The direct and indirect effects of city size, trade openness and exchange rates on prices and incomes across cities*

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Abstract

We relate prices and incomes across a panel of cities across the world to city sizes, trade openness, and exchange rates. Prices (but not incomes) are negatively associated with city sizes and trade openness. There is no evidence that city size and trade openness affect incomes indirectly through their effect on prices. Greater price dispersion is associated with higher average prices and income dispersion, but with lower average incomes and less trade openness, while greater income dispersion is associated with higher average incomes and price dispersion, but with lower average prices. We find variation in the determinants of prices and wages across different groups of countries, and over time. Prices and incomes are strongly associated with each other, consistent with the Penn effect. Exchange rate pass-through is high in most goods and occupations.

JEL Classification: R11, F15.
Keywords: City size; Penn effect; globalisation; price and income dispersion.

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1 Introduction

The economic literature on cities posits that cities exist because of the presence of some form of agglomeration economies, defined as "… a large concept that includes any effect that increases firms' and workers' income when the size of the local economy grows" (Combes and Gobillon (2015), p. 249). On the other hand, the fact that many cities exist, rather than only one city, indicates that there are costs associated with cities, and that these costs are also rising with the size of the city (Duranton and Puga (2014)). Or, as Fujita et al (1999) suggest, there may be limits to the extent of agglomeration economies, so that the "no black hole" condition is satisfied.

This paper explores both the benefits and costs of cities. We investigate the implications of city size and globalisation on prices and incomes for a range of goods and occupations in a sample of cities from across the world, using data from the UBS Prices and Earnings (PnE) survey. Our main results are as follows. First, we find that, overall, city size and trade openness have negative effects on prices, but no significant effect on incomes. Nor do we find evidence that city size and trade openness affect incomes indirectly through their effect on prices. Second, we find heterogeneity of results across different goods: city size and trade openness have strong negative effects on prices of some goods, but not for other goods. A third and closely related result is that we find that the determinants of prices differ between cities in high-income countries and other cities, and also over time. On the other hand, overall there is less difference in the determinants of incomes across different groups of cities or over time.

A fourth main result is that greater price dispersion is associated with higher average prices and income dispersion, but with lower average incomes and less trade openness. On the other hand, greater income dispersion is associated with higher average incomes and price dispersion, but with lower average prices. Fifth, we find strong evidence of a positive relationship between prices and incomes, supportive of the Penn effect (Gilbert and Kravis (1954)), and the results of Yankow (2006). Finally, there is evidence of complete exchange rate pass-through for many goods and occupations: the US dollar prices for the goods and occupations we study are fairly insensitive to exchange rates.

The paper is closest in spirit to Bardhan et al (2004), who find using a cross-section of UBS PnE data that house prices are positively related to city size (this finding is corroborated by Thissen et al (2010) using different data). We extend the analysis of Bardhan et al (2004) in several ways. First, we use a panel of cities over a long time period, from 1970 to 2015 at three-year intervals. Although using such a long panel poses difficulties with regard to product comparability over time (which we discuss further below), it enables us to observe changes in prices and wages over time, and to control for city and time fixed effects which may otherwise influence the results. The larger sample also allows us to conduct analysis on the robustness of our results, by dividing the sample into sub-samples. Second, we extend the analysis to consider the prices of other goods and services, as well as incomes in several occupations. The available data also enables us to investigate the determinants of price and income dispersion within cities. Third, we take into account the simultaneous determination of prices, incomes and trade openness, using an instrumental variables estimator. This allows us to take a causal interpretation of our results. Fourth, we consider whether city size, trade openness and exchange rates have any indirect effects on prices and incomes, in addition to any direct effects.

Data from the UBS PnE publication has not frequently been used in the academic literature. An exception is Lutz (2002, 2003), who investigates price convergence and exchange rate forecasts using a range of data on product prices. This work is closer to the literature on Purchasing Power Parity, where Cumby (1997) was one of the first to use a panel of data on the price of a specific product (in that case, a Big Mac). He showed that Big Mac prices exhibited much more rapid convergence to the Law of One Price than price indices which gave rise to the PPP puzzle (see Rogoff (1996)). Other work using different but related data includes Parsley and Wei (2004), who use data from the Economist Intelligence Unit, and Parsley and Wei (2008), who use data from the Mercer Cost of Living Survey.

The more recent literature on price variation across locations tends to make use of scanner data, for instance Handbury and Weinstein (2015), who find that prices of food products fall with city size, in line with the prediction of the model of economic geography (Fujita et al (1999)). Such data has many advantages, including superior detail and quality to previous data (Handbury and Weinstein (2015) use data on hundreds of thousands of identical goods purchased by 33,000 households in the US). Compared to this line of research, the present paper uses data that is less detailed, but which allows for a comparison over a much longer time period, for a broader range of goods and services, and also for workers' incomes.

Disaggregated price data has also been used in the recent macroeconomic literature. Gopinath and Rigobon (2008) use US Bureau of Labor Statistics (BLS) data to show that there is extensive price stickiness at international borders, and that exchange rate pass-through is low. Nakamura and Steinsson (2008), also using BLS data, show the importance of sales and product substitution in defining the frequency of price changes.

Burstein and Gopinath (2014) survey the literature relating prices to exchange rates, while Nakamura and Steinsson (2013) do the same for the microeconomic evidence on price rigidity. This literature motivates us to include exchange rates as a potentially important determinant of prices and incomes.

The paper is also related to the literature which relates the size of cities to economic performance and other variables. In this literature, city size may take the role of the dependent or independent variable. For instance, Ades and Glaeser (1995) find that dictatorships are more likely to have large cities. Henderson (2003) finds that there is an optimal degree of urbanisation which maximises productivity growth of a country. This literature is ably summarised by Henderson (2005).

Finally, the paper is related to the literature on trade and inequality. This literature has progressed tremendously since the classic analysis of Stolper and Samuelson (1941); a recent study is Fajgelbaum and Khandelwal (2016). Recent work includes that which develops models of labour market frictions (for instance, Davidson and Matusz (2004) and Helpman et al (2013)), and the recent empirical work which emphasises the impact of local exposure to imports on labour market outcomes (for instance, Autor et al (2013); this line of inquiry can be traced back to Krugman (2000, 2008)). Of particular note with the recent Autor et al (2013) paper is that they directly estimate the impact of trade on employment and wages, whereas most of the older literature, by estimating Stolper-Samuelson effects, emphasised the indirect impact of trade on wages and other factor prices through its impact on goods prices. We exploit this distinction between direct and indirect effects in the approach we use. Helpman (2017) provides a survey of this literature, while Hornbeck and Moretti (2018) estimate the direct and indirect effects of local TFP growth on wages, rents and inequality across US cities.

The next section discusses the data and methods used in the paper. Section 3 examines the relationship between prices and wages, and city size, trade openness and exchange rates. Section 4 examines price and wage dispersion, and how these may be related to globalisation and city size. Section 5 performs sensitivity analysis on our results, by dividing the sample into cities in high- and low-income countries and over time. The final section provides some concluding comments. An extensive Appendix collects much additional analysis as indicated below.

2 Data and Methods

2.1 Data

The data used in this paper come from two main sources. Data on prices and incomes for 82 cities are obtained from the Union Bank of Switzerland (UBS) Prices and Earnings publication. The first edition was published in 1971 (based on data collected in 1970, and henceforth denoted as 1970), with the second edition published in 1973, and every three years thereafter. We make use of data from the first edition to the 2015 edition[1]. The number of cities surveyed has increased over time, from 31 cities in 1971, to 73 cities in 2009. The majority of the cities in the sample are national capitals. A total of 28 cities have appeared in every publication between 1971 and 2015. Other cities have entered the sample in more recent years; these tend to be from developing economies (for instance, Kuala Lumpur). On the other hand, a few cities have been dropped from the sample (for instance, Panama). Appendix A lists all the cities included in the sample. Cities in Europe are over-sampled, reflecting UBS' location; for example, of the 37 cities in the 1973 edition, there is only one African city (Johannesburg), one in Australia (Sydney), 7 cities in Asia, 5 in South America, 5 in North America, and 18 in Europe. In the 2012 edition, there were 3 African cities, 2 in Oceania, 17 in Asia, 7 in South America, 7 in North America, and 36 in Europe.

Table 1: List of goods and services and occupations.

Goods and services	Occupations
Rent of 4-bedroom apartment	Primary school teacher
Rent of 3-bedroom apartment	Bus driver
Local rent	Mechanic
Basket of services	Construction worker
Basket of food and beverages	Toolmaker
Men's clothes	Cook
Women's clothes	Textile worker
Electrical appliances	Bank teller
Car	Manager
Public transport	Engineer
Taxi	Department head
Restaurant meal	Secretary
Hotel	Sales assistant
Short stay	

[1] There is also a 2018 edition. However, it is less comprehensive than the 2015 (and earlier) editions. For instance, there is no data on rents. Hence we do not use data from this edition.

From the Prices and Earnings database, there is data on the total cost of a basket of over 100 goods and services, a basket of over 30 food items, a basket of over 20 services (the precise number of food items and services varies over time, and no data is available on the prices of the components of the basket), clothing, household appliances, apartment rents, public transport, cars, restaurant and hotel prices, and the price of a short city break. For incomes, there is data on gross earnings for a range of occupations. In 1973, these occupations were primary school teachers, bus drivers, car mechanics, bank tellers, personnel managers, and secretaries. By 2012, the number of occupations had increased to 15 occupations. All data are converted into US dollars at the exchange rate prevailing at the time of the survey[2]. Table 1 presents the list of goods and services and occupations used in this paper; we do not use data on all available goods and occupations, but only those which have remained in the sample for a long time period.

The prices and wages are collected by several independent observers in each city, in March or April. Overall prices are weighted identically across cities. If a product or service is not available in a city, its price is replaced with the value of a local substitute or extrapolated based on local price levels. The composition of the basket changes over time in response to technological change and changes in consumer behaviour. For example, in 2009 the iPod was introduced into the basket, while in 2012 the iPod was in turn replaced by an iPhone 4S, and in 2015 the iPhone 4S was replaced by the iPhone 6. Changes in product quality are an inevitable part of technological progress, and provided the rate of technological progress is the same across all cities, it will be absorbed by the year fixed effects included in all our regressions. Cars proved to be more problematic, since different models of cars are used in each city, and models change over time. For example, in London, in 2009 the car was a Ford Focus, whereas in 2012 it was an Audi A3. Therefore, we may expect the car price data to be more noisy than that for other variables, but since car prices only appear as the dependent variable in our regressions, the additional noise will enter into the error term, and should not otherwise affect our parameter estimates. Details of goods and occupation definitions and the methodology underlying the Prices and Earnings data are available on the UBS website (UBS (2018)).

Data at the country level on GDP, exports and imports have been obtained from the World Bank's World Development Indicators, and are in nominal, current price US dollars. Compared to constant price data, current price data is available for a larger sample. Since only ratios of these variables are used, the fact that we do not use

[2] Although we can convert prices and incomes into domestic currency values, given the long time period of our sample, this would introduce more variability in the data when compared with using US dollar values.

constant price data is immaterial. City population data is obtained from the United Nations World Urbanization Prospects database. This data is available at 5-year intervals, and we interpolate the data to obtain values for the years of the Prices and Earnings data. For three cities – Nicosia, Luxembourg and Ljubljana – data was obtained from other sources as they were not included in the World Urbanisation Prospects data.

Figure 1: Distribution of prices and incomes over time

Figure 1(a): Prices

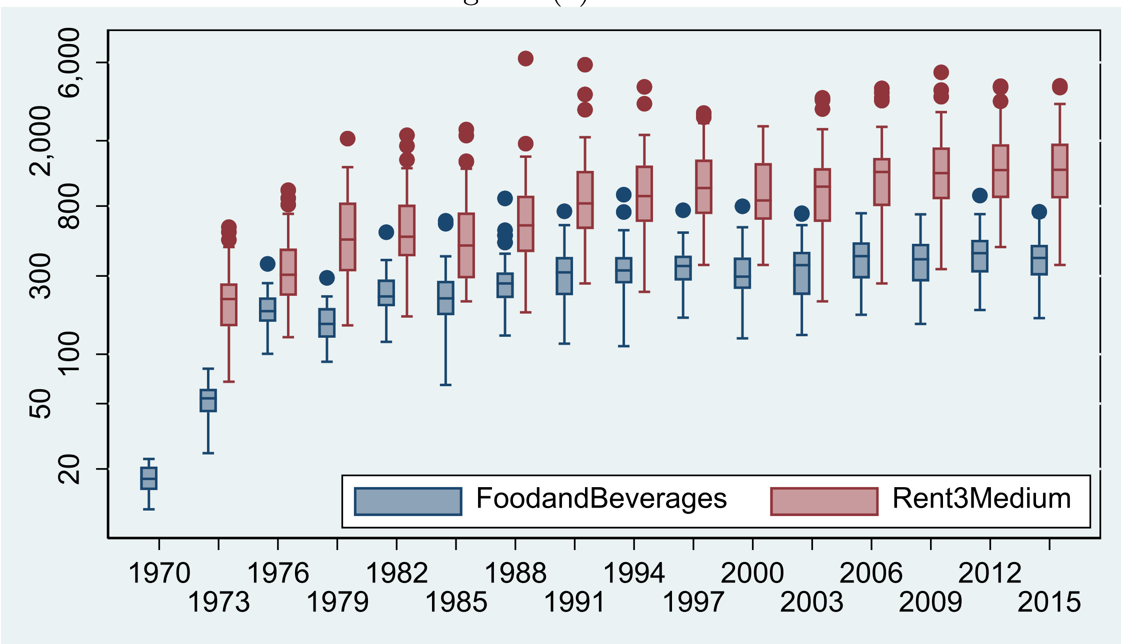

Figure 1(b): Salaries

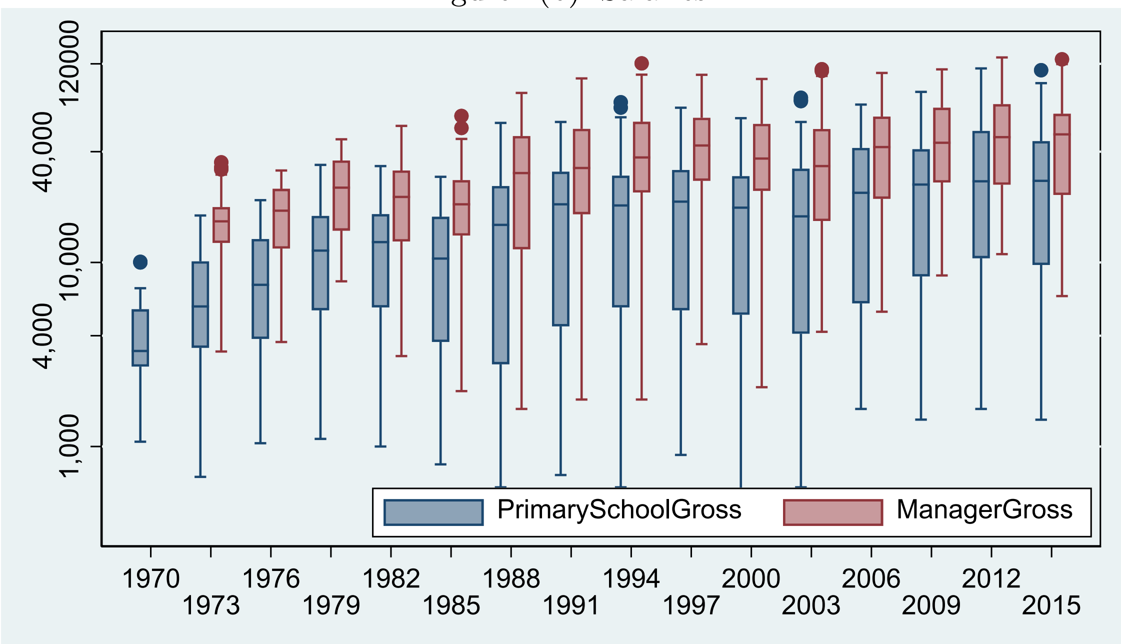

Figure 1 presents the distribution of food prices and rent of a 3-bedroom apartment, and gross incomes of school teachers and managers over time. Although as discussed above the sample is not constant over time, several trends can be identified. Rents increased rapidly over the sample period, and on average more rapidly than food prices. The period of rapid inflation in the 1970s can be identified for both food prices and rents. For salaries, primary school teachers are on average paid much less than managers, but their salary also exhibits much more variation across cities than managers' salary. Note also that the long left tails of the income variables indicate that (since the vertical axis is a log scale) while incomes are right-skewed, they are less so than prices.

2.2 Methods: Price and income determination

Consider a simple model of economic geography with two regions, North and South (see Fujita et al (1999), Redding (2011)). Prices and incomes are simultaneously determined by the following equations:

$$P_M = [\lambda(w_M)^{1-\sigma} + (1-\lambda)\tau^{1-\sigma}(w_M^*)^{1-\sigma}]^{\frac{1}{1-\sigma}} \tag{1}$$

$$w_M = [Y(P_M)^{\sigma-1} + \tau^{1-\sigma}Y^*(P_M^*)^{\sigma-1}]^{\frac{1}{\sigma}} \tag{2}$$

Where $\tau > 1$ is the iceberg transport cost, P_M is the price index in manufacturing, w_M is the manufacturing wage, $\sigma > 1$ is the elasticity of substitution between varieties in the consumer's utility function, λ is the share of manufacturing workers who locate in the North, Y is regional aggregate income, and asterisks indicate Southern variables. From equations (1) and (2), it can be seen that not only do prices and incomes depend on each other, but they also depend, possibly indirectly, on market access and the size of the local market. For instance, a lower transport cost would reduce prices and hence raise nominal and real wages; similarly, because of transport costs, the location with a larger manufacturing sector will have lower prices and higher wages. What equations (1) and (2) do not show, however, is that lower transport costs may lead to a change in the *distribution* of prices and incomes, since locations may differ in the goods in which they have a comparative advantage. Therefore, while equations (1) and (2) may be expected to hold for aggregate prices and incomes, they may be less successful in identifying the sign of the coefficients when considering prices and incomes of individual goods and occupations, as we do here.

To investigate the direct effects of market access and local market size on prices and wages, we proxy market access with trade openness (following Autor et al (2013)), and local market size with city population, and separately estimate equations of the following form (which we refer to as the *Baseline* specification), for good/occupation j in city i in year t:

$$\ln(p_{jit}) = \alpha_i + \alpha_t + \beta_1 \ln(Pop_{it}) + \beta_2 \ln(Openness_{ct}) + \beta_3 \ln(ExRate_{ct}) + \varepsilon_{it} \quad (3)$$

$$\ln(Income_{jit}) = \alpha_i + \alpha_t + \beta_1 \ln(Pop_{it}) + \beta_2 \ln(Openness_{ct}) + \beta_3 \ln(ExRate_{ct}) + \varepsilon_{it} \quad (4)$$

where Pop_{it} is city population, $Openness_{ct}$ is the sum of exports and imports, divided by GDP[3], at the country level, $ExRate_{ct}$ is the US dollars per unit of domestic currency, and α_i and α_t are city and year fixed effects. The inclusion of these city and year fixed effects allows us to control for unobserved, time-invariant heterogeneity across cities, and for common shocks across cities. It also means that the parameter estimates are identified from across-time, within-city variation in the data. Including exchange rates as an explanatory variable in equations (3) and (4) helps us identify the degree of exchange rate pass-through (Burstein and Gopinath (2014)). Since prices are in US dollars, and given the definition of the exchange rate above, complete exchange rate pass-through would imply $\beta_3 = 0$, and incomplete pass-through would imply $\beta_3 > 0$. Because the prices and incomes used are not for the same industries (see Table 1), we estimate equations (3) and (4) separately for each good and occupation, rather than as a system of simultaneous equations.

Although equations (3) and (4) are informative about the effects of market access and local market size on prices and incomes, equations (1) and (2) suggest that they may be misspecified, since they neglect the simultaneous determination of prices and incomes. We therefore also estimate the following equations (which we refer to as the *Extended* specification), where we control for average income in the price equation, and the overall price of the basket of goods and services in the income equation:

$$\ln(p_{jit}) = \alpha_i + \alpha_t + \beta_1 \ln(Pop_{it}) + \beta_2 \ln(Openness_{ct}) + \beta_3 \ln(ExRate_{ct}) + \beta_4 \ln(\overline{Income_{it}}) + \epsilon_{it} \quad (5)$$

[3] We also have data on inflows and outflows of foreign direct investment (FDI), but FDI is highly correlated with trade, so we do not use FDI in the analysis. A solution similar to that proposed by Bardhan et al (2004), to use the first principal component of FDI openness and trade openness to avoid multicollinearity, yields similar results to including trade openness on its own.

$$\ln(Income_{jit}) = \alpha_i + \alpha_t + \beta_1 \ln(Pop_{it}) + \beta_2 \ln(Openness_{ct}) + \beta_3 \ln(ExRate_{ct}) + \beta_5 \ln(\overline{p_{it}}) + \epsilon_{it} \quad (6)$$

where $\overline{Income_{it}}$ is the (unweighted) average gross income across all occupations[4], and $\overline{p_{it}}$ is the price of the overall basket of goods and services. Using unweighted average income does not take into account the fact the cities at different levels of development are likely to have different occupational structures. We circumvent this in section 5 below by dividing the sample into different sub-samples of more homogeneous cities. In addition to accounting for income as a determinant of prices (and vice versa), equations (5) and (6) also provide a test of whether market access and local market size have direct or indirect effects on prices and incomes. If they have direct effects, then the estimates of β_1, β_2 and β_3 in equations (5) and (6) will be significantly different from zero. If they only have indirect effects, for instance if they affect prices only through their impact on income, then the estimates of β_1, β_2 and β_3 in equations (5) and (6) will not be significantly different from zero, even if they were significant in equations (3) and (4)[5] (this also explains why equations (3) and (4) are necessary: without them, we would not be able to infer the existence or otherwise of the indirect effect). Note in addition that in equation (6), $\beta_5 = 1$ implies constant real income, so equation (6) is an unconstrained version of a regression of real income on city size and trade openness.

2.3 Instrumental variables methods

As suggested by equations (1) and (2), in equations (5) and (6) respectively, average incomes and prices are likely to be jointly determined with the dependent variable. We employ an instrumental variables estimator to overcome this potential endogeneity bias. As an instrument for the average gross income $\overline{Income_{it}}$ in equation (5), we use the gross income of primary school teachers and bus drivers. The identifying assumption is that the gross income of primary school teachers and bus drivers will influence prices only through their effect on the average gross income. Similarly, as an instrument for the price of the overall basket $\overline{p_{it}}$ in equation (6), we use the price of a basket of food and beverages, and the price of a basket of services. The identifying

[4] The PnE database also includes a variable which is the average gross hourly earnings across occupations, weighted by occupational distribution. However, this variable is only available for a much shorter time period, and the weighting data that would allow us to extend the series is not available.

[5] Equations (3) and (4) are somewhat related to reduced form regressions in the IV literature, in which the dependent variable is regressed directly on the exogenous (excluded) instruments. However, in our case, population and trade openness are exogenous covariates, rather than excluded instruments; see Angrist and Pischke (2009) for a discussion.

assumption is that the prices of food and beverages, and the price of a basket of services, will influence wages only through their effect on the price of the overall basket. The usual tests for overidentification, under- and weak identification show that the instruments used satisfy the exclusion restrictions;[6] details are provided in Appendix D. We implement the instrumental variables in a two-step GMM estimator, which is more efficient in the presence of heteroscedasticity of unknown form than the traditional IV/2SLS estimator. Our use of GMM methods means that we can interpret the coefficients of the regression as causal effects of the explanatory variables on the dependent variables, which is an important difference relative to Bardhan et al (2004).

Recent literature (Autor et al (2013)) suggests that trade openness may also be jointly determined with prices and incomes. We therefore also instrument trade openness in equations (3) to (6). As an instrument for openness of country c in year t, we use the export openness (exports divided by GDP) and import openness (imports divided by GDP) of the rest of the countries in the sample, in year t.[7] The identifying assumption is that there may be some external influence which affects trade openness across countries (for instance, WTO trade negotiations), but other countries' trade openness affects a country's prices and incomes only through its effect on the country's own openness.

Other extensions could be considered. For instance, we could investigate whether the effect of average income on price depends on the degree of trade openness, by interacting openness with average income in equation (5). We do not pursue this line of inquiry here, since theory does not provide clear guidance as to which variables we should interact, or what would be the expected sign of the coefficients of these interactions.

2.4 Methods: Determinants of price and income dispersion

In the second part of the analysis, we investigate whether city size and trade openness affect price and wage dispersion in a city. There are two potential, opposing economic forces at work. On the one hand, we may expect larger cities, and cities which are more open, to have lower price and wage dispersion, because of the greater availability

[6] There are also other possible combinations of incomes and prices that could serve as instruments. Another possible instrument is to use the average price across other cities in the same year as an instrument for prices (likewise for incomes), in a similar manner to Autor et al (2013).

[7] This is not dissimilar to the instrument used in Autor et al (2013). They instrument the product of local labour share and Chinese imports in a sector in the US (exposure to Chinese imports), with the product of lagged local labour share and (current) Chinese imports in the sector in other developed economies.

of goods and services. On the other hand, the literature on heterogeneous firms in international trade (Melitz (2003)) suggests that greater openness may lead to increasing wage dispersion because of reallocation towards more productive firms. In addition, price and income dispersion are also likely to be associated with each other; Appendix E provides some details of how this relationship may occur.

As a measure of dispersion, we use the coefficient of variation (CV, the standard deviation normalised by the mean). This has the advantage of being simple to calculate, and it satisfies the requirements for a measure of economic inequality: anonymity, scale invariance, population independence, and the Pigou-Dalton transfer principle (Cowell (2011)). Appendix E performs the analysis for three popular alternative measures of dispersion: the Gini coefficient, the Hoover index, and the Theil index.

We proceed in slightly different ways for prices and incomes. For incomes, we calculate the unweighted CV across the occupations listed in Table 1. As above, in Section 5 below we report results dividing the sample into more homogeneous sub-samples to get around the fact that we use unweighted CV for incomes. For prices, we first calculate the price of each good in Table 1 relative to the annual average across cities. This standardises the prices, so that a more valid comparison across different goods can be made. We then weight each standardised price by its weight in the US CPI index for that year (the rationale for using US CPI weights and more details are in Appendix B). Then we calculate the CV of prices from the weighted standardised prices. We then estimate:

$$\begin{aligned}\ln[CV(p_{it})] = \alpha_i + \alpha_t + \beta_1 \ln(Pop_{it}) + \beta_2 \ln(Openness_{ct}) + \beta_3 \ln(ExRate_{ct}) \\ +\beta_4 \ln(\overline{Income_{it}}) + \beta_5 \ln(\overline{p_{it}}) + \beta_6 \ln[CV(Income_{it})] + \epsilon_{it}\end{aligned} \tag{7}$$

$$\begin{aligned}\ln[CV(Income_{it})] = \alpha_i + \alpha_t + \beta_1 \ln(Pop_{it}) + \beta_2 \ln(Openness_{ct}) + \beta_3 \ln(ExRate_{ct}) \\ +\beta_4 \ln(\overline{p_{it}}) + \beta_5 \ln(\overline{Income_{it}}) + \beta_7 \ln[CV(p_{it})] + \epsilon_{it}\end{aligned} \tag{8}$$

We use the natural logs of $CV(p_{it})$ and $CV(Income_{it})$ since both variables are highly right-skewed. As with the previous set of regressions, we estimate two versions of equations (7) and (8). First, we estimate the equations only including city population, trade openness and exchange rates. Then, we extend the analysis to include measures of income and price dispersion, and average prices and incomes, as explanatory variables for price and income dispersion, respectively. That is, we hypothesise that price dispersion depends on average incomes, average prices, and income dispersion, and likewise that income dispersion depends on average incomes, average prices, and price dispersion. As before, the full versions of equations (7) and (8) enable us to separately identify the direct effect of market access and local market size on price and income dispersion, versus indirect effects which may operate through average prices and incomes, and income and price dispersion.

We assume that the average price and income levels are not endogenous to the dependent variable. On the other hand, we assume that price and income dispersion are jointly determined, and hence instrument income dispersion in equation (7) with the gross income of primary school teachers and bus drivers, and instrument price dispersion in equation (8) with the price of food and beverages, and services (i.e. the same instruments as in the previous section). As with equations (3) to (6), the identifying assumption is that the gross income of primary school teachers and bus drivers do not affect price dispersion, beyond their indirect effect through income dispersion. Similarly, the price of food and beverages, and services, are assumed to affect income dispersion only through their impact on price dispersion. In addition, as in the previous sub-section, we assume that trade openness is endogenous to price and income dispersion, and is instrumented in the same way as discussed there.

3 Prices and incomes

In Figures 2 and 3 we show graphically our econometric results. The results reported are from a two-step GMM estimator, with city and year fixed effects. *Baseline* estimates correspond to those from equations (3) and (4) and assume that trade openness is endogenous, while *Extended* estimates are from equations (5) and (6) and assume that trade openness and prices (incomes) are endogenous. Each sub-figure is sorted by the magnitude of the coefficient from the extended estimates. All results reported satisfy the Hansen test for overidentification, and the Kleibergen-Paap weak identification and under-identification tests, indicating that the instruments are valid. Appendix C tabulates the results for food and beverages, the monthly rent on a 3-bedroom apartment, and gross incomes for school teachers and managers, reporting both conventional FE and GMM results for both baseline and extended specifications. Results for other prices and incomes are available from the author upon request. Appendix D provides additional details on the rests of the tests for overidentification, weak identification, and under-identification, along with some results using the GMM Continuously Updated Estimator (CUE) which is more robust to the presence of weak identification. The CUE results are very similar to the GMM results reported here and in Appendix C.

Figure 2(a) shows that, on average, trade openness has a negative effect on prices: cities in economies that become more open have lower prices. This relationship is statistically significant for five of the fourteen goods: overall services, taxis, restaurants, local rents, and electrical appliances. Similarly, in Figure 2(b), we find overall a negative effect of city population on prices, as in Handbury and Weinstein (2015): cities that become larger experience lower prices. This relationship is statistically significant for four goods: local rents, cars, electrical appliances, and taxis. In Figure 2(c) we find evidence of complete exchange rate pass-through ($\beta_3 = 0$) for most goods and services when the extended estimates are used, except for public transport, where we find incomplete pass-through ($\beta_3 > 0$). That is, exchange rates have no significant effect on the US dollar prices of most goods in these cities. This may indicate the sensitivity of domestic prices to exchange rates, since the goods and services whose prices are collected by UBS are those which are of interest to international consumers[8] (see Burstein and Gopinath (2014)). Figure 2(d) shows that average income is a positive and significant determinant of the prices of all goods and services. In general the coefficient is significantly less than 1; a 1 percent increase in average income, all else equal, raises the price of a good or service by just under half a percent.

A few additional remarks can be made. In Figures 2(a) and 2(b), the coefficients from the baseline and extended estimates are very similar to each other. This suggests that any significant effects may be attributed to the direct effect of trade openness and city size on prices, whether or not we control for average income. On the other hand, the coefficients on exchange rates in Figure 2(c) exhibit more variation between the baseline and extended estimates, although there is still little evidence to suggest that the coefficients are different from each other (Schenker and Gentleman (2001) warn of the danger of visual comparisons between confidence intervals). Here, the extended results may be preferred, since they control for average income, and the difference between the baseline and extended results may be attributable to bias resulting from the omission of average income from the baseline results. Overall our results are different from those obtained by Bardhan et al (2004) who find that city size and trade openness have positive effects on apartment rents (we find no significant effects), and may be explained by the fact that we use different data (a panel versus a cross-section) and different estimation methods (GMM instead of OLS)[9].

[8] From the UBS Prices and Earnings website: "…we created a standardised basket … which replicates the spending and consumption of a typical three-person European family" (UBS (2018)).

[9] It is worth noting that we are unable to replicate exactly the results in Bardhan et al (2004) (although we get very close) even if we use the same sample as they do, probably because they use different data sources for the other variables in the analysis.

Figure 2: The determinants of prices.

Figure 2(a): Trade openness

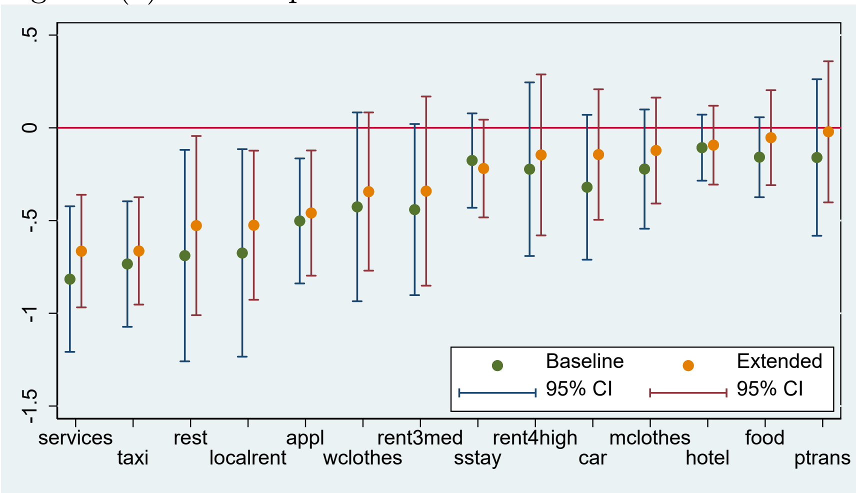

Figure 2(b): City population

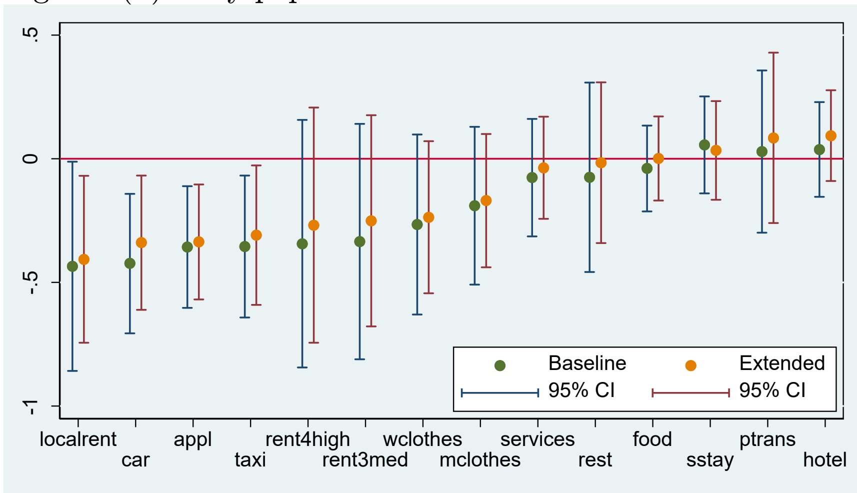

Figure 2(c): Exchange rates

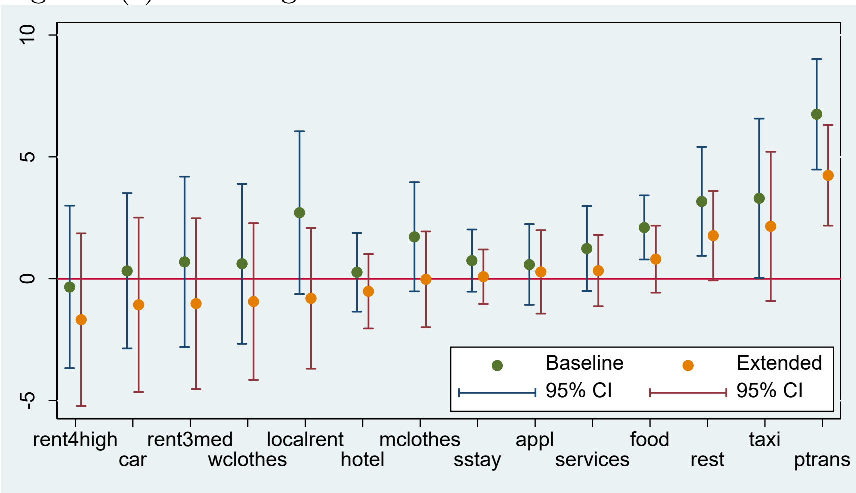

Figure 2(d): Income

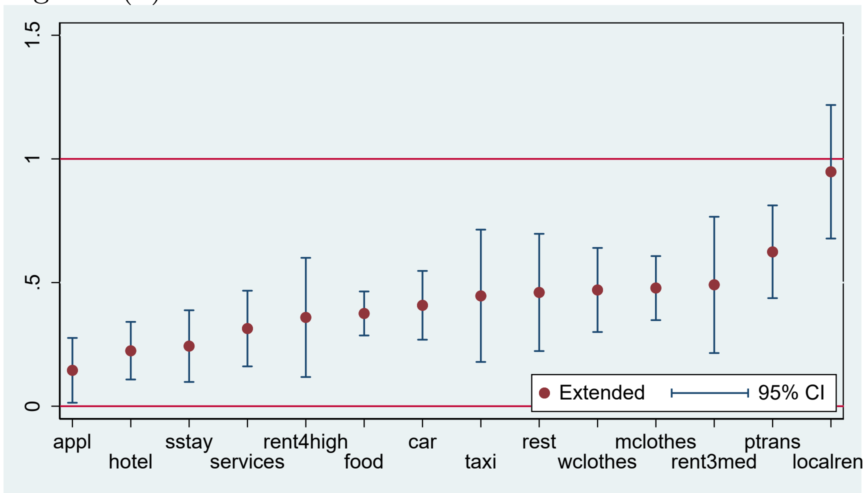

Figure 3: The determinants of gross incomes.

Figure 3(a): Trade openness

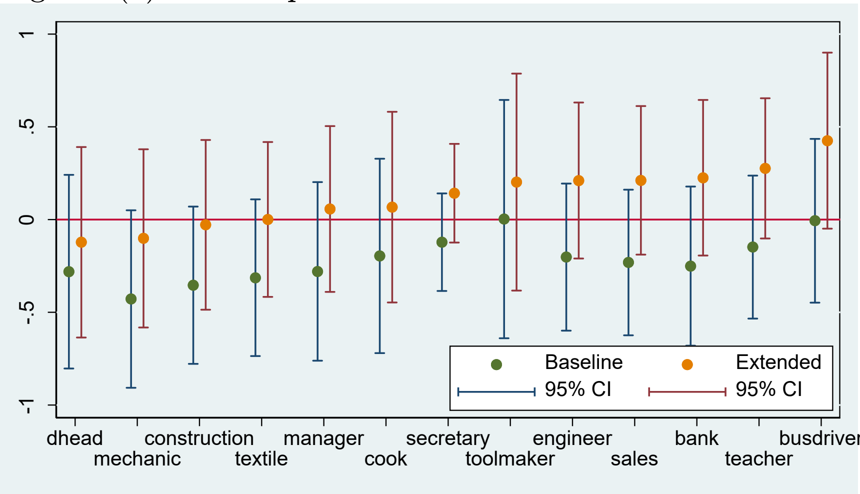

Figure 3(b): City population

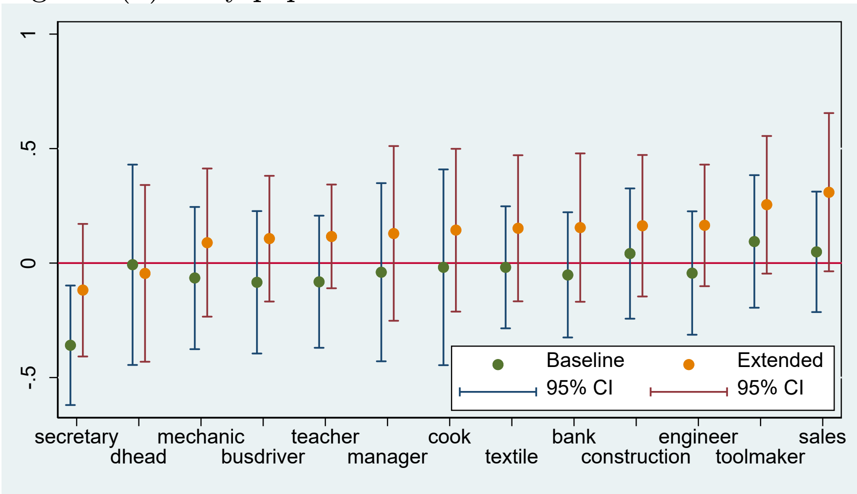

Figure 3(c): Exchange rates

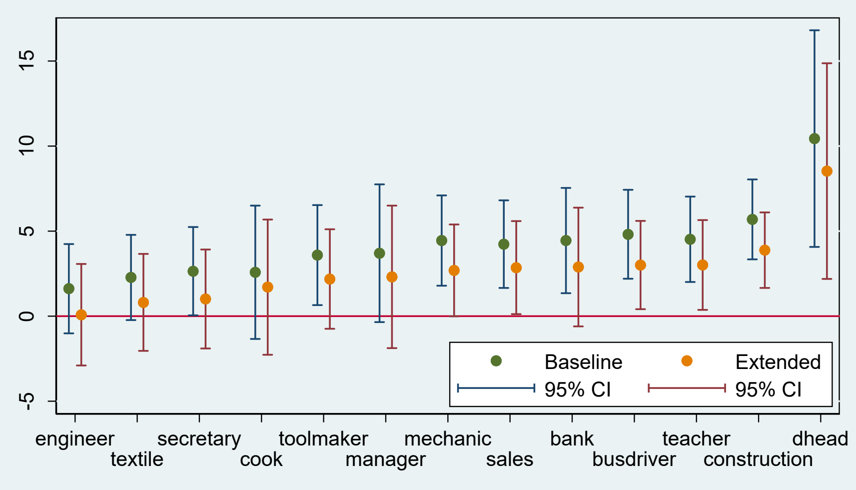

Figure 3(d): Price

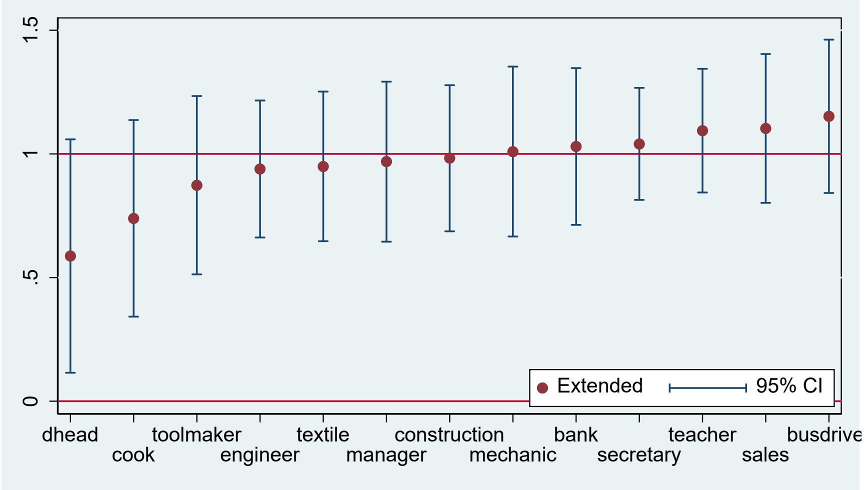

Figure 3, which reports the results for the determinants of gross incomes, gives starker results. In Figures 3(a) and 3(b), neither city size nor trade openness have a significant impact on incomes of any type of worker. Since all our estimates include city and year fixed effects, the insignificance of city size and trade openness indicate that, *for a given city*, a change in its size, or a change in its degree of openness, will not in general affect gross incomes. If workers in one city are paid more than they are in another city (as shown in Figure 1), this must be because of unobserved city-specific reasons which are absorbed by the city fixed effects. Note also that the insignificance of city size and trade openness cannot be attributed to the idea that their effects operate only indirectly, through prices, since they are insignificant in both the baseline and the extended model.

For exchange rates, Figure 3(c) shows that there is complete exchange rate pass-through for seven of the thirteen occupations when considering the extended model: engineers, textile workers, cooks, secretaries, toolmakers, managers, and bank tellers, and incomplete pass-through for the other six occupations: sales assistants, mechanics, teachers, bus drivers, construction workers, and department managers[12]. Based on this composition, it may be argued that occupations which have a greater exposure to international markets have greater exchange rate pass-through than occupations which primarily serve the domestic market, which is what we may expect.

Figure 3(d) shows that average prices have a positive and statistically significant impact on gross incomes across all occupations. However, unlike in Figure 2(d), here the coefficient is never statistically distinguishable from 1. This indicates, perhaps unsurprisingly, that the cost of living is the main determinant of incomes. It also indicates that the average price level has no additional impact on incomes beyond its impact on real income; all else equal, a 1 percent increase in average price results in, on average, a 1 percent increase in nominal income, leaving real income unchanged. Taken together, Figures 2 and 3 may be regarded as evidence for the Penn effect, that prices are positively associated with income.

4 Price and income dispersion

As discussed in Appendix B, there is more than one way of defining the weights used in constructing the CV of the price of a basket of goods and services. In the results reported here, we use CPI-U, with weights prior to 1979 being obtained by linearly

[12] A departmental manager is a middle manager in the metal processing, machinery or tool-making industry, while a manager is a middle manager in a pharmaceutical, chemical or food industry.

extrapolating the 1979 to 1982 trend[13]. Figure 4 shows the distribution of the CV of the price of the basket of goods and services and the occupations over time. In both cases there is considerable variation in the CV, with prices displaying a higher average CV, but incomes having greater variation (note the different vertical axes in the two sub-figures). There is no obvious pattern of convergence (or divergence) of either prices or incomes over time. Appendix E presents results using alternative measures of dispersion: the Gini coefficient, the Hoover index, and the Theil index. The results using these alternative measures of dispersion are similar to those obtained using CV.

Table 2 shows the results of regressions (7) and (8) on the determinants of price and income dispersion. Unsurprisingly, price and income dispersion are positively related to each other, although the relationship is not always statistically significant. Average income always has a negative and significant effect on price dispersion. One possible explanation for this is that in cities with higher incomes, there are fewer low-priced goods and services (perhaps because of the higher hourly wage), but at the same time there are fewer very high-priced goods and services, perhaps because the greater demand from higher income consumers ensures that such goods and services are not under-supplied[14].

City population has a consistently negative effect on price dispersion. That larger cities have lower price dispersion is again supportive of the idea that larger cities are able to supply a wider range of goods and services, and hence are better able to match demand to supply. Openness also has a negative effect on price dispersion, although this relationship is not significant when the endogeneity of openness is controlled for. This also supports the idea that greater access to global markets ensures that goods and services are available, and hence that there are fewer outliers in prices, but the evidence for this is not strong. Average prices have a positive and significant effect on price dispersion, but exchange rates do not have any significant effect on price dispersion.

[13] Using alternative definitions of the weights, as discussed in Appendix B, yields results which are qualitatively similar to those reported.

[14] A simple regression of average income on minimum (standardised) prices, controlling for average prices with all variables in natural logs and city and year fixed effects, finds that average income is indeed positively (and significantly) associated with minimum prices. However, we find a negative but insignificant effect of average income on maximum prices. The evidence is broadly supportive of the argument made in the text.

Figure 4: Distribution of the dispersion of prices and incomes over time

Figure 4(a): CV of prices

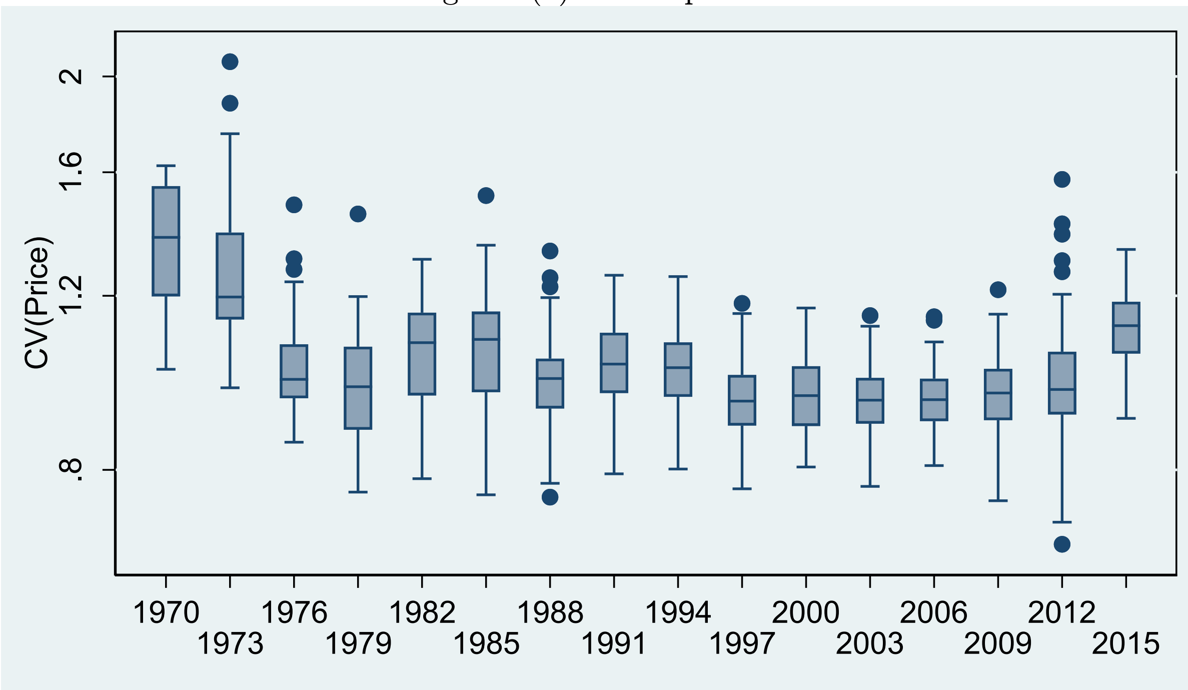

Figure 4(b): CV of incomes

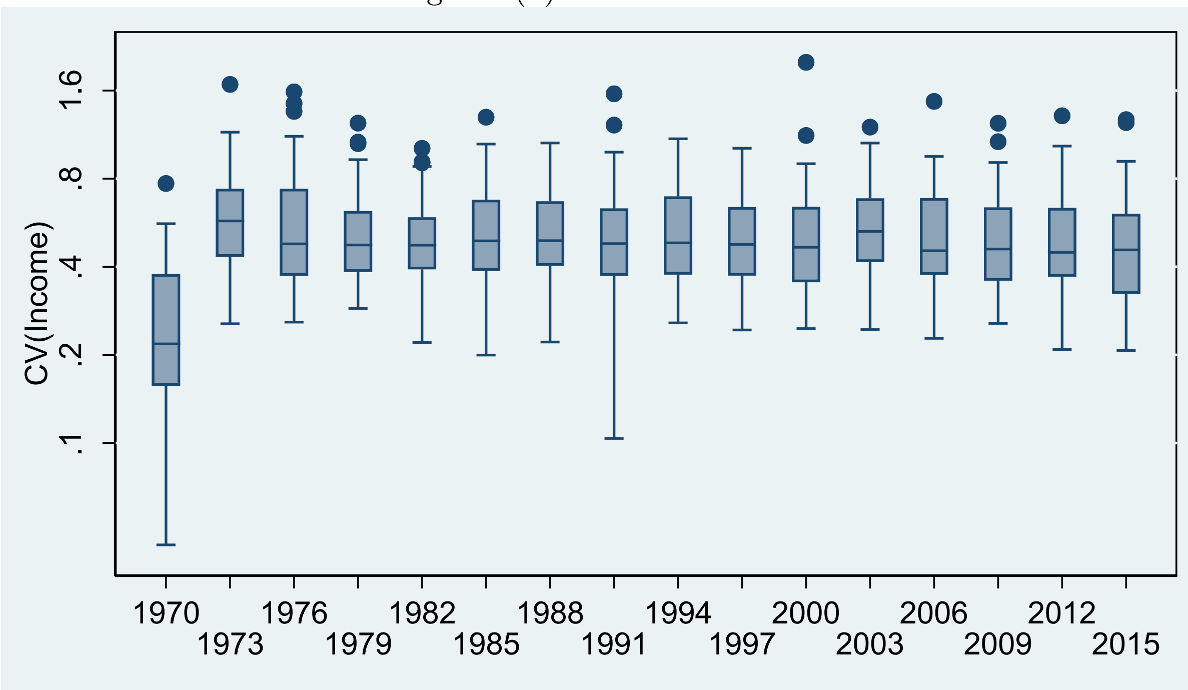

Table 2: The determinants of price and income dispersion

Dep. Var.	$\ln[CV(Price_{it})]$				$\ln[CV(Income_{it})]$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Est. Method	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM
$\ln(Pop_{it})$	-0.12	-0.12	-0.11	-0.11	0.09	0.09	0.02	0.03
	(0.06)+	(0.06)+	(0.05)^	(0.06)^	(0.10)	(0.10)	(0.10)	(0.13)
$\ln(Openness_{ct})$	-0.08	-0.08	-0.07	-0.09	0.04	0.03	0.03	-0.01
	(0.03)+	(0.07)	(0.04)^	(0.08)	(0.09)	(0.11)	(0.09)	(0.14)
$\ln(ExRate_{ct})$	-0.47	-0.47	-0.37	-0.31	-0.26	-0.29	-0.95	-0.16
	(0.34)	(0.34)	(0.33)	(0.35)	(1.14)	(1.15)	(1.20)	(1.19)
$\ln(\overline{Income_{it}})$			-0.05	-0.07			0.27	0.30
			(0.02)*	(0.02)*			(0.07)*	(0.07)*
$\ln(\overline{p_{it}})$			0.07	0.08			-0.25	-0.32
			(0.03)+	(0.03)+			(0.08)*	(0.09)*
$\ln[CV(Income_{it})]$			0.02	0.08				
			(0.02)	(0.04)^				
$\ln[CV(Price_{it})]$							0.17	1.10
							(0.13)	(0.33)*
N x T	840	840	840	840	778	778	778	778
N	82	82	82	82	82	82	82	82
Hansen test	0.44	0.44	0.10	0.06	0.07	0.02	0.26	1.50
Hansen p-value	0.80	0.51	0.95	0.97	0.96	0.88	0.88	0.47
K-P UnderID test	.	22.84	.	22.90	.	24.14	.	26.87
K-P test p-value	.	0.00	.	0.00	.	0.00	.	0.00
K-P weak ID test	.	8.60	.	3.15	.	16.83	.	7.42
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ^ significant at 10%; + significant at 5%; * significant at 1%. Standard errors are clustered by city. Under IV-GMM estimation, $\ln(Openness_{ct})$, $\ln[CV(p_{it})]$ and $\ln[CV(Income_{it})]$ are treated as endogenous, and are instrumented with export openness and import openness of the other countries in the sample, prices of food and beverages, and services, and gross incomes of primary school teachers and bus drivers. See the text for additional details. The Hansen test is the Hansen J (chi-squared) test for overidentification. The K-P UnderID test is the Kleibergen-Paap chi-squared test for underidentification. The K-P weak ID test is the Kleibergen-Paap F test for weak identification.

On the other hand, columns (5) to (8) of Table 2 show that there is no evidence that city size, trade openness or exchange rates affect income dispersion. That is, we do not find any Stolper-Samuelson-type effects of openness on income dispersion, whether directly or indirectly through its effect on price dispersion (if there were an indirect effect, then columns (5) and (6) omitting price dispersion would yield significant coefficients on openness). Income dispersion is higher the higher are average incomes, but are lower the higher are average prices. Since in general incomes are rising over time, the first of these effects may be indicative of Piketty's (2013) rising inequality. The second effect may indicate that higher average prices, through its effect on average incomes, may compress the income distribution, thus reducing income dispersion[15].

Although Table 2 shows that the IV-GMM results are sometimes different from the FE results, we find little difference between the baseline and extended results. This suggests that there is little evidence of indirect effects of city size, trade openness and exchange rates on price and income dispersion. Finally, Table 2 reports several diagnostic tests of the IV-GMM estimators. The results of the Hansen test of overidentification, and the Kleibergen-Paap tests for underidentification and weak identification, are satisfactory, giving us confidence in the instruments used to control for simultaneity.

5 Sensitivity analysis

The results in the previous two sections are, of course, averages across cities in a wide range of countries over a long time period. This raises the question of whether the results are consistent across these dimensions of the data. To address this, we perform the following sensitivity analyses. First, we divide the sample into two groups: cities in high income countries, and other cities. The rationale for this exercise is as follows. In standard trade theory, high income countries may be expected to export a different bundle of goods from other countries. As a result, we may expect that the impact of trade on the price of a good or service to differ across cities in countries with different income levels. We use the World Bank's definition of high income countries, and include only countries which are classified as high income in the year 2000 or before. This results in 46 cities in high income countries (totalling 533 observations), and 36 cities in other countries (totalling 307 observations).

[15] Similarly to footnote 14 above, a simple regression of average prices on maximum income, controlling for average income with all variables in natural logs and city and year fixed effects, finds a negative (and significant) association between average prices and maximum income. However, we find a positive but insignificant effect of average prices on minimum income. The evidence is broadly supportive of the argument made in the text.

Second, we divide the sample using cities in OECD and non-OECD countries, again using countries which were part of the OECD in 2000 or before. This results in 43 cities in OECD countries (totalling 504 observations), and 39 cities (totalling 336 observations) in non-OECD countries. Although there is considerable overlap between high income and OECD countries, the overlap is not perfect. Appendix A shows which cities are included in the high income and OECD samples. Third, because of the long time period of our sample, the model parameters may change over time. We therefore divide the sample into two sub-periods: pre-2000 and 2000 and after. This results in 428 observations in the earlier sub-period, and 412 observations in the later one. For each exercise, we estimate specifications (5), (6), (7) and (8), including dummy variables for different groups, and interacting the dummies with all the explanatory variables (this is equivalent to estimating each equation separately for each sub-group). We then perform a joint test of the difference in the coefficients of interest between the two groups.

The results, estimated using IV-GMM, are reported in Table 3. Column (1) shows that the determinants of the prices of many services are different between cities in high income countries as compared with other cities. This may indicate that the demand for services is income-elastic. However, column (2) casts doubt on this conclusion, since there are much smaller differences between OECD and non-OECD cities. This suggests that the results in column (1) are mainly driven by high income, non-OECD cities, which are primarily in the Middle East. Column (3) shows that the determinants of prices have changed significantly over time. This may be indicative of technological change which changes consumer behaviour. Appendix F presents an analysis of the reasons for the differences in results between cities in high- and low-income countries in Table 3.

Table 3: Tests of the difference in coefficient estimates across different sub-samples.

Goods	(1) High Income	(2) OECD	(3) Post-2000	Occupations	(4) High Income	(5) OECD	(6) Post-2000
Rent 4 bedroom	1.30	1.00	4.49*	Teacher	0.99	0.91	2.85+
Rent 3 bedroom	0.80	0.74	9.21*	Bus driver	0.89	1.07	1.16
Local rent	0.11	1.07	2.49+	Mechanic	0.92	3.01+	2.84+
Services	1.28	2.01	2.73+	Construction	1.46	2.25^	0.87
Food	1.29	4.08*	1.72	Toolmaker	0.94	1.33	1.08
Men's clothes	1.91	1.49	1.68	Cook	1.59	1.38	0.23
Women's clothes	4.20*	1.68	1.49	Textile worker	0.57	2.03^	0.25
Appliances	1.48	1.46	0.89	Bank teller	2.65+	4.40*	0.72
Car	1.49	1.16	1.77	Manager	0.85	1.77	2.03^
Public transport	3.00+	1.04	3.28+	Engineer	0.89	1.93	1.46
Taxi	2.79+	1.14	1.97	Department head	2.58+	1.74	
Restaurant meal	3.13+	1.25	3.09+	Secretary	0.55	3.61*	0.49
Hotel	4.06*	2.30^	3.15+	Sales assistant	1.30	2.55+	1.45
Short stay	5.99*	1.76	2.63+				
$CV(Price_{it})$	3.91*	1.08	1.03	$CV(Income_{it})$	2.28+	0.55	0.36

Notes: ^ significant at 10%; + significant at 5%; * significant at 1%. Each entry is the test statistic of an F-test of the joint significance of the difference in coefficients between cities in high income countries and other cities (columns (1) and (4)), between cities in OECD countries and other cities (columns (2) and (5)), and between observations before 2000 and after 2000 (columns (3) and (6)). Variables tested for goods: Trade openness, average income, city size, and exchange rates. Variables tested for incomes: Trade openness, average prices, city size, and exchange rates. Variables tested for $CV(Price_{it})$: Trade openness, average income, average price, city size, $CV(Income_{it})$, and exchange rates. Variables tested for $CV(Income_{it})$: Trade openness, average income, average price, city size, $CV(Price_{it})$, and exchange rates. Department head is missing in column (6) since data for this occupation is available only after 2000.

Columns (4) to (6), for workers' incomes, shows quite different results. There is only limited evidence of differences in the determinants of incomes between cities in high income countries and other cities, but more evidence of differences between OECD and non-OECD countries. This may suggest that the determinants of incomes are driven by labour market institutions which exhibit greater differences between OECD and non-OECD countries. This is supported to some extent by the analysis of different time periods in column (6), which shows only limited evidence of differences over time, which may indicate the persistence of labour market institutions. Finally, the determinants of price and income dispersion exhibit differences across groups only when comparing cities in high-income countries and other cities, which again suggests differences in the characteristics of the markets for goods and workers across these countries.

6 Conclusions

In this paper we investigate the determinants of prices and incomes across a range of goods and services and occupations, using data on a panel of cities across the world. We find evidence of a negative effect of city size and trade openness on prices of some goods, but not on incomes. Price and income dispersion are positively related to each other. Greater price dispersion is also associated with higher average prices and lower average incomes and less trade openness, while greater income dispersion is associated with higher average incomes and lower average prices. The determinants of prices differ between cities in high-income countries and other cities, as well as over time, but we find less across-group variation in incomes. In addition, we find strong evidence of the Penn effect relating prices and incomes to each other, and also that exchange rate pass-through is high for most goods and services and occupations.

A particular novelty of the present paper is the attempt to distinguish between the direct and indirect effects of city size, trade openness, and exchange rates on prices and incomes. In most theoretical models, these variables affect prices through their effects on incomes, and vice versa. We do indeed find some evidence of direct effects of these variables on prices (but not on incomes), but little evidence that they also affect prices indirectly through their effect on incomes.

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Appendix A: List of cities

Amsterdam#*	Jakarta	Oslo#*
Athens#*	Jeddah	Panama
Auckland#*	Johannesburg	Paris#*
Bangkok	Karachi	Prague*
Barcelona#*	Kiev	Riga
Basel#*	Kuala Lumpur	Rio de Janeiro
Beijing	Lagos	Rome#*
Berlin#*	Lima	San Francisco#*
Bogota	Lisbon#*	Santiago
Bratislava*	Ljubljana#	Sao Paolo
Brussels#*	London#*	Seoul#*
Bucharest	Los Angeles#*	Shanghai
Budapest*	Luxembourg#*	Singapore#
Buenos Aires	Lyon#*	Sofia
Cairo	Madrid#*	Stockholm#*
Caracas	Manama#	Sydney#*
Chicago#*	Manila	Taipei#
Copenhagen#*	Mexico City*	Tallinn
Doha#	Miami#*	Tehran
Dubai#	Milan#*	Tel Aviv#
Dublin#*	Montreal#*	Tokyo#*
Dusseldorf#*	Moscow	Toronto#*
Frankfurt#*	Mumbai	Vienna#*
Geneva#*	Munich#*	Vilnius
Helsinki#*	Nairobi	Warsaw*
Hong Kong#	New Delhi	Zurich#*
Houston#*	New York#*	
Istanbul*	Nicosia#	

Note: A city is included in the list if it appears at least once in the sample. # indicates the city is in a World Bank-defined high income country, while * indicates that the city is in the OECD (both definitions as of 2000).

Appendix B: The basket of goods and services

The UBS Prices and Earnings publication indicates that the basket of goods and services is based on Western European consumer preferences, but does not report the weights used. Given the difficulty of obtaining the weights used in the Consumer Price Index over a long time period, we use the weights used in the United States. More recent data (1987 onwards) is available online at the Bureau of Labour Statistics website, while older data is available from PDF files from the FRASER (Federal Reserve Archival System for Economic Research) website of the Federal Reserve Bank of St. Louis.

There are two measures of inflation: CPI-W, which is available for the entire sample period (indeed since 1913), and CPI-U, which was introduced in 1978. To extend CPI-U to earlier time periods, we use one of two methods: (1) we use the same weights as in 1979 for earlier years; (2) we extrapolate the trend from 1979 to 1982 backwards in a linear fashion. CPI-W is based on the expenditures of households in which more than one-half of the household's income comes from clerical or wage occupations, and at least one of the household's earners has been employed for at least 37 weeks during the previous 12 months. The CPI-W population represents about 28 percent of the total US population (Reed and Stewart, 2014). On the other hand, CPI-U covers all urban consumers, representing about 88 percent of the total US population (Reed and Stewart, 2014). In practice, the two measures of inflation are highly correlated with each other (above 0.95).

We match as best we can the products in PnE with the categories in the US CPI index. Table B1 provides the concordance between the two sources, and an indication of the weights from CPI-U and CPI-W. The results in the text use CPI-U, extrapolated linearly to pre-1979 data, but the results are similar if one of the other CPI measures is used.

Table B1: Concordance between Prices and Earnings goods and services, and US CPI categories.

		1979		2015	
Prices & Earnings	**US CPI**	**CPI-U**	**CPI-W**	**CPI-U**	**CPI-W**
Rent4room	Shelter	30.91	28.038	33.15	31.56
Rent3room	Shelter	30.91	28.038	33.15	31.56
LocalRent	Shelter	30.91	28.038	33.15	31.56
Services	Services less rent	21.692	19.677	30.343	28.798
Food & Beverages	Food at home	12.202	13.427	8.23	9.374
Men's clothes	Men's & boys' apparel	1.396	1.391	0.789	0.836
Women's clothes	Women's & girls' apparel	1.701	1.719	1.25	1.269
Electric appliances	Durables	22.672	22.692	9.647	10.327
Car	Private transport	17.506	19.962	14.125	16.151
Public transport	Public transport	1.066	0.94	1.135	0.822
Taxi	Public transport	1.066	0.94	1.135	0.822
Restaurant meal	Food away from home	5.454	5.81	5.785	5.944
Hotel	Other services	4.285	3.711	11.954	11.34
Short stay	Other services	4.285	3.711	11.954	11.34

Notes: To avoid multiple-weighting, we divide the weights by the number of goods and services in that category (so for example each of Rent4room, Rent3room and LocalRent would have a weight of 30.91/3 = 10.303 based on CPI-U in 1979). Columns do not sum to 100, since the Prices and Earnings goods and services do not constitute the universe of goods and services used in the US CPI.

Appendix C: Regression results

Table C1: The determinants of food prices and apartment rents

Dep. Var.	ln(*Food price*)				ln(*Rent*)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Est. Method	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM
$\ln(Pop_{it})$	-0.04	-0.03	-0.01	0.00	-0.28	-0.31	-0.28	-0.25
	(0.09)	(0.09)	(0.08)	(0.09)	(0.20)	(0.24)	(0.20)	(0.21)
$\ln(Openness_{ct})$	-0.20	-0.16	-0.15	-0.05	-0.17	-0.46	-0.17	-0.34
	(0.07)*	(0.11)	(0.07)+	(0.13)	(0.15)	(0.23)+	(0.15)	(0.26)
$\ln(ExRate_{ct})$	2.18	2.19	1.10	0.81	-0.61	0.58	-0.61	-1.02
	(0.66)*	(0.66)*	(0.63)ˆ	(0.69)	(1.90)	(1.76)	(1.90)	(1.76)
$\ln(\overline{Income_{it}})$			0.29	0.37			0.41	0.49
			(0.04)*	(0.04)*			(0.10)*	(0.14)*
N x T	840	840	840	840	811	811	811	811
N	82	82	82	82	82	82	82	82
Hansen test	1.88	1.73	2.41	2.54	2.89	1.12	2.89	1.89
Hansen p-value	0.39	0.19	0.30	0.28	0.24	0.29	0.24	0.39
K-P UnderID test	.	22.84	.	24.69	.	25.27	.	26.33
K-P test p-value	.	0.00	.	0.00	.	0.00	.	0.00
K-P weak ID test	.	8.60	.	3.86	.	15.50	.	7.26
Open endog p-value		0.686		0.665		0.182		0.181
Income endog p-value				0.013				0.179
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ˆ significant at 10%; + significant at 5%; * significant at 1%. Standard errors are clustered by city. Under IV-GMM estimation, average gross income is treated as endogenous, and is instrumented with gross income of primary school teachers and bus drivers. The Hansen test is the Hansen J (chi-squared) test for overidentification. The K-P UnderID test is the Kleibergen-Paap chi-squared test for underidentification. The K-P weak ID test is the Kleibergen-Paap F test for weak identification.

Table C2: The determinants of school teachers' and managers' gross income

Dep. Var.	ln(*Teacher gross income*)				ln(*Manager gross income*)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Est. Method	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM	FE	IV-GMM
$\ln(Pop_{it})$	-0.08	-0.08	0.09	0.12	-0.03	-0.04	0.11	0.13
	(0.14)	(0.14)	(0.12)	(0.11)	(0.19)	(0.20)	(0.19)	(0.19)
$\ln(Openness_{ct})$	-0.13	-0.15	0.10	0.28	-0.24	-0.28	-0.03	0.06
	(0.12)	(0.19)	(0.11)	(0.19)	(0.17)	(0.24)	(0.16)	(0.22)
$\ln(ExRate_{ct})$	4.54	4.52	3.01	3.01	3.93	3.70	2.40	2.31
	(1.24)*	(1.26)*	(1.32)+	(1.33)+	(1.86)+	(2.03)^	(1.85)	(2.11)
$\ln(\overline{p_{it}})$			0.91	1.09			0.78	0.97
			(0.10)*	(0.13)*			(0.14)*	(0.16)*
N x T	781	781	781	781	779	779	779	779
N	82	82	82	82	82	82	82	82
Hansen test	0.04	0.02	1.99	1.20	0.42	0.34	0.07	0.15
Hansen p-value	0.98	0.88	0.37	0.55	0.81	0.56	0.97	0.93
K-P UnderID test	.	24.19	.	18.24	.	24.18	.	18.25
K-P test p-value	.	0.00	.	0.00	.	0.00	.	0.00
K-P weak ID test	.	16.82	.	6.59	.	16.87	.	6.62
Open endog p-value		0.899		0.240		0.768		0.653
Price endog p-value				0.057				0.046
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ^ significant at 10%; + significant at 5%; * significant at 1%. Standard errors are clustered by city. Under IV-GMM estimation average prices are treated as endogenous, and are instrumented with the price of a basket of food, and the price of a basket of services. The Hansen test is the Hansen J (chi-squared) test for overidentification. The K-P UnderID test is the Kleibergen-Paap chi-squared test for underidentification. The K-P weak ID test is the Kleibergen-Paap F test for weak identification.

Appendix D: Identification

In this Appendix we provide additional details on the results of the Hansen test for over-identification, and the Kleibergen-Paap tests for under-identification and weak identification. The results for the regressions corresponding to Figures 2 and 3 are reported in Table D1. In addition, it was shown by Stock and Yogo (2005) that when the method of Limited Information Maximum Likelihood (LIML) or the GMM Continuously Updated Estimator (CUE) is used, the test statstics for weak identification remain the same, but the critical values decrease, implying that these methods are superior to IV/GMM in the presence of weak instruments. We report in the notes to Table D1 the critical values from Stock and Yogo (2005) for both IV/GMM and LIML/CUE methods at the 20% maximal size. Overall (1) we almost always do not reject the null hypothesis that the regressions are over-identified; (2) we always reject the null hypothesis of under-identification; (3) using IV/GMM we reject the null of weak identification for the direct models, but not for the extended models; (4) using LIML/CUE we always reject the null of weak identification for all models. In addition, we report in Table D2 the estimation results using CUE for the same goods and occupations as in Appendix C, for the specifications in columns (4) and (8) of Tables C1 and C2. The regression coefficients are very similar to those obtained using IV/GMM.

Table D1: Detailed results for tests of over-identification, under-identification, and weak identification.

	Baseline	Hansen	Hansen p	KP UnderID	KP UnderID p	KP weak ID
Good						
rent4high	1	0.081	0.7756	23.953	0.000	15.459
rent4high	0	0.919	0.6316	24.857	0.000	29.157
rent3med	1	0.988	0.3202	25.316	0.000	14.857
rent3med	0	1.887	0.3892	26.331	0.000	32.115
localrent	1	0.617	0.4323	24.348	0.000	16.476
localrent	0	1.538	0.4634	25.358	0.000	7.795
services	1	0.016	0.8999	23.137	0.000	8.175
services	0	0.281	0.8688	24.689	0.000	3.858
food	1	1.856	0.173	23.137	0.000	8.175
food	0	2.542	0.2806	24.689	0.000	3.858
mclothes	1	0.015	0.9026	25.605	0.000	14.91
mclothes	0	0.567	0.7533	26.564	0.000	7.212
wclothes	1	0.053	0.8178	25.363	0.000	15.131
wclothes	0	0.204	0.9031	26.305	0.000	7.337
appl	1	1.321	0.2505	23.127	0.000	8.439
appl	0	2.749	0.2529	24.743	0.000	4.053
car	1	0.087	0.7678	21.875	0.000	8.196
car	0	1.054	0.5904	23.261	0.000	3.89
ptrans	1	3.404	0.065	25.699	0.000	15.258

ptrans	0	6.565	0.0375	26.563	0.000	7.214
taxi	1	0.003	0.953	25.461	0.000	14.854
taxi	0	3.593	0.1659	26.44	0.000	7.198
rest	1	0.342	0.5589	23.258	0.000	8.148
rest	0	0.118	0.9425	24.608	0.000	3.839
hotel	1	2.778	0.0956	23.137	0.000	8.175
hotel	0	4.344	0.114	24.689	0.000	3.858
sstay	1	7.302	0.0069	22.651	0.000	10.604
sstay	0	6.854	0.0325	21.478	0.000	4.773
Occupation						
teacher	1	0.023	0.8797	24.193	0.000	16.824
teacher	0	1.201	0.5486	18.236	0.000	6.592
busdriver	1	1.048	0.306	24.263	0.000	16.975
busdriver	0	4.729	0.094	18.036	0.000	6.699
mechanic	1	0.324	0.569	24.182	0.000	16.847
mechanic	0	3.248	0.1971	18.222	0.000	6.602
construction	1	2.573	0.1087	24.182	0.000	16.847
construction	0	6.134	0.0466	18.222	0.000	6.602
toolmaker	1	0.28	0.5966	24.397	0.000	16.342
toolmaker	0	2.028	0.3627	19.386	0.000	6.189
cook	1	0.043	0.8357	24.386	0.000	16.287
cook	0	0.769	0.6809	19.135	0.000	6.23
textile	1	0.009	0.925	23.67	0.000	17.448
textile	0	0.777	0.678	17.556	0.001	6.795
bank	1	1.128	0.2881	24.369	0.000	17.014
bank	0	0.555	0.7576	18.2	0.000	6.608
manager	1	0.342	0.5586	24.181	0.000	16.865
manager	0	0.154	0.926	18.251	0.000	6.624
engineer	1	0.417	0.5185	24.4	0.000	16.176
engineer	0	0.092	0.9552	19.118	0.000	6.175
dhead	1	0.081	0.7757	13.21	0.001	16.372
dhead	0	0.585	0.7463	9.448	0.024	6.48
secretary	1	3.206	0.0733	24.178	0.000	16.867
secretary	0	2.438	0.2955	18.222	0.000	6.607
sales	1	1.202	0.273	24.254	0.000	16.73
sales	0	1.07	0.5857	19.255	0.000	6.309

Notes: Baseline takes a value equal to 1 for the baseline specification, and 0 for the extended specification. Hansen refers to the Hansen J test for over-identification. Hansen p is the p-value of this test. KP UnderID is the Kleibergen-Paap test for under-identification, and KP UnderID p is the p-value of this test. KP weakID is the Kleibergen-Paap test for weak identification. The Stock and Yogo (2005) critical values at the 20% maximal size are 8.75, 7.54, 4.42, and 2.99 for GMM in the baseline specification, GMM in the extended specification, LIML in the baseline specification, and LIML in the extended specification, respectively.

Table D2: Results using GMM Continuously Updated Estimator (CUE).

	(1)	(2)	(3)	(4)
Dep. Var.	Food cost	Rent 3 bed	Teacher	Manager
$\ln(Pop_{it})$	0.01	-0.24	0.11	0.13
	(0.09)	(0.20)	(0.11)	(0.19)
$\ln(Openness_{ct})$	-0.11	-0.36	0.29	0.06
	(0.14)	(0.25)	(0.19)	(0.22)
$\ln(ExRate_{ct})$	0.82	-1.06	2.97	2.31
	(0.65)	(1.81)	(1.32)+	(2.10)
$\ln(\overline{Income_{\iota t}})$	0.37	0.49		
	(0.05)*	(0.13)*		
$\ln(\overline{p_{\iota t}})$			1.11	0.97
			(0.13)*	(0.16)*
N x T	840	811	781	779
N	82	82	82	82
Hansen test	2.28	1.81	1.14	0.15
Hansen p-value	0.32	0.40	0.57	0.93
K-P UnderID test	24.69	26.33	18.24	18.25
K-P test p-value	0.00	0.00	0.00	0.00
K-P weak ID test	3.86	7.26	6.59	6.62
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: ^ significant at 10%; + significant at 5%; * significant at 1%. Standard errors are clustered by city. Estimation method is the GMM Continuously Updated Estimator (CUE). Average prices and average incomes are treated as endogenous, and are instrumented with the price of a basket of food and the price of a basket of services, and with gross income of primary school teachers and bus drivers, respectively. The Hansen test is the Hansen J (chi-squared) test for overidentification. The K-P UnderID test is the Kleibergen-Paap chi-squared test for underidentification. The K-P weak ID test is the Kleibergen-Paap F test for weak identification.

Appendix E: Price and income dispersion

We describe two exercises in this Appendix. First, we outline a simple model to provide some justification for expecting price and income dispersion to be associated with each other. To see how this may be the case, suppose there is a large number of goods $i = 1, \ldots, n$, each produced using a good-specific type of labour l_i under perfectly competitive markets. Then, in equilibrium with zero profits, we have:

$$w_i = p_i \times MPL_i \qquad (E1)$$

Where w_i is the wage rate of labour type i, p_i is the price of good i, and MPL_i is the marginal product of labour in good i. Suppose that prices are Normally distributed with mean μ_p and standard deviation σ_p (for example, price dispersion may occur because of demand shocks). Then, if MPL_i is a constant, the variance of wages will be equal to the variance of prices:

$$\sigma_w^2 = \sigma_p^2 \qquad (E2)$$

In which case there is obviously a positive (and one-to-one) relationship between the two variances. It is also easy to show that, provided MPL_i and p_i are independent of each other, and MPL_i is also Normally distributed with mean μ_{MPL} and standard deviation σ_{MPL} (for example, dispersion in the marginal product of labour may occur because of technology shocks):

$$\sigma_w^2 = \sigma_p^2 \sigma_{MPL}^2 + \sigma_p^2 \mu_{MPL} + \sigma_{MPL}^2 \mu_p \qquad (E3)$$

So once again we have a positive (but not a one-to-one) relationship between the variance of wages and the variance of prices.

As shown in Table 1, we do not have data on the prices of all goods and services, nor do we have the incomes of all occupations. However, provided we have a sufficiently large sample of goods and of occupations, then by the Law of Large Numbers, the sample variance s^2 will converge almost certainly to the population variance σ^2, so we can replace the population parameters in equations (E2) and (E3) with their sample parameters, to obtain a positive relationship between the (sample) variance of wages and the (sample) variance of prices.

In the text, we use the coefficient of variation (CV) as the measure of dispersion. As a measure of dispersion, it satisfies the requirements for a measure of economic inequality: anonymity, scale invariance, population independence, and the Pigou-Dalton transfer principle (Cowell, 2011). Nevertheless, one may ask whether our results are robust to alternative measures of dispersion. In this Appendix, we calculate three alternative measures of dispersion: the Gini coefficient, the Hoover index, and the Theil index[16]. First, we report the correlation between the different measures of dispersion, for prices and for incomes, in Table E1. We find that the measures of dispersion are

[16] Sen (1973) shows how a measure of social welfare which takes into account distributional concerns can be computed based on the Gini coefficient.

positively correlated with each other, although the correlation is much higher for incomes than for prices. Second, we perform the analysis in Table 2 for the different measures of dispersion, and the results for the specification in columns (4) and (8) of Table 2 are reported in Tables E2 and E3. We find similar results to those reported in Table 2.

Table E1: Correlation between measures of dispersion.

Goods				
	Gini	Hoover	Theil	CV
Gini	1.0000			
Hoover	0.8317	1.0000		
Theil	0.8837	0.5074	1.0000	
CV	0.5539	0.3929	0.5779	1.0000
Occupations				
	Gini	Hoover	Theil	CV
Gini	1.0000			
Hoover	0.9907	1.0000		
Theil	0.9618	0.9625	1.0000	
CV	0.9727	0.9695	0.9757	1.0000

Notes: N = 873 for goods, N = 862 for occupations.

Table E2: Alternative measures of price dispersion.

Dependent variable	(1) $\ln[Gini(p)]$	(2) $\ln[Hoover(p)]$	(3) $\ln[Theil(p)]$
$\ln(Pop_{it})$	-0.03	-0.07	0.09
	(0.12)	(0.14)	(0.20)
$\ln(Openness_{ct})$	0.09	0.08	0.20
	(0.16)	(0.18)	(0.32)
$\ln(ExRate_{ct})$	-1.50	-1.71	-2.42
	(0.89)ˆ	(0.95)ˆ	(1.88)
$\ln(\overline{Income_{it}})$	-0.19	-0.24	-0.35
	(0.05)*	(0.05)*	(0.11)*
$\ln(\overline{p_{it}})$	0.14	0.21	0.17
	(0.09)	(0.11)ˆ	(0.17)
$\ln[Gini(Income)]$	0.34		
	(0.12)*		
$\ln[Hoover(Income)]$		0.34	
		(0.11)*	
$\ln[Theil(Income)]$			0.29
			(0.12)+
N x T	840	840	840
N	82	82	82
Hansen test	1.18	0.46	1.80
Hansen p-value	0.55	0.80	0.41
K-P UnderID test	22.73	22.37	22.84
K-P test p-value	0.00	0.00	0.00
K-P weak ID test	3.14	3.14	3.13
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: ˆ significant at 10%; + significant at 5%; * significant at 1%. Standard errors are clustered by city. Estimation method is IV-GMM. $\ln(Openness_{ct})$, $\ln[Gini(Income)]$, $\ln[Hoover(Income)]$ and $\ln[Theil(Income)]$ are treated as endogenous, and are instrumented with export openness and import openness of the other countries in the sample, and gross incomes of primary school teachers and bus drivers. The Hansen test is the Hansen J (chi-squared) test for overidentification. The K-P UnderID test is the Kleibergen-Paap chi-squared test for underidentification. The K-P weak ID test is the Kleibergen-Paap F test for weak identification.

Table E3: Alternative measures of income dispersion.

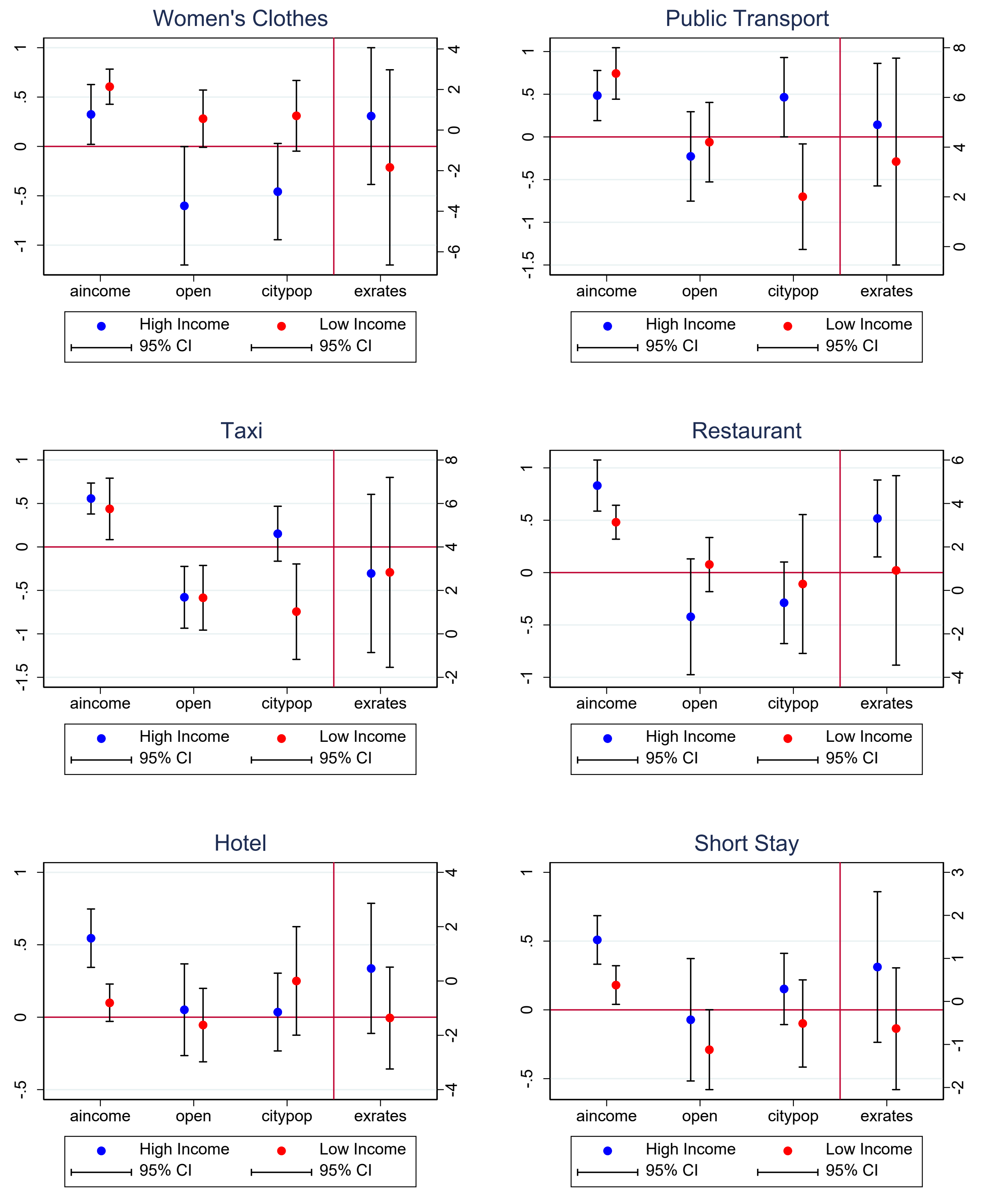
Dependent variable	(1) $\ln\left[\begin{matrix} Gini \\ (Income) \end{matrix}\right]$	(2) $\ln\left[\begin{matrix} Hoover \\ (Income) \end{matrix}\right]$	(3) $\ln\left[\begin{matrix} Theil \\ (Income) \end{matrix}\right]$
$\ln(Pop_{it})$	0.01	0.00	-0.04
	(0.11)	(0.12)	(0.21)
$\ln(Openness_{ct})$	-0.09	-0.15	-0.18
	(0.15)	(0.17)	(0.32)
$\ln(ExRate_{ct})$	0.65	0.51	0.67
	(0.91)	(0.96)	(2.05)
$\ln(\overline{Income_{\iota t}})$	0.32	0.35	0.67
	(0.06)*	(0.07)*	(0.13)*
$\ln(\overline{p_{\iota t}})$	-0.30	-0.36	-0.55
	(0.09)*	(0.11)*	(0.18)*
$\ln[Gini(p)]$	0.59		
	(0.17)*		
$\ln[Hoover(p)]$		0.61	
		(0.20)*	
$\ln[Theil(p)]$			0.66
			(0.18)*
N x T	778	778	778
N	82	82	82
Hansen test	2.84	2.43	1.92
Hansen p-value	0.24	0.30	0.38
K-P UnderID test	12.59	12.01	11.99
K-P test p-value	0.01	0.01	0.01
K-P weak ID test	3.19	2.82	3.15
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: ^ significant at 10%; + significant at 5%; * significant at 1%. Standard errors are clustered by city. Estimation method is IV-GMM. $\ln(Openness_{ct})$, $\ln[Gini(p)]$, $\ln[Hoover(p)]$ and $\ln[Theil(p)]$ are treated as endogenous, and are instrumented with export openness and import openness of the other countries in the sample, prices of food and beverages, and prices of services. The Hansen test is the Hansen J (chi-squared) test for overidentification. The K-P UnderID test is the Kleibergen-Paap chi-squared test for underidentification. The K-P weak ID test is the Kleibergen-Paap F test for weak identification.

Appendix F: Further analysis of cities in high- and low-income countries

Column (1) in Table 3 showed that for some goods the determinants of prices were systematically different between cities in high- and low-income countries. In this Appendix we expand the analysis of the goods with statistically significant differences between the two groups of cities: women's clothes, public transport, taxis, restaurant meals, hotels, and short stays. Figure F1 presents the differences between the coefficient estimates of the two groups of cities (note that exchange rates are on a separate axis from the other variables). The figure shows that there is no simple explanation for why the determinants of prices are different for the two groups of cities. For example, for womens' clothes, much of the difference lies in the different effects of trade openness and city population. Both are negatively related to the price of women's clothes in high-income cities, while they are positively related to the price of women's clothes in low-income cities. For public transport and taxis, the difference is because of the effect of city population, whereas for restaurant meals, hotels, and short stays, the difference is mainly because of the different effects of average income.

Figure F1: Differences between coefficient estimates.



Note: Exchange rates are on the right-hand axis, all other variables are on the left-hand axis.