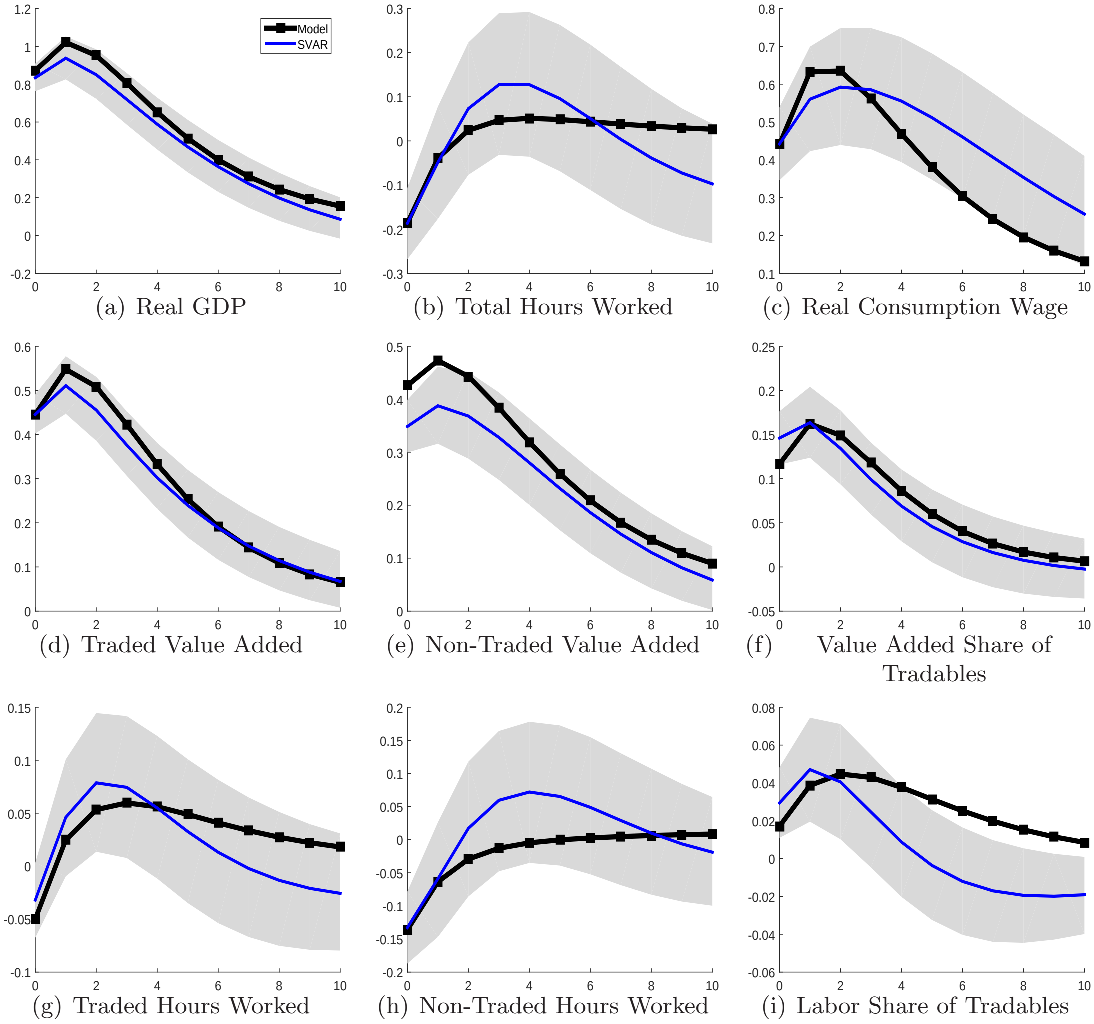
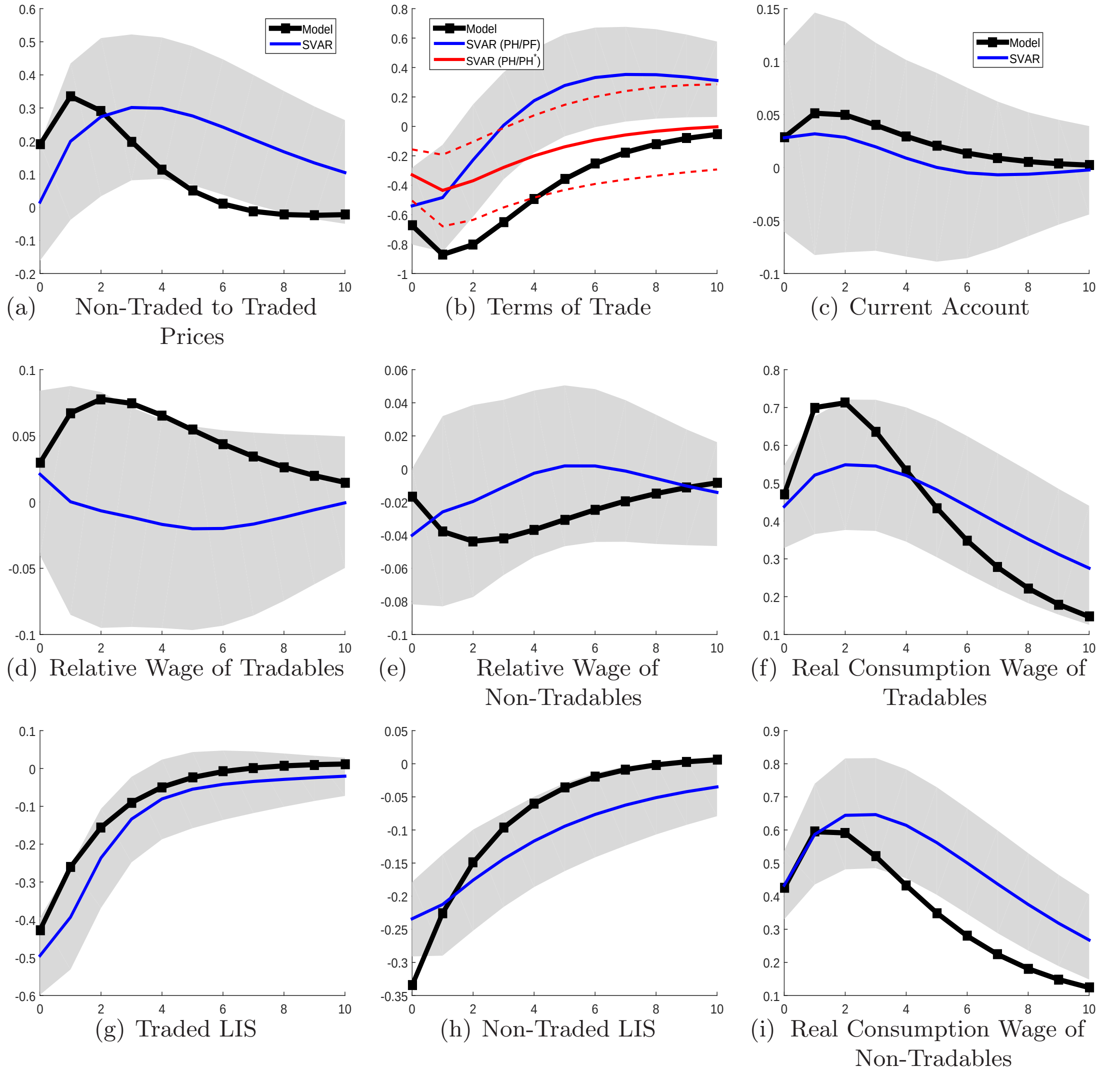


Figure 60: Theoretical vs. Empirical Responses Following Temporary Increase in Aggregate TFP: Effects on Value Added and Hours Worked. Notes: Effects of a 1% temporary increase in aggregate TFP. Solid blue line displays point estimate of VAR with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario where we consider a semi-small open economy with tradables and non-tradables, CES production functions, imperfect mobility of labor across sectors, endogenous terms of trade, and FBTC. The set of parameters is identical to the set of values chosen in the main text.



(a) Non-Traded to Traded Prices
(b) Terms of Trade
(c) Current Account
(d) Relative Wage of Tradables
(e) Relative Wage of Non-Tradables
(f) Real Consumption Wage of Tradables
(g) Traded LIS
(h) Non-Traded LIS
(i) Real Consumption Wage of Non-Tradables

Figure 61: Theoretical vs. Empirical Responses Following Temporary Increase in Aggregate TFP: Effects on Prices and Wages. Notes: Effects of a 1% temporary increase in aggregate TFP. Solid blue line displays point estimate of VAR with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario where we consider a semi-small open economy with tradables and non-tradables, CES production functions, imperfect mobility of labor across sectors, endogenous terms of trade, and FBTC. The set of parameters is identical to the set of values chosen in the main text. Note that for the terms of trade, we compare the model's predictions shown in the black line with squares with empirical responses where we consider two alternative ways to construct the relative price of home-produced traded goods. In the blue line (associated with the confidence interval displayed by the shaded area), we construct the terms of trade as the ratio of the value added deflator of tradables to the deflator of imports of goods and services. In the red line, we construct the terms of trade as the ratio of the traded value added deflator to the weighted sum of the traded value added deflator of the sixteen trade partners of the corresponding country i, the weight being equal to the share $\alpha^{M,i,k}$ of imports from the trade partner k, i.e, $\text{TOT}_{it} = P^{H}_{it}/P^{H,\star}_{it}$ where $P^{H,\star}_{it} = \Pi_{k\neq i}\alpha^{M,i,k}P^{H,k}_{t}$.

U.7 Temporary Aggregate Technology Shocks: Alternative Preferences

In the previous subsection, we have contrasted the predictions of the baseline model with empirical responses following a temporary increase in aggregate TFP. In this subsection, we move a step further and investigate the performance of the semi-small open economy model with alternative preferences such as GHH [1988] preferences, Shimer [2009] preferences, a combination of non-separability in preferences between consumption and leisure in the lines of Shimer [2009] and time non separable preferences though external habits in the lines of Carroll et al. [2000].

Temporary aggregate technology shocks: Baseline model vs. variants of the baseline model. In Fig. 62 and Fig. 63, we show empirical responses in the solid blue line with the confidence bounds shown in the shaded area and the theoretical responses of the baseline model displayed by solid black line with squares. We contrast the predictions of the baseline model with the predictions of three variants of the model detailed above. In the first variant shown in the dash-dot black line with diamonds, we allow for non-separability in preferences between consumption and leisure as proposed by Shimer [2009] (see subsection U.3). In the second variant shown in the dashed red lines, in addition to non separable preferences, we also allow for a *outward-looking* consumption habit behavior as suggested by Carroll, Overland and Weil [2000] (see subsection U.4). In the third variant shown in the dotted red line with stars, we allow for preferences proposed by Greenwood, Hercowitz, and Huffman [1988] where the wealth effect on labor supply is shut down (see subsection U.2). Whilst we do not show the responses of aggregate and sectoral TFPs, they are identical to those displayed by Fig. 59. We consider the same temporary aggregate technology shocks in the baseline models and its variants. The calibration of the variants of the baseline model is detailed in subsection U.2-U.4.

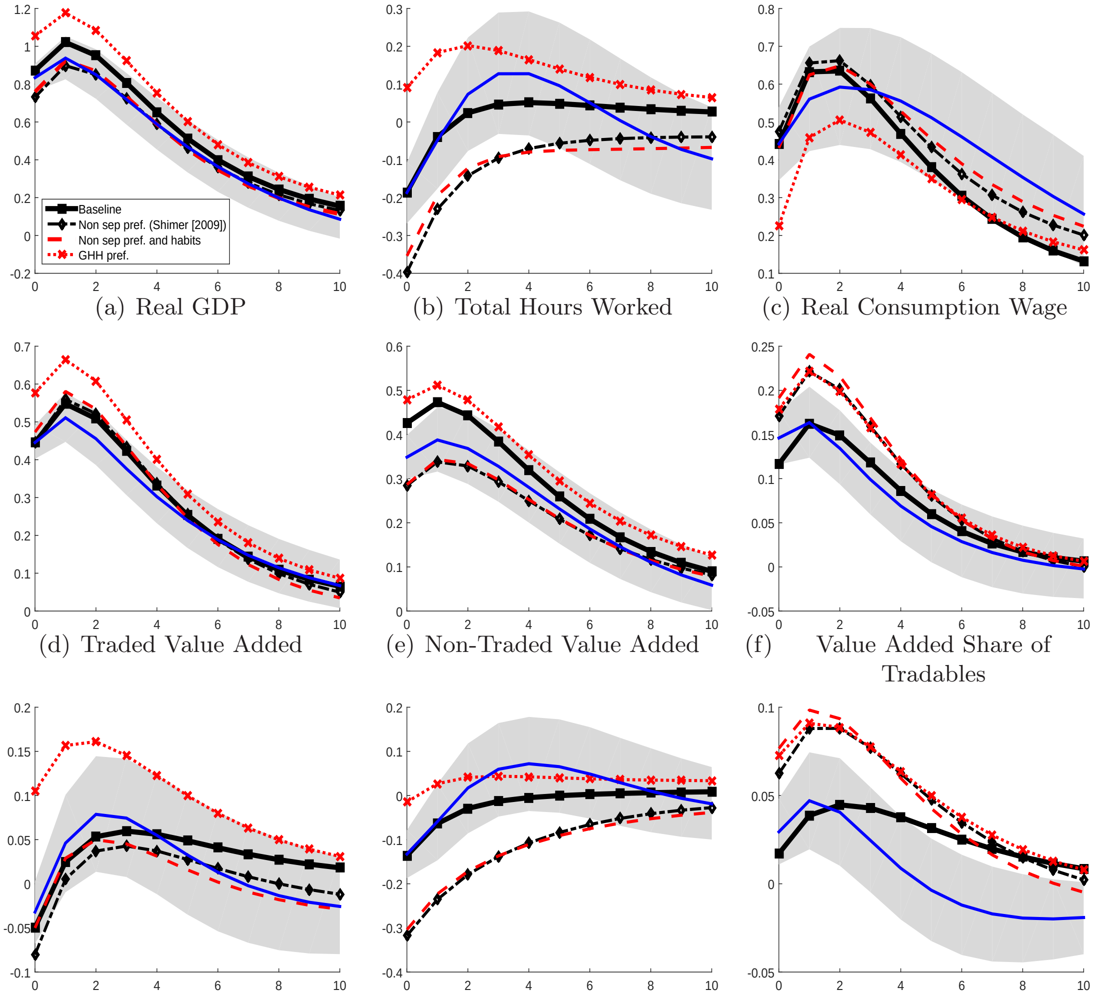
Inspection of Fig. 62 and Fig. 63 reveals that the performance of the baseline model with MaCurdy preferences, an IES for consumption of two and a Frisch elasticity of labor supply of 1.6 is significantly higher than that for the variants. While we have seen in subsection U.2 that the performance of the variant of the baseline model where we allow for GHH [1988] preferences is equivalent to that of the the baseline model when we consider a permanent increase in traded relative to non-traded TFP, the conclusion is different when we consider a temporary increase in aggregate TFP. By shutting down the wealth effect, the model with GHH preferences (shown in the dotted red line with stars) produces an increase in total hours worked on impact instead of a decline, in contradiction with our evidence, as shown in Fig. 62(b). Therefore, the model predicts an increase in traded and non-traded hours worked which does not fit our VAR evidence and GHH preferences also lead the model to overstate the rise in Y^H and Y^N. As displayed by Fig. 63(b), because GHH preferences produce an increase in L and thus in L^H, the model overstates substantially the decline in the terms of trade and thus the rise in the labor share of tradables displayed by Fig. 62(i). Because exports rise by a larger amount, Fig. 63(c) reveals that the model with GHH preferences also overpredicts the increase in the current account.

When we turn to non-separable preferences proposed by Shimer [2009] (shown in dash-dot black line with diamonds) or when we augment non-separable preferences with habits (shown in dashed red line), as proposed by Carroll et al. [2000], it stands out that these two variants do not improve the performance of the semi-small open economy model. Because these two variants imply that the IES for consumption is lower than one, the strong wealth effect produces a fall in labor supply which leads the model to overstate the decline in total hours worked, as shown in Fig. 62(b). Therefore, both variants overstate considerably the decline in non-traded hours worked, as can be seen in Fig. 62(h). Because the non-traded sector is more intensive in labor than the traded sector, the rise in traded TFP relative to non-traded TFP further lowers the terms of trade, as displayed by Fig. 63(b). The excessive terms of trade deterioration compared with what we estimate empirically leads the two variants to overstate the rise in the labor share of tradables, as displayed by Fig. 62(i), and to overpredict the current account surplus, as shown in Fig. 63(c).

U.8 Temporary vs. Permanent Shock to Aggregate TFP

Since a substantial fraction of economic fluctuations come from transitory and permanent technology shocks, we investigate the effects of a temporary and a permanent increase in aggregate TFP. This analysis will enable us to assess the behavior of the international RBC model when the economy is subject to permanent and transitory shocks to total factor productivity and to see if the model can account qualitatively for observed empirical facts (i.e., correlations) in OECD countries.

Dynamic effects of permanent vs temporary technology shocks. In Fig. 64, we plot the dynamic responses of selected macroeconomic variables (whose behavior is analyzed in the international RBC literature) to a 1% increase in aggregate TFP. We consider two types of aggregate technology shock, i.e., a permanent vs. temporary shock. We estimate three different VAR models where aggregate TFP is ordered first. The first VAR model includes aggregate TFP, real GDP, total hours worked, and the real consumption wage. The second VAR model includes aggregate TFP, real GDP, consumption, investment, and the current account. The third VAR model includes aggregate

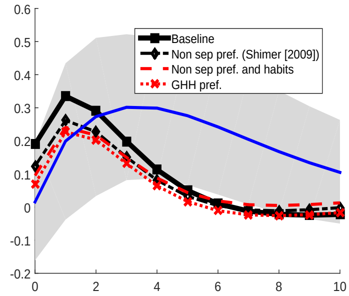


(a) Real GDP (b) Total Hours Worked (c) Real Consumption Wage

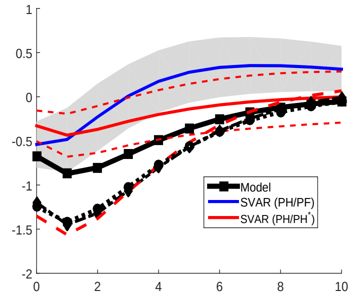
(d) Traded Value Added (e) Non-Traded Value Added (f) Value Added Share of Tradables

(g) Traded Hours Worked (h) Non-Traded Hours Worked (i) Labor Share of Tradables

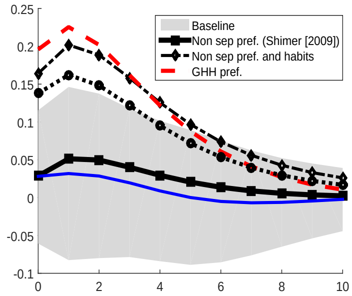
Figure 62: Theoretical vs. Empirical Responses Following Temporary Increase in Aggregate TFP: Effects on Value Added and Hours Worked. Notes: Effects of a 1% temporary increase in aggregate TFP. Solid blue line displays point estimate of VAR with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario where we consider a semi-small open economy with tradables and non-tradables, CES production functions, imperfect mobility of labor across sectors, endogenous terms of trade, and FBTC. The set of parameters is identical to the set of values chosen in the main text. We contrast the predictions of the baseline model with the predictions of three variants of the baseline model. In the first variant shown in the dash-dot black line with diamonds, we allow for non-separability in preferences between consumption and leisure as proposed by Shimer [2009]. In the second variant shown in the dashed red lines, in addition to non separable preferences, we also allow for a *outward-looking* consumption habit behavior as suggested by Carroll, Overland and Weil [2000]. In the third variant shown in the dotted red line with stars, we allow for preferences proposed by Greenwood, Hercowitz, and Huffman [1988] where the wealth effect on labor supply is shut down.



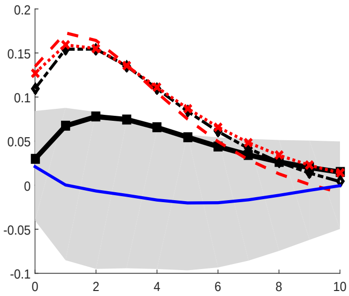
(a) Non-Traded to Traded Prices



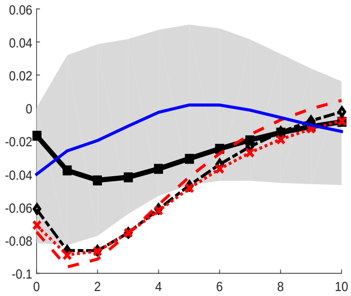
(b) Terms of Trade



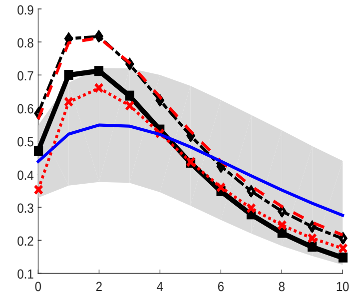
(c) Current Account



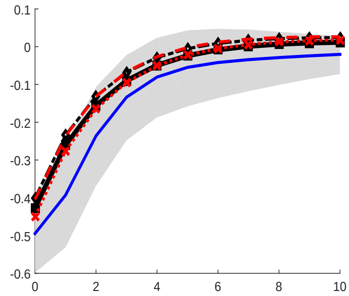
(d) Relative Wage of Tradables



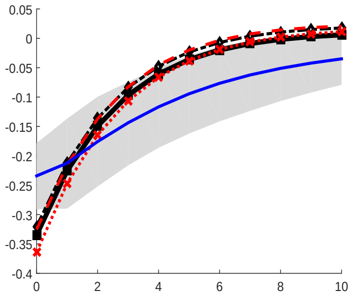
(e) Relative Wage of Non-Tradables



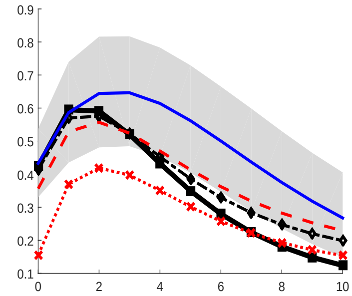
(f) Real Consumption Wage of Tradables



(g) Traded LIS



(h) Non-Traded LIS



(i) Real Consumption Wage of Non-Tradables

Figure 63: Theoretical vs. Empirical Responses Following Temporary Increase in Aggregate TFP: Effects on Prices and Wages. Notes: Effects of a 1% temporary increase in aggregate TFP. Solid blue line displays point estimate of VAR with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario where we consider a semi-small open economy with tradables and non-tradables, CES production functions, imperfect mobility of labor across sectors, endogenous terms of trade, and FBTC. The set of parameters is identical to the set of values chosen in the main text. We contrast the predictions of the baseline model with the predictions of three variants of the baseline model. In the first variant shown in the dash-dot black line with diamonds, we allow for non-separability in preferences between consumption and leisure as proposed by Shimer [2009]. In the second variant shown in the dashed red lines, in addition to non separable preferences, we also allow for a *outward-looking* consumption habit behavior as suggested by Carroll, Overland and Weil [2000]. In the third variant shown in the dotted red line with stars, we allow for preferences proposed by Greenwood, Hercowitz, and Huffman [1988] where the wealth effect on labor supply is shut down. Note that for the terms of trade, we compare the model's predictions shown in the black line with squares with empirical responses where we consider two alternative ways to construct the relative price of home-produced traded goods. In the blue line (associated with the confidence interval displayed by the shaded area), we construct the terms of trade as the ratio of the value added deflator of tradables to the deflator of imports of goods and services. In the red line, we construct the terms of trade as the ratio of the traded value added deflator to the weighted sum of the traded value added deflator of the sixteen trade partners of the corresponding country i, the weight being equal to the share $\alpha^{M,i,k}$ of imports from the trade partner k, i.e, $\text{TOT}_t = P_t^H/P_t^{H,\star}$ where $P_{it}^{H,\star} = \Pi_{k\neq i}\alpha^{M,i,k}P_t^{H,k}$.

Table 32: Conditional Correlations: Technology Shock

Shock	Conditional Correlations				
Temporary shock	(Y_R, C) (1)	(Y_R, J) (2)	(L, TFP) (3)	(CA, Y_R) (4)	(CA, TOT) (5)
Data	0.715	0.873	-0.037	0.945	-0.955
Model	0.998	0.982	-0.880	0.982	-0.989

Notes: Each cell in Table 32 shows the correlations between two macroeconomic variables conditional on a temporary technology shock. In the first row, we show the correlation between the two corresponding variables following a temporary technology shock whilst the second row shows the correlation predicted by the model.

TFP, the ratio of traded to non-traded value added, and the terms of trade defined as the ratio of the value added deflator to the deflator of imports of goods and services. We estimate the three VAR models in panel format on annual data for the seventeen OECD countries of our sample over the period running from 1970 to 2013.

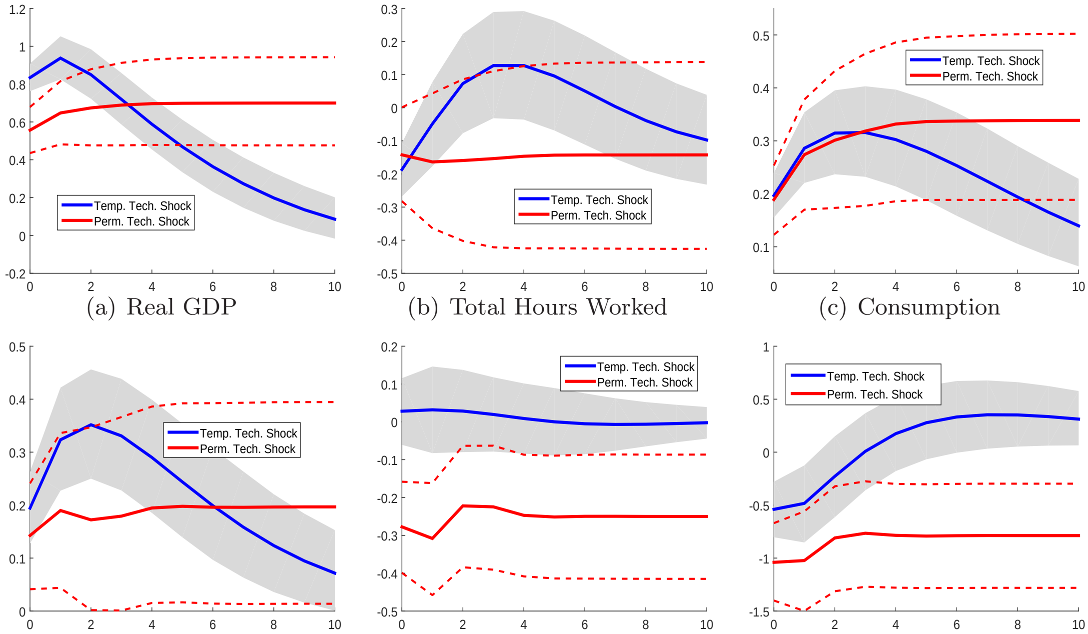
When we identify a permanent technology shock, all variables enter the VAR model in growth rate. As in Gali [1999], we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of TFP. In line with the recommendation of Chaudourne, Fève and Guay [2014], to ensure that the identification of permanent technology shocks is not contaminated by persistent non-technology shocks, we adjust aggregate TFP with the capital utilization rate (in the three VAR models). We normalize the rise in the capital-utilization-adjusted-aggregate-TFP to 1% in the long-run. When we identify a temporary technology shock, all variables enter the VAR model in log level and we perform a Cholesky decomposition. It is worth mentioning that the identification of temporary technology shocks is not subject to biases, as stressed by Christiano, Eichenbaum, and Vigfusson [2006], and therefore aggregate TFP collapses to the unadjusted Solow residual. We normalize the rise in aggregate TFP by 1% on impact.

The solid blue line shows the effects of a temporary increase in aggregate TFP by 1% (on impact) whilst the solid red line displays the dynamic responses to a permanent increase in the capital-utilization-adjusted-aggregate-TFP by 1% in the long-run. VAR estimates reveal that a technology shock increases real GDP, consumption, and investment, and lowers hours worked on impact. Impact responses are similar whether the shock is permanent or temporary. The most important difference is that a temporary shock generates a hump-shaped adjustment whilst variables tend to jump immediately to their steady-state level. When we turn to the current account and the terms of trade shown in Fig. 64(e) and Fig. 64(f), we find that both a permanent and a temporary technology shock lowers the relative price of home-produced traded goods (i.e., the terms of trade deteriorate). While a permanent technology shock deteriorates the current account, a temporary technology shock slightly improves the current account as agents smooth consumption which gives rise to an increase in savings.

To conclude, the analysis of the dynamic effects of permanent and temporary (aggregate) technology shocks has revealed that real both GDP, consumption, investment increase, hours worked fall, the current account deteriorates only when the shock is permanent, and the price of home-produced traded goods falls relative the price of foreign-produced traded goods.

Correlations conditional on a temporary shock to aggregate TFP. The first row of Table 32 shows correlations between selected macroeconomic variables we estimate empirically conditional on a temporary technology shock. Our evidence shows that following a temporary technology shock, consumption (denoted by C) and investment (denoted by J) are pro-cyclical, total hours worked are negatively correlated with aggregate TFP although the correlation is low, the current account is procyclical and the current is negatively correlated with the terms of trade. All these results are in line with those documented by Mendoza [1995] who computes unconditional correlations. As shown in the second row of the Table 32, our model reproduces reasonably well the correlations we estimate empirically although the model overstates the negative correlation between aggregate TFP and total hours worked. When we calculate the correlation over the first eight (instead of the first ten years) years, we find that a correlation of -0.52 in the data and -0.84 in the model.

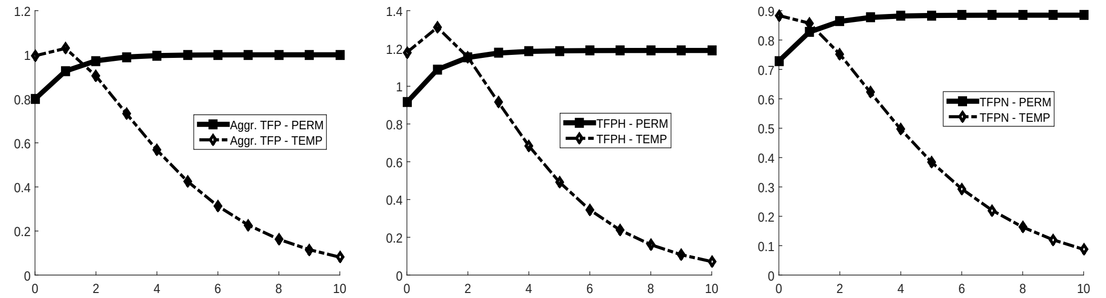
Permanent vs. temporary technology shock: Calibration. In Fig. 65-67, we explore the dynamic effects of a permanent and a temporary technology shock. The values of parameters are identical to those described in section 4.1 in the main text. We have to calibrate the law of motion of the technology shock. Whilst in section U.6 we detail how we calibrate the model to a temporary technology shock, we explain how we calibrate the model to a permanent technology shock. We adopt a two-step approach. First, we estimate a VAR model in panel format on annual data. The VAR model contains aggregate variables such as aggregate TFP (ordered first), real GDP, total hours worked and the real consumption wage; all variables enter the VAR model in



(a) Real GDP (b) Total Hours Worked (c) Consumption

(d) Investment (e) Current Account (f) Terms of Trade

Figure 64: Empirical Responses to a Technology Shock: Temporary vs. Permanent Increase in Aggregate TFP. Note: Effects of a 1% increase in aggregate TFP. Solid blue lines display point estimates of VAR model with shaded area indicating 90% confidence bounds when technology shocks are identified as temporary. The solid red lines display point estimates of VAR model with dashed red lines indicating 90% confidence bounds when technology shocks are identified as permanent. We estimate three different VAR models where aggregate TFP is ordered first. The first VAR model includes aggregate TFP, real GDP, total hours worked, and the real consumption wage. The second VAR model includes aggregate TFP, real GDP, consumption, investment, and the current account. The third VAR model includes aggregate TFP, the ratio of traded to non-traded value added, and the terms of trade defined as the ratio of the value added deflator to the deflator of imports of goods and services. When we identify a permanent technology shock, all variables enter the VAR model in growth rate. As in Gali [1999], we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of TFP. In line with the recommendation of Chaudourne, Fève and Guay [2014], to ensure that the identification of permanent technology shocks is not contaminated by persistent non-technology shocks, we adjust aggregate TFP with the capital utilization rate.



(a) Aggregate TFP (b) Traded TFP (c) Non-Traded TFP

Figure 65: Dynamic Responses to a Technology Shock: Temporary vs. Permanent Increase in Aggregate TFP. Notes: Dynamic effects of a 1% increase in aggregate TFP. The thick solid black line with squares show theoretical responses following a permanent increase in aggregate TFP. The dash-dot black line with diamonds shows the dynamic responses to a temporary increase in aggregate TFP. The calibration of the model is identical to that described in section 4.1. Whilst in the main text we consider a 1% permanent increase in traded relative to non-traded TFP in the long-run, in Fig. 65, we explore the effects of a permanent increase in aggregate TFP in the long-run and contrast the effects with those following a temporary increase in aggregate TFP on impact.

growth rate; we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of aggregate TFP. Once we have identified the permanent shock to aggregate TFP denoted by ε_{it}^{ZA}, in the second step, we estimate a VAR model which includes the identified technology shock ordered first, sectoral TFPs and the aggregate TFP, i.e., $[\varepsilon_{it}^{ZA}, \hat{Z}_{it}^{H}, \hat{Z}_{it}^{N}, \hat{ZA}_{it}]$. The solid black line with squares in Fig. 65(a) shows the adjustment of aggregate TFP following a permanent technology shock. As can be seen in Fig. 65(b) and Fig. 65(c), the permanent technology shock is associated with a larger increase in traded than in non-traded TFP.

To achieve a perfect match with the data, we specify the law of motion for labor- and capital-augmenting efficiency as in the main text, i.e., see eq. (31). To infer the dynamics of A^j and B^j in the data, we solve the log-linearized version of technological frontier, i.e., $\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right) \hat{B}^j(t)$, and the log-linearized version of the demand of factors of production, i.e., $\left(\hat{B}^j(t) - \hat{A}^j(t)\right) = \frac{\sigma^j}{1-\sigma^j} \hat{S}^j(t) - \hat{k}^j(t)$, for labor and capital-augmenting efficiency which leads to (38a)-(38b). We plug estimated values for σ^j and empirically estimated responses for $s_L^j(t)$ and $k^j(t)$ into (38a)-(38b) to recover the dynamics for $A^j(t)$ and $B^j(t)$. Inserting (31) into the log-linearized version of the technology frontier, i.e., allows us to recover the dynamics of TFP in sector j:

$$\hat{Z}^j(t) = \hat{Z}^j + \left(1 - z^j\right) e^{-\chi^j t}, \tag{469}$$

where $\bar{z}^j = s_L^j \bar{a}^j + \left(1 - s_L^j\right) \bar{b}^j$. Inserting (469) into the sectoral decomposition of aggregate TFP growth described by eq. (2) allows us to recover the dynamics of aggregate TFP

$$\hat{Z}^A(t) = \nu^{Y,H} \hat{Z}^H(t) + \left(1 - \nu^{Y,H}\right) \hat{Z}^N(t). \tag{470}$$

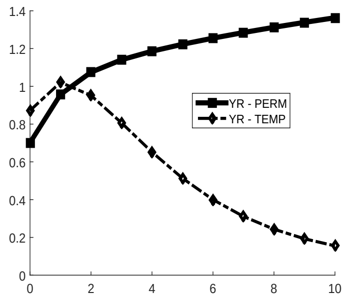
We normalize $\hat{Z}^A(\infty)$ to 1% in the long-run.

Permanent vs. temporary technology shock: Numerical results. In Fig. 66-67, solid black line with squares displays baseline model's predictions following a permanent increase in aggregate TFP while dash-dot black line with diamonds shows the responses to a temporary increase in aggregate TFP. As can be seen in Fig. 66(a), Fig. 67(d) and Fig. 67(e), both temporary and permanent technology shocks increase significantly real GDP, consumption and investment. Consumption and investment are pro-cyclical as they are positively correlated with real GDP. The reason is that a technology shock produces a positive wealth effect which leads agents to consume more. A technology shock also increases the marginal product of capital and lowers both non-traded and traded prices and thereby the aggregate price of investment which thus increases Tobin's q.

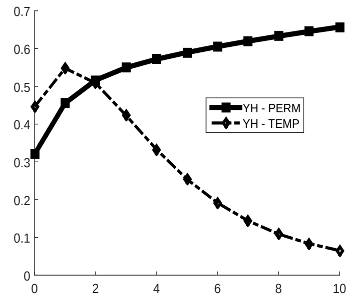
Fig. 67(f) reveals that a temporary technology shock increases the current account while a permanent technology shock deteriorates the current account. Whereas in both cases, the excess supply on the traded goods marker causes a terms of trade deterioration which exerts a positive impact on net exports as a result of the assumption of a price elasticity of exports larger than one (i.e., $\phi_X > 1$), as evidence suggests, a permanent technology shock generates a stronger wealth effect which further increases imports and thus deteriorates the current account. Regardless of the persistence of the technology shock, in accordance with the business cycle facts documented by Mendoza [1995], we find a pro-cyclical current account. This results from the negative correlation between the current account and the terms of trade and the fact that a technology shock deteriorates the terms of trade which are counter-cyclical, in line with the theoretical predictions of Backus, Kehoe and Kydland [1994] (note that the definition of the terms of trade of the authors is the inverse of our measure).[45]

Most importantly, the reallocation of labor across sectors is distinct whether we consider a permanent or a temporary technology shock. Fig. 66(h) shows that a temporary technology shock increases the labor share of tradables while a permanent technology shock leads to a reallocation of labor toward the non-traded sector. Intuitively, the change in the labor share of tradables is the result of two opposite effects. First, a rise in aggregate TFP is associated with a rise in traded and non-traded TFP which produces an excess supply on the traded and non-traded goods market and thus lowers traded and non-traded good prices. Because the elasticity of substitution between traded and non-traded goods is lower than one, non-traded good prices decline disproportionately which lowers the share of non-tradables at current prices, see Fig. 67(c). Because the wealth effect is smaller following a temporary technology shock and thus consumption in non-tradables increases less, the excess supply on the non-traded goods market is more pronounced which results in a greater decline in the share of non-tradables at current prices, i.e., $\frac{P^N(t)Y^N(t)}{Y(t)}$. Second, Fig. 67(g) and Fig. 67(h) reveal that the traded and non-traded labor income shares decline significantly because traded and non-traded firms bias technological change toward capital following both both temporary and permanent technology shocks. Because the traded LIS falls more than the non-traded LIS, technological change is more biased toward capital in the traded than in the non-traded sector which increases the demand for labor in the non-traded sector. Following a temporary technology shock, the pronounced decline in the share of non-tradables at current prices dominates which leads to a reallocation of hours worked toward the traded sector. Conversely, the latter effect dominates following a permanent technology shock so that the labor share of tradables declines as a result of technological change biased toward capital in the traded sector. Regardless of whether the technology shock is permanent or temporary, Fig. 66(g) shows that the value added share of tradables at constant prices increases because traded TFP increases relative to non-traded TFP.

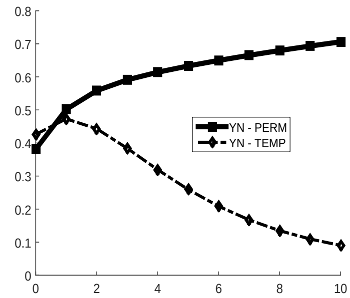
[45] The negative correlation between the terms of trade and the current account fits well our evidence for the US and the evidence documented by Mendoza [1995] for the US and Canada.



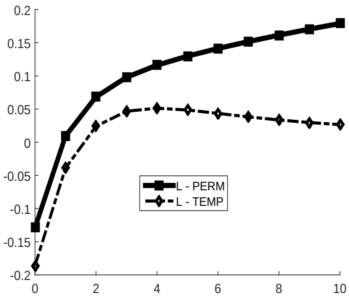
(a) Real GDP



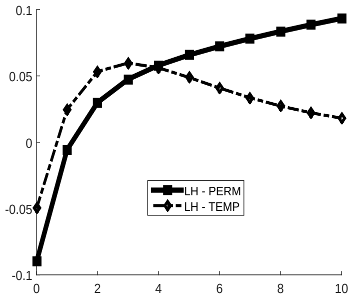
(b) Traded Value Added



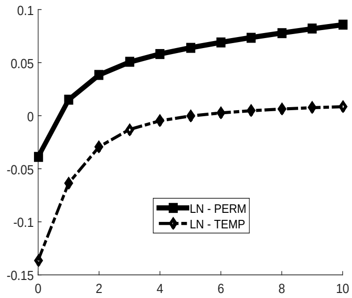
(c) Non-Traded Value Added



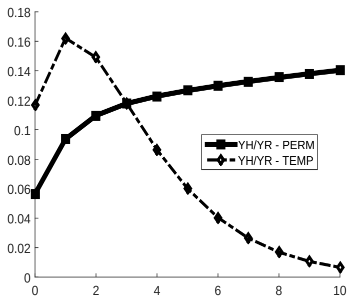
(d) Total Hours Worked



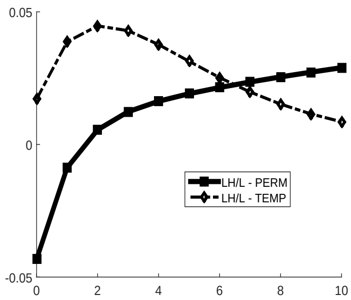
(e) Traded Hours Worked



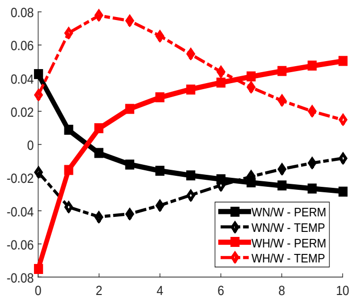
(f) Non-Traded Hours Worked



(g) Value Added Share of Tradables

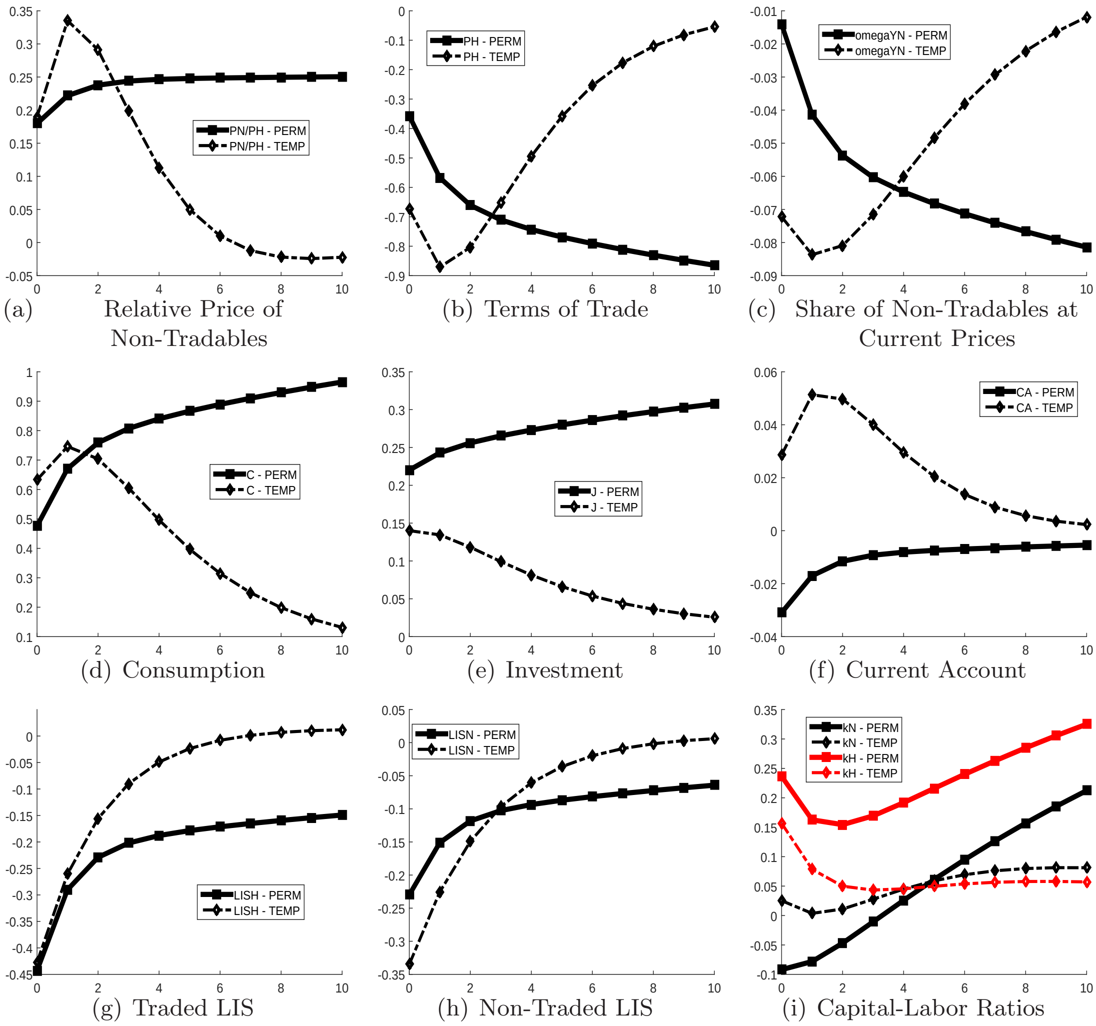


(h) Labor Share of Tradables



(i) Relative Wage

Figure 66: Dynamic Responses to a Technology Shock: Temporary vs. Permanent Increase in Aggregate TFP. Notes: Dynamic effects of a 1% increase in aggregate TFP. The thick solid black line with squares show theoretical responses following a permanent increase in aggregate TFP. The dash-dot black line with diamonds shows the dynamic responses to a temporary increase in aggregate TFP. The calibration of the model is identical to that described in section 4.1. Whilst in the main text we consider a 1% permanent increase in traded relative to non-traded TFP in the long-run, in Fig. 66, we explore the effects of a permanent increase in aggregate TFP in the long-run and contrast the effects with those following a temporary increase in aggregate TFP on impact.



(a) Relative Price of Non-Tradables
(b) Terms of Trade
(c) Share of Non-Tradables at Current Prices
(d) Consumption
(e) Investment
(f) Current Account
(g) Traded LIS
(h) Non-Traded LIS
(i) Capital-Labor Ratios

Figure 67: Dynamic Responses to a Technology Shock: Temporary vs. Permanent Increase in Aggregate TFP. Notes: Dynamic effects of a 1% increase in aggregate TFP. The thick solid black line with squares show theoretical responses following a permanent increase in aggregate TFP. The dash-dot black line with diamonds shows the dynamic responses to a temporary increase in aggregate TFP. The calibration of the model is identical to that described in section 4.1. Whilst in the main text we consider a 1% permanent increase in traded relative to non-traded TFP in the long-run, in Fig. 67, we explore the effects of a permanent increase in aggregate TFP in the long-run and contrast the effects with those following a temporary increase in aggregate TFP on impact.

U.9 Symmetric vs. Asymmetric Technology Shock across Sectors

Time-varying contribution of asymmetric technology shocks across sectors to aggregate TFP variations. In subsection 2.2, we have shown that asymmetric technology shocks across sectors were accounting for a greater share of the variations of aggregate TFP after 1992. In this subsection, we explore the impact of the growing importance of asymmetric technology shocks across sectors for the response of total hours worked to permanent shocks to aggregate TFP and the reallocation of labor across sectors. To conduct this analysis in a deterministic model, we break down labor-augmenting and capital-augmenting productivity into two components:

$$A^j(t) = \left(A_S^j(t)\right)^{\eta} \left(A_D^j(t)\right)^{1-\eta}, \qquad B^j(t) = \left(B_S^j(t)\right)^{\eta} \left(B_D^j(t)\right)^{1-\eta}. \tag{471}$$

According to (471), changes in labor- and capital-augmenting productivity can be driven by factor-augmenting technological change which is symmetric across sectors, as captured by the terms $A_S^j(t)$ and $B_S^j(t)$, and also can be brought about by variations in factor-augmenting productivity which are asymmetric across sectors, denoted by $A_D^j(t)$ and $B_D^j(t)$. Parameter η captures the intensity of factor-augmenting productivity in symmetric variations whilst $1-\eta$ captures the intensity of changes in factor-augmenting productivity which are asymmetric across sectors.

Like in the main text, we assume a mapping between labor- and capital-augmenting productivity and TFP within sector $j = H, N$ by considering that firms choose an optimal mix of $A^j(t)$ and $B^j(t)$ along the technology frontier:

$$Z^j(t) = \left(A^j(t)\right)^{s_L^j(t)} \left(B^j(t)\right)^{1-s_L^j(t)}. \tag{472}$$

In addition, as demonstrated formally in Online Appendix C, the variation in aggregate TFP is a weighted sum of variations in traded and non-traded TFPs:

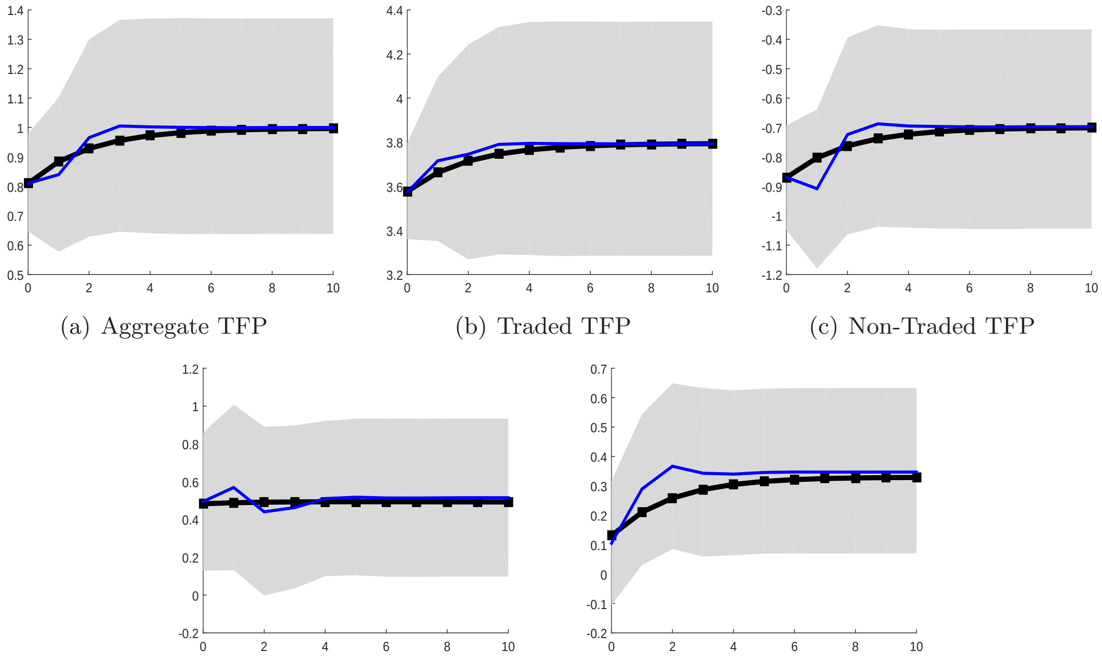
$$\hat{Z}^A(t) = \nu^{Y,H} \hat{Z}^H(t) + \left(1 - \nu^{Y,H}\right) \hat{Z}^N(t). \tag{473}$$

Before the great moderation, the bulk of changes in aggregate TFP is driven by variations in sectoral TFPs which are symmetric across sectors, i.e., η converges to one until 1992. After 1992, a substantial fraction of aggregate TFP fluctuations are driven by asymmetric variations in sectoral TFPs; more specifically, η collapses to 0.6 after 1992 and might further increase in the future. We explore below the impact of the growing importance of asymmetric variations in sectoral TFPs on the responses of total hours worked and labor reallocation to an aggregate technology shock.

Calibration strategy. To explore the impact of the growing importance of asymmetric variations in sectoral TFPs, we proceed as follows. Parameter values are identical to those discussed in the main text, i.e., in subsection 4.1. We now consider an aggregate technology shock as captured by a 1% permanent increase in aggregate TFP. Because the permanent change in aggregate TFP can be brought about by variations in symmetric and asymmetric variations in sectoral TFPs, we have to calibrate symmetric and asymmetric technology shocks.

To determine the responses of Z_{it}^j to a shock to Z_{it}^A, we adopt a two-step method. In the first step, we identify symmetric and asymmetric technology shocks across sectors by adopting the same methodology as in the main text, i.e., in section 2.2. We augment the VAR model with aggregate TFP $[\hat{Z}_{it}^H - \hat{Z}_{it}^N, \hat{Z}_{it}^A, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}]$ where $Z_{it} = Z_{it}^H / Z_{it}^N$ is the ratio of traded to non-traded TFP, $Y_{R,it}$ is real GDP, L_{it} is total hours worked, and $W_{C,it}$ is the real consumption wage, and we augment the VAR model with aggregate TFP denoted by Z_{it}^A. We impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_{it}^A while only asymmetric technology shocks increase permanently Z_{it}^H / Z_{it}^N in the long-run. Once we have identified symmetric and asymmetric technology shocks across sectors, we can estimate the dynamic adjustment of sectoral TFPs to a 1% permanent increase in aggregate TFP depending on whether the shock is symmetric or asymmetric. We denote identified asymmetric technology shocks across sectors by $\epsilon_{SYM,it}^{ZA}$ and identified asymmetric technology shocks across sectors by $\epsilon_{ASYM,it}^{ZA}$. In the second step, we estimate a VAR model which includes sectoral TFPs and aggregate TFP whilst identified technology shocks are ordered first, i.e., $x_{it}^{ZA} = [\epsilon_{x,it}^{ZA}, \hat{Z}_{it}^H, \hat{Z}_{it}^N, \hat{Z}_{it}^A]$ where $x = SYM, ASYM$, and adopt a Cholesky decomposition.

To determine if symmetric and asymmetric technology shocks are hicks-neutral or factor-biased, we estimate the VAR model which includes the ratio of traded to non-traded TFP, aggregate TFP, the LIS in sector j, and the capital-labor ratio in sector j, i.e., $[\hat{Z}_{it}^H - \hat{Z}_{it}^N, \hat{Z}_{it}^A, \hat{s}_{L,it}^j, \hat{k}_{it}^j]$, we impose the long-run restrictions detailed above to identify symmetric and asymmetric technology shocks across sectors, and we estimate the responses of s_L^j and k^j to a 1% permanent increase in aggregate TFP for symmetric and asymmetric technology shocks across sectors. Once we have estimated the dynamic responses of sectoral LISs and sectoral capital-labor ratios to a 1% permanent increase in aggregate TFP when technology shocks are fully asymmetric across sectors (i.e., $\eta = 0$) or fully



(a) Aggregate TFP (b) Traded TFP (c) Non-Traded TFP

(d) Traded LIS (e) Non-Traded LIS

Figure 68: Dynamic Responses of Aggregate TFP, Sectoral TFPs, and LISs to Asymmetric Technology Shocks across Sectors: Model vs. Data Notes: Solid blue line displays point estimate of VAR with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario where we consider a semi-small open economy with tradables and non-tradables, CES production functions, imperfect mobility of labor across sectors, endogenous terms of trade, and FBTC.

symmetric across sectors (i.e., $\eta = 1$), we can recover the dynamics of labor- and capital-augmenting productivity by using formulas (38a)-(38b) in the main text.

TFP and LIS: Model vs. Data. Fig. 68 contrasts empirical responses shown in the blue line with theoretical responses displayed by the solid black line with squares for aggregate TFP, traded and non-traded TFPs, and for the traded and non-traded LISs. When aggregate technology shocks are only made up of asymmetric technology shocks across sectors, the rise in aggregate TFP shown in Fig. 68(a) is associated with a permanent rise in traded TFP relative to non-traded TFP. Importantly, as discussed in length in the main text, both the traded and non-traded LISs displayed by Fig. 68(d) and Fig. 68(e) increase and their magnitude reveals that technological change is more biased toward labor in the traded than in the non-traded sector.

While in Fig. 68, we focus on asymmetric technology shocks across sectors, in Fig. 69, we consider that the aggregate technology shock is only made up of symmetric technology shocks across sectors. Fig. 69 contrasts empirical responses shown in the blue line with theoretical responses displayed by the solid black line with squares for aggregate TFP, traded and non-traded TFPs, and for the traded and non-traded LISs. When aggregate technology shocks are only made up of symmetric technology shocks across sectors, the rise in aggregate TFP shown in Fig. 69(a) is associated with a rise in traded and non-traded TFP of the same magnitude. In contrast to asymmetric technology shocks across sectors, both the traded and non-traded LISs displayed by Fig. 69(d) and Fig. 69(e) decline and their magnitude reveals that technological change is more biased toward capital in the traded than in the non-traded sector.

Dynamic responses to aggregate technology shocks against the growing importance of asymmetric technology shocks across sectors. In Fig. 70, we plot the dynamic responses of total hours worked, and the dynamic adjustment of the labor share and the value added share of tradables following a 1% permanent increase in aggregate TFP in the long-run. Because the permanent change in aggregate TFP can be driven by symmetric and asymmetric technology shocks across sectors, we explore the impact of the growing importance of asymmetric variations in sectoral TFPs by lowering the intensity η of aggregate TFP variations in symmetric technology shocks across sectors from one to 0.4.

As shall be useful below, it is convenient to differentiate first a symmetric from an asymmetric technology shock across sectors and describe the transmission mechanism. Like in the main text, the technology shock is asymmetric because traded TFP increases permanently relative to non-traded TFP. While in the main text, we normalize the permanent rise in the weighted ratio to 1%, in this subsection, we consider a rise in traded relative to non-traded TFP which increases aggregate TFP by 1%. The asymmetric technology shock causes an excess demand in the non-traded goods market and an excess supply in the home-produced traded goods market. Because the elasticity of

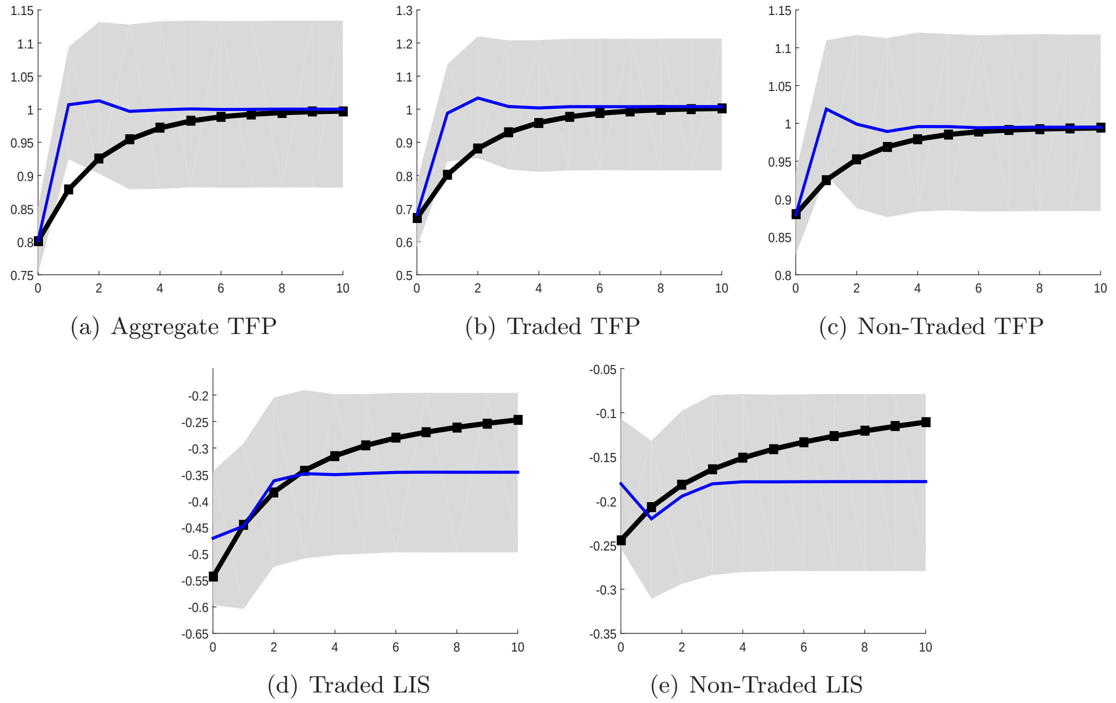
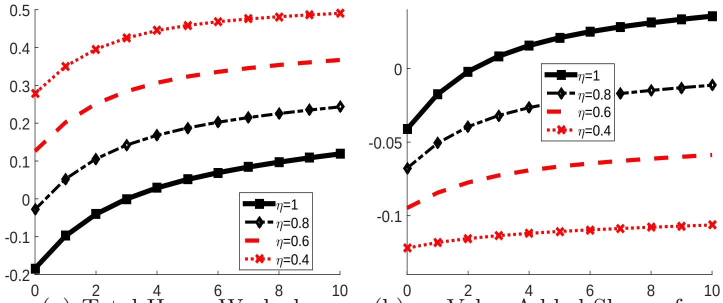


Figure 69: Dynamic Responses of Aggregate TFP, Sectoral TFPs, and LISs to Symmetric Technology Shocks across Sectors: Model vs. Data Notes: Solid blue line displays point estimate of VAR with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario where we consider a semi-small open economy with tradables and non-tradables, CES production functions, imperfect mobility of labor across sectors, endogenous terms of trade, and FBTC.

substitution between traded and non-traded goods is smaller than one, the relative price of non-traded goods appreciates disproportionately which increases labor demand in this sector and thus shifts hours towards the non-traded sector, i.e., $d\nu^{L,H}(0) < 0$. Because technological change is more biased toward labor in the traded than in the non-traded sector, see Fig. 68(d) and 68(e), which has a positive impact on labor demand in the traded sector, the FBTC dififerential mitigates the shift of labor toward the non-traded sector. While productive resources move away from the traded sector, technological change biased toward tradables increases the value added share of tradables at constant prices, i.e., $d\nu^{Y,H}(0) > 0$. The response of total hours worked to the aggregate technology shock depends on the strength of the wealth and substitution effect. By assuming an IES for consumption of two, the wealth effect is mitigated which results in an increase in labor supply on impact. The rise in total hours worked, i.e., $\hat{L}(0) > 0$, is amplified by technological change which is biased toward labor in both sectors.

When the shock is symmetric across sectors, an excess supply shows up in both the traded and non-traded goods markets which lowers both the terms of trade and non-traded prices. Because the home- and foreign-produced traded goods are gross substitutes (i.e., $\rho > 1$ and $\rho_J > 1$) while traded and non-traded goods are gross complements (i.e., $\phi < 1$), the fall in the relative price of home-produced traded goods $P^H(t)$ increases labor demand in the traded sector whilst the decline in non-traded prices lowers labor demand in the non-traded sector. Therefore, when the technology shock is symmetric across sectors, labor shifts towards the traded sector. When the wealth effect is mitigated, total hours worked increase. However, Fig. 69(d) and 69(e) reveals that technological change is biased toward capital in both sectors which lowers the demand for labor and thus results in a decline in total hours worked, i.e., $\hat{L}(0) < 0$. Because the magnitude of the decline in the traded LIS is larger than the decline in the non-traded LIS, technological change is more biased toward capital in the traded than in the non-traded sector which results in a fall in the labor share of tradables, i.e., $d\nu^{L,H}(0) < 0$. Because the technology shock is symmetric across sectors and labor shifts away from the traded sector, the value added share of tradables slightly declines, i.e., $d\nu^{Y,H}(0) < 0$.

In Fig 70, we explore the impact of a decrease in η which reflects the growing importance of asymmetric technology shocks across sectors. As displayed by Fig. 70(a), when the aggregate technology shock is only driven by symmetric technology shocks, as shown in the solid black line with squares, total hours worked fall on impact because symmetric technological change is biased toward capital in both sectors which lowers labor demand. Because asymmetric technology shocks are associated with technological change biased towards labor, as the intensity of asymmetric technology shocks increases, the response of total hours worked increases and turns out to be positive. Therefore, the growing importance of asymmetric technology shocks across sectors can rationalize the time-



(a) Total Hours Worked (b) Value Added Share of Tradables (c) Value Added Share of Tradables

Figure 70: Dynamic Responses to an Aggregate Technology Shock vs. Intensity of Asymmetric Technology Shocks Notes: Dynamic adjustment to a 1% permanent increase in aggregate TFP in the long-run. The set of parameters is identical to the set of values chosen in the main text. We contrast the predictions of the baseline model as we lower the intensity η of symmetric technology shocks across sectors. The thick solid black line with squares shows the model's predictions when variations in aggregate TFP are only driven by symmetric technology shocks across sectors. The dash-dot black line with diamonds shows the predictions of the baseline model when asymmetric technology shocks account for 20% of the variations of aggregate TFP. In the dashed red lines, we show the predictions of the baseline model when asymmetric technology shocks account for 40% of the variations of aggregate TFP. In the dotted red line with stars, we show the predictions of the baseline model when asymmetric technology shocks account for 60% of the variations of aggregate TFP.

increasing response of total hours worked to an aggregate TFP shock, a finding documented by Galí and Gambetti [2009], Cantore et al. [2017].

As displayed by Fig. 70(b) and Fig. 70(c), as the intensity of asymmetric technology shocks increases, the labor share of tradables declines more and the value added share of tradables at constant prices increases by a larger amount. The reason is that asymmetric technology shocks across sectors provide high incentives to reallocate labor towards the non-traded sector as they strongly appreciate the relative price of non-tradables and thus exert a negative impact on $\nu^{L,H}$ which is more pronounced than that following symmetric technology shocks across sectors. Conversely, because asymmetric technology shocks across sectors are associated with an increase in traded relative to non-traded TFP, the increase in the value added share of tradables is more pronounced when η is lowered.

Table 33 summarizes the impact responses of total hours worked, real GDP, labor share and value added share of tradables, the traded and non-traded LISs to a 1% permanent increase in aggregate TFP. Column 1 shows the intensity η of aggregate technology shocks in symmetric technology shocks across sectors. The last two columns of Table 33 shows the responses of the terms of trade and the current account. Whilst an aggregate TFP shock lowers the price of home- relative to foreign-produced traded goods, the terms of trade deterioration is amplified when asymmetric technology shocks across sectors become more important because traded value added increases more. Across all scenarios, the current account deteriorates because a permanent increase in aggregate TFP lowers savings and increases investment.

V Extension to Developing/Emerging Countries

The objective of this section is twofold. First, we investigate whether our conclusions reached in the main text by using a sample of seventeen OECD countries also hold for developing countries. Our second objective is to analyze whether labor reallocation between sectors and changes in the value added share of tradables display marked differences between developing countries.

Dataset. To conduct the analysis, we use a sample of 50 developing countries. Data are taken from the Economic Transformation Database [2018] (ETD thereafter) which is a project sponsored by both United Nations and the University of Groningen. Data are publicly available at the following web link `https://www.rug.nl/ggdc/structuralchange/etd/`. Whilst the dataset includes 51 countries, including Japan, because this country is part of our sample of OECD countries, we exclude the japenese economy. The fifty countries include: 20 Asian countries, 21 African countries, and 9 Latin American countries, see Table 34.

ETD provides some sectoral data for value added and employment by economic activity, distinguishes 12 sectors in the International Standard Industrial Classification, Revision 4 (ISIC rev. 4) classification, and has time series that run until 2018. We stop in 2013 to be consistent with our sample of OECD countries. Employment in ETD is defined as 'all persons engaged', including all paid employees, the self-employed, and family workers. Unfortunately, time series for hours worked are not available (the data are irregular and information on hours worked typically covers only the formal sector). Except for one sub-sector, the split of the twelve industries between the traded

Table 33: Aggregate and Sectoral Effects of a Permanent Increase in Aggregate TFP against the Weight η of Symmetric Technology Shocks across Sectors

Sym. tech. shock.	Aggregate		Sectoral share		LIS		TOT and CA	
intensity, η	$\hat{L}(0)$	$\hat{Y}_R(0)$	$d\nu^{L,H}(0)$	$d\nu^{Y,H}(0)$	$ds_L^H(0)$	$ds_L^N(0)$	$\hat{P}^H(0)$	$dCA(0)/Y$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1.00	-0.18	0.67	-0.04	-0.01	-0.54	-0.24	-0.24	-0.04
0.95	-0.15	0.70	-0.05	0.02	-0.49	-0.23	-0.30	-0.04
0.90	-0.11	0.72	-0.05	0.06	-0.44	-0.21	-0.36	-0.04
0.85	-0.07	0.75	-0.06	0.10	-0.39	-0.19	-0.42	-0.04
0.80	-0.03	0.77	-0.07	0.13	-0.34	-0.17	-0.49	-0.03
0.75	0.01	0.80	-0.07	0.17	-0.28	-0.15	-0.55	-0.03
0.70	0.05	0.82	-0.08	0.20	-0.23	-0.13	-0.61	-0.03
0.65	0.09	0.85	-0.09	0.24	-0.18	-0.11	-0.67	-0.03
0.60	0.13	0.87	-0.10	0.27	-0.13	-0.09	-0.73	-0.03
0.55	0.17	0.90	-0.10	0.30	-0.08	-0.08	-0.79	-0.03
0.50	0.20	0.92	-0.11	0.34	-0.03	-0.06	-0.85	-0.03
0.45	0.24	0.95	-0.12	0.37	0.03	-0.04	-0.91	-0.03
0.40	0.28	0.97	-0.12	0.41	0.08	-0.02	-0.97	-0.03
0.35	0.32	1.00	-0.13	0.44	0.13	0.00	-1.02	-0.03
0.30	0.35	1.02	-0.14	0.47	0.18	0.02	-1.08	-0.03
0.25	0.39	1.04	-0.14	0.51	0.23	0.04	-1.14	-0.03
0.20	0.43	1.07	-0.15	0.54	0.28	0.06	-1.20	-0.03

Notes: Columns 1 shows the intensity η of the factor-augmenting productivity in symmetric technology shocks. Columns 2-3 display impact responses of total hours worked and real GDP. Columns 4-5 show impact responses of the labor share and the value added share (at constant prices)of tradables. Columns 6-7 display impact responses of the traded and non-traded labor income shares. Columns 8-9 show impact responses of the terms of trade and the current account (in % of GDP).

Table 34: Countries Included in Economic Transformation Database [2018], 1990-2013.

Country	Continent	Country	Continent
(1)	(2)	(3)	(4)
Argentina	Latin America	Malaysia	Asia
Bangladesh	Asia	Mauritius	Africa
Bolivia	Latin America	Mexico	Latin America
Botswana	Africa	Morocco	Africa
Brazil	Latin America	Mozambique	Africa
Burkina Faso	Africa	Myanmar	Asia
Cambodia	Asia	Namibia	Africa
Cameroon	Africa	Nepal	Asia
Chile	Latin America	Nigeria	Africa
China	Asia	Pakistan	Asia
Taiwan	Asia	Peru	Latin America
Colombia	Latin America	Philippines	Asia
Costa Rica	Latin America	Republic of Korea	Asia
Ecuador	Latin America	Rwanda	Africa
Egypt	Africa	Senegal	Africa
Ethiopia	Africa	Singapore	Asia
Ghana	Africa	South Africa	Africa
Hong Kong	Asia	Sri Lanka	Asia
India	Asia	Tanzania	Africa
Indonesia	Asia	Thailand	Asia
Israel	Middle East (Asia)	Tunisia	Africa
Kenya	Africa	Turkey	Middle East (Asia)
Laos	Asia	Uganda	Africa
Lesotho	Africa	Vietnam	Asia
Malawi	Africa	Zambia	Africa

Notes: Columns 1 and 3 display the names of the countries. Columns 2 and 4 display the continent of the country. While Israel and Turkey should be classified as Middle East countries, we classify these two countries in the group of Asian countries (as indicated in parentheses) as the time horizon is not long enough to enable us to run a regression for a sample of two countries for which data are running from 1990 to 2013 only. Economic Transformation Database [2018]. Sample: 50 emerging countries, 1990-2013.

and the non-traded sector is straightforward and identical to the classification we adopt for the KLEMS and OECD STAN datasets detailed in section K. More specifically, we classify industries as tradables or non-tradables as follows:

- **Traded sector** includes six sub-sectors: Agriculture (A), Mining and Quarrying (B), Manufacturing (C), Transport Services (H), Business Services (J+M+N), Financial services (K).
- **Non-traded sector** includes six sub-sectors: Utilities (E), Construction (F), Trade Services and Accommodation and Food Service Activities (G+I), Real Estate (L), Government Services, Other Services (O-U).

Whilst the mapping between industries of EU KLEMS [2011], [2017] and OECD [2011], [2017] databases on one hand and industries of ETD [2018] on the other, is clear, the sector 'Real Estate, Renting and Business Services' in ISIC-rev.3 is split into two sub-sectors 'Real Estate Activities', 'Professional, Scientific, Technical, Administrative and Support Service Activities' in ISIC-rev.4. In line with the evidence documented by Jensen and Kletzer [2006], 'Real Estate Activities' (L) is classified as non-tradables and 'Professional, Scientific, Technical, Administrative and Support Service Activities' (M& N) should be classified as tradables. Note that 'Professional, Scientific, Technical, Administrative and Support Service Activities' (M& N) and 'Information and Communication' (J) are aggregated in ETD [2018] within the sector 'Business Services' '(J,M&N).

Empirical strategy. We measure technological change at a sectoral level by using sectoral labor productivity which is computed as value added at constant prices divided by employment (i.e., persons engaged') of the corresponding broad sector $j = H, N$. Denoting labor productivity in sector j by A^j, the ratio of traded to non-traded labor productivity, denoted by A, is computed as follows for country i at year y: $A_{it} = \frac{A^H_{it}}{A^N_{it}}$.

Because most of the literature related to the effects of technology shocks explores the impact of a permanent increase in labor productivity on aggregate labor, we estimate a VAR model which includes the ratio of traded to non-traded labor productivity, A_{it}, and a vector of aggregate variables such as real GDP, Y_{it}, and total employment, L_{it}, To estimate the sectoral composition effects of a technology shock biased toward tradables, we consider VAR models which include the ratio of traded to non-traded labor productivity, A_{it}, and a vector of sectoral variables such as value added at constant prices, Y^j_{it}, employment, L^j_{it}, in sector j or alternatively the value added share, $\nu^{Y,j}_{it}$, the labor share, $\nu^{L,j}_{it}$, in sector j. We also consider a VAR model which includes relative prices to inspect the transmission mechanism. All variables enter the VAR model in rate of growth. We estimate the reduced form of VAR models by panel OLS regression with country and time fixed effects. Note that we cannot add wages as a control as we do in the main text as time series for sectoral wages were not directly available.

Empirical results and discussion. We generate impulse response functions which summarize the responses of variables to a 1% permanent increase in traded relative to non-traded labor productivity. Fig. 71 displays the estimated effects of the technology shock. The horizontal axis measures time after the shock in years and the vertical axis measures percentage deviations from trend. In each case, the solid line represents the point estimate. The thick blue line shows results for the whole sample of fifty developing countries. The shaded area indicates 90% confidence bounds obtained by bootstrap sampling.

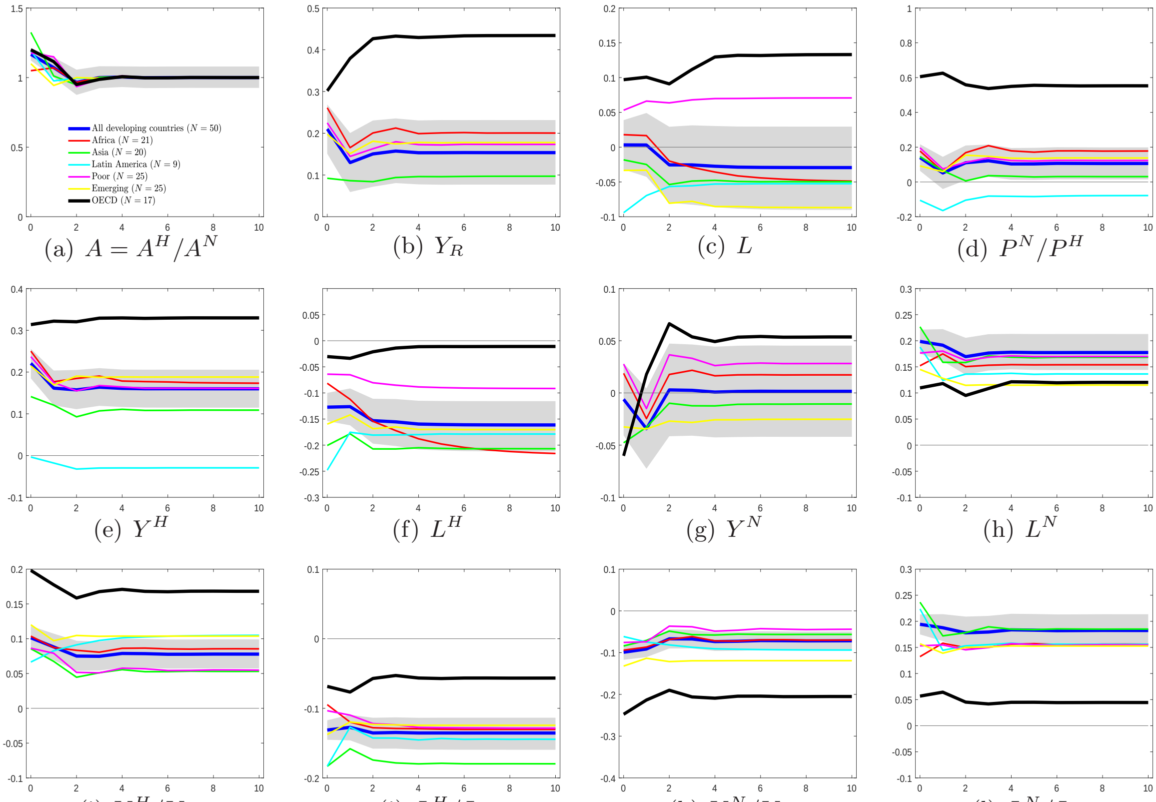
OECD countries: black line. To contrast our results for the 50 developing countries with our results in the main text, we estimate the same VAR models as detailed above for our sample of seventeen OECD countries over 1990-2013 to ensure consistency. The dynamic responses to a 1% permanent increase in traded relative to non-traded labor productivity are shown in the thick sold black line for our sample of OECD countries. First, all the results reached in the main text hold when we use labor productivity to measure technology change and restrict the period to 1990-2013. More specifically, as displayed by the black line for OECD countries, a permanent increase in A^H/A^N has an expansionary effect on real GDP and total hours worked, and appreciates the relative price of non-tradables, as can be seen in the first row of Fig. 71. The second row of Fig. 71 also corroborates our findings in the main text as the asymmetric technology shock increases significantly traded value added (at constant prices), Y^H, and non-traded employment, L^N, whilst non-traded value added and traded employment remain fairly unresponsive. Most importantly, as can be seen in the third row of Fig. 71, the permanent rise in A^H/A^N shifts labor towards the non-traded sector, as reflected by a decline in the labor share of tradables, and also increases the value added share of tradables at constant prices.

Developing countries (50) shown in blue line vs. OECD countries. While our results are unchanged for our sample of OECD countries, it is interesting to compare the responses with those estimated for the group of fifty developing countries shown in the thick solid blue line. Before discussion empirical IRFs, we have estimated a VAR model included the ratio of traded to non-traded labor productivity, aggregate labor productivity, and total hours worked over 1990-2013 and we find that 10% of the FEV of aggregate labor productivity is attributable to asymmetric technology shocks across sectors. This figure is four times smaller than that estimated for OECD countries since as stressed by Foerster et al. [2011], Garìn et al. [2018], the growing contribution of asymmetric shocks across sectors is the result of the decline in the variance of aggregate shocks, i.e., caused by a greater macroeconomic stability. Inspection of the last row of Fig. 71 reveals that just like in industrialized countries, a permanent increase in traded relative to non-traded productivity produces a shift of labor toward the non-traded sector and increases the traded-goods-share of real GDP. The results indicate that asymmetric technology shocks across sectors produce a reallocation of employment in developing countries which is about three times larger than the magnitude estimated for OECD countries, see Fig. 71(l). While more labor shifts toward the non-traded sector in developing countries, the smaller increase in total hours worked results in a similar response for L^N, see Fig. 71(h). Because the traded sector experiences a greater labor outflow in developing countries, see Fig. 71(j), the value added share of tradables at constant prices increases by a smaller amount, see Fig. 71(i). As shown in Fig. 71(d), higher labor mobility curbs inflation of non-tradables. One additional explanation is that OECD countries can be considered to have an unlimited access to world capital markets which, as stressed in the main text, amplifies the demand boom for non-tradables and thus further appreciates the relative price of non-tradables.

These results reveal that developing countries experience lower labor mobility costs than industrialized countries. As shown empirically by Cardi et al. [2020], the reason lies in the skill composition of the labor force. Mobility costs captured by the parameter ϵ which captures the elasticity of substitution between traded and non-traded labor, accord well with the sector-specific skills theory according to which a substantial amount of human capital may be destroyed upon switching industry. Cardi et al. [2020] find empirically that our measure of the degree of labor mobility across sectors is positively correlated with the share of young (share of workers aged 15-24 years in total labor force) and low-education workers (share of workers with primary education in total labor force), in line with the evidence documented by Kambourov and Manovskii [2009] which reveals that industry (and occupational) mobility declines with worker's age and education. Intuitively, younger and unskilled workers accumulate relatively less sector-specific human capital, and thus are expected to be more prone to shift from one sector to another. The results documented by Cardi et al. [2020] also show that ϵ takes lower values in countries where employment protection legislation (adjusted with the share of permanent workers) is stricter and union density is higher. Drawing on Tang [2012], in countries where labor laws are more protective or where employees are more protected by labor unions, workers expect a more stable relationship with their employers and obtain higher bargaining power vis-a-vis their employers. Thus, they have more incentives to acquire firms specific skills relative to general skills on the job and thus are less prone to change jobs/sectors. Because the share of young works and low-skilled workers in the labor force and labor laws are less protective (on average) in developing than in OECD countries, labor mobility costs should be lower, as our evidence suggests.

Emerging (yellow) vs. poor (magenta) countries, African (red) vs. Asian (green) vs. Latin American (cyan) countries. Because developing countries are made of very different countries which are heterogenous in terms of institutions, macroeconomic stability, skill composition of the labor force, and level of development, we split the sample of countries into poor and emerging countries, i.e., poor countries are those where PPP GDP (US dollar) per capita ranges from zero to 3000 per year while emerging are countries for which PPP GDP per capita (in US dollar) range from 3001-25000. When we contrast the results for emerging (shown in the yellow line) with those for poor economies (shown in magenta), we don't find marked differences except for total employment which increases in poor countries and falls in emerging countries. One potential explanation to this is that asymmetric technology shocks are associated with technological change biased toward labor in poor countries and biased toward capital in emerging countries.

Finally, we contrast the evidence between the three groups of countries, i.e., African countries shown in the red line, with Asian countries shown in the green line, and Latin American countries shown in the cyan line. Inspection of the second and the first row reveals that the responses of total and traded employment, i.e., L and L^H, together with the responses of traded value added, Y^H, redisplay a marked difference in Latin American countries compared with the two other groups of countries as total employment declines significantly, traded value added does not increase, traded employment falls dramatically. The fall in Y^H is caused by the large decline in L^H which is the result of the combined effect of the decline in L and the shift of labor towards the non-traded sector. In addition, as can be seen in Fig. 71(d), while the appreciation in the relative price of non-tradables is less pronounced in developing (thick blue line) than in OECD countries (thick black line), as a result of the greater shift of labor towards the non-traded sector which curbs non-traded inflation, the relative price of non-tradables does not appreciate in Latin American countries following a permanent increase in traded relative to non-traded labor productivity. This result is puzzling because the transmission mechanism lies in the appreciation in the relative price of non-tradables which provides incentives to shift labor towards the non-traded sector. Future work should check this result. One potential explanation is that permanent changes in sectoral TFPs have been associated with sudden stops episodes which have temporary but long-lasting effects on labor reallocation, see e.g., Arrellano et al. [2018] who assume a default risk in an economy subject to aggregate productivity shocks that affect both sectors symmetrically. One alternative explanation is that we should take account the role of international spillovers, especially for Latin American countries. Because business cycles between latter economies and the U.S. are substantially correlated, we believe that international transmission of U.S. technology shocks might play a key role for Latin American economies, see e.g., Miyamoto and Nguyen [2017] who uncover an endogenous transmission of technology shocks through international trade from the U.S. to Canada.



(a) $A = A^H/A^N$ (b) Y_R (c) L (d) P^N/P^H

(e) Y^H (f) L^H (g) Y^N (h) L^N

(i) Y^H/Y (j) L^H/L (k) Y^N/Y (l) L^N/L

Figure 71: Dynamic Effects of a Technology Shock Biased toward the Traded Sector: OECD vs. Emerging Countries (1990-2013). Notes: Exogenous 1% permanent increase of labor productivity of tradables relative to non-tradables. Horizontal axes indicate years. Sectoral labor productivity is computed as the ratio of value added at constant prices to employment of the corresponding sector. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added, sectoral value added share), percentage deviation from trend in total hours worked units (sectoral hours worked, sectoral hours worked share), percentage deviation from trend (relative labor productivity of tradables, relative price of non-tradables). The black line shows results for the panel of seventeen OECD countries. To enable a consistent comparison with the sample of developing countries, we have re-estimated the effects of a permanent increase in traded relative non-traded productivity by using labor productivity to measure technological change over 1990-2013. The red line, the green line and the cyan line shows results for Africa (21 countries), Asia (20 countries), Latin America (9 countries). We also split the sample of 50 developing countries into a sub-sample of 25 emerging countries whose results are shown in the yellow line and a sub-sample of poor countries shown in the magenta line. The thick blue line shows results for all developing countries and shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. Database: Economic Transformation Database [2018]. Sample: 50 emerging countries, 1990-2013.

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