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In utero seasonal food insecurity and cognitive development: Evidence from Ethiopia *

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Abstract

Food insecurity is pervasive and highly seasonal in Ethiopia. In this study, we investigate the effect of seasonal food insecurity on child development. Exploiting the Young Lives Ethiopia dataset, we study the impact of in utero exposure to seasonal food insecurity on cognitive development for children of age 8 up to 12. We find that at age 8 in utero exposure to food insecurity shocks negatively, although insignificantly, affects cognitive development. But, at age 12, such exposure significantly reduces cognitive development. In utero exposure to seasonal food insecurity translates into a loss of 0.52 standard deviations in maths achievements score. Exposure during the first and second trimesters of pregnancy are found to have stronger detrimental effects. We also find stronger effects for boys.

Keywords: Food Insecurity; Ethiopia; In utero; Cognitive Development.

JEL Classification: I15; O13; O15

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1 Introduction

Early cognitive abilities play an important role in determining long-term schooling and wages (Currie and Thomas, 2012). The development of these skills begins in utero and continue to evolve over the life-cycle through a dynamic process of skill formation (Heckman, 2007). Large-scale shocks such as famine, natural disasters, and civil wars experienced during prenatal and early life environment have been found to be strong predictor of future outcomes (Almond and Currie, 2011; Currie and Vogl, 2013). Nonetheless, food shortages are much more frequent and potentially more detrimental on most children's life cycle. Each year, more people die from hunger than AIDS, malaria and tuberculosis combined (WFP, 2013). Ethiopia is a case in point. According to FAO (2009), about 44% of the total population in Ethiopia were undernourished between 2004 and 2006. This could be attributed to chronic food insecurity, a pervasive phenomenon in the country. A substantial number of people in Ethiopia are facing difficulties in feeding themselves on a regular basis around the rainy and planting seasons. According to the International Food Policy Research Institute and the Ethiopian Development Research Institute, more than 25% of households in Tigray region, close to 30% of households in Oromia (the most populous region) and 25% of households in Southern Nations, Nationalities, and Peoples'(SNNP) region reported food gaps during the raining season in 2006. For Amhara (the second most populous) region the food gap stands at less than 20% (Hoddinott et al., 2011).[1] In the same year, close to 20% and 15% of households reported food gaps for 3 months and 4 months, respectively. The impact of prenatal exposure to such seasonal food insecurity is largely unknown.

In this study, we examine the impact of in utero exposure to seasonal food insecurity on cognitive development. We exploit a unique dataset from the Young Lives Ethiopia study and apply a novel identification strategy. We estimate the effect of variation in number of days to prenatal food insecurity exposure on cognitive development outcomes by controlling for community and birth month fixed effects together with child and household characteristics. We find that cognitive development is strongly and adversely affected by seasonal food insecurity. One additional month exposure to prenatal food insecurity results in lower maths achievements score by about 0.14 standard deviations. A child in our sample is exposed to on average 3.74 months of in utero food insecurity. This would mean a loss of 0.52 standard deviations in maths achievements score as a result of the exposure. We further investigate the heterogeneous effects of seasonal food insecurity, by shedding light on the timing of food shortages during particular trimesters, and on the gender imbalances. Exposure during the first and second trimesters of pregnancy are detrimental for maths acquisition, with partial effects of 0.15 and 0.147 standard deviations, respectively. The detrimental impact of in utero exposure to seasonal food insecurity on maths achievements scores is even stronger for boys.

Our paper directly relates to the emerging literature exploring the effect of prenatal shock on human capital development of children (Neelsen and Stratmann, 2011; Almond et al., 2015). The so called 'foetal origins' hypothesis advocated by Barker describes that conditions in utero (e.g. nutritional deficiencies) have long lasting health effects (Almond and Currie, 2011; Barker, 1990). Prenatal nutrition shocks should also have significant detrimental effects on brain development (Almond and Mazumder, 2011; Almond et al., 2015;

[1]The data may not be representative of the country since the information is obtained from chronically food-insecure woredas (districts).

Umana-Aponte et al., 2011). To establish causal effects, studies exploit famines and other shocks like natural disasters, wars, and disease epidemics as exogenous natural experiments. Almond and Currie (2011) and Currie and Vogl (2013) provide extensive review of the literature. More directly to our study Dercon and Porter (2014) find detrimental impact of the 1984/85 Ethiopian famine on height of young adults. No effect is found from exposure in utero.

Though dramatic, famines, natural disasters and civil wars are not necessarily part of the day-to-day life in developing countries. Chronic malnutrition is a recurrent concern and may hinder the accumulation of human capital even further (WFP, 2013). Furthermore, events such as famines and civil wars may generate large mortality and fertility selection that are difficult econometric challenges to deal with (Neelsen and Stratmann, 2011; Gørgens et al., 2012). So, we study the impact of a regular and more moderate fetal shock: in utero exposure to seasonal food insecurity. In doing so, we contribute to an emerging literature seeking to identify the consequences of relatively mild, though frequent, shocks. In this study, we focus on experiences of food shortages around the rainy and planting seasons. Miller (2015) also explores the impact of prenatal seasonal food scarcity in Ethiopia on child health outcomes. However, that study exploits seasonal food scarcity information whose pattern does not correspond to the conventionally observed seasonality in Ethiopia. In particular, he uses community-level food insecurity data that point to relative food scarcity from October to January. But, this period coincides with post harvest in Ethiopia, and is usually characterized by relatively higher food availability and lower prices.

With the exception of Miller (2015), the related literature has focused on assessing the consequences of periods of Ramadan fasting. Almond and Mazumder (2011) assesses exposure to Ramadan on short term health like birth weights and birth sex ratio in the US, and log-term health outcomes such as disabilities in Uganda and Iraq. Van Ewijk (2011) identifies the negative effects of fasting during pregnancy on long-term general health outcomes in Indonesia. But recently, studies that investigate the consequences of Ramadan on education and economic outcomes are emerging. Almond et al. (2015) examine the Ramadan exposure on maths and reading test scores for children of age 7 using English registry data. Majid (2015) studies the effect of Ramadan fasting on children cognition and long-term labour market outcome in Indonesia. Building on Miller (2015), we also investigate the consequences of relatively mild food shortages in utero on cognitive development of Ethiopian children. What is missing in the literature is analysis of the effect of in utero or early childhood exposures on outcomes measured at different ages in the life cycle for the same cohort to show how persistent the effect is (Almond et al., 2015; Majid, 2015). Majid (2015) follows individuals exposed to Ramadan in utero. He finds increased participation on child labour and a detrimental effect on adult labour supply. But, this evidence is only suggestive since persistence is conjectured from comparison of different outcomes. In this study, we assess the effect of in utero seasonal food insecurity on cognitive development by exploiting the same outcome for children followed at age 8 and 12. By doing so, we show that the effects of in utero exposure accumulate over time and become even stronger towards puberty.

Our paper is also related to the literature seeking to explore the importance of the timing of shocks occurring in utero on child outcomes. The evidence so far is quite mixed. While the first and second trimester seem to be crucial for academic outcomes, the third trimester is especially important for short term health outcomes like birth weight. Almond et al. (2015) establish that the early stage of prenatal Ramadan experience (first and to some extent second trimester) is very important for child academic development. Schwandt (2014) finds evidence of a labour market effect of influenza exposure in the second trimester. On the contrary, Painter et al. (2005) and Schwandt (2014) identify stronger impacts resulting from shocks occurring at later stage of pregnancy (third trimester) on birth weight. In this study, consistent with the literature on cognition and academic development, we find significant negative effects of shocks during the first trimester and the second trimester on cognition of children.

We also explore the heterogeneous impact of seasonal food insecurity by gender. Generally, stronger effects of shocks in utero on boys outcomes is expected as they are more vulnerable in womb than girls (Eriksson et al., 2010; Kraemer, 2000). However, the nature of gender imbalances differs across existing studies. While the Great Chinese Famine has been found to be more detrimental for girls in terms of health and education (Luo et al., 2006; Mu and Zhang, 2011), stronger effects on boys have been found from famines during World War II in Greece, Germany and The Netherlands (Berg et al., 2016) and during the Dutch Potato Famine in the mid-nineteenth century (Lindeboom et al., 2010). The differences in the results are puzzling. The use of different outcomes variables and contextual differences may be behind the mixed nature of the evidence but selection effects in utero may potentially drive some of these results (Mu and Zhang, 2011; Dagnelie et al., 2014). If selection in utero is significant, surviving male children would be the stronger since in utero shocks have stronger effects on boys than girls. As a result, we may find small, or no, effects on boys. In our case, one advantage in investigating the role of mild-level shocks in food insecurity is that selection in utero is likely to be less of a concern. The issue is further discussed in Section 4.

2 Data and Identification Strategy

We exploit data from the Young Lives Ethiopia (YLE) surveys. YLE is part of the Young Lives Project, an international study of childhood poverty tracking 12,000 children in four countries (Ethiopia, Peru, Vietnam, and India) over a 15-year period. The Ethiopian data originate from 20 sites located in the five biggest regions of the country in which more than 96% of the Ethiopian children live. These regions include: Amhara, Oromia, Tigray, and the Southern Nations, Nationalities, and Peoples' Region (SNNPR) (Figure A.1 in Appendix A). To choose the 20 sites of the study in each country, a sentinel site sampling approach was applied (Barnett et al., 2013). In Ethiopia the purposive sampling process follows the following three principles: (1) oversampling of food deficit districts (2) the profile of the selected districts/sites should reflect the diversity of the country (3) the possibility of tracking children in the future at reasonable cost. The sites in Ethiopia are selected in such a way that: first, four regional states (Amhara, Oromia, SNNPR, Tigray, and one city administration (Addis Ababa)) were chosen; second, up to five woredas (districts) were selected from each region(this accounts for 20 districts in total); third, from each woreda at least one kebele (local administrative area) was selected; and finally, 100 households with a child born in 2001-02 that constitute the younger cohort and 50 households with a child born in 1994-95 that make up the older cohort were randomly chosen from each site.[2] The YLE survey contains information on children's health, education, schooling, time-use, feelings and attitudes, and cognitive tests. Household information includes: family background, education, consumption, social networks, livelihoods and wealth indicators. In this study, we exploit information about the so-called young cohort. The young cohort for Ethiopia comprises 1,999 children born between May 2001 and May 2002 in the 20 sites across the country. In the baseline survey of 2002, these children were aged between 6 and 18 months old.[3] These children were then surveyed again in 2006, 2009 and 2013 (Figure A.2 in Appendix A). We focus on 24 out of 26 communities, since two communities lack the food security information needed for our analysis.

We seek to identify the causal impact of in utero exposure to food insecurity on cognitive development outcomes, using the following ordinary least-square specification:

$$Y_{idc} = \alpha_c + \theta_m + \beta \text{Exposure}_{dc} + X_{idc} + \varepsilon_{idc}, \tag{1}$$

where Y_{idc} is an outcome variable designated by cognitive development measure of maths achievements scores for individual i, born on date d, in community c. Exposure_{dc} is the number of days (by month) of exposure to seasonal food insecurity in utero, based on each child's date of birth. X_{idc} denote the household and child characteristics. We also introduce community and month of birth fixed effects, α_c and θ_m, to deal with omitted factors at the community level and seasonality effect that would threaten the causal interpretation of our results. Exploiting within-community and month variation, our coefficient of interest, β captures the average effect of a month of exposure to relative seasonal food insecurity on maths score. Standard errors are clustered at the community level to deal with correlation within location of residence. Given the low number of communities which might underestimate intra-group correlation, we also show the robustness of our results to the use of wild boostrapping method (Cameron et al., 2008; Cameron and Miller, 2015).

We now discuss these variables in turn. The dependent variable, Y_{idc}, is from a standard achievements test used to measure children's cognitive development. It provides a quantitative achievement score that measures various numerical abilities considered as appropriate for the age of the children. Panel A in Table 1 shows the descriptive statistics of our outcome variable, maths score. Maths test score, for the younger cohort, is measured only at age 8 (round 3) and age 12 (round 4) in the YLE survey. The descriptive statistics shows the means, standard deviations, minimums and maximums of the raw scores in maths. In our statistical analysis, however, we use the scores standardized by age (where the means and standard deviations used for standardization are computed for every age group).[4]

[2] See http://www.younglives.org.uk/content/sampling-and-attrition for details.

[3] The survey also collects similar information for the older cohort, born around 1994-95.These children were 7-8 years old during the first round survey in 2002. We do not have birth information such as prematurity for this cohort that are essential for computing our exposure variables. Thus, this cohort cannot be exploited for our main analysis. We will nonetheless use the information about this cohort to assess the relationship between cognitive development and long-term education outcomes to shed light on the long-run significance of our results.

[4] Standardizing the outcomes without controlling for differences in age gives very similar result as stan-

Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: Outcome variables					
Maths round 3	6.523	5.364	0	28	1695
Maths round 4	10.503	6.053	0	27	1508
Panel B: Exposure variables					
Exposure, 9 months	3.702	1.657	0	8.133	1875
Exposure in 1st Trimester	1.265	1.175	0	3	1875
Exposure in 2nd Trimester	1.25	1.227	0	3	1875
Exposure in 3rd Trimester	1.187	1.134	0	2.833	1875
Panel C: Control variables					
Age round 3	97.476	3.767	90.312	114.345	1875
Age round 4	142.549	12.015	91.803	156	1875
Child is boy	0.517	0.5	0	1	1875
Female headed	0.141	0.348	0	1	1874
Wealth round 1	0.212	0.174	0.005	0.737	1857
Number of older siblings	2.132	1.981	0	10	1875
Mom edu. (1 to 4 years)	0.144	0.351	0	1	1865
Mom edu. (5 to 8 years)	0.157	0.364	0	1	1865
Mom edu. (>8 years)	0.09	0.286	0	1	1865
Premature	0.119	0.324	0	1	1875
Tigrian	0.234	0.424	0	1	1875
Oromo	0.18	0.385	0	1	1875
Gurage	0.082	0.274	0	1	1875
Wolayta	0.056	0.23	0	1	1875
Other	0.151	0.359	0	1	1875
Work exposure	3.352	1.769	0	8.167	1875
Muslim	0.171	0.376	0	1	1875
Ramadan	0.813	0.39	0	1	1875
Ramadan X Muslim	0.129	0.335	0	1	1875
Unplanned	0.374	0.484	0	1	1779

Source Authors' computation from Young Lives Data

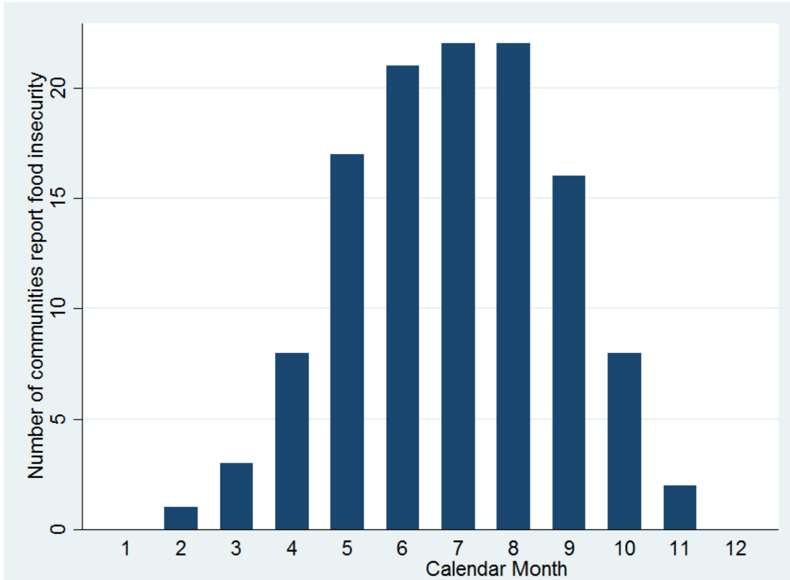
Our main variable of interest, Exposure$_{dc}$ seeks to capture seasonal food insecurity in utero, by exploiting both food security information at the community level and variations at the individual level based on the date of birth. At the community level, food insecure months are identified in the YLE community surveys, where the community leaders are asked in which months of the year food becomes harder or more expensive to obtain. We use information on community-level food insecurity from the community survey that was conducted in the second round (2006). The same information was also collected in the first round (2002). However, the pattern does not correspond to the conventionally observed seasonality in Ethiopia.[5] In particular, the 2002 survey on food insecurity reports higher average relative food insecurity from October to January. But, this period coincides with post harvest in Ethiopia, and is thus characterised by relatively higher availability of food and lower prices. Thus, the information must have been reported and documented with errors. On the contrary, the food insecurity information reported in 2006 corresponds with the reality in Ethiopia. This is further corroborated by monthly food price data. Figure 1 depicts that relative food insecurity is reported from May to September. Figures C.2 and C.3 in Appendix C also show that food prices both in rural and

dardizing the outcomes by age.

[5]Note that using food insecurity information from 2002 community survey confirms our results but with much lower magnitude.

urban parts of the country are higher from May to September.

FIGURE 1. Reported Seasonal Food Insecurity by Calendar Month



Source: Authors' calculations using data from Young Lives Study, Ethiopia

As indicated in Figure 1, food insecurity is more likely to be reported during the rainy and planting period of the main harvesting season. Such harvesting seasons vary across agro-ecological zones but the main harvesting season would usually fall from October to December. In each month from June to August, more than 20 of the surveyed communities report relative food insecurity. More than 15 of them also report relative food insecurity in May or September. The rest of the year is largely food secure. A similar pattern, although more concentrated in July and August, is also observed in urban areas (Figure C.1 in Appendix C). The seasonal pattern of food insecurity should not come as a surprise. In rural Ethiopia where subsistence agriculture is the prominent form of livelihood, households experience severe food shortages during the rainy/ planting season. Post harvest, farmers have usually enough food with a high level of supply associated with relatively low prices (Figures C.2 and C.3 in Appendix C). That is why we observe less food insecurity following harvests (from November to April). But when the rainy and planting seasons come, food availability decreases and pushes market prices upward, threatening food security. More than 60% communities report food insecurity for 4 to 5 months in a similar range to Hoddinott et al. (2011) (Figure B.1 in Appendix B).

The community-level measurement of food insecurity is then used to determine how much a child is exposed to food insecurity in utero.[6] Similar to Miller (2015), we compute the number of days a child has faced a food insecure environment while he/she was in utero. One lives in utero for approximately 38 weeks or 266 days starting from conception. Premature births may be an issue here. 8% of the children in our sample are indeed born before the end of the term. We have data on the number of weeks of prematurity for only 75% of pre-term babies. For the remaining 25%, we substitute the missing observations by the median weeks of prematurity, 2 weeks. Thus, for premature babies, the number of days of exposure are

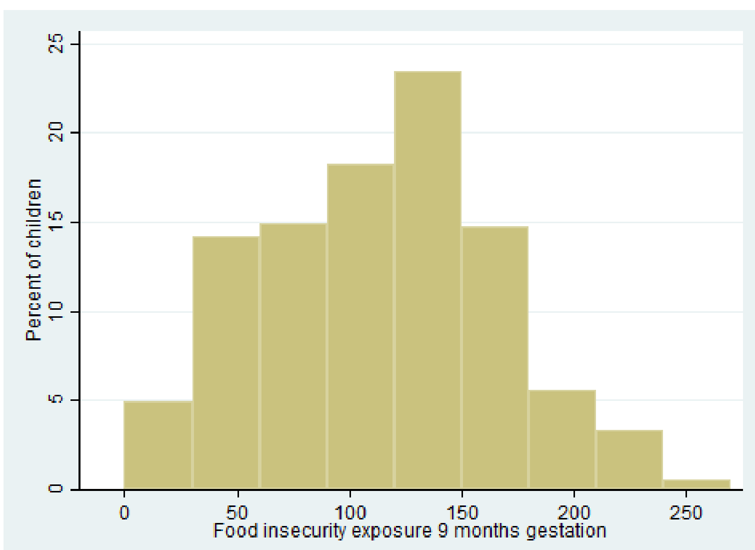
[6]We describe the reliability of the community-level food insecurity information in the construction of our in utero exposure in Appendix C.

calculated after adjustment is made for the reported number of weeks of prematurity. Miller (2015) adopts the same correction. As a result, our measure of food insecurity exposure in full 9 months is calculated as the number of days a child is facing food insecurity in utero from conception to birth in those 266 days of prenatal experience. The calculation of our prenatal food insecurity exposure is described in Table 2. Assume for example, a child is conceived in a particular community on 26 May 2001. In theory the child will be born on 16 February 2002. In this community, food is relatively unavailable in May, June, July, August and September. The child born in that community will be exposed to prenatal food insecurity for 4 months (June, July, August and September) and 6 days (from May), resulting in 126 days of prenatal food insecurity exposure. Panel B shows a child born in another community on 11 January 2002. This child will be exposed to 3 months (June, July, August) of prenatal food insecurity, resulting in 91 days of exposure.

Table 2: Calculating the number of days a child exposed to prenatal seasonal food shortage

Panel A, Community X									
Date	Concieved on 26 May 2001								Born on 16 Feb 2002
Month	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Food insecurity	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Panel B, Community Y										
Date	Conceived on 10 Apr 2001									Born on 11 Jan 2002
Month	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan
Food insecurity	No	No	Yes	Yes	Yes	No	No	No	No	No

FIGURE 2. Prenatal Days Exposed to Reported Seasonal Food Insecurity in 9 months exposure



Source: Authors' calculations using data from Young Lives Study, Ethiopia

We also compute the number of days the child has been exposed to food insecurity in each trimester of gestation. In our study, the first and second trimester (after conception) are 90 days each and the third trimester accounts for 86 days. All exposure variables are then converted into monthly units by dividing the number of exposure days by 30 so that our results can be interpreted on a monthly basis. Panel B in Table 1 reports the means, standard deviations, minimums and maximums of exposure in full 9 months and at each trimester level. On average, a child has experienced 111 days (3.70 months) of food insecurity out of 266. Figure 2 also provides the histogram of the exposure measure in full 9 months of gestation.

The construction of our dependent variables and our main variable of interest sheds light on the importance of controlling for observed and unobserved characteristics at the community and monthly level. Food security is known to vary significantly across communities, mainly due to diverse agro-ecological zones and differences in terms of access to infrastructure. For instance, Stifel and Minten (2017) find that households in Ethiopia living in remote areas are systematically more likely to be food insecure. Cognitive developments are also likely to differ across communities. We therefore not only control for household and child characteristics, X_{idc}, but also for community fixed effects, α_c. Control variables include age of child in months, household wealth index, number of older siblings, and a set of dummies for gender of the child, gender of the household head, education the mother, ethnicity, and prematurity. With the exception of age, all control variables are computed at baseline (2002). To assess the risk of bad controls (Angrist and Pischke, 2009), we always present our main results without and with these control variables. Panel C in Table 1 presents the descriptive statistics of these variables. The seasonal nature of food security also calls for including months of birth fixed effects, θ_m.

3 Results

3.1 Exposure in utero

Table 3 presents the estimated effects of in utero exposure to food insecurity on maths score at age 8 and 12. Columns (1) and (3) provide estimates from regressions without controls, whereas column (2) and (4) present those with controls. Although insignificant, our results suggest that there is a negative effect of the exposure on maths score at age 8. However, in utero exposure to food insecurity has a significant and detrimental impact on cognitive development at age 12. Specifically, the maths score of children exposed to food insecurity at prenatal stage significantly decreases at age 12 (columns 3 and 4). The results show that the effects of in utero exposure accumulates overtime. This is consistent with the idea highlighted by Heckman and Masterov (2007): 'disadvantages just like advantages accumulate overtime'. At age 12, the magnitude of the coefficient increases from -0.12 to -0.14 when controls are included, albeit insignificantly. In column (4), an extra month exposure to food insecurity during the 9 months of gestation decreases the cognitive ability measured by maths achievement score at age 12 by 0.14 standard deviations.[7]

Given the fact a child in our analytical sample faces on average 3.74 months of in utero food insecurity, a child loses on average approximately 0.52 standard deviations of maths scores as a result of this. This is a large effect compared to other existing studies. Berhane et al. (2016) for instance document the effect of childhood positive shock (exposure to productive safety net) and negative shock (drought) in Ethiopia on Peabody Picture Vocabulary Test (PPVT). They find that exposure to drought reduces child cognitive skills

[7]Detailed results of Table 3 including control variables are provided in columns (1) and (2) of Table D.1 of Appendix D.

Table 3: Estimated effect of in utero food insecurity exposure, (full pregnancy)

Dep. variable: Maths achievement) score	(1) age 8	(2) age 8	(3) age 12	(4) age 12
Exposure	-0.010	-0.023	-0.120***	-0.140***
	(0.020)	(0.019)	(0.028)	(0.034)
Observations	1,458	1,438	1,458	1,438
R-squared	0.391	0.432	0.301	0.353
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable across columns is age standardized maths score at age eight and twelve. The variable of interest captures prenatal exposure to seasonal food insecurity (full 9 months exposure). Controls include (X): age of child in months, household wealth index, number of older siblings, and dummies for gender, gender of household head, mother's education, child ethnicity, prematurity. We restrict the sample to children for which we observe the outcomes of interest at all age (round) stages.

by 0.18 standard deviations, while access to safety net increases cognition by 0.18 standard deviations. We provide evidence that exposure to mild level food shortages at the prenatal stage has a greater impact to that of childhood exposure to drought and safety net. Such detrimental impact is likely to have long-term consequences on socio-economic outcomes. Using data from the older cohort at age 18 or 19 in round 4 (2013) and conditional on the same individual control variables, we estimate correlations between cognitive development (maths scores) at age 12 and graduating from high school or joining college at age 18 or 19. The maths score of the older cohort was collected in round 2 (2006). In comparison with round 2, the number of questions for maths score increases in round 4. We therefore standardize maths scores in terms of percentages of correct answers. We find correlations of about 0.13 and 0.07 between maths score and the probability of graduating from high school or joining college, respectively. This analysis is presented in Table 4. In other

Table 4: Correlation between cognition and long-term academic achievements

Dep. variable: Probability of graduating from high school and joining college	(1) graduate	(2) graduate	(3) college	(4) college
1 standard deviation=24.6%				
Math12 (% correct)	0.157***	0.130***	0.086***	0.068***
	(0.012)	(0.013)	(0.010)	(0.010)
Observations	881	869	881	869
R-squared	0.139	0.198	0.066	0.108
Controls	No	Yes	No	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable across columns are indicators that show whether a child graduates from high school (column 1 and 2) and go to college (column 3 and 4) at age 18 or 19. The independent variable is % correct in maths score at age 12 (standardized to have mean 0 and standard deviation 1). Controls include (X): age of child in months, household wealth index, and dummies for gender, mother's education, and child ethnicity.

words, one standard deviation (24.6%) increase in maths score, for instance, is associated with a 13% and 7% increase in graduating from high school or joining college, respectively. Given the standard deviation in maths score (21.5%) in our analytical sample, we can conjecture that exposed children would have a 6%

and 3.2% lower probability of graduating from high school or joining college, respectively. We have to be cautious in interpreting these results as they are predicted from correlations rather than causal relationships between maths and long-term schooling outcomes. The predicted effects of the exposure on graduating from high school or joining college are likely to be upper bound estimates.

3.2 Exposure in utero, by trimester

We further investigate the effect of food insecurity exposure on cognitive development by pregnancy trimester. Table 5 presents the estimated effects of food insecurity exposure in each trimester on maths achievements score. Similar to Table 3, we find significant and negative effects of the exposure only at age 12. Though the effects from exposure to all stages of gestation are negative and significant, the coefficients in the first and second trimesters are bigger in size. In other words, consistently with the 'critical period' hypothesis, the detrimental consequences of seasonal food insecurity in utero on cognitive development are stronger from exposures in early stages of pregnancy (first and second trimesters of gestation). Specifically, an extra month exposure in food insecurity during the first trimester decreases the maths measure at age 12 by about 0.15 standard deviations. One month exposure in the second trimester reduces the maths score at age 12 by 0.147 standard deviations. The difference between the effects from exposure in the first trimester and the second trimester is small/insignificant. One month exposure in the third trimester reduces the maths score at age 12 by 0.10 standard deviations. The stronger effect during the first and second trimester confirms the importance of the early stage of pregnancy for child development (Almond et al., 2015).[8]

Table 5: Estimated effect of in utero food insecurity exposure, by trimester

Dep. variable: Maths achievement score	(1) age 8	(2) age 8	(3) age 12	(4) age 12
First Trimester	0.011	-0.014	-0.122***	-0.151***
	(0.027)	(0.024)	(0.031)	(0.036)
Second Trimester	-0.032	-0.037	-0.135***	-0.147***
	(0.022)	(0.024)	(0.031)	(0.040)
Third Trimester	0.014	-0.002	-0.083*	-0.109*
	(0.036)	(0.033)	(0.047)	(0.054)
Observations	1,458	1,438	1,458	1,438
R-squared	0.391	0.432	0.302	0.353
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable across columns is age standardized maths score at age eight and twelve. The variable of interest captures prenatal exposure to seasonal food insecurity (exposure at trimester level). Controls include (X): age of child in months, household wealth index, number of older siblings, and dummies for gender, gender of household head, mother's education, child ethnicity, prematurity. We restrict the sample to children for which we observe the outcomes of interest at all age (round) stages.

[8]Detailed results of Table 5 including control variables are provided in columns (3) and (4) of Table D.1 of Appendix D.

3.3 Heterogeneity analysis

To shed light on gender imbalances in the response of cognitive developments to food insecurity, we estimate Equation (1) on two separate samples, 753 boys and 685 girls. In Table 6, we find strong evidence for a differentiated effect of seasonal food insecurity in utero on boys' and girls' maths scores. At age 12, we find negative and significant effects both on boys' and girls' maths scores. However, at age 8, though we find negative and significant effect on boys' outcome, the effect is insignificant on girls. The effect is much stronger on boys' maths scores than on girls ones.

Table 6: Heterogeneous effect of in utero food insecurity exposure, by gender

Dep. variable: Maths achievement score				
	Boys		Girls	
	(1)	(2)	(3)	(4)
	age 8	age 12	age 8	age 12
Exposure	-0.088*	-0.215***	0.031	-0.087*
	(0.044)	(0.061)	(0.036)	(0.044)
Observations	753	753	685	685
R-squared	0.429	0.362	0.475	0.392
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable across columns is age standardized maths score at age 8 and 12. The variable of interest captures prenatal exposure to seasonal food insecurity measures (full 9 months exposure). Controls include (X): age of child in months, household wealth index, number of older siblings, and dummies for gender, gender of household head, mother's education, child ethnicity, prematurity. We restrict the sample to children for which we observe the outcomes of interest at all age (round) stages.

4 Threats to Identification

The above results rely on a number of identifying assumptions and specification choices. We therefore examine how our results may be threatened by (1) mortality selection; (2) fertility selection, (3) reporting errors (4) the existence of other mechanisms; (5) attrition and missing data; and (6) alternative computation of standard errors.

Mortality selection. Our sample only includes surviving children. Although our prenatal shock is of mild (and frequent) nature, we cannot exclude that mortality in utero would drive our estimates towards zero. Surviving children may indeed appear to be the strongest, the healthiest, and those with better genes. Similarly, the gender-based analysis could be biased due to differentiated mortality risk for boys and girls. The medical research indeed documents that boys fetuses are more vulnerable to shocks and at greater mortality risk than female fetuses (Eriksson et al., 2010; Kraemer, 2000). Empirical studies also document how negative prenatal exposure could alter sex composition at birth (Van Ewijk, 2011; Almond and Mazumder, 2011; Dagnelie et al., 2014).

We cannot directly test the effect of the exposure on prenatal death differential between boys and girls.

Table 7: Effect of exposure on the probability of the child surveyed is male

	Dep. variable: Dummy indicating child being a male	
	(1)	(2)
	Male	Male
Exposure	0.014	
	(0.013)	
First Trimester		0.028
		(0.026)
Second Trimester		0.011
		(0.013)
Third Trimester		0.006
		(0.023)
Observations	1,875	1,875
R-squared	0.019	0.019
Community FE	Yes	Yes
Birth Month FE	Yes	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is dummy indicating child being a male. The main independent variable is prenatal exposure to seasonal food scarcity (exposure in whole nine months in column 1 and exposure by trimester in column 2).

We do not have information about miscarriages and prenatal deaths. However, following Van Ewijk (2011), we test the role of selection by estimating the exposure effect on probability of being a male at round 1 (age 1). We do not find strong evidence for mortality selection. Food insecurity shocks in utero do not seem to translate into changes in the sex ratio at age 1. According to Table 7, exposure to seasonal food insecurity both during full pregnancy (column 1) and at trimester level (column 2) do not affect sex ratios at age 1. So, the causal interpretation of our main results is not threatened by mortality selection in utero.

Fertility selection. Another threat for our identification is related to the fertility decisions made by parents. For instance, Do and Phung (2010) find that parents may give birth during good years and these planned children tend to have more years of schooling. In our case, parents may end up investing more in

Table 8: Relationship between prenatal days of exposure and indicator of baby is desired

	Dep variable: Days Exposure			
	(1)	(2)	(3)	(4)
	Full 9 months	1st Trimester	2nd Trimester	3rd Trimester
Unplanned	0.732	0.521	0.946	-0.733
	(0.964)	(0.748)	(0.760)	(0.581)
Observations	1,761	1,761	1,761	1,761
R-squared	0.844	0.711	0.763	0.703
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are days of exposure to seasonal food insecurity during full gestation and by trimester. The main independent variable is an indicator whether the baby is desired. Controls include (X): age of child in months, household wealth index, number of older siblings, and dummies for gender, gender of household head, mother's education, child ethnicities, prematurity.

children whose birth was planned during less food insecure periods. Therefore, our result might not be due to exposure to food insecurity but to unplanned pregnancies in bad times. Given that about 37% of pregnancies in our sample were unplanned, this may be a non-trivial issue. Similar to Lokshin and Radyakin (2012) and Miller (2015), we therefore investigate whether the unplanned pregnancies in our sample are correlated with our exposure to food insecurity. We estimate the effect of being "unplanned" (an indicator that takes value of one if the pregnancy was reportedly unwanted) on the number of food insecure days one faced in utero. A positive and significant coefficient of "unplanned" with large magnitude would imply unplanned pregnancies experience more exposure days in utero. Table 8 indicates that there is no significant relationship between the two, which suggests no concentration of unplanned pregnancies in food insecure times. So, fertility selection problem does not threaten the causal interpretation of our results.

Reporting errors. Our estimates assume that within a month the timing of birth can be considered as random. One concern may be that dates of birth are reported with errors and such reporting errors would be correlated with household socio-economic characteristics. We do not have any prior on the direction of the resulting bias. To explore the importance of the issue, we estimate the probability of being born in a particular week of a month as a function of mother education and household wealth. Our dependent variable birth week has unordered structure of four responses. The appropriate model to estimate the relationship between birth week and household characteristics is a multinomial logit (MNL) model. We also estimated the relationship using a multinomial probit (MNP) model for the sake of comparison. In Table 9, we present results from multinomial logit regression (columns 1-3) and multinomial probit regression (columns 4-6) by defining four possible outcomes depending on the week of a month a child is born. We do not find any evidence that being born at the beginning or at the end of a month is correlated with socio-economic characteristics.

Table 9: Relationship between household characteristics and probability of being born in a certain week

Dep. variable: Probability of being born in a certain week of a month						
	MLogit			MProbit		
	(1)	(2)	(3)	(4)	(5)	(6)
	1st week	3rd week	4rth week	1st week	3rd week	4rth week
Wealth round 1	0.623	-0.017	0.426	0.419	-0.020	0.305
	(0.555)	(0.512)	(0.477)	(0.388)	(0.371)	(0.357)
Mom educ. (1 to 4 years)	-0.199	0.028	0.206	-0.131	0.018	0.157
	(0.227)	(0.201)	(0.191)	(0.158)	(0.147)	(0.143)
Mom educ. (5 to 8 years)	-0.149	0.012	0.021	-0.096	0.014	0.016
	(0.237)	(0.218)	(0.206)	(0.166)	(0.159)	(0.154)
Mom educ. (>8 years)	-0.133	-0.125	0.211	-0.078	-0.076	0.169
	(0.319)	(0.311)	(0.279)	(0.226)	(0.222)	(0.209)
Controls	Yes			Yes		
Observations	1,846			1,846		
Log-likelihood value	-2512.82			-2512.8724		

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.The first three columns indicate estimation based on multinomial logit regression and the last three are from multinomial probit estimation. The dependent variable across columns is the probability of being born in the first, second, third or fourth week of a certain month. The second week is left as a base/reference. The variables of interest are household and mother socio-economic characteristics: education of the mother and household wealth. We also controlled for number of older siblings, and set of dummies for gender, child ethnicity, and prematurity.

Other mechanisms. Our results may be driven by omitted factors that vary by month and community. We see two possibilities, either exposure to more and harder work during pregnancy, or the occurrence of Ramadan. The first concern is that mothers may engage in more physically demanding work during their pregnancy period. This may impact on more calories burned, which could in turn affects child development in utero (Miller, 2015; Strand et al., 2011). The concern is that pregnancies may coincide with seasonal variation in labour demand/supply. Labour demand/supply is seasonal in Ethiopia due to the nature of seasonality of agricultural production. The causal impact on cognitive development might be due to an increase in work requirements and the resulting stress that coincides with food insecure times rather than the direct effect of food insecurity exposure. To assess the importance of this alternative mechanism, we estimate the main specification, augmented with a proxy for exposure to work during pregnancy.[9] Column (1) and (2) of Table 10 show that work exposure does not have a significant impact on cognitive development. The inclusion of this auxiliary variable does not alter the main coefficient of interest, capturing the impact of seasonal food insecurity.

Table 10: Controlling for Work and Ramadan exposures

Dep. variable: Maths achievement score				
	Work exposure		Ramadan exposure	
	(1)	(2)	(3)	(4)
	age 8	age 12	age 8	age 12
Exposure	-0.029	-0.145***	-0.023	-0.140***
	(0.019)	(0.033)	(0.020)	(0.034)
Work Exposure	-0.026	-0.020		
	(0.024)	(0.020)		
Ramadan X Muslim			-0.106	0.036
			(0.100)	(0.115)
Observations	1,438	1,438	1,438	1,438
R-squared	0.432	0.353	0.433	0.356
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable across columns is age standardized maths scores at age 8 and 12. The variables of interest are prenatal exposure to seasonal food insecurity and work (in Panel A) exposure to food insecurity and Ramadan (in Panel B). In panel B we also controlled for Muslim and Ramadan exposure dummies. Controls include (X): age of child in months, household wealth index, number of older siblings, and dummies for gender, gender of household head, mother's education, child ethnicity, prematurity. We restrict the sample to children for which we observe the outcomes of interest at all age (round) stages.

Second, the literature tends to show that Ramadan has detrimental effects on academic test scores (Almond et al., 2015; Majid, 2015). If the observance of Ramadan coincides with food insecure months, our results may be explained by a higher proportion of Ramadan-exposed Muslim pregnancies during times of relative food scarcity as opposed to the exposure to seasonal food insecurity. Given the fact about 14% of children in our analytical sample are originating from Muslim households, the issue cannot be overlooked. We assess the importance of that channel by augmenting the model with a Ramadan effect. Columns (3) and

[9] We use the following question to construct exposure to work in utero: "In which months of the year is there relatively more work to do?" In utero work exposure is constructed in a similar way to that of exposure to food insecurity.

(4) of Table 10 report the results that include effects of Ramadan on the test scores. The main coefficient of interest remains virtually unchanged even after controlling for Ramadan effects.

Attrition and missing data. Attrition appears to be small in our sample. The attrition on the younger cohort between round 1 and round 4 is 2.2%.[10] Missing data with respect to our measures of cognitive developments is a larger concern, especially in round 4 (at age 12). In round 4, 13% of children have missing information on maths outcome. If the probability of having missing information is correlated with our exposure measure, our results might be biased. Moreover, the significant result that we found at age 12 might be driven by missing information on the outcome variable. In particular, if strongest children are missing (have missing outcome) by age 12 and that is systematically correlated with our exposure measure, the estimated coefficients would be biased upwards. We therefore assess how the probability to have missing data on maths score is related to exposure and an interaction term between exposure and the child health-as a measure of child's strength (height at the first round of the survey is used as a proxy). Table 11 reveals no significant correlations. Moreover, our results of the effect of exposure on maths outcome are based on a longitudinal sample where the same children are considered in all rounds. Nonetheless, not imposing such a sample restriction does not alter our main results (Tables D.2 in the Appendix D).

Table 11: Correlation between exposure and probability of missing

	Dep. variable: probability of missing in maths			
	(1)	(2)	(3)	(4)
	miss 8	miss 12	miss 8	miss 12
Exposure	-0.002	0.003	-0.016	-0.065
	(0.012)	(0.010)	(0.049)	(0.065)
Height Round 1 * Exposure			0.000	0.001
			(0.001)	(0.001)
Observations	1,875	1,875	1,825	1,825
R-squared	0.044	0.162	0.048	0.175
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable across columns is a dummy variable that shows whether the particular outcome is missing at that specific age (round). The independent variables are prenatal exposure to seasonal food scarcity measures and an interaction of round 1 height and the exposure measure.

Alternative Standard errors. According to Angrist and Pischke (2009), the computation of clustered standard errors with a low number of clusters might produce incorrect standard errors. In Table 12, our main results are shown to be robust(except for the third trimester result, which becomes insignificant) to the computation of standard errors clustered at the community level, based on wild cluster bootstrap-t procedure proposed by Cameron et al. (2008) and Cameron and Miller (2015).

[10] See http://www.younglives.org.uk/content/sampling-and-attrition and also Barnett et al. (2013).

Table 12: Wild cluster bootstrap-t procedure

Dep. variable: Mathematics achievement score				
	Full 9 months		By Trimester	
	(1)	(2)	(3)	(4)
	age 8	age 12	age 8	age 12
Exposure	-0.023	-0.136***		
	(0.21)	(0.00)		
First Trimester			-0.011	-0.148***
			(0.61)	(0.00)
Second Trimester			-0.035	-0.142***
			(0.11)	(0.00)
Third Trimester			-0.004	-0.106
			(0.88)	(0.10)
Observations	1438	1438	1438	1438
R-squared	0.070	0.067	0.071	0.068
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yess

P-values are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5 Conclusions

We examine the effect of in utero seasonal food insecurity on childhood cognitive development. We exploit a unique data set from the Young Lives Ethiopia. We estimate the effect of variation in the number of days to prenatal food insecurity exposure on cognitive development outcomes by controlling for community and birth month fixed effects together with and child and household characteristics using OLS. We find that at age 12, cognitive development is strongly and adversely affected by in utero exposure to seasonal food insecurity. We also find negative yet insignificant effect at age 8. At age 12, a month increase in prenatal food insecurity exposure reduces quantitative (maths) achievements scores by 0.14 standard deviations. Based on the average number of months a child in our sample faces food insecurity in utero (3.74 months), we estimated that on average the exposure results in a loss of 0.52 standard deviations in maths achievements score. The effects from exposure during the first and second trimesters of gestation are particularly robust and large.

Such detrimental impact is likely to have long-term consequences on socio-economic outcomes. Policy interventions that address seasonal food insecurity and programs that target pregnant women to enhance their resilience to seasonal food shortages could protect the development of children and minimize the long-term economic cost. Social safety nets or cash transfer programs together with nutrition and micronutrient supplementation programs are the obvious policy options. In Ethiopia, starting from 2005, the Productive Safety Net Programme (PSNP) targets to address seasonal food insecurity. Unfortunately, our data do not allow us to investigate the mitigating effect of the PSNP since the sample children were in utero between 2000 and 2002 before the implementation of the PSNP. Understanding how specific programs build resilience to seasonal food insecurity is a path for future research.

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Separate Appendixes with Supplemental Material for:

In utero seasonal food insecurity and cognitive development: Evidence from Ethiopia

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March 2, 2017

Abstract

This document contains a set of appendixes with supplemental material.

Keywords: Food Insecurity; Ethiopia; In utero; Cognitive Development.

JEL Classification: I15; O13; O15

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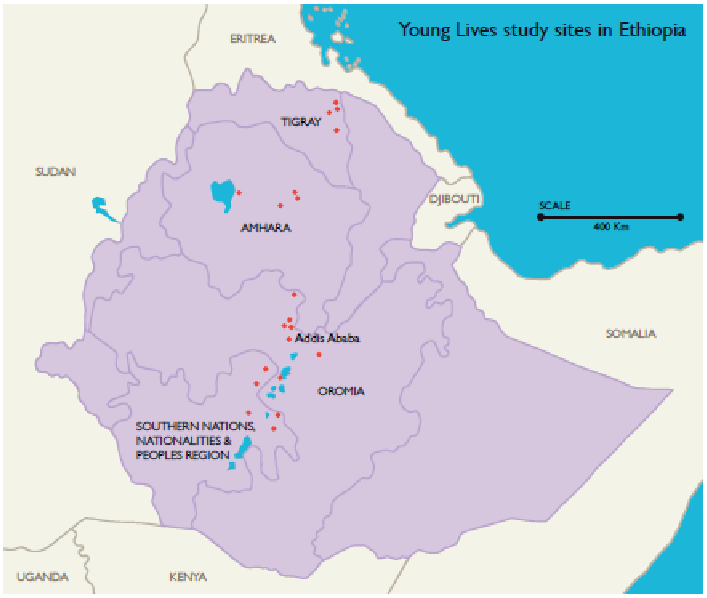
Appendix A Young Lives cohorts and Study Area

FIGURE A.1. Young Lives study sites in Ethiopia



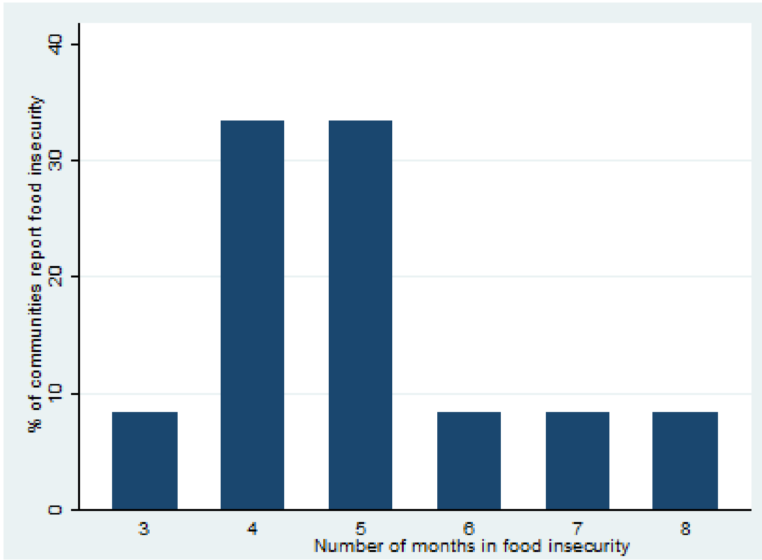
Source: (http://www.younglives.org.uk/content/sampling-and-attrition)

FIGURE A.2. Young Lives longitudinal cohort

Source:(http://www.younglives.org.uk/content/sampling-and-attrition)

Appendix B Intensity of food insecurity

Figure B.1. Number of Reported Months of Seasonal Food Insecurity

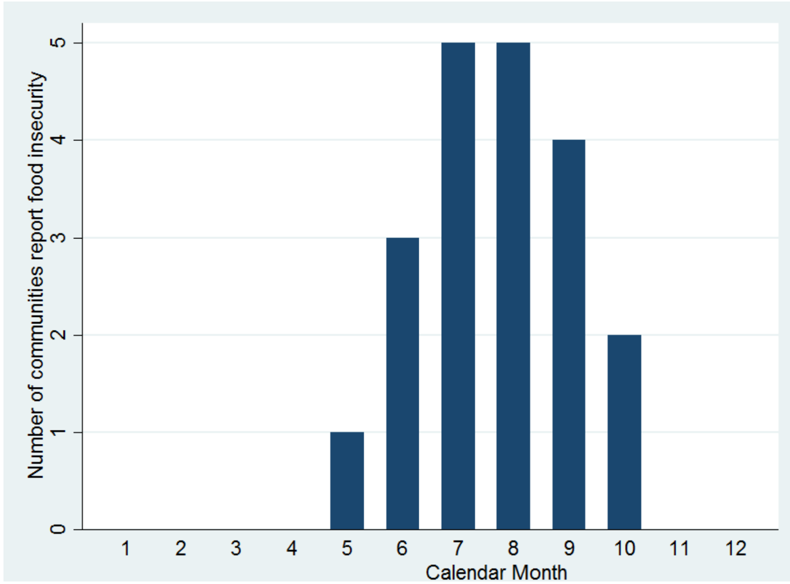


Source: Authors' calculations using data from Young Lives Study, Ethiopia

Appendix C Do the food insecurity data reflect the time the children were in utero?

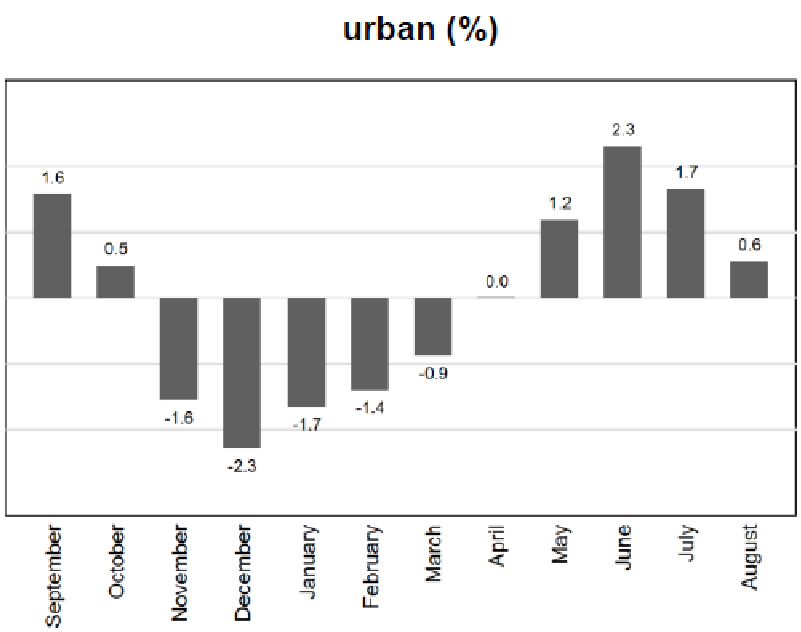
Children in our sample were born between May 2001 and May 2002. They must have been in utero between 2000 and 2002. The seasonal variation in food insecurity is defined from 2006 data. This gap may be a concern. However price data (Figures C.2 and C.3) confirm the repeated nature of the seasonal pattern in the country. To be more precise, Figure C.4 shows monthly price data from FAO (2004) for Addis Ababa of the four major grains harvested in Ethiopia from July 2000 to October 2003. It shows higher prices from May to October and lower from November to April. By comparing and contrasting the price information with food insecurity data for Addis Ababa (Figure C.1 shows communities in Addis Ababa report relative food insecurity from May to October), one can conclude that the food insecurity information reported by communities corresponds to the time in which the children were in utero.

FIGURE C.1. Reported Seasonal Food Insecurity by Calendar Month, Addis Ababa



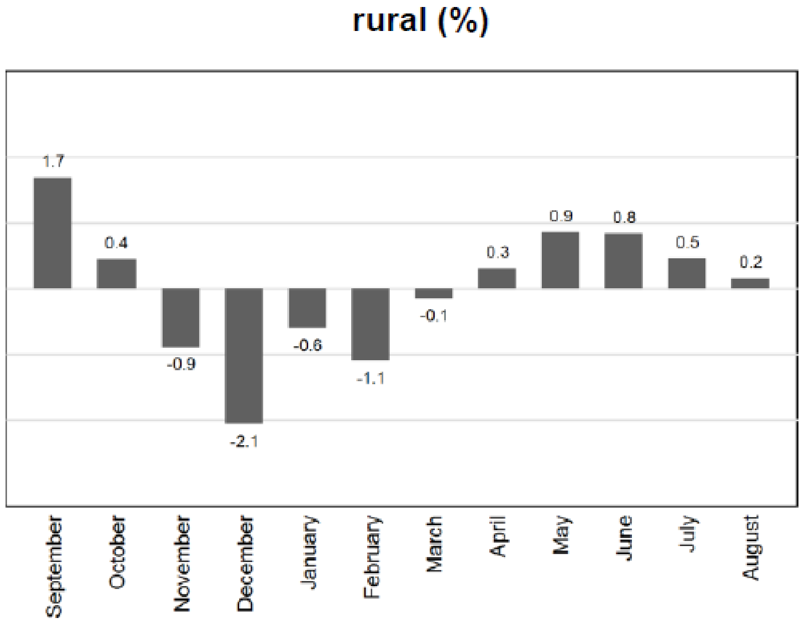
Source: Authors' calculations using data from Young Lives Study, Ethiopia

FIGURE C.2. Monthly food price changes in Ethiopia, percentage deviation from annual average, urban



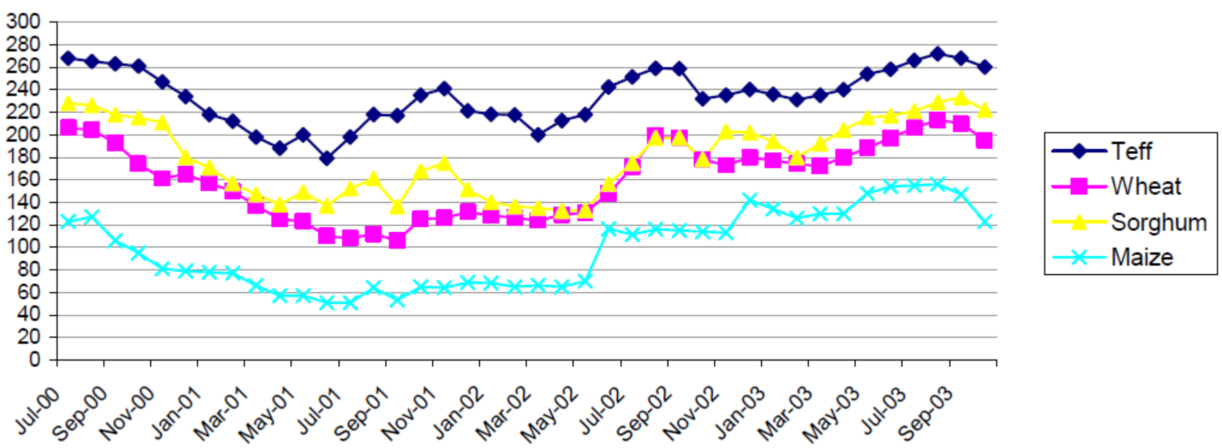
Source:Hirvonen et al. (2016). Notes: It is calculated from Central statistical Authority of Ethiopia price data spanning 2002-2011. Price deviations reflect the average monthly departures from the annual mean of the seasonal food price index.

Figure C.3. Monthly food price changes in Ethiopia, percentage deviation from annual average, rural



Source:Hirvonen et al. (2016). Notes: It is calculated from Central statistical Authority of Ethiopia price data spanning 2002-2011. Price deviations reflect the average monthly departures from the annual mean of the seasonal food price index.

Figure C.4. Monthly Average Prices of Main Cereals, Addis Ababa



Source:FAO (2004)

Appendix D Supplementary Tables

Table D.1: Estimated Effect of In-Utero food insecurity exposure, with controls

	Dep. variable: Maths achievement score			
	Full 9 months		By Trimester	
	(1)	(2)	(3)	(4)
	age 8	age 12	age 8	age 12
Exposure	-0.023	-0.140***		
	(0.019)	(0.034)		
First Trimester			-0.014	-0.151***
			(0.024)	(0.036)
Second Trimester			-0.037	-0.147***
			(0.024)	(0.040)
Third Trimester			-0.002	-0.109*
			(0.033)	(0.054)
Age round 3	-0.019*		-0.019*	
	(0.010)		(0.010)	
Child is boy	-0.001	-0.015	-0.001	-0.015
	(0.048)	(0.049)	(0.048)	(0.049)
Female headed	-0.186***	-0.236***	-0.185***	-0.236***
	(0.062)	(0.046)	(0.063)	(0.047)
Wealth round 1	1.287***	1.214***	1.288***	1.210***
	(0.235)	(0.218)	(0.233)	(0.217)
Number of older siblings	0.001	0.002	0.002	0.002
	(0.012)	(0.011)	(0.012)	(0.011)
Mom educ. (1 to 4 years)	0.103	0.145	0.102	0.145
	(0.091)	(0.113)	(0.091)	(0.113)
Mom educ. (5 to 8 years)	0.244***	0.207***	0.241***	0.206***
	(0.084)	(0.066)	(0.084)	(0.067)
Mom educ. (>8 years)	0.400***	0.449***	0.398***	0.450***
	(0.095)	(0.079)	(0.094)	(0.080)
Premature	-0.083	-0.120*	-0.076	-0.111*
	(0.063)	(0.061)	(0.063)	(0.062)
Tigrian	0.075	0.159	0.074	0.158
	(0.207)	(0.114)	(0.209)	(0.114)
Oromo	-0.078	-0.012	-0.079	-0.015
	(0.129)	(0.105)	(0.130)	(0.102)
Gurage	0.146	0.310***	0.142	0.302***
	(0.270)	(0.079)	(0.267)	(0.077)
Wolayta	-0.216	-0.361***	-0.218	-0.356***
	(0.132)	(0.103)	(0.136)	(0.107)
Other	-0.017	0.103	-0.014	0.107
	(0.175)	(0.110)	(0.177)	(0.112)
Age round 4		-0.007		-0.008
		(0.009)		(0.009)
Observations	1,438	1,438	1,438	1,438
R-squared	0.432	0.353	0.432	0.353
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Result without restriction on sample

	Dep. variable: Maths achievement score			
	Full 9 months		By Trimester	
	(1)	(2)	(3)	(4)
	age 8	age 12	age 8	age 12
Exposure	-0.025	-0.111***		
	(0.016)	(0.029)		
First Trimester			-0.026	-0.116***
			(0.026)	(0.030)
Second Trimester			-0.030	-0.118**
			(0.023)	(0.042)
Third Trimester			-0.011	-0.087*
			(0.032)	(0.043)
Age round 3	-0.024**		-0.024**	
	(0.010)		(0.010)	
Child is boy	0.010	-0.026	0.010	-0.026
	(0.047)	(0.046)	(0.047)	(0.046)
Female headed	-0.204***	-0.249***	-0.205***	-0.249***
	(0.055)	(0.047)	(0.055)	(0.048)
Wealth round 1	1.202***	1.237***	1.202***	1.236***
	(0.197)	(0.225)	(0.197)	(0.223)
Number of older siblings	0.005	0.001	0.005	0.001
	(0.011)	(0.011)	(0.011)	(0.011)
Mom educ. (1 to 4 years)	0.093	0.148	0.093	0.147
	(0.080)	(0.110)	(0.080)	(0.110)
Mom educ. (5 to 8 years)	0.240***	0.221***	0.239***	0.220***
	(0.075)	(0.067)	(0.075)	(0.068)
Mom educ. (>8 years)	0.402***	0.449***	0.401***	0.449***
	(0.082)	(0.075)	(0.081)	(0.075)
Premature	-0.080	-0.127**	-0.075	-0.120*
	(0.052)	(0.060)	(0.052)	(0.060)
Tigrian	0.118	0.076	0.117	0.073
	(0.181)	(0.121)	(0.181)	(0.119)
Oromo	-0.075	-0.021	-0.076	-0.023
	(0.119)	(0.100)	(0.120)	(0.097)
Gurage	0.121	0.254***	0.117	0.247***
	(0.240)	(0.079)	(0.237)	(0.077)
Wolayta	-0.316***	-0.236	-0.317***	-0.233
	(0.104)	(0.140)	(0.103)	(0.143)
Other	-0.054	0.122	-0.053	0.124
	(0.146)	(0.113)	(0.147)	(0.113)
Age round 4		-0.007		-0.007
		(0.009)		(0.009)
Observations	1,674	1,483	1,674	1,483
R-squared	0.457	0.353	0.457	0.353
Community FE	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes

Robust standard errors (clustered at the community level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.