Inter-generational Effects of Early Childhood Shocks on Human Capital: Evidence from Ethiopia

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Abstract

In this paper I investigate the impacts of parental early childhood shocks on the human capital of children using various measures of health capabilities, schooling achievements, and standardized math and Peabody Picture Vocabulary Test (PPVT) test scores. I use parents' age during the 1983-85 Ethiopian famine, geographic variation of the famine, and the duration of exposure to identify effects. This paper uses the Ethiopia Young Lives panel survey of children who were tracked from the age of 6-18 months over an 11 year period. I find that children born to mothers who were exposed to the famine in their first 3 years have poor health endowments, lower schooling achievement and perform poorly in standardized tests.

Key words: Intergenerational shocks, Famine, Human capital, Ethiopia

JEL Codes: D03, O12, Y40

1 Introduction

Environments during the prenatal period and later in childhood can have significant effects on later life outcomes (Currie, 2011; Almond, 2006; Almond, Chay, & Lee, 2005). The impact of early adverse exposure may transcend the generation that was directly exposed to the shocks and impact their offspring (Almond, Edlund, Li, & Zhang, 2010; Meng & Qian, 2009; Chen & Zhou, 2007). The existing literature primarily focuses on maternal malnutrition as the main pathway through which these impacts are transmitted from parents to children. Nutritional disruptions and associated adaptive biochemical changes can lead to diminished cognitive and non-cognitive outcomes for the child. Other less well understood mechanisms include parental psycho-emotional responses to severe shock experiences such as changes in parents' occupational and educational aspirations for their children, and preferences for marriage age.

This study is motivated by a growing body of literature in epidemiology and economics documenting that adverse exposure to shocks during prenatal and perinatal periods (Currie, 2011; Currie & Almond, 2011; Almond et al., 2005; Gluckman & Hanson, 2004; Barker, 1995, 1990) and at various stages of the postnatal period (Shah & Steinberg, 2013) has critical implications for later life outcomes. Because unobserved individual and family characteristics may confound differences in early childhood environments, recent studies rely on natural experiments to identify the impacts of early life environment on health, schooling and labor market outcomes (Dercon and Porter (2014); Rosales (2014); Currie and Rossin-Slater (2013); Shah and Steinberg (2013); Akresh, Bhalotra, Leone, and Osili (2012); Scholte, Van den Berg, and Lindeboom (2012); Kelly (2011); Almond et al. (2010); Meng and Qian (2009); Alderman, Hoddinott, and Kinsey (2006); Almond (2006)).

Studies of the effects of early childhood shocks have mainly focused on individuals who were directly exposed to shocks. Surprisingly, there is little work on the intergenerational transmission of shocks. Significant disruptions *in utero* and during the first few years after birth may leave deep scars that may last generations because events during these critical periods may delay or retard the expression of parts of the genome that are crucial for cognitive and motor functions (Petronis, 2010). Maternal malnutrition, for example, can lead to ill-health of her offspring, both as children and as adults (Osmani & Sen, 2003). Trajectories taken during early periods of developmental plasticity in response to environmental influences "set parameters for the adult individual; for instance, her height, which means that maternal

constraints affect not only her children, but also her daughters' children" (Almond et al., 2010, p. 341).

Previous studies on intergenerational effects of childhood shocks find that parental adverse childhood experience has a negative impact on child outcomes. There is, however, little evidence on whether the timing of parents' exposure to the shock matters. Understanding the sensitive periods to shock is essential for a more efficient targeting of vulnerable groups during shocks. Further, there is little evidence on whether exposure to shocks of certain durations is more damaging than others. This is crucial for identifying groups who are in need the most, and channeling resources accordingly. I address these concerns in this paper. First, I use whether a parent was born during the 1983-1985 Ethiopian famine to identify the average effect of childhood famine exposure on human capital outcomes of her offspring. Second, I use parental birth year to investigate whether exposure at certain period matter more than at others. Finally, I use the number of months with significant rainfall deficit to identify critical famine duration thresholds.

The great Ethiopian famine is believed to have caused the death of hundreds of thousands of people. Rains failed in most of the country in successive cropping seasons in 1983-85, with northern parts of the country (Tigray and Amhara regions) more severely hit. Central highlands and western parts of the country were largely spared. I exploit this uneven geographic distribution of the famine and parents' age during the famine to identify the impacts of the famine on the human capital of children at different stages in their lives.

This paper contributes to two sets of literature. First, it contributes to the early developments literature by extending the study of the impacts of adverse early childhood exposure on late childhood and early adulthood outcomes to intergenerational transmissions of exposure to severe shocks (Currie & Almond, 2011; Currie, 2011; Heckman, 2007; Cunha & Heckman, 2007). Second, this paper will provide a test of intergenerational persistence of poverty. The effects of childhood shocks experienced by a parent may persist into her offspring. The results of this paper will provide suggestive evidence (or lack of) for poverty persistence. Third, it will provide a test for the potential (or lack of) for gradual recovery from the effects of early disadvantages using panel data over a 14 year period.

2 Background

Ethiopia has a long history with famine and severe droughts, the 1983-1985 famine being the worst in recent history.[1] Estimates of the number of people killed range between 400,000 and over a million. Devereux (2000) estimates that between 600,000 and one million people were killed due to the famine. De Waal (1991) rather puts the figure closer to 400,000, though he notes that this is likely to be a lower bound. Kidane (1990) argues the true figure of the casualties of the famine is 700,000. Despite the differences in the estimates of famine casualties, it is clear that the last in a long list of famine episodes in Ethiopia has had a devastating impact. Indeed, Ó Gráda (2007) notes that in terms of the number of deaths relative to the Ethiopian population of the time, the 1983-1985 famine ranks as one of the worst in the world in recent history. While most of the country was affected, the epicenter of the famine was in the northern provinces of Tigray, Wello, and Eritrea (De Waal, 1991).

2.1 Ethiopian 1983-1985 Famine

The famine started mid-1983 when *meher* (main planting season in Ethiopia) rains failed[2]. The first signs of famine began to emerge in February 1983 with inflow of malnourished people into relief centers. Widespread famine first occurred in Tigray and Wello, and it quickly spread to the rest of the country when the 1984 *belg* rains failed in the *belg* growing highland areas in central Ethiopia (De Waal, 1991). The drought condition continued in *meher* 1984 through *belg* 1985. The famine was most severe in 1984. Using historical rainfall data for the 1961-1999 period for the Meher season, Segele and Lamb (2005) show that 1984 was by far the driest year[3]. Low pre-*meher* rains were followed by early onset of *meher* rains, which quickly dried up. The extended dry spell led to a very short effective growing season and widespread crop failures throughout the country. The famine ended with the return of normal *meher* rains in 1985.

[1] For a more complete chronology of droughts and famines in Ethiopia, please see Webb, Von Braun, and Yohannes (1992).

[2] The rainfall patterns in Ethiopia are characterized by bi-modal distribution, with the main rainy season *meher* between July and September and a short rainy season (*belg*) between March and May. The *meher* (also popularly called *kiremt*) rains account for 85-90% of annual agricultural output. The *belg* rains are limited in geographic coverage to the central and eastern highlands of the country.

[3] Using annual rainfall data (including both *meher* and *belg* rains) for the 1961-1987 period, Webb et al. (1992) report similar results. They show 1984 was the driest year for the whole of Ethiopia, as well as the northern provinces of Wello and Tigray, and Hararghe in the east.

The famine condition was further exacerbated by insurgencies and the government's counter-insurgency strategies in northern Ethiopia. To counter the rebel movements, the government had mobilized large military campaigns, which diverted resources from relief efforts. Webb and von Braun (1994) report that in 1984 the government had allocated 46% of the national budget to military spending. Moreover, the government had restricted access to relief aid in rebel controlled areas. People who had been severely weakened by the famine had to be moved out of rebel held areas to relief centers in government controlled areas. While the move to relief centers allowed access to much needed food, poor health facilities and hygiene conditions led to spread of infectious diseases in the centers and the death of thousands. Further, restrictions on movement of people and goods in the northern provinces constrained migration of able bodied individuals to relatively less affected parts of the country in search of employment and limited commercial imports of food from surplus growing areas, compounding the impacts of the famine.

The 0-10 and 60 and above age groups were disproportionately affected by the famine. Kidane (1990) shows that in his sample, about 26% of children under the age of 5 and 14% of children between the age 5 and 10 died during the 1983-1985 famine. Likewise 54% of people in the 60 plus age group perished. In a more nationally representative work, Kidane (1989) cites the Central Statistical Office (1985) which shows the mortality rate for the 0-4 age group to be 32% for males and 28% for females, and for the 5-9 age group, 17% and 19% for males and females, respectively. Similarly, the mortality rate for the 60-64 group was 12% for males and a staggering 52% for females. These figures are even worse for the 65+ group. Though we can't be sure that famine is the sole factor deriving the high mortality, the fact that compared to 1981, the share of 0-14 and 65+ age groups in the population significantly decreased in 1984-1985 suggests that the famine is likely the prime cause of the jump in mortality of these groups (Kidane, 1989).

3 Theoretical Framework

I show the impacts of parental exposure to famine on offspring outcomes based on a dynamic model of human development developed by Heckman (2007); Cunha and Heckman (2007); Cunha, Heckman, and Schennach (2010). Human capital is multidimensional. At any given time t, the human capital vector is given as $\theta_t = (\theta_{c,t}, \theta_{n,t}, \theta_{h,t})$, where θ_c, θ_n, and θ_h are cognitive, non-cognitive/socio-emotional, and health capabilities, respectively. Further, the

formation of capabilities/skills follows a multistage technology in the sense that skills at one stage of the life cycle serve as inputs at a later stage. Investments in skills will, therefore, have lasting effect by increasing the stock of skills, which will be used as inputs in the formation of future skills.

In this framework, early life adverse exposure may have persistent negative impact on outcomes later in life for at least two reasons. First, skills are dynamically self-reinforcing. High cognitive skill in one period leads to higher cognitive skill in a later period, and a higher health capability cross fertilizes (creates conductive environment for acquisition of) cognitive skill. Heckman and co-authors refer to this effect as "self-productivity," and includes own and cross capability effects. Second, shocks reduce the productivity of future investments in human capital, a process called "dynamic complementarity." Shocks to a child's health, for example, will have a negative effect on returns to investment on future learning (Cunha & Heckman, 2007; Cunha et al., 2010).

There are multiple sensitive periods in a child's life that are critical to the development of human capital. Some skills are more readily acquired at one stage than another, and some skill deficits are more malleable at one stage than another. The most important period in a child's development is the period *in utero* (Almond, 2006). Adverse experiences at this stage are known to cause significant damages to birth weight, cognitive ability, later life height and weight, and lead to various diseases (Barker, 1995; Gluckman & Hanson, 2004; Rosales, 2014). Even within the prenatal period, early exposure can have a different impacts than exposure later during pregnancy. Rosales (2014) shows that exposure to shocks during the first two trimesters has adverse effect on cognitive ability, whereas exposure during the third trimester reduces child height.

The fist two-three years after birth are also critical for the formation and shaping of skills that determine later life outcomes. Children who are exposed to shocks during this period tend to perform relatively poorly in school and labor markets (Shah & Steinberg, 2013). Cunha, Heckman, Lochner, and Masterov (2006) find similar results in a randomized evaluation of the Abecedarian program in the US. They find significant cognitive and non-cognitive gains for children who enrolled in the program earlier, but not for those who only experienced the intervention later. Even later years in childhood (10-12) can be crucial to the development of human capability. Newport (1990) finds negative relationship between age of acquisition of primary and secondary languages and language proficiency, with the relationship flattening out around the age of 12. Likewise, the fact that IQ scores tend to stabilize around age

10 (Schuerger & Witt, 1989) suggests that the critical period for acquisition of cognitive capability is before age 10. Non-cognitive skills are malleable even after age 20 (Dahl, 2004). Once critical periods are missed, remediation interventions may not reverse the damages already done.

Following Heckman (2007); Cunha and Heckman (2007); Cunha et al. (2010), the technology summarizing the formation of skill $k \in \{c, n, h\}$ is given as:

$$\theta_{k,t+1} = f_k(\theta_t, I_t, \theta_p, \eta_t) \tag{1}$$

where, θ_k, θ_p, I_t, and η_t denote the stock of skill k at time t, parental investments in children at time t, parental endowments, and shocks in time t. f_k is assumed to be monotonically increasing in all of its arguments, twice differentiable, and concave in I. After solving recursively, (1) can be rewritten as:

$$\theta_{k,t+1} = f_k(\theta_0, I_0, I_1, ..., I_t, \theta_p, \eta_0, \eta_1, ..., \eta_t) \tag{2}$$

where θ_0 is initial skills endowment of the child, which is determined by both genetic and environmental factors. Equation (2) shows that the stock of skills at any given time t depends on endowments, investments, and shocks at different stages in the life cycle. Returns on investment is especially higher for disadvantaged children at very early ages. On the contrary, return on investments late in adolescence is very low, since early disadvantages persist through the self productivity and dynamic complementarity processes (Cunha et al., 2006), which brings to fore the potential trade-off between efficiency and equity in the timing of investments.

For ease of exposition, I divide the developmental periods of a child in two: early childhood, including the period *in utero*, denoted period 0; and late childhood, which constitutes the rest of childhood, denoted period 1. Adulthood is denoted period 2. Following Cunha et al. (2010), the process of human capital development can be described by an overlapping generations model, in which each individual lives for three periods $t \in [0, 2]$ in a household consisting of an adult and a child - the first two periods ($t = 0$ and $t = 1$) as a child and

$t = 2$ as a parent. The technology of skill k formation in adulthood is[4]:

$$\theta_{k,2} = f_k(\theta_1, I_1, \theta_p, \eta_1). \tag{3}$$

Since our interest is in childhood outcomes, we focus on the first two periods of the life cycle. Thus, the stock of skills in late childhood can be described by

$$\theta_{k,1} = f_k(\theta_0, I_0, \theta_p, \eta_0). \tag{4}$$

The arguments of (4), θ_0, I_0, and η_0 are all vectors of endowments of, investments in, and shocks on cognitive, non-cognitive, and health capabilities. Parental investments and endowments are endogenous and are affected by shocks. Therefore, parental investment in skill k is given as:

$$I_{k,0} = g_k(\theta_0, \theta_p, \eta_0). \tag{5}$$

Similarly, parental endowments, $\theta_p = \theta_2^p$, where θ_2^p is parents' stock of skills in adulthood depends on parents' childhood capabilities[5], θ_1^p, childhood investments, I_1^p, parental endowment at childhood, θ_p^p, and childhood shocks, η_1^p.

$$\theta_p = q(\theta_1^p, I_1^p, \theta_p^p, \eta_1^p). \tag{6}$$

This framework allows analyzing the effects of shocks suffered by parents in childhood on the human capital stock of their children. For analytical ease, below I use a compact form of the skills vector, which can easily be extended to look at shocks to a specific skill type.[6]

Assuming shocks are uncorrelated over time, formally, the effect of a parent's childhood

[4]For simplicity, I assume that investments and shocks in adulthood have little impact on human capital. This is not a strong assumption. Empirical studies consistently find small/insignificant returns to investment during adolescence [Source: (Heckman, 2007)+].

[5]I follow similar indexing notation for both the child and the parent. To distinguish between generations, I use the index (superscript) parent skills with p and grand parents skills with g.

[6]The effect of a shock to a parent's skill $m \in \{c, nc, h\}$, on a child's capability k can be stated as:

$$\frac{\partial \theta_{k,1}}{\partial \eta_{m,1}^p} = \sum_{l=c,nc,h} \sum_{j=c,nc,h} \frac{\partial \theta_{k,1}}{\partial I_{l,0}} \frac{\partial I_{l,0}}{\partial \theta_{j,p}} \frac{\partial \theta_{j,p}}{\partial \eta_{m,1}^p} + \sum_{j=c,nc,h} \frac{\partial \theta_{k,1}}{\partial \theta_{j,p}} \frac{\partial \theta_{j,p}}{\partial \eta_{m,1}^p}. \tag{7}$$

shock on her offspring can be stated as:

$$\frac{\partial \theta_{k,1}}{\partial \eta_1^p} = \frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p}\frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\frac{\partial \theta_p}{\partial \eta_1^p}. \tag{8}$$

Early childhood investments in parent's capabilities, I_1^p, is endogenous, i.e., $I_1^p = g(\theta_1^p, \theta_p^p, \eta_1^p)$. Thus, $\frac{\partial \theta_p}{\partial \eta_1^p}$ in (8) can be rewritten as:

$$\frac{\partial \theta_p}{\partial \eta_1^p} = \frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \eta_1^p}. \tag{9}$$

Substituting (9) in (8), we find a decomposable impact of parental early shocks on child outcomes as:

$$\begin{aligned}\frac{\partial \theta_{k,1}}{\partial \eta_1^p} &= \left(\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\right)\left(\frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \eta_1^p}\right) \\ &= \underbrace{\frac{\partial \theta_{k,1}}{\partial \theta_p}\frac{\partial \theta_p}{\partial \eta_1^p}}_{\text{Self Productivity}} + \underbrace{\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p}\frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \eta_1^p}}_{\text{Mixed channel}} + \underbrace{\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p}\frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \eta_1^p}}_{\text{Dynamic complementarity}}.\end{aligned} \tag{10}$$

Equation (10) presents a compact solution of the effects of parental shock exposure on a child's human capital k. It includes both direct (effect of a shock to a parent's health in childhood on her child's health) and cross (effect of shocks to a parent's health in childhood on her child's cognitive capabilities) effects (please see Appendix (?)). The first term measures the pure self-productivity effect of parental exposure to adverse shocks. Shocks experienced by a parent reduce the parent's capabilities, which in turn reduce a child's human capital through the "skill begets skill" notion. It is, therefore, expected to be negative. The effects of famine exposure partly results from the fact famine leads to greater health hazards such as communicable diseases[7], and parental mental health problems (Almond & Mazumder, 2011).

The last term in (10) is the pure dynamic complementarity effect. Parents' childhood shock exposure reduces the return on investments in their human capital, which may reduce the

[7] According to some estimates, up to 50,000 people have died due to communicable diseases in feeding and resettlement camps during the 1983-1985 Ethiopian famine. Individuals, especially mothers and children, who were already weakened by food shortages, and thus suffered reduced immunity, perished in the camps due to poor hygiene and poor health services (Gill, 2010).

stock of parents' stock of skills at adulthood. Low parental skills (children's parental endowment), in turn, may lead to low child capabilities. The sign of the dynamic complementarity effect is, however, not straight forward due to complications of competing mechanisms. Even though $\frac{\partial \theta_{k,1}}{\partial I_0}$ and $\frac{\partial \theta p}{\partial I_1^p}$ are both positive, the signs of $\frac{\partial I_{k,0}}{\partial \theta_p}$ and $\frac{\partial I_1^p}{\partial \eta_1^p}$ are ambiguous. First, famine can have general equilibrium wage and relative price effects (Rosales, 2014). A fall in wage rates reduces the opportunity cost of time invested in child care, and conceivably lead to increase in time investments (Shah & Steinberg, 2013). By contrast, a rise in the relative price of food may have a negative real income effect and retard investments on children. Second, the income effect of a fall in agricultural outputs during famines may reduce investments in children for farm households. Moreover, parental remediation of adverse exposures can compensate for the effects of shock if parents invest more in the affected child or reinforce the effect if, rather, investments are directed to the unaffected child to maximize returns. These combine to generate ambiguous dynamic complementarity effect.

The two middle terms in (10) constitute a mixed channel, which emanates from the intergenerational nature of the mechanism deriving the effects of shocks. The second term measures the effect of a parent's childhood shock exposure on her child that is transmitted through the child's indirect investment channel. Since $\frac{\partial \theta_{k,1}}{\partial I_0} > 0$, $\frac{\partial I_0}{\partial \theta_p} > 0$, and $\frac{\partial \theta_p}{\partial \eta_1^p} < 0$, this term is unambiguously negative. The third term captures the effect of parental shock exposure channeled through the child's indirect parental endowment channel. It's sign is, however, ambiguous since $\frac{\partial I_1^p}{\partial \eta_1^p}$ cannot be readily signed, leaving the mixed channel effect ambiguous. Therefore, the theoretical predictions of the impacts of early parental shocks on the human capital of children is not clear.

In this paper I use exogenous exposure to severe famine in Ethiopia in the early 1980s to identify the causal effects of parental early childhood shocks on their children's outcomes. I use rich panel data to estimate the net effects of the famine on cognitive and health outcomes of the children of parents who were exposed. To identify mechanisms, I estimate the effects on child health endowments and household inputs including income, consumption, parental health, and parental socio-emotional variables.

4 Data

In this study, I use age during the 1983-1985 Ethiopian famine and the geographic variation in the intensity of the famine as exogenous sources of variation to identify the causal impacts parental famine exposure on the human capital of children. I use the Ethiopia Young Lives data, which track two cohorts of children, young and old cohort, over an 15 year period. In 2002, a baseline survey was conducted on a sample of 2,000 children born in 2001-2002 (6-18 months old - young cohort (YC)) and of another 1,000 children born in 1994-1995 (7-8 years old - old cohort (OC)) living in 20 sites across Addis Ababa, Amhara, Oromia, Southern Nations and Nationalities Region (SNNPR), and Tigray regions. Follow up surveys were conducted in 2006, 2009, and 2013[8].

The survey has child, household, and community modules. In the household module, data on household composition, parental background, assets, food and non-food consumption, expenditure, social capital, child care, child health and exposure to various shocks were collected. Caregiver perceptions, attitudes and aspirations for child and family were also covered. Data on time use of family members, child weight and height were also collected. The child module, asks children about their attitudes to work and school, perception of how they were treated by others, as well as their hopes and aspirations for the future. Data on children's test scores (language comprehension and math) has been collected beginning in round 2. The community survey provides information on the economic, social, and environmental context of each community. It asks questions on access to various services (such as education, health, electricity, telephone etc.), population, religion, and ethnicity, language, political representation, crimes, environmental changes, and community networks.

The household survey data are matched with weather (rainfall) data. The weather data are from NASA's AgMERRA[9] climate dataset, which provides daily time series over the 1980-2010 period (Elliott et al., 2014; A. Ruane & Goldberg, 2014; A. C. Ruane et al., 2015). The

[8]For this draft I use the first three rounds of the data. The latest (2013) round of the data are scheduled for release in September 2015. I plan to update the paper as the data become available.

[9]AgMERRA stands for Agricultural Modern-Era Retrospective analysis for Research and Applications. The AgMERRA dataset provides daily, high-resolution meteorological time series by combining daily resolution data from retrospective analysis with ground level and remotely-sensed observational datasets for temperature, precipitation and solar radiation. It gives particular consideration to agricultural areas, and agronomic factors that affect plant growth such as mean growing season temperature and precipitation, seasonal cycles, inter-annual variability, the frequency and sequence of rainfall events, and the distribution of sub-seasonal extremes, leading to substantial reduction in bias (A. C. Ruane, Goldberg, & Chryssanthacopoulos, 2015).

dataset are originally provided at 0.25 degree (≈25km×25km) resolution. These data are converted to woreda level rainfall data by applying weights based on the area size of the grid cell relative to the woreda, i.e., percentage of each woreda's area occupied by the grid cell. All grid cells that fully fall within a woreda receive equal weights whereas intersected (grids that fall between two or more woredas) receive smaller weight proportional to area size.

4.1 Measuring Famine Magnitude

To measure the magnitude of the famine in a woreda I compute two measures: the deviation of average rainfall during the 1983-1985 famine period from historical average ($anndev$), and the number of months with rainfall shortage of over one standard deviation ($mondry$). The annual rainfall deviation variable $anndev$ is constructed as:

$$anndev_{w,y} = \frac{rain_{w,y} - \overline{rain}_w}{sdrain_w} \tag{11}$$

where $rain_{w,y}$ is annual precipitation in woreda w in year y in millimeters, ($\overline{rain}_w$) is historical (1980-2010) average of rainfall in woreda w, and $sdrain_w$ is standard deviation of annual rainfall in woreda w over the same 1980-2010 period[10]. While this measure is a good proxy of the depth of the famine, it doesn't fully reflect its breadth. The number of months with significant rainfall shortages during the famine period, addresses this issue.

$$\begin{aligned} mdev_{w,m,y} &= \frac{rain_{w,m,y} - \overline{rain}_{w,m}}{sdrain_{w,m}} \\ mondry_{w,y} &= \sum_{Jan1983}^{Dec1985} 1(mdev_{w,m,y} < -1) \end{aligned} \tag{12}$$

where $mdev_{w,m,y}$ is deviation of woreda w rainfall in the month of m and year y from historical average rainfall for the month measured in standard deviations. The famine measure $mondry_{w,y} \in [0, 36]$ is computed by adding up dummy variables for each month of the 36 month famine period. The dummy variable for a given month m in 1983-1985 takes the value 1 if rainfall for the month was one or more standard deviation below historical average for the month over the 1980-2010 period, excluding 1983-1985, or 0 otherwise. By adding over the 36 months of the famine, we obtain a measure of the breadth of the famine. Given the

[10] To avoid the effect of the outlier famine years, the 1983-1985 period is excluded in computing mean and standard deviation. As a robustness check, I use a measure that includes the 1983-1985 period.

bi-modal nature of rainfall in Ethiopia, I also construct variations of *anndev* and *mondry* for the *meher* and *belg* seasons, which I use as a robustness check.

With over 1100 mm average annual rainfall, Ethiopia is one of the wettest places in Sub-Saharan Africa. Yet, it remains one of the most vulnerable to weather shocks, due mainly to uneven distribution of rainfall and considerable variation over time. Periods of consecutive drought years as in the mid 1980s, cause catastrophic crises. As shown in Figure 1, the Ethiopian 1983-1985 famine was associated with annual precipitation falling below historical average for four years in a row. Rainfall was especially low in 1984, with levels of below 80% of historical average for the whole country.

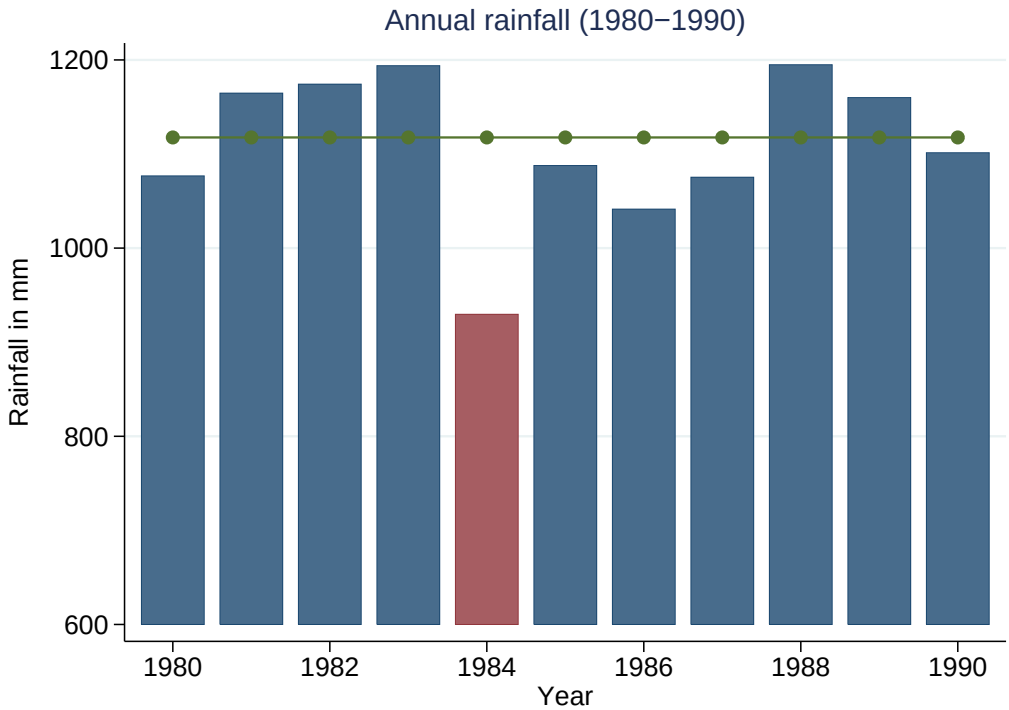

Figure 1: Patterns of annual rainfall in 1980-1990
The bars measure the annual rainfall for each year. For clarity, the bar for 1984 is colored in red. The green horizontal line over the bars shows the historical average rainfall for the 1981-2010 period.

The geographic variation of rainfall is shown in Figure 2. Among the four largest regions of Ethiopia, Oromia and SNNPR get the highest levels of precipitation with over 1200 mm of annual rainfall, whereas Tigray, with just over 600 mm, gets the lowest. In all four regions 1984 had the lowest rainfall level. Even if rainfall levels are lowest in Tigray, to the extent

endogenous adaptation of farming practices and livelihood diversification due to historical experiences of rainfall shortages is possible, resilience to drought may organically emerge. However, volatility of rainfall under these circumstances, as is the case Tigray region, has led to recurrent disasters. The SNNPR also displays considerable rainfall volatility in the 1980-1990 period[11].

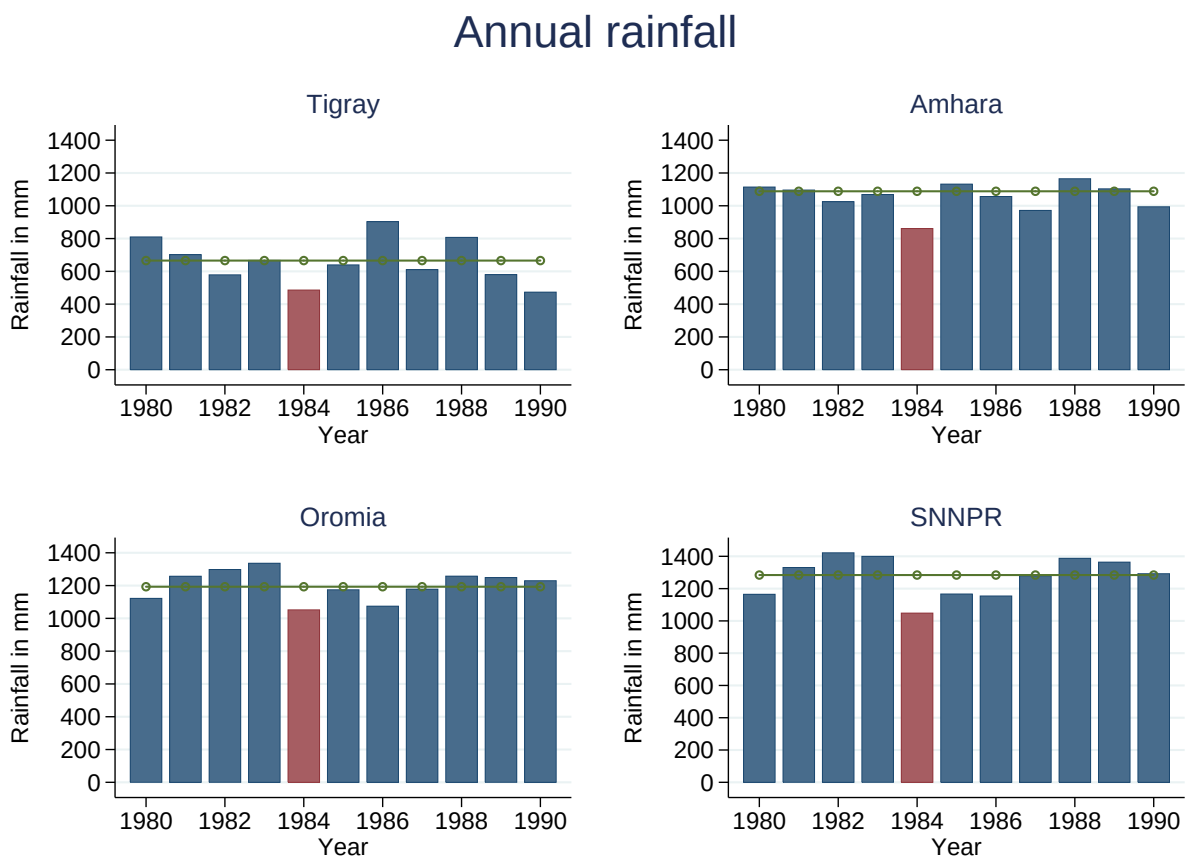

Figure 2: Patterns of annual rainfall in 1980-1990 by Region
The bars measure the annual rainfall for each year. For clarity, the bar for 1984 is colored in red. The green horizontal line over the bars shows the historical average rainfall for the 1981-2010 period.

Figure 3 presents the deviation of the average annual rainfall during 1983-1985 from the historical average. The depth of the famine was greater in the northeastern, southern,

[11]Like Segele and Lamb (2005) and Webb and von Braun (1994), Appendix Figures 6 and 8, show that the year 1984 had the worst *meher* and *belg* rains. The month of August and April, during which *meher* and *belg* rains peak, respectively, had the worst rainfall in recent history (Appendix Figures 7 and 9). Figures 10 - 8 in the Appendix section present the historical trends of rainfall in the four largest regions of Ethiopia for each month. The figures show, in terms of precipitation levels, 1984 was the worst throughout.

and western parts of Ethiopia, which saw rainfall drop of up to 5 standard deviations, on average. The northwestern and central parts of the country were largely spared, with some areas recording higher than normal rainfall. The northern, southern and east-central parts of the country were already getting low rainfall before the famine (Figure 14). Sharp decline in rainfall during the famine in these areas, therefore, had significant effects on peoples' livelihoods. Crop production is the main sources of sustenance in most of Ethiopia. Crop failure due to insufficient rains can have lasting severe consequences. In most of these ares the main source of livelihood is crop production. During the 1983-1985 period, repeat exposure of adverse rainfall events led to livelihood collapse in many parts of Ethiopia[12].

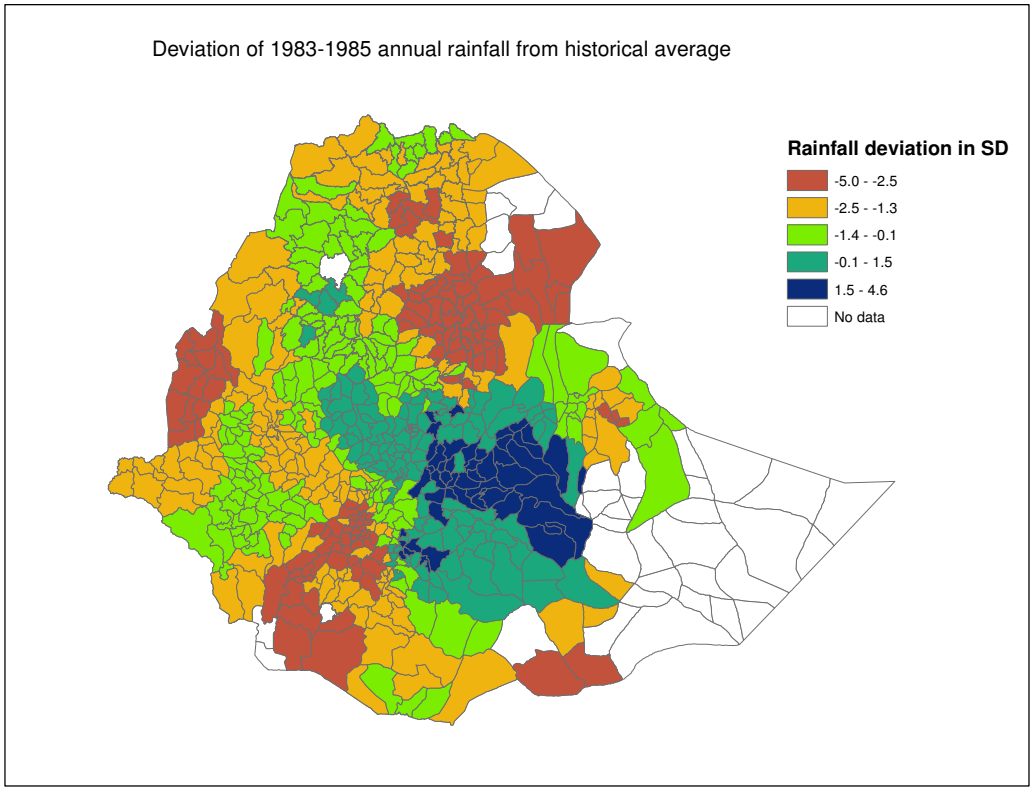

Figure 3: Deviation of annual 1983-1985 annual rainfall from historical averages in SD

Figure4 reports the number of months with over one standard deviation rainfall shortfall during the famine period. Like Figure 2, it shows that the eastern and northeastern parts of Ethiopia saw little variation in rainfall. In most of the country, rainfall was below historical

[12]This, along with other political reasons, prompted the government into the now infamous resettlement program which led to the death of tens of thousands of people (Gill, 2010).

averages for at least 3 of the 36 months in the 1983-85 famine period. Particularly, western Ethiopia suffered low rainfall for up to 16 months. The Southern part of the country also registered very low rainfall during this period - between 9 and 12 months of the famine period had > 1 negative rainfall deviations.

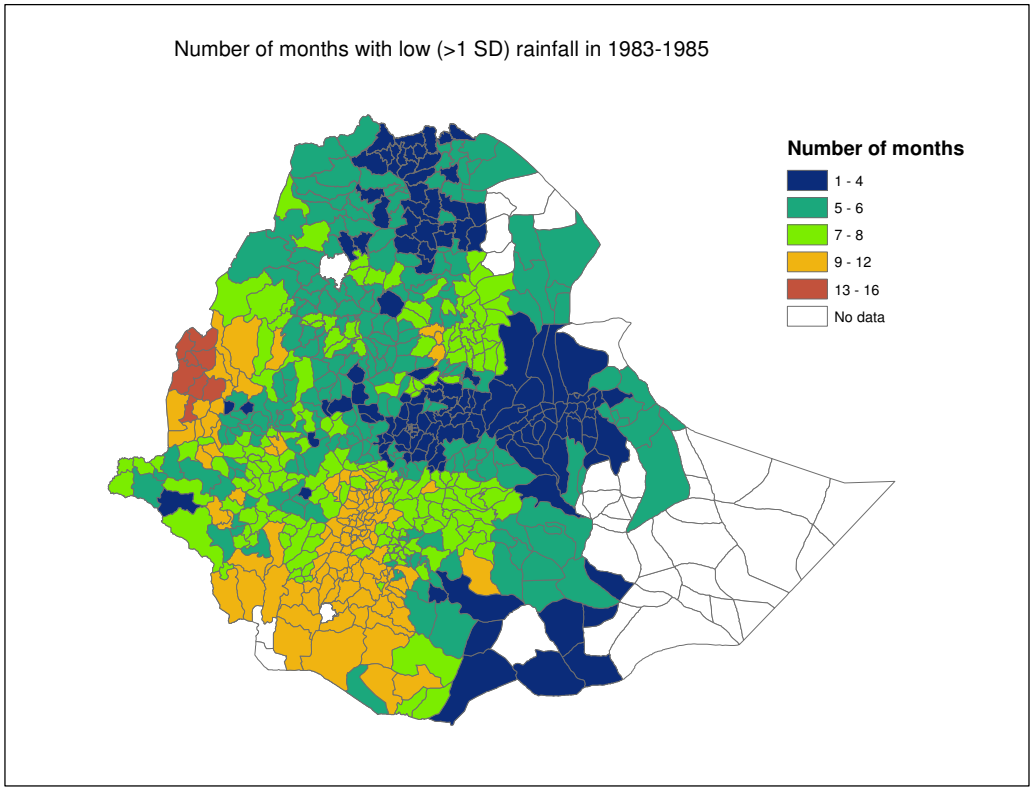

Figure 4: Number of months with low rainfall (< -1 SD) in 1983-1985

The Young Lives study sites are located in geographic areas with varying degrees of famine exposure during the 1983-1985 period (Figure 5). Two sites are located in severely affected woredas and six sites are in highly but relatively less severely affected woredas. Seven study sites are in woredas with no considerable change in rainfall during the famine period, and the remaining fives sites are in woredas with positive rainfall deviations. We exploit this significant variation in famine severity as an exogenous source of variation to identify the causal impacts of childhood famine exposure of parents on various outcomes of their children.

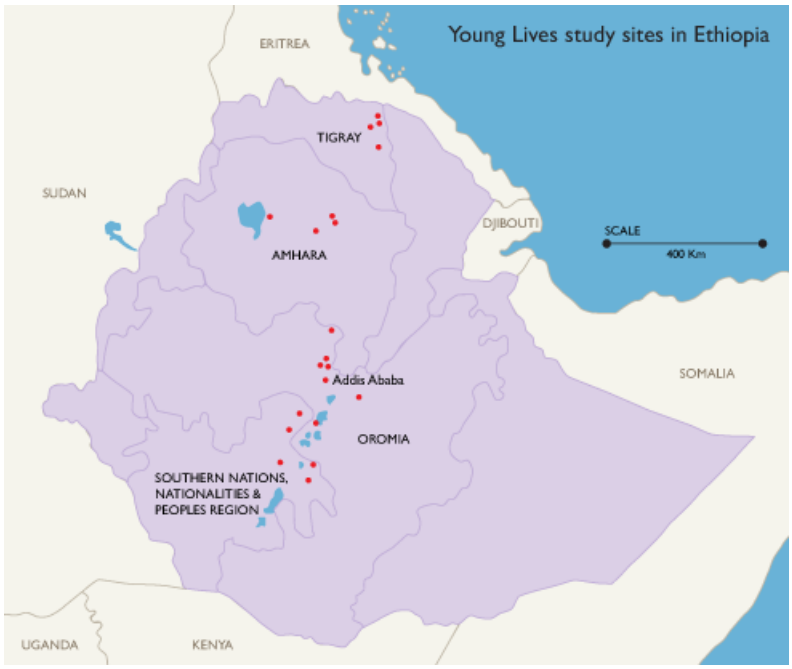

Figure 5: Young Lives study sites
This figure shows the distribution of Young Lives study sentinels (sites) across Tigray, Amahara, Oromia, SNNPR regions and Addis Ababa. Source: Young Lives.

4.2 Measuring Human Capital

In line with the multidimensional nature of human capital (Heckman, 2007), I use multiple measures of cognitive, psychological, and health capabilities of children as the outcome variables. To measure cognitive capability of children, I use standardized scholastic aptitude test scores. More specifically, I use the Peabody Picture Vocabulary Test (PPVT) to measure the receptive vocabulary and of children and Math test. The PPVT measures individuals scholastic (cognitive) ability. It doesn't test reading ability (Dunn & Dunn, 1981). The Ethiopia Young Lives PPVT test consists of 204 stimulus words of increasing difficulty and corresponding 204 image plates each containing four black-and-white images. The interviewer reads a stimulus word from a list, and respondents are asked to select one of the four pictures that best describes the word. The starting point (and the level of difficulty) of the test is determined based on the respondent's age (see Dunn and Dunn (1981) for details on how PPVT tests are administered). The PPVT raw score is the total number of correct answers by the respondent. The math test measures the analytical ability of respondents. Like the PPVT it's structured in an increasing order of difficulty for different age groups.

The raw math score is the total number of correct answers by the respondent.

To measure children's non-cognitive human capital, I construct self-esteem (Rosenberg, 1965) and locus-of-control (Levenson, 1981) measures from reported answers to various psychological questions. I also have access to children's occupational and educational aspirations. For the health dimension of human capital, I use the conventional height-for-age and weight-for-height z-scores that are computed based on the Center for Disease Control (CDS) growth charts, dummy variables for stunting and wasting.

The mechanisms of parent-to-child transmission of famine exposure impacts explored in this paper are child health endowment, household inputs, parental health, and parental socio-emotional variables. The health endowment of a child at birth is measured by birth weight, which was collected in the baseline for the young cohort. However, due to lack of formal records and recall issues, the data on birth weights is plagued by missing values. I instead use mother's self reported birth weight on a five-scale measure ranging between "very small" and "very large". Household inputs are measured by real total expenditure, real food expenditure and educational expenses. For non-cognitive/ psycho-emotional capability I use composite measures of maternal self-esteem and locus-of-control, as well as parents' occupational and educational aspirations for their children. Finally, for parental health, I use maternal height and weight.

4.3 Descriptive Statistics

Table 1: Descriptive statistics: Round 3

	Young cohort		Old cohort	
Variables	Mean	Obs	Mean	Obs
Child age (in months)	97.44	1883	180.36	974
Child gender(male=1)	0.53	1885	0.51	974
Child weight (kg)	20.49	1884	40.47	969
Child height (cm)	120.67	1884	154.72	968
Stunted (%)	0.21	1882	0.29	968
Underweight (%)	0.35	1882	-	-
Child years of schooling	0.83	1462	5.55	965
PPVT raw score	79.20	1857	150.37	962
Math raw score	6.59	1808	5.85	935
PPVT rasch score	304.39	774	303.81	457
Math rasch score	300.00	1808	300.00	935
HH head gender (male=1)	0.81	1886	0.73	974
HH head education	3.76	1627	3.72	843
HH head age (years)	44.22	1884	42.00	961
Caretaker gender (male=1)	0.04	1873	0.08	961
Father age (year)	43.66	1632	50.85	725
Father's literacy	0.40	1583	0.39	692
Father's years of schooling	4.10	1410	4.19	622
Mother age (year)	34.43	1858	41.05	896
Mother's literacy	0.24	1857	0.19	872
Mother's years of schooling	2.56	1675	2.40	803
Education would like for child	15.04	1870	14.97	961
Expect child to achieve education	0.98	1821	0.97	926
Household size	6.19	1886	6.35	968
Wealth index	0.33	1886	0.35	974
Food expenditure (Birr, Ad. Equiv., monthly)	168.44	1883	166.06	974
Non-food expenditure (Birr, Ad. Equiv., monthly)	96.35	1883	96.92	974
Total expenditure (Birr, Ad. Equiv., monthly)	264.79	1883	262.99	974
Number of cattle	2.15	1886	2.26	974
Land area (hectare)	1.60	1612	1.48	803
PSNP participation	0.26	1886	0.25	803

5 Empirical Strategy

5.1 Direct Effects of Famine

To systematically estimate the impacts of parents' exposure to the 1983-85 famine on the outcomes of their children, we estimate the reduced form equation

$$Y^k_{i,w,v,t} = \beta_0 + \beta_1 anndev_{w,t} + \beta_2 mondry_{i,w,t} + \mathbf{\Gamma'_1 X}_{i,w,v} + \lambda_w + \tau_v + \eta_t + \varepsilon_{i,w,v,t} \tag{13}$$

using Ordinary Least Squares (OLS). $Y^k_{i,w,t}$ is the human capital outcome $k \in \{c, n, h\}$ of child i in woreda w, survey round v and parent birth cohort t, where birth cohort constitutes *pre-famine*, *famine*, and *post-famine* cohorts. A parent is considered to be in the "famine cohort" if she was affected in the first three years of life after birth - born 1981-1985. The famine severity measure $anndev_{w,t}$ is deviation of average annual rainfall during 1983-1985 from historical rainfall in standard deviations. Greater *anndev* means less exposure to famine. Likewise, $mondry_{i,w,t}$ is the number of months during the famine the mother of the child was exposed to rainfall one or greater standard deviation below the historical average. It varies across children depending on mother's birth year, and woreda of residence $\mathbf{X}_{i,w,v}$ is a vector of individual, household characteristics. The woreda fixed effect, λ_w, controls for time invariant characteristics that is common to all children in the same village. The survey round fixed effect τ_v controls for factors that are common to children surveyed in a given round. η_t is cohort fixed effect and captures common shocks to all children born to parents of the same cohort. Finally, $\varepsilon_{i,w,v,t}$ is a random error term.

Previous studies have shown the intergenerational effect of a famine is not the same for males and females. Children born to mothers who experienced the famine *in utero* are likely to suffer more than those born to famine affected fathers (Almond et al., 2010; Meng & Qian, 2009; Chen & Zhou, 2007). Moreover, data on fathers is missing for several key variables for significant number of children. Therefore, we estimate (13) for mothers only.

The coefficient on *anndev*, β_1 measures the average effect of increase in rainfall deviation. The coefficient is expected to be positive. A positive β_1 in a regression of positive outcome variables such as schooling achievement, after controlling for parents' age, schooling, income, wealth, and family characteristics, suggest that children further away from famine epicenters perform relatively better. The coefficient on *mondry*, β_2 measures the average effect on

child outcomes of parental exposure to an additional month of famine in childhood, and it is expected to be negative[13]. To address potential spatial correlation, standard errors are clustered at the community level.

The key identifying assumption required for consistent estimation of the causal effects of parents' early life famine exposure on the later life outcomes of their children is independence between measures of famine exposure (*anndev* and *mondry*) and the error term, after controlling for woreda, survey round, and cohort fixed effects, and various individual and household characteristics. Therefore, as long as there were no systematic differences in the growth rates of cognitive, non-cognitive, and health capabilities between villages affected more severely by the 1983-1985 famine and those who didn't, the parameter estimates *anndev* and *mondry* are consistent.

5.2 Mechanisms

To identify the mechanisms through which parental exposure affects the human capital of children, we investigate 1) impact on children birth endowment using mother's self reported birth weight); 2) effect on household expenditure, because exposure to famine is likely to have negative effect on the earnings of parents who were exposed at early age, which will in turn affect the human capital; 3) effect on mother's psycho-emotional factors (such as self-esteem, locus-of-control and aspirations), which will impact the parental input in children's education with negative consequences for human capital; 4) effect on mother's health (height and weight).

To identify the effect of the famine on birth endowment of children, we estimate, using OLS

$$P^k_{i,w,v,t} = \beta_0 + \beta_1 anndev_{w,t} + \beta_2 mondry_{i,w,t} + \mathbf{\Gamma_1'} \mathbf{X}_{i,w,v} + \lambda_w + \tau_v + \eta_t + \varepsilon_{i,w,v,t} \tag{14}$$

where $P_{i,w,v,t}$ stands for parent outcomes. The rest of the variables are as defined before. β_1 measures the effect of increase in rainfall deviation on parent later outcomes. Similarly, β_2 measures the effect of exposure to an additional month of famine on parent later outcomes. λ_w, τ_v, and η_t capture woreda, survey round, and cohort fixed effects.

[13]Too much rainfall is not desirable for agricultural production. As a robustness check we include a quadratic famine severity term, which is be expected to have a negative coefficient, to test if excluding it causes upward bias on β_2.

6 Results

Tables 2, and 3 show regression the results for health, and schooling child outcomes. Table 2, presents the effects of parental famine exposure on children's weight-for-age (*zwfa*), height-for-age (*zhfa*), and underweight and stunted dummies. The results in columns 1 and 3 show that children born to parents who were exposed to the famine in their first three years (*famine exposed*) have significantly lower height-for-age, and hence more likely to be stunted. The geographic variation in the severity of the famine (measured in deviation of rainfall from historical average in standard deviations) appears to have little direct effect on child outcomes. The duration of exposure (measured in number of months of famine exposure), however, has a statistically significant effect on child height directly as well by interacting with rainfall deviation. At the average rainfall deviation of -0.96, an additional month of famine exposure of a mother increases her child's likelihood of being stunted by about 2%, on average[14].

Parental early exposure of the 1983-1985 famine appears to have little effect on child weight-for-age or probability of being underweight (columns 2 and 4). Both rainfall deviation and the duration of exposure do not have direct effect on child weight. I find a weak interaction effect suggesting likelihood of spillover of the effects of the famine to relatively less affected areas.

Column 1 of Table 3 shows the effect of parental famine exposure on the probability of enrollment of children. A child born to a month was exposed to famine for one month during her first three years is about 2% less likely to be enrolled (column 2). Likewise, the children of a mother exposed to the famine for about 13 months are likely to have one less year of schooling. Children of an exposed mother score significantly less on the standardized PPVT and Math tests (colums 3 and 4).

7 Conclusion

Parental exposure to famine has an effect that transcends generations. I find that children born to mothers affected by the 1983-1985 Ethiopian famine have lower health capabilities,

[14]In the Young Lives data, demographic data are more complete for caregivers than for mothers or fathers of children in the survey. Over 90% of the caregivers are mothers. In empirical estimation data on caregivers is used instead. As a robustness check I also present results using mothers' data.

Table 2: Effects of parental famine exposure on child health outcomes

variables	(1) zhfa	(2) zwfa	(3) Stunted	(4) Underweight
Rainfall deviation (SD)	-0.035	0.014	0.014	-0.007
	(0.029)	(0.017)	(0.010)	(0.007)
Famine exposure (months)	-0.063***	-0.004	0.023***	-0.007
	(0.019)	(0.014)	(0.007)	(0.007)
Rainfall deviation×Famine exposure	-0.007*	-0.006*	0.006***	0.002
	(0.004)	(0.003)	(0.002)	(0.001)
Child controls	Yes	Yes	Yes	Yes
Cohort dummy	Yes	Yes	Yes	Yes
Hh controls	Yes	Yes	Yes	Yes
Hh income & wealth	Yes	Yes	Yes	Yes
Observations	2,912	2,912	2,912	2,912
Number of children	1,715	1,715	1,715	1,715

Clustered standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: Child controls include a child gender dummy (male=1) and child age (in months). Household controls include household size, location (urban/rural), age, gender and level of education of household head and care giver, household total expenditure, wealth index (reflects housing quality, consumer durables, access to water, electricity, and sanitation, among others), and total land area.

lower schooling achievements, and perform poorly in standardized tests.

Table 3: Effects of parental famine exposure on child schooling outcomes

variables	(1) Enrollment	(2) Grade	(3) PPVT	(4) Math
Rainfall deviation (SD)	0.001	-0.105**	-0.697	-0.211
	(0.022)	(0.044)	(0.978)	(0.227)
Famine exposure (months)	-0.017*	-0.076***	-0.296	-0.183**
	(0.009)	(0.014)	(0.450)	(0.069)
Rainfall deviation×Famine exposure	0.002	-0.003	-0.306*	-0.035*
	(0.003)	(0.005)	(0.177)	(0.020)
Child controls	Yes	Yes	Yes	Yes
Cohort dummy	Yes	Yes	Yes	Yes
Hh controls	Yes	Yes	Yes	Yes
Hh income & wealth	Yes	Yes	Yes	Yes
Observations	2,914	2,852	924	1,197
R-squared			0.103	0.343
Number of children	1,718	1,707	924	1,197

Clustered standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Note: Child controls include a child gender dummy (male=1) and child age (in months). Household controls include household size, location (urban/rural), age, gender and level of education of household head and care giver, household total expenditure, wealth index (reflects housing quality, consumer durables, access to water, electricity, and sanitation, among others), and total land area.

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A Appendix Tables

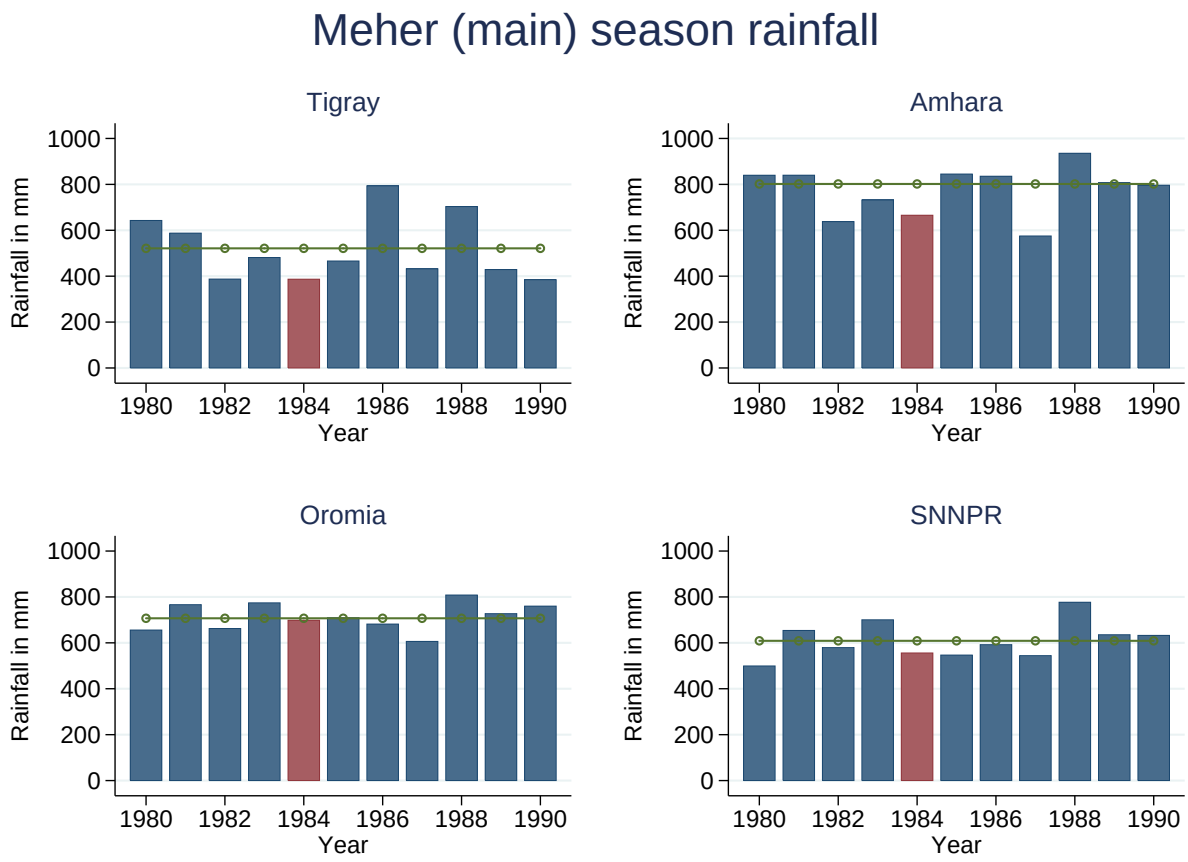

Figure 6: Patterns of Meher rains 1980-1990

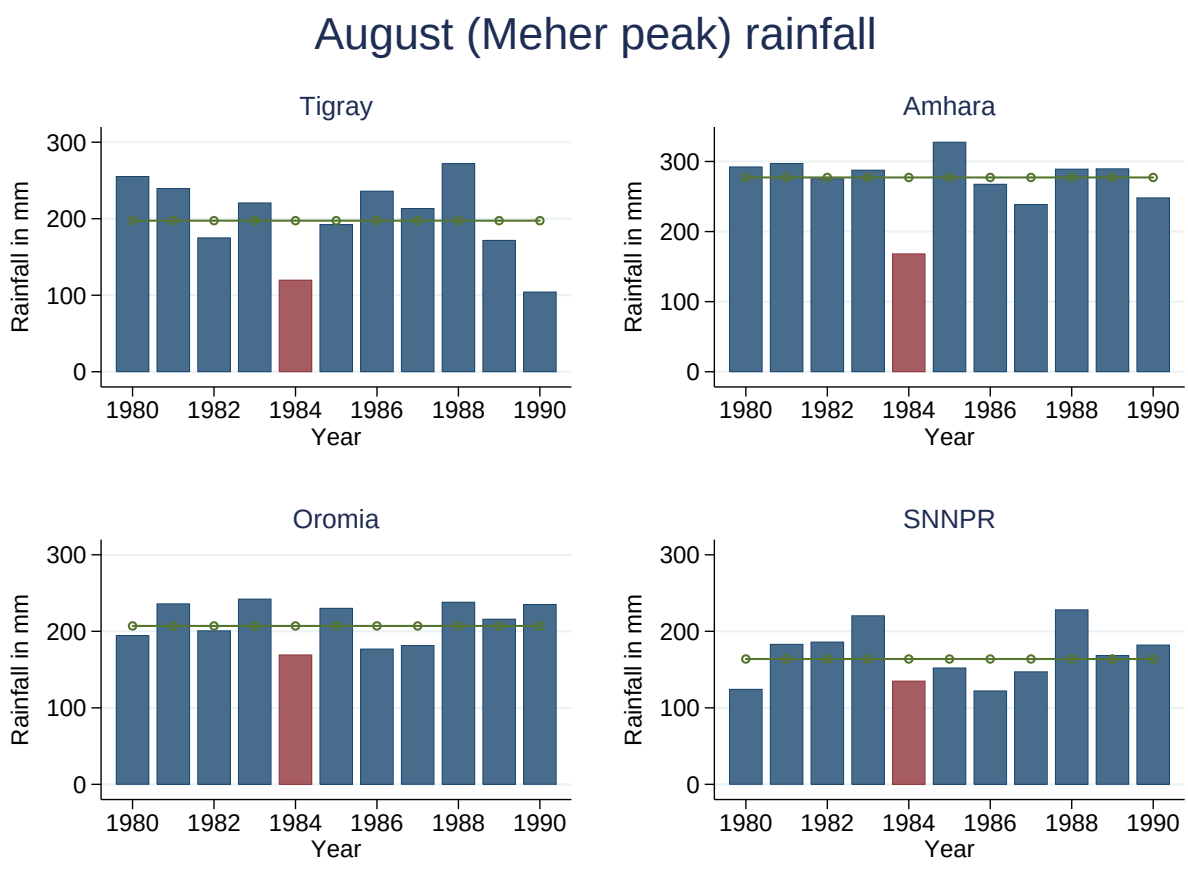

Figure 7: Patterns of August rains 1980-1990

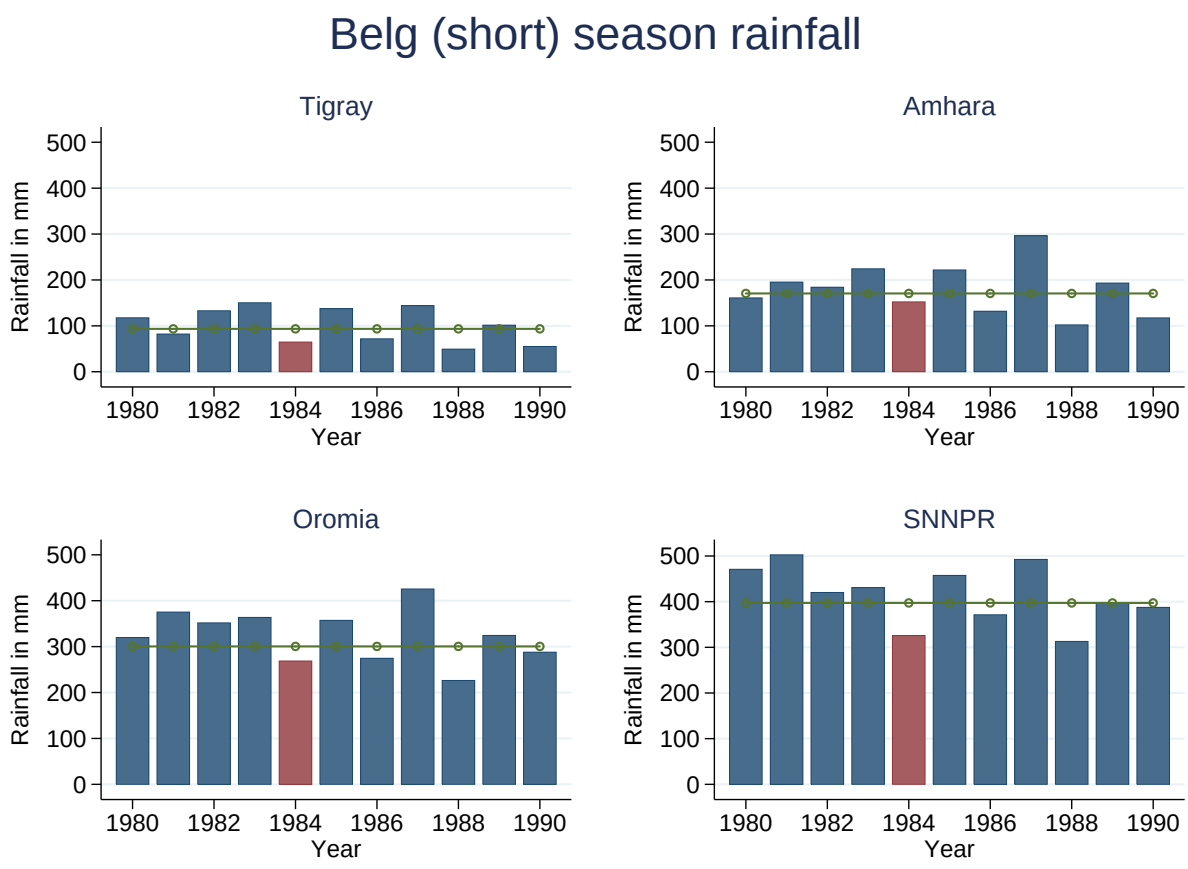

Figure 8: Patterns of Belg rains 1980-1990

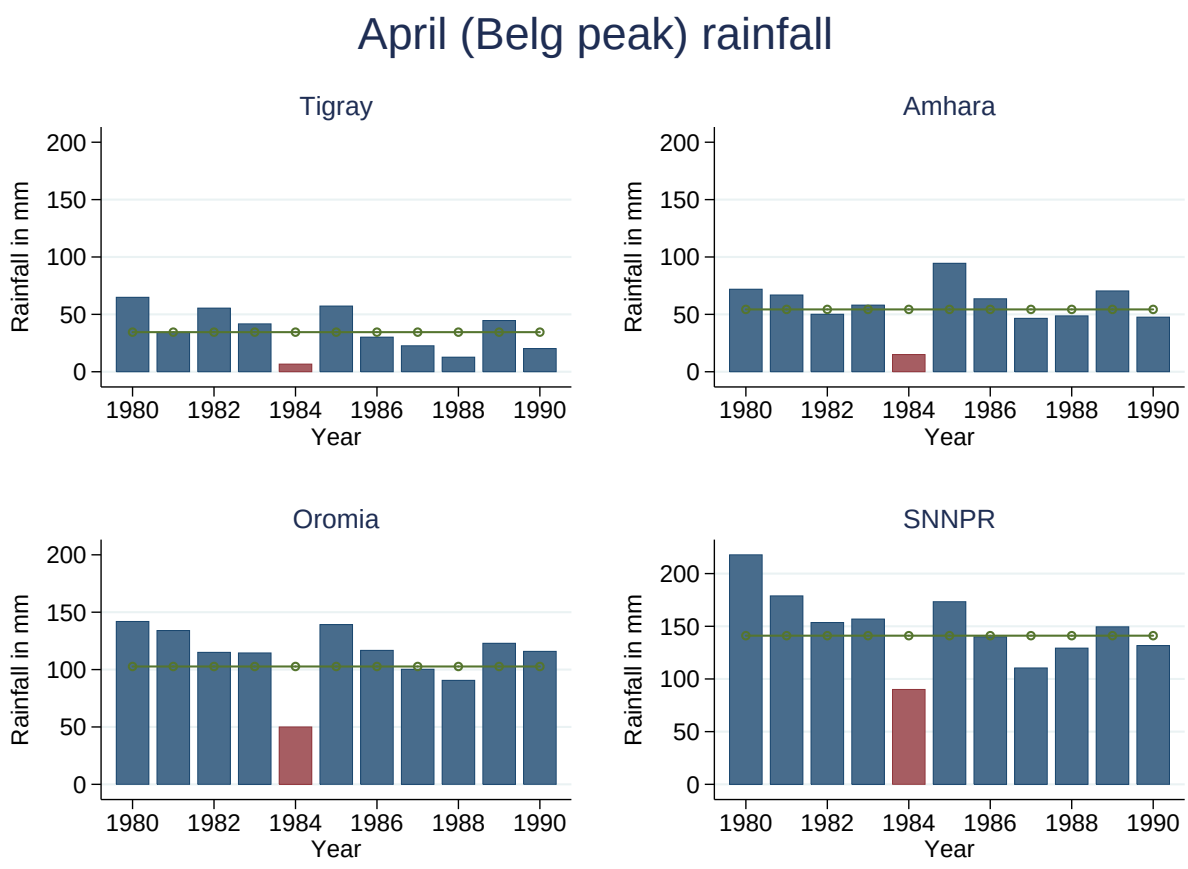

Figure 9: Patterns of April rains 1980-1990

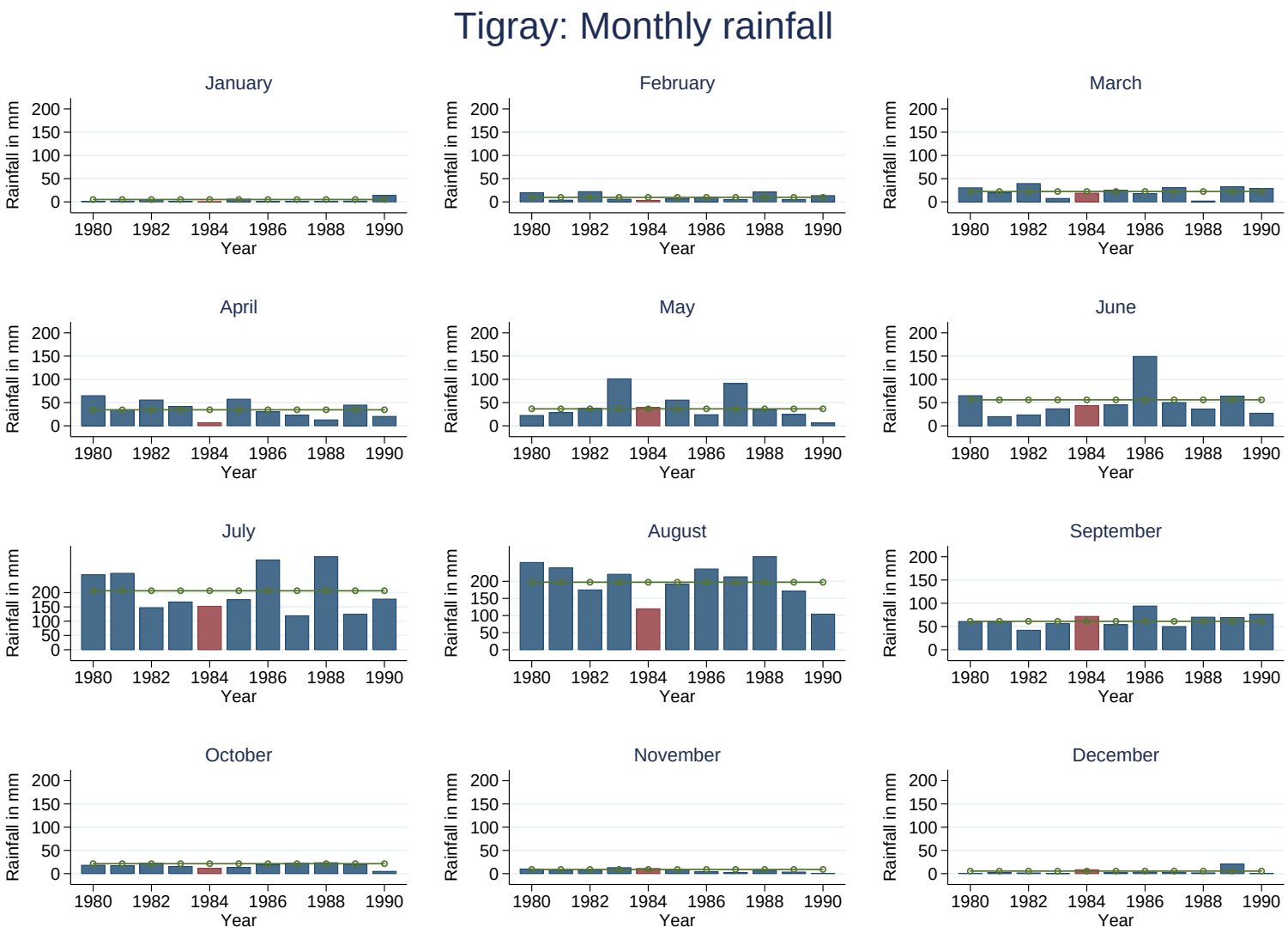

Figure 10: Monthly rainfall patterns in Tigray region (1980-1990)

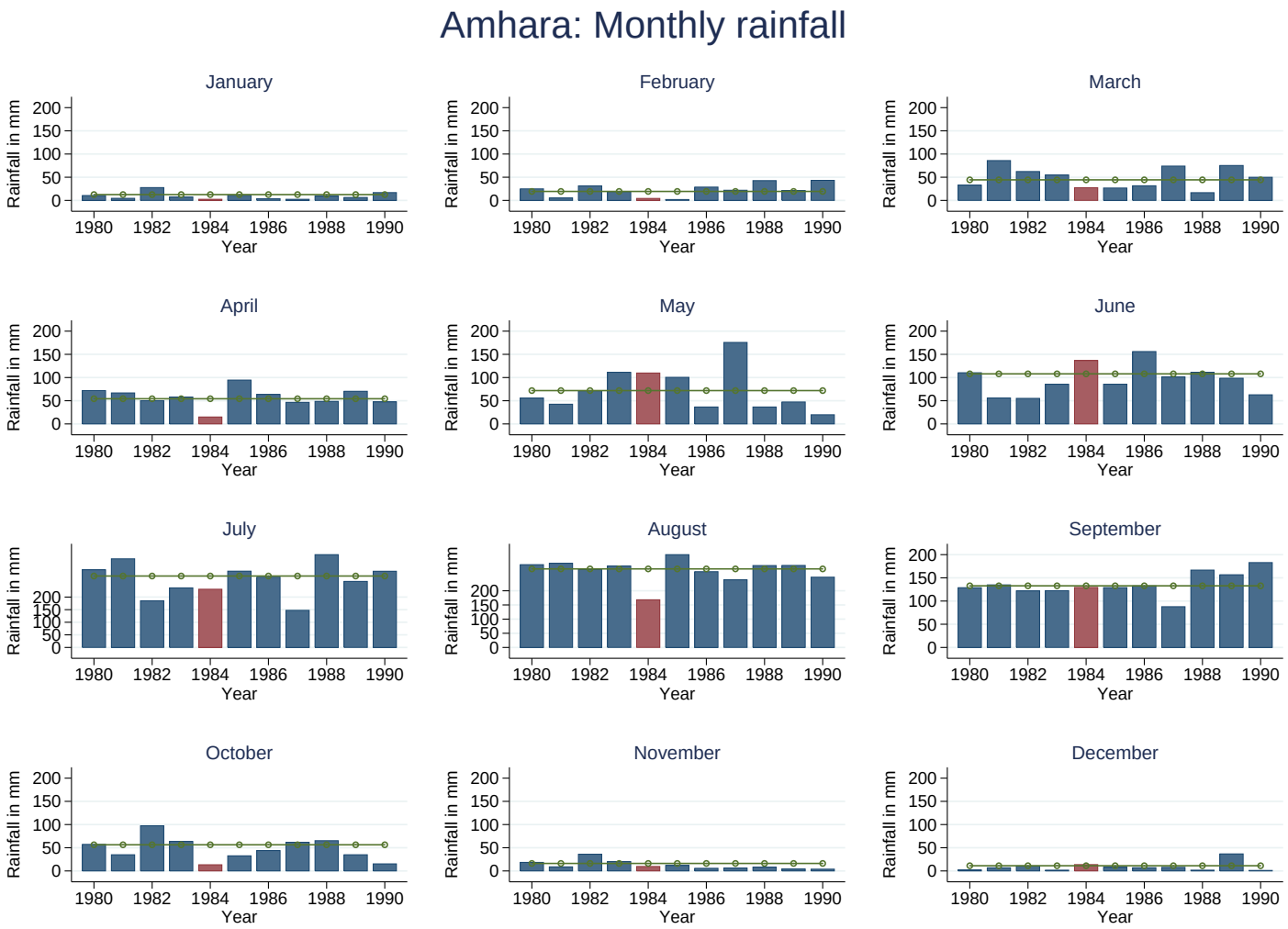

Figure 11: Monthly rainfall patterns in Amhara region (1980-1990)

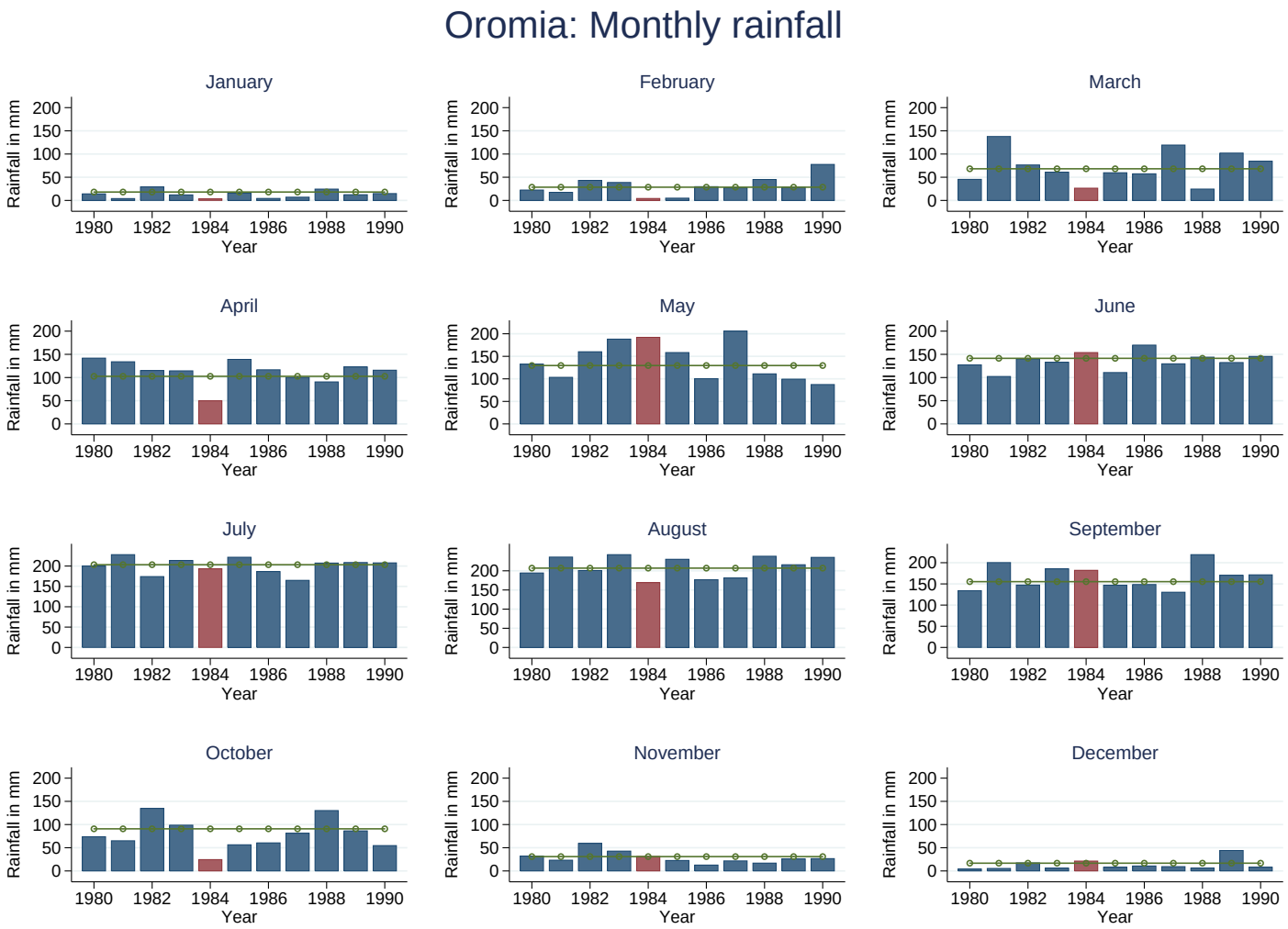

Figure 12: Monthly rainfall patterns in Oromia region (1980-1990)

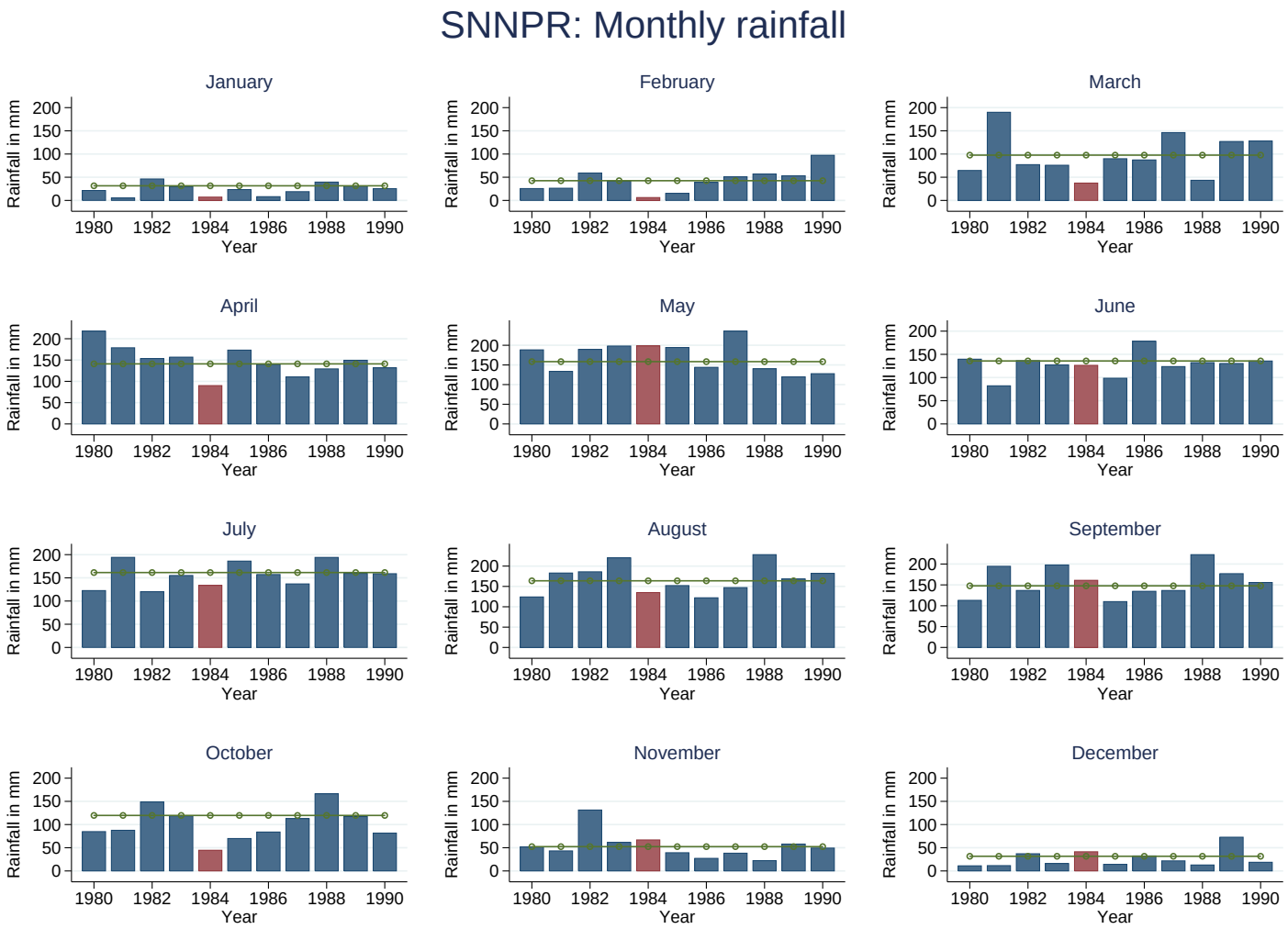

Figure 13: Monthly rainfall patterns in SNNPR (1980-1990)

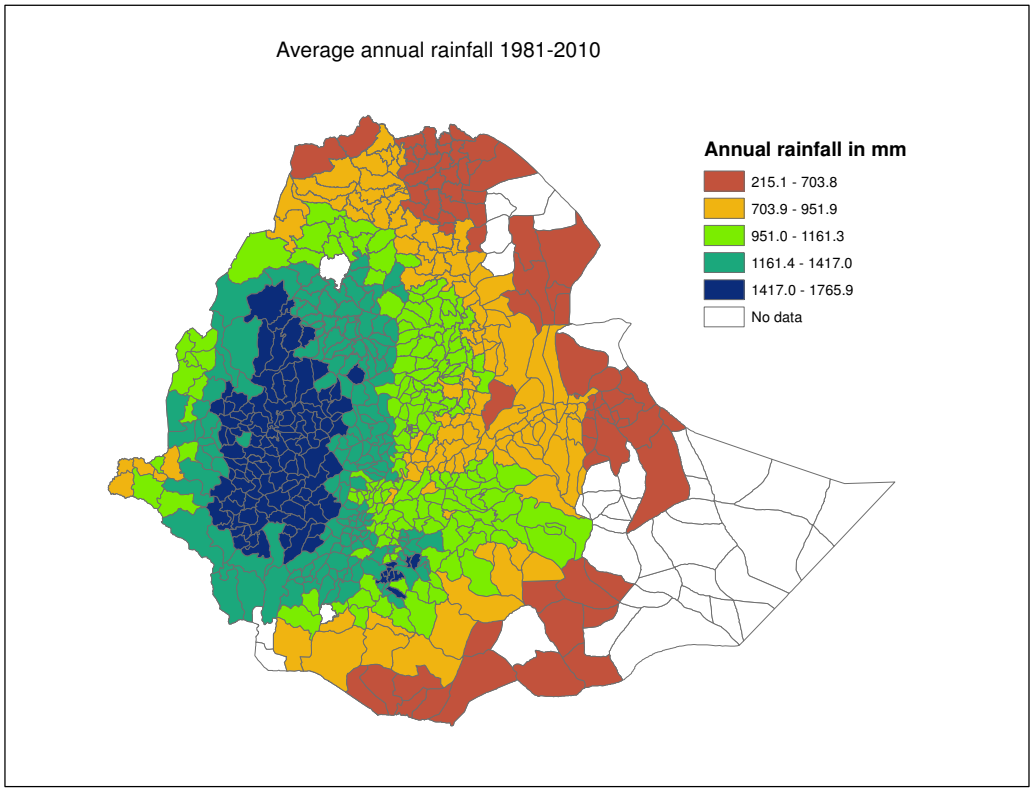

Figure 14: Historical average annual rainfall in mm
Figure 1 shows the historical rainfall patterns at the woreda level using data from 1981-2010. The geographic distirubtion of rainfall is calculated as an average rainfall in the 1981-2010 period.

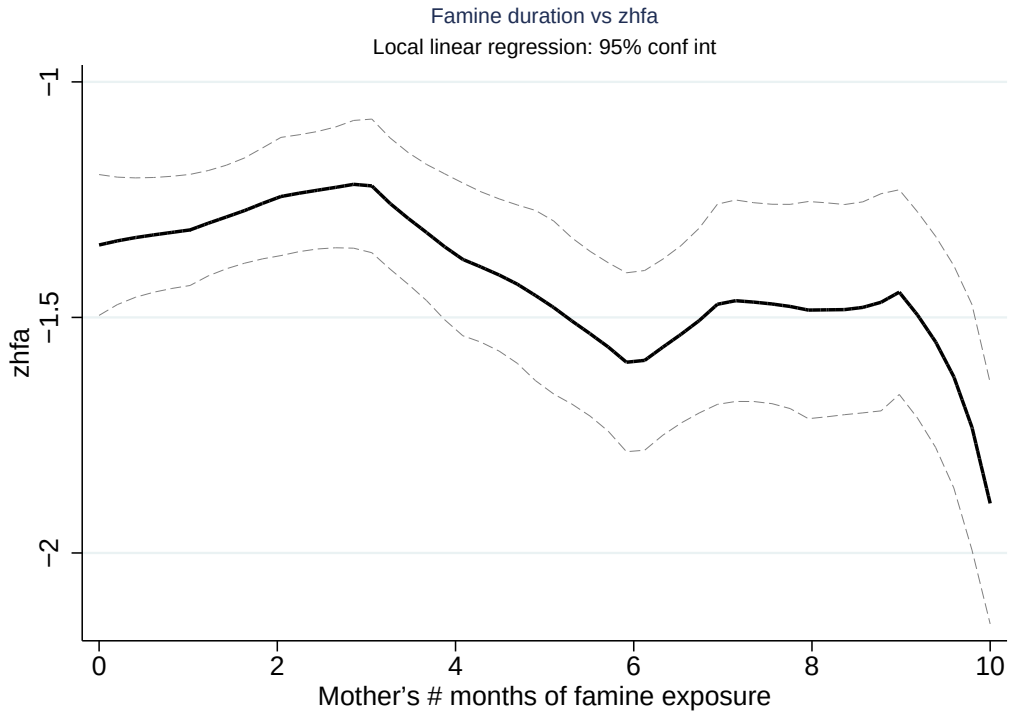

Figure 15: Relationship between duration of famine exposure and height-for-age, all survey rounds

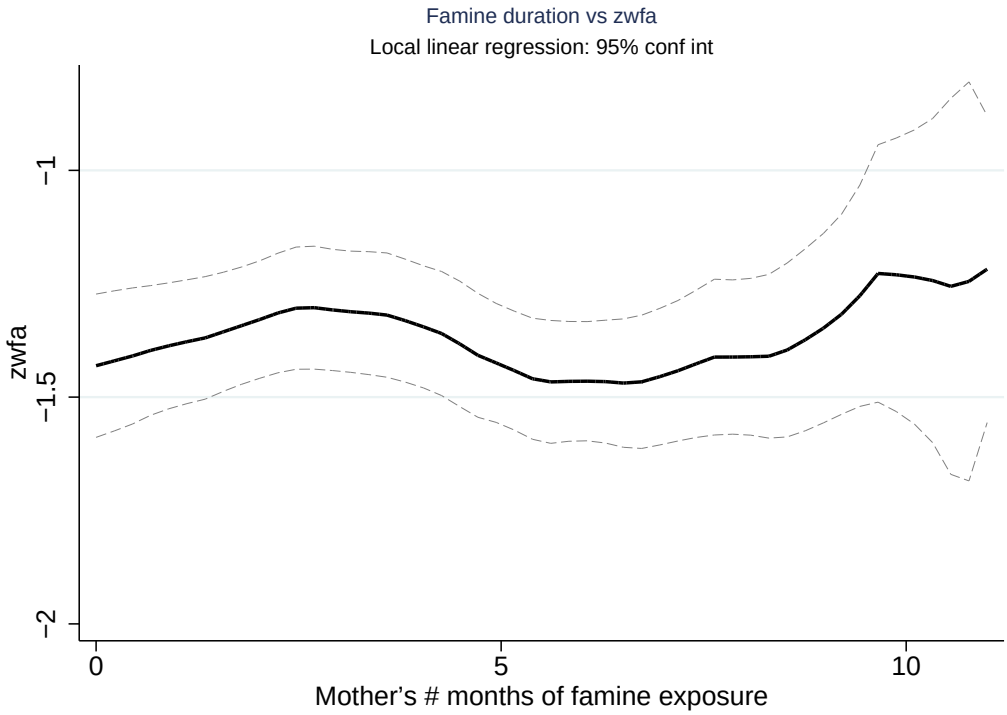

Figure 16: Relationship between duration of famine exposure and weight-for-age, all survey rounds

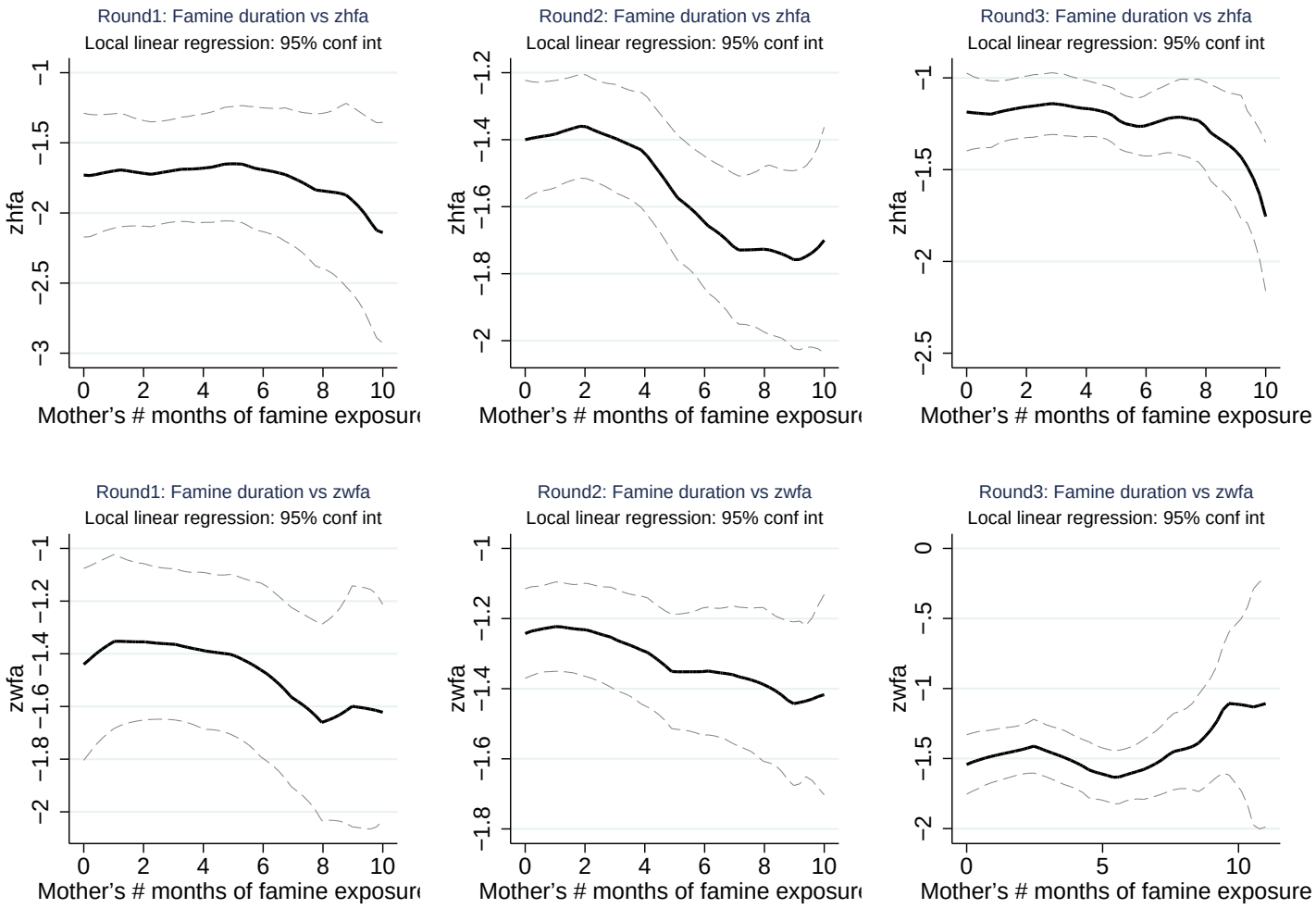

Figure 17: Relationship between duration of famine exposure and child health outcomes (height-for-age & weight-for-age) by survey round

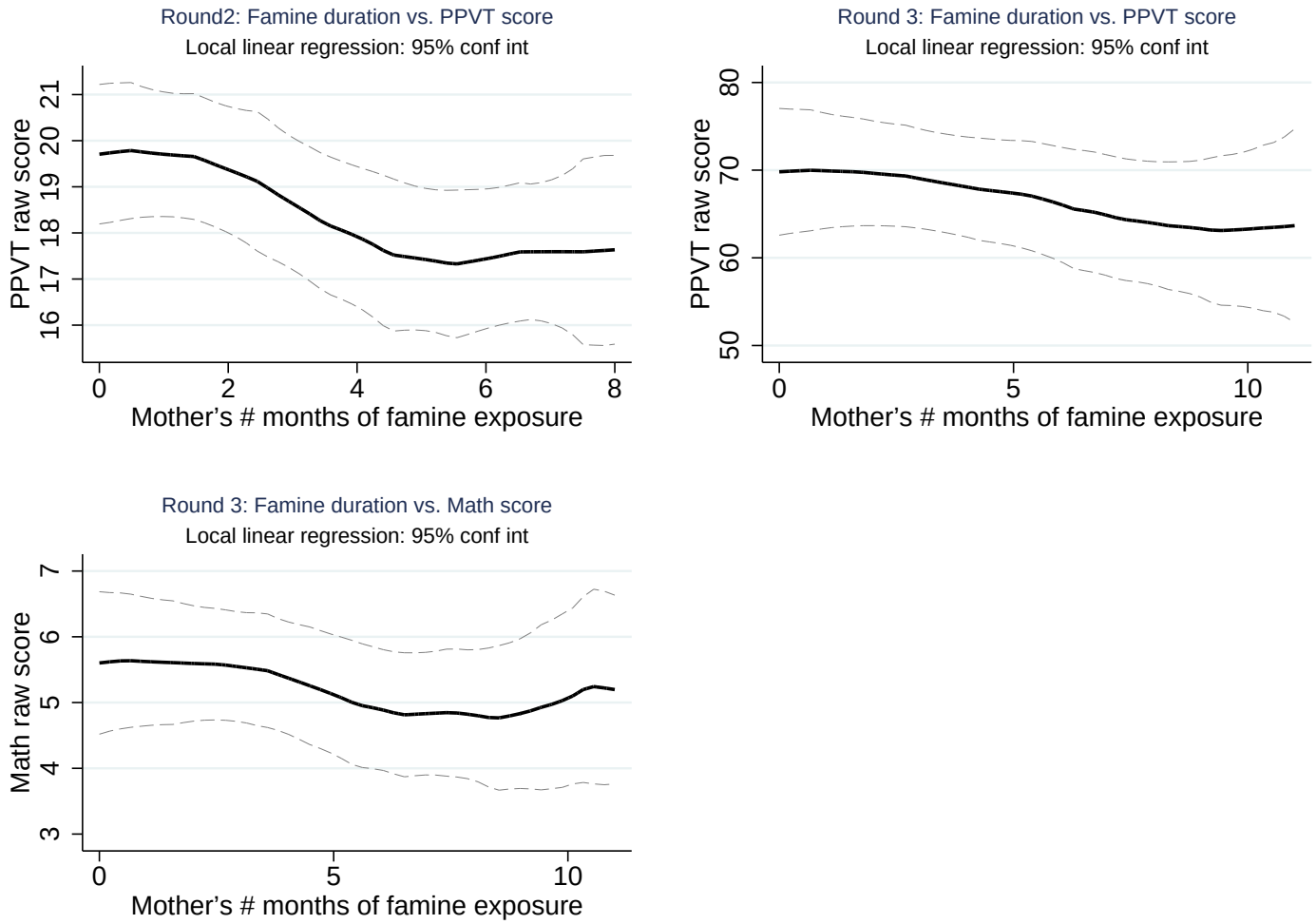

Figure 18: Relationship between duration of famine exposure and child schooling outcomes (PPVT and Math raw scores) by survey round