Three Essays on Climate Change and Child Welfare in sub-Saharan Africa

By

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Abstract

This thesis presents three empirical essays that examine important aspects of child development and investigates the role of climate change in putting millions of children at risk in disadvantaged regions and in thus shaping their overall welfare and development.

In the first essay, we examine the impact of extreme weather events arising from climate change (droughts) on child educational outcomes in Ethiopia. Overall, our findings from our child fixed-effect model points to the fact that children suffer greatly in terms of their educational outcomes when exposed to droughts. Our results also suggests that boys (in terms of their cognitive ability), younger children, and children from less educated households are the most vulnerable to the adverse impacts of droughts on educational outcomes.

In the second essay, we combine satellite PM2.5 data with individual-level data to examine the impact of in-utero air pollution on child health outcomes in Ethiopia. Employing the instrumental variable regression with wind speed as an instrument, we find mild evidence for the harmful effects of air pollution on child health. We show that within our preferred model specification which incorporates monthly adjustments for seasonality in our pollution variable, exposure to ambient air pollution has little to no effect on child health. Whilst we find no significant impact on our child stunting measure (height-for-age), we find weak effects on our wasting measure, with children exposed to PM2.5 during the first trimester being smaller on average and weighing less than their peers of the same age and gender not exposed to polluted air. Our study also finds mild evidence for the existence of heterogeneity in the impact of air pollution on child health in our sample.

In the final essay, we investigate the impact of extreme weather events (droughts) on child marriage and fertility outcomes for young girls in Kenya. The findings from this paper provide evidence for the adverse effects of droughts on child marriage. The findings also show child fertility outcomes to be adversely impacted by droughts. Finally, our findings show that girls living in rural households with lower levels of income are more susceptible to the adverse effects of droughts on marriage and fertility.

Dedication

To my loving siblings.
To my inspiring parents.
This is for us.

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Chapter 1

General Introduction

Climate change is a global emergency. As highlighted by the Intergovernmental Panel on Climate Change (2021), climate change is fast becoming one of the greatest challenges to have confronted human, social, economic and political systems. The stakes are high and the impacts and uncertainties are massive (Schlosberg, 2011). According to the IPCC (2021), humanity's delay in taking drastic action against climate change will result in increasingly dangerous levels of global warming and safety thresholds being exceeded. Currently, global warming levels are at an all-time high (1.2°C above pre-industrial levels) and although the rapid increase in changing climate has been partly attributed to natural causes, increasing human activities particularly fossil fuel burning play a significant role in influencing Earth's average surface temperature. As indicated in the United Nations (2021*b*) report on climate change, the release of greenhouse gasses from human activities are responsible for 1.1°C of global warming since the 1900s, and in the coming years, human activities are expected to play an even more pertinent role in climate change, arguably making global temperature rise to hazardous levels, exceeding 1.5°C level of warming.

For 1.5°C level of global warming comes more intense and erratic extreme weather events including heatwaves, hurricanes, floods, storms, and droughts (IPCC, 2021). The impacts of these on the health and functions of ecosystems as well as the large variety of species that live in them are critical. According to the National Academy of Sciences (2019), significant changes are already being observed to land and water ecosystems such as ocean acidification, soil erosion, low soil nutrient recycling and low soil moisture, all of which threaten biodiversity, livestock, agricultural productivity and global food production. In particular, the resulting impact of land and water degradation from extreme weather events arising from climate change on crop production and food insecurity is alarming. According to the FAO (2021), nearly 800 million people experienced food insecurity between 2019-2020, with extreme weather events acting as a leading contributor. Food production is highly vulnerable to climate change and as climate change gets more pervasive, food production is placed at more risk and expected to experience massive declines of up to 30% in the coming years (Hobert and Negra, 2020). Therefore, unless urgent action is taken, the impact will be threats to livelihoods, loss of income and increasing food prices that could result in excruciating poverty levels for vulnerable populations (Hobert and Negra, 2020).

It has been widely acknowledged that children, particularly those living in lower-income households from developing regions are the most vulnerable group of individuals. These group are the most at risk and face the greatest threats from the adverse effects of climate change (UNICEF, 2021*a*). This is not only because they have no say with regard to how their welfare is being determined, but also because they are the weaker species given their biological, behavioral and cognitive features (Arpin et al., 2021; UNICEF, 2021*a*). Moreover, statistics show that, already, the risk of malnutrition for children born into the poorest homes is twice as high than for children born into richer homes (UNICEF, 2015; Arpin et al., 2021). The risk of a child dying (infant mortality) in the rural, most remote parts of the world is fourteen times as high than in developed regions (World Health Organization, 2021). Access to education is also largely restricted in the developing world, with 1 in 5 children of primary school age and 1 in 3 children of secondary school age outside of school, compared to 1 in 50 children in developed countries (Roser, 2021; UNESCO, 2022). Children among the rural poor are extremely vulnerable to exploitation, discrimination, violence and abuse, all of which are aggravated with the growing threats and challenges that climate change pose to household income and livelihoods. For many low-income (rural) economies, agriculture is the leading source of income and as climate change increases the frequency and intensity of extreme weather events such as droughts, significant declines in agricultural productivity are expected, resulting in depletions in household income assets and savings. This further deteriorates investments in children's wellbeing and development outcomes (Hoddinott and Kinsey, 2001; Pereira, 2017). In turn, shortages in early childhood investments have long term consequences for future outcomes like wages and employment opportunities, thus making it extremely difficult for children from disadvantaged regions to overcome their current living conditions and break out of the vicious cycle of poverty, consequently causing this vicious cycle to be transmitted across generations (Alderman et al., 2006; Baird et al., 2016).

Given this, it becomes of utmost importance to understand the role that climate change plays in shaping the development outcomes of children as it has significant implications particularly when designing policies aimed at protecting vulnerable children from adverse weather events arising from climate change, promoting child welfare, and enhancing resilience. While research on extreme weather events and child welfare in developed countries is relatively large, research in developing countries, in particular, Africa, is still very much limited. Thus, the overall objective of this thesis is to explore the risks that climate change pose to the welfare of children in sub-Saharan Africa. More specifically, this thesis examines the extent of vulnerability of young children in sub-Saharan Africa to extreme weather events arising from climate change with regards to their educational outcomes, health outcomes, marriage and fertility outcomes through exploiting variations in weather conditions over time and space.

The thesis is broken down into three essays written in the standard economic journal article format. In the first essay, we draw on a unique and detailed panel data tracking child development outcomes over 15 years in an East African country, Ethiopia, to examine the impacts that extreme weather events, specifically droughts, have on child educational outcomes. Ethiopia offers an interesting case study because of its high vulnerability to extreme weather events (droughts), resulting from the country's heavy reliance on rainfed agriculture (Randell and Gray, 2016). Merging weather station data with our child level data, we add to the climate and education literature by constructing an exogenous measure for drought (the Standardised Precipitation Evapotranspiration Index) for the various communities in our survey. Employing a child fixed effect model, the essay provides evidence for the adverse effect of droughts on child educational outcomes. We find that droughts have negative effects on cognitive ability and years of schooling, but not on enrolment. More specifically, children score significantly lower on their PPVT (-0.36 SD) and Mathematics test (-0.16 SD), as well as accumulate fewer years of schooling (23 weeks reduction) as a result of a drought. These findings are explained in terms of the pathways - household expenditure per capita, child labour and child study hours, which show that households exposed to droughts experience reductions in their educational expenditure (45%), with no effect on food or health expenditure, as well as resort to child labour as a form of drought coping mechanism. We also find children to allocate less time to studying (outside of school) as a result of a drought. Finally, in our analysis of the effectiveness of the Ethiopian Safety Net (Cash Transfer) Programme in acting as a buffer against droughts, our results show little to no effect of the cash transfer programme in shielding households, thus indicating its ineffectiveness in reducing risk exposures and protecting vulnerable rural households from adverse weather events.

The second essay of this thesis, also within the scope of climate change and environmental degradation, examines the impact of in-utero air pollution on child health outcomes in Ethiopia. In recent years, air pollution has become one of the biggest health environmental hazards. This is particularly the case in developing regions where access to healthcare and resources to tackle pollution is restricted (Cesur et al., 2017). Thus, the second essay of this thesis examines the extent to which air pollution impacts health, specifically for children in their first year of life and subsequently in their fourth to fifth year of life in order to identify any short-to-medium run effects of air pollution on child health. The study, employing the same data as in the first essay, contributes to the literature on pollution and health by focusing on a sub-Saharan African country where literature in this region is scarce due to limited data on pollution levels. By combining satellite PM2.5 data with individual-level data, we are able to assign in-utero pollution measures to each child in our survey and estimate the causal effect of PM2.5 exposure during pregnancy on child health using wind speed as an instrumental variable. Overall, our findings from our IV analysis provide very mild evidence for negative effects of air pollution on child health. Whilst we find no significant impact on our child stunting measure (height-for-age), we find that children exposed to PM2.5 during the first trimester are smaller on average, weighing less than their peers of the same age and gender not exposed to polluted air. A unit increase in in-utero PM2.5 Trimester I exposure is seen to lower weight-for-age z-scores by approximately 0.66 standard deviations. We find no effect of PM2.5 during Trimester II and III of pregnancy, thus highlighting the importance of the early stages of pregnancy in fetal growth and development.

Finally, the third essay of this thesis investigates the role of extreme weather events (droughts) in determining child marriage outcomes for young girls in Kenya. Child marriage rates are well known to be particularly rampant in sub-Saharan Africa, with a staggering 40% of girls marrying before age 18 (Smaak and Varia, 2015; UNICEF, 2022). The reasons for this include a combination of factors such as high poverty levels, low levels of educational exposure, culture and religious beliefs (Smaak and Varia, 2015). Also, the common traditional practice of the bride price system has placed many young girls at risk in this region as households, particularly poorer households, view bride price payments as a source of income (Rusare, 2021; Lowes and Nunn, 2017). This implies that during times of economic distress, girls are at more risk and are hence more vulnerable to the dangers that child marriage poses. Thus, the third essay of this thesis explores the extent of vulnerability of young girls with regard to their marital outcomes and consequently their fertility outcomes to exogenous shocks in income (droughts) in a sub-Saharan African country, Kenya. Kenya acts as an interesting case study because it is a country that is not only characterised with a high prevalence of child marriage given its estimate of 30% of girls marrying before age 18, but also with a high variability in weather conditions putting many households at risk as agriculture constitutes the backbone of Kenya's economy (Warria, 2019; USAID, 2021). Thus, employing a pooled sample of cross-sectional data together with weather data for Kenya, our study utilises the Cox proportional hazards model and provides evidence for the adverse effects of droughts on child marriage. In this regard, we contribute to the very limited literature on household shocks and child marriage in Africa through our usage of survival analysis methods which accounts for data censoring and truncation, and through employing exogenous measures of income shocks rather than the commonly used self-reported measures in the marriage literature.

Overall, our results from the third essay provide evidence for girls being at risk of marriage when exposed to droughts. More specifically, we find that young girls (aged 10-24) exposed to droughts in a given year are more likely to experience the marriage hazard within that same year by approximately 9%. With respect to the hazard of child marriage (ages 10-17), our results show a higher effect of droughts, indicating an increase in the child marriage probability of 13%. Our results also show corresponding effects on fertility outcomes, indicating increases in the probability of first birth within the same period and also in the following period of approximately 9-17% as a result of a drought. Finally, in our analysis of heterogeneity, our findings suggests that girls from rural households with lower levels of income are the most vulnerable to the adverse effects of droughts on child marriage and fertility outcomes.

The rest of this thesis is organised as follows. The first essay, “The Impact of Droughts on Child Educational Outcomes in Ethiopia” is presented in chapter 2. The second essay, “The Impact of In-utero Air Pollution on Child Health in Ethiopia” is presented in chapter 3. The third essay, “Droughts and its Impacts on Child Marriage Outcomes in Kenya” is presented in chapter 4. Finally, a brief conclusion is presented in chapter 5.

Chapter 2

The Impact of Droughts on Child Educational Outcomes in Ethiopia

Abstract

This paper examines the effect of extreme weather events (droughts) on the educational outcomes of children tracked from infant-hood through to adolescence in Ethiopia. Merging our child level data with gridded weather data enables us to construct a proxy of droughts for geographically dispersed communities in our survey. Employing a child fixed-effect model, we find that children from drought affected households score significantly lower on measures of cognitive ability (0.16-0.43 standard deviations reduction), and that years of schooling is negatively impacted. Our results also show that children who suffer from consecutive drought exposures from previous years (accumulated droughts) are much more prone to the adverse effects of droughts on educational outcomes. An investigation of the mechanisms reveals that the effect of droughts on child education appears to be driven by drought affected households reducing their educational expenditure (45%), with no effect on food or health expenditure; an increase in the hours children work; and a decrease in the hours children study.[1]

[1]A version of this chapter has been submitted (revise and resubmit status) to the journal of development studies.

2.1 Introduction

In recent years, climate scientists have started to pay more attention to the relationship between climate change and extreme weather events. The study of "extreme event attribution" argues there is mounting evidence that human activity is raising the risk of certain extreme weather, especially those linked to heat such as wildfires, droughts, floods and heatwaves (Mann, 2017; Trenberth et al., 2017). Extreme weather events have also been associated with a rise in the social and economic costs of natural disasters (UNISDR, 2017). These costs can be particularly high and damaging in the developing world, where a large majority of households rely heavily on agriculture as their major source of income. Sub-Saharan Africa is one region in the developing world that is especially vulnerable to extreme weather events given its estimate of 70% of the workforce employed in the agricultural sector and more than 95% of farmland, rainfed (Pereira, 2017). Indeed, with rainfed agriculture, significant variation in rainfall may lead to substantial reductions in agricultural productivity and farm yields, especially in semi-arid regions. With such reductions in productivity, food insecurity is likely to arise especially among poorer households who have no means of mitigating the negative impacts of extreme weather events due to their inability to access formal credit markets (World Food Programme, 2019). Under such instances, extreme weather events such as droughts are likely to keep affected households in poverty as well as push non-poor households into poverty.

Children, particularly those from poorer households, are thought to be amongst the groups most vulnerable to extreme weather events. Extreme weather events, specifically droughts, through their negative impact on household income, can reduce households' investment in children's well-being, including investment in human capital. These adverse events are thought to be especially detrimental during critical stages of development such as in-utero and early childhood (Hoddinott and Kinsey, 2001; Alderman et al., 2006). Human capital investment, namely education, is often affected if households with limited finance are unable to pay school fees, or if children are needed to participate in labour activities to help contribute to household income. Despite the potentially large negative effects of extreme weather events on educational outcomes, much of the literature to date have focused on health outcomes (Hoddinott and Kinsey, 2001; Alderman et al., 2006; Maccini and Yang, 2008; Bonjean et al., 2012; Andalón et al., 2016). Only a handful of studies (Jensen, 2000; Beegle et al., 2006; Randell and Gray, 2016) have examined the educational impact of extreme weather events on children particularly in developing regions like Africa, where the effects of extreme weather events such as droughts are likely to be more pronounced due to high levels of poverty, relatively low levels of human capital, and inadequate infrastructure.

In this paper, we investigate how extreme weather events, specifically droughts, affect the educational outcomes of children from rural households in Ethiopia by exploiting fluctuations in rainfall over time and space. Droughts in Ethiopia are recurrent and constitute a potentially major productivity shock since agriculture is the heart of Ethiopia's economy, accounting for 50% of the country's GDP, 95% of foreign exchange earnings, and 85% of total employment (Randell and Gray, 2016). More specifically, we use longitudinal data for children in agricultural households in rural Ethiopia to examine the extent of vulnerability of Ethiopian children to contemporaneous droughts. To do this, we investigate the impact of droughts on cognitive ability, school enrolment, and grade attainment, as well as the impact on child labour and real per capita expenditure of Ethiopian households on education, food and healthcare.

The literature suggests two opposing effects of droughts on educational outcomes: the "pro-education" substitution effect and the "anti-education" income effect (Ferreira and Schady, 2008). With regard to the latter, reduced agricultural productivity negatively impacts household income which in turn reduces demand for education. The substitution effect, in contrast, reduces employment opportunities and the price of time (wages), thus encouraging more time to be spent on education which in turn improve educational outcomes. To the extent that the price of time and income are both important determinants of education, the expected overall effect on educational outcomes is ambiguous.

The ambiguity regarding the effect of extreme weather events on educational outcomes is reflected in the empirical literature that has, to date, not formed a consensus as to the direction in which education is affected.[2] Some studies show negative effects, suggesting a larger income effect (Bustelo et al., 2012; Groppo and Kraehnert, 2017; Nguyen and Minh Pham, 2018; Aguilar and Vicarelli, 2022), while others show no effect on educational outcomes, suggesting a substitution effect that cancels out any income effect (Vásquez and Bohara, 2010). For

[2] The literature review provided in this study is comprehensive and up-to-date. It is conducted using a wide range of databases including Google Scholar, Science Direct, Journal Storage (JSTOR) and EconLit.

example, the study by Aguilar and Vicarelli (2022) in Mexico use longitudinal data on 4000 rural households to examine the impact of the 1999 El Niño flooding on the cognitive ability of children. Employing the difference-in-difference method, the authors in their study find that children who were exposed to the 1999 flooding were significantly worse off on measures of cognitive ability, scoring about 0.15-0.19 standard deviations less than children of the same age not exposed to the shock. A similar effect is also seen in Bustelo et al. (2012) who in their study on natural disasters and child schooling outcomes find that the 1999 earthquake that occurred in the west-central region of Colombia led to a negative and significant impact on schooling outcomes of children in the short term. Bustelo et al. (2012) find school enrolment to reduce by approximately 14% in the year following the shock. In the medium term, however, the negative effects are seen to disappear amid post-earthquake relief in Colombia. In another study in India, Peru, Ethiopia and Vietnam, Nguyen and Minh Pham (2018), on the impact of natural disasters (as measured by household reported occurrences of floods, droughts and frosts) on the educational outcomes of children, find mixed results for the different countries. The authors find that for India, Ethiopia and Vietnam, floods and droughts have negative and significant impacts on the number of grades completed of children (1-3% reduction). They also find children's cognitive ability to be negatively impacted by droughts and frosts in India. In Peru, however, no significant impact of natural disasters is found on child educational outcomes.

The similar insignificant effect in Peru is also found in Guatemala in a study by Vásquez and Bohara (2010) on natural disasters and child educational outcomes. Vásquez and Bohara (2010), using cross-sectional data from the Guatemala National Survey of Living Standards to investigate the impact of household reported measures of earthquakes and hurricanes on the trade-off between child labour and schooling, find no significant impact of natural disasters on child schooling outcomes (measured as school dropout rates). Vásquez and Bohara (2010), in their study, explain that this insignificant effect is as a result of households resorting to child labour as a form of coping mechanism when hit by an adverse shock. Lastly, in a study by Groppo and Kraehnert (2017) on extreme weather events (severe winter triggered by excessive snowfall) and child schooling outcomes in Mongolia, the authors find that children who live in regions more adversely impacted by extreme weather conditions experience significant reductions in schooling and are less likely to complete mandatory schooling education in

Mongolia. Groppo and Kraehnert (2017), in their study, find this effect to be largely driven by the loss of livestock as well as the inability of herding amongst affected households in rural Mongolia.

Within the context of Africa, where households are largely credit-constrained due to the non-existence of well-functioning credit markets, the effect of extreme weather events on child educational outcomes is seen to be generally negative as the income effect is found to dominate (Jensen, 2000; Beegle et al., 2006; Dillon, 2012; Björkman-Nyqvist, 2013; Marchetta et al., 2019). For example, in Cote d'Ivoire, Jensen (2000) finds that children from drought affected households are approximately 20% less likely to enrol in school due to lower household income in the year of the drought and in subsequent years. Similarly, in Tanzania, children exposed to rainfall shocks are found to engage in more child labour activities, and as a result, experience lower enrolment rates compared to children not exposed to rainfall shocks (Beegle et al., 2006). In a study of Uganda, Björkman-Nyqvist (2013) investigates whether there is a differential gender effect and finds that boys are more likely to be shielded from negative rainfall shocks, whereas exposed girls experience higher dropout rates, lower enrolment rates, and poorer academic performance conditional on enrolment. Finally, in Madagascar, Marchetta et al. (2019), examining the impact of weather shocks on schooling and labour market outcomes of teenagers and young adults, find that negative rainfall deviations and cyclones are associated with declines in school enrolment of young teens by approximately 2-15%, and also associated with significant movement into the labour market. Marchetta et al. (2019), in their study, find this effect to be largely driven by the agricultural households in their survey, as well as amplified for children from relatively poorer households with limited access to credit markets.

Our study builds on the existing research and makes three important contributions. First, unlike studies like Beegle et al. (2006), Vásquez and Bohara (2010) and Nguyen and Minh Pham (2018) that use self-reported measures of shocks, our study uses an objective measure of household shock. More specifically, using geographical information on the location of households from our household survey, we construct a drought index from physical measurements of rainfall and temperature, thus allowing for an arguably more accurate and exogenous measure of weather shocks. Second, given the multidimensional nature of human capital, our study uses a comprehensive group of indicators of educational outcomes. Previous studies on extreme weather events and child education have tended to focus on school enrolment (Jensen, 2000; Beegle et al., 2006), largely ignoring the cognitive aspects of education. While school enrolment is somewhat indicative of schooling effort, it is not always considered to be a reliable measure of schooling since dropout rates and grade repetition are relatively common in developing countries. As such, in addition to using school enrolment, we also use years of education as well as two widely used, internationally recognised, tests of cognitive ability that measure different aspects of cognition: the Peabody Picture Vocabulary Test (PPVT); and Mathematics test scores. In this sense, our data (Young Lives Survey) is unique because it provides information on almost all indicators of child education, namely school enrolment, years of schooling, grade repetition, and cognitive ability. To the best of our knowledge, no previous study has used such a comprehensive group of indicators in examining the effects of extreme weather events on children. Third, our study is able to exploit the longitudinal nature of the Young Lives survey that enables us to use panel data methods instead of the usual cross-sectional approach taken in the previous studies (Jensen, 2000; Björkman-Nyqvist, 2013). The panel structure of our dataset allows us to implement child-fixed effects, allowing us control for time-invariant unobservables.

To briefly summarise our results, we show that droughts have a negative impact on educational outcomes. More specifically, we find that children from drought affected households in rural Ethiopia experience a reduction in years of schooling of 13%, as well as a reduction in cognitive test performance (Peabody Picture Vocabulary Test and Mathematics) of 0.16-0.43 standard deviations. An investigation into the mechanisms underpinning these results shows that when faced with a drought, households protect their expenditure on food and health but reduce spending on education by an average of 45%. We also find evidence for an increase in the incidence of child labour and a reduction in children's study hours, with children working approximately 0.32 hours more and studying for 0.15 hours less daily, as a result of a drought.

The rest of this paper is organised as follows. Section 2.2 presents a conceptual framework; 2.3 discusses the data and presents the descriptive statistics; section 2.4 outlines the identification strategy; section 2.5 discusses the results and sensitivity analysis; and section 2.6 concludes.

2.2 Conceptual Framework

We present a conceptual framework highlighting the linkages between extreme weather events (droughts), agricultural production, and educational outcomes for children in rural agricultural households in Figure 2.1. Changes in weather conditions (droughts) affect agricultural productivity, which in turn affects household income. In response to these shocks, households may undertake a number of adaptation mechanisms that influence educational outcomes. On one hand, they could adjust their expenditure behaviours by changing food consumption habits, participating less in health seeking behaviours, and withdrawing their children from school due to their inability to pay school fees and other educational expenses. On the other hand, households could engage their children in income generating activities (farm and non-farm activities) as a means to buffer against adverse shocks. As a result, children may be less likely to spend quality time studying outside of school, consequently leading to an impairment in educational outcomes. An alternative outcome is that in times of reduced agricultural productivity, the returns to child labour are lower than the returns to schooling, and therefore children may be more likely to remain in school.

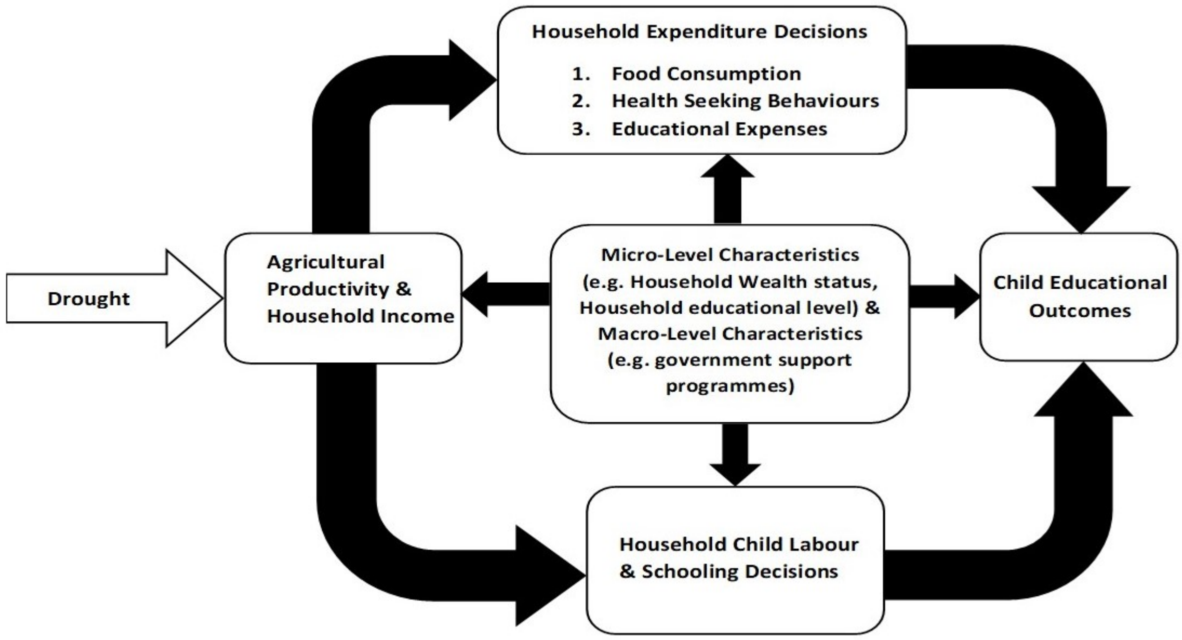

Figure 2.1: A Conceptual Framework Showing the Relationship Between Droughts and Child Educational Outcomes.

These coping adjustments (changes in household expenditure and child labour), in general, have been shown in the literature to influence the educational outcomes of children living in these households (Sackey, 2007; Grimm, 2011; Zabaleta, 2011; Emerson et al., 2017; Lee et al., 2021). For example, the study by Sackey (2007) on the determinants of school attendance and attainment in Ghana shows that household income and expenditure is an important factor influencing child schooling, with higher household expenditure associated with higher rates of school attendance for children in Ghana. Similarly, in another study by Grimm (2011) on household expenditure patterns and child schooling in sub-Saharan Africa, Grimm (2011) shows that changes (reductions) in household income (proxied by changes in expenditure patterns) results in significant declines in schooling outcomes of children. In term of child labour, Zabaleta (2011), in his study on child labour and schooling outcomes of children in Nicaragua, show that children involved in more labour activities accumulate fewer years of schooling and are less likely to complete primary school. In another study by Lee et al. (2021) on child labour and academic achievement in francophone Western and Central Africa, the authors in their study show that engaging in child labour led to significant reductions in child test scores (Reading and Mathematics) by approximately 3-5 standard deviations. Finally, in a study by Emerson et al. (2017) on child labour and child learning in Sao Paulo, Emerson et al. (2017) show that students in grades 1-8 who work while in school scored significantly lower (12-15% of a standard deviation) in Mathematics and Portuguese tests than their peers not engaged in child labour.

The impact of droughts on child educational outcomes is also mediated by micro-level or household characteristics (e.g., wealth, educational status) as well as macro-level factors such as government support programmes. For example, households with a higher level of education may have better awareness and access to informational sources that aid their adaption to droughts (Olaleye, 2010). Also, government support programmes such as cash transfer programmes may be relevant in acting as a buffer for households in times of financial crises (Gilligan et al., 2009; Hoynes and Schanzenbach, 2018). These programmes are likely to play a pertinent role in protecting households and shielding them from significant variations in income and expenditure that may arise from extreme weather events (droughts), consequently leading to less impaired educational outcomes for children.

2.3 Data

2.3.1 Household Data

We use data from the Young Lives survey, an international longitudinal study of 12,000 children growing up in four developing countries (Ethiopia, India, Peru and Vietnam) over 15 years. According to Young Lives (2019), the overall objective of the survey is "to shed light on the causes and consequences of child poverty, and generate sufficient evidence to enable policymakers to design effective poverty alleviation schemes". The survey, which began in 2002, follows two cohorts of children, a younger (the main cohort) and an older cohort. The younger cohort consists of 2,000 children in each country born between May 2001 and May 2002 (between the ages of 6-18 months at the time the first round was conducted), while the older cohort consists of 1,000 children born between January 1994 and May 1995 (ages 7.5-8.5 years during the first round of the survey). The survey has five rounds, 2002, 2006, 2009, 2014 and 2017, when children are approximately one, five, eight, twelve, and fifteen years old in the younger cohort; and eight, twelve, fifteen, nineteen and twenty-two years old in the older cohort. Thus, the younger cohorts are tracked from infancy to their mid-teens and the older cohorts are tracked into adulthood.

In this study, we focus on the younger cohort for Ethiopia, employing data from Waves 3-5 of the survey.[3] The survey randomly selects children from 20 sentinel sites in five regions of Ethiopia: Addis Ababa; Amhara; Oromia; Southern Nations Nationalities and Peoples' Region (SNNP); and Tigray, with the poorer areas deliberately over-sampled.[4] The oversampling of poor areas is consistent with Young Lives' overall aim of tracking childhood poverty in Ethiopia. Nonetheless, the inclusion of richer areas in the sample is sufficient to allow for meaningful comparisons across groups.

The survey has three main modules: a child module; a household module; and a community module. The child module collects information on the index child and the caregiver, providing information on the child's health and well-being, and the caregiver's (mother's) health and

[3]We focus on the younger cohort as it is more relevant for examining the effect of shocks on schooling outcomes and cognitive ability in the early stages of a child's life. Information from waves 1 and 2 are not used in our analysis since the children were not of school age at this time.

[4]The panel dimension of the survey is determined on the basis of one "index" or "panel" child per family.

well-being during and after pregnancy. Beginning from wave 2, information on children's test scores (PPVT, maths and reading), motivation, attitude to work and school, perception of how they are seen by others, and their aspirations for the future, is collected. The household module contains information on household members, collecting detailed information on individual labour hours and income, household consumption and expenditure, household asset holdings, as well as information on crops harvested and sold for agricultural households. The final section of the Young Lives survey, the community module, includes information on the services provided in each community (health and educational services), average wages, price levels and migration flows in and out of a community. Table 2.1 presents a list of the main variables used in our analysis and the survey round in which they were collected.

We restrict our sample to children from rural households since the impact of droughts is likely to be more relevant for households in rural areas who rely predominantly on agriculture as their main source of income. This leaves us with an unbalanced panel of 2,260 observations exclusive of missing values in outcome and control variables, with a maximum of 944 children present from waves 3-5 from a total of 13 sentinel sites/clusters in rural Ethiopia.[5] The attrition rate in the survey is very low by international standards, standing at only 5.6% between 2002 and 2017. The main reasons for attrition are mortality (3.3%) and international migration of households (2.3%) (Young Lives, 2019).

2.3.2 Weather Data

Monthly rainfall data for Ethiopia is obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a database developed by the U.S. geological survey and the Climate Hazards Group, at the University of California, Santa Barbara. CHIRPS is a 35+ year quasi-global rainfall dataset, spanning 50-degree-South to 50-degree-North (and all longitudes), starting in 1981 to the present day. The database blends 0.05° ($\sim$ 5.3 km) resolution satellite imagery with interpolated weather station data to create gridded rainfall estimates for trend analysis and seasonal drought monitoring.[6] This data is combined with

[5] The sample size before removing missing values in outcome and control variables was 2,992.

[6] The rainfall data is calculated by combining a pentadal precipitation climatology, the Cold Cloud Duration (CCD) information based on thermal infrared data archived from the Climate Prediction Centre (CPC) and the National Climatic Data Centre (NCDC), atmospheric model rainfall fields from the NOAA Climate Forecast

maximum, minimum, and average surface temperature data taken from the University of East Anglia Climate Research Unit (CRU). The CRU, a database created through the interpolation of weather station data from over 4,000 stations throughout the world, provides monthly gridded climate data for the globe from 1900 to present at a 0.5° resolution (Harris et al., 2014).

Our weather data is merged with the household data by overlaying the latitude and longitude data from the centroid of each young lives sampled communities on the gridded weather dataset, with all households within each community assigned the same level of rainfall and temperature. Appendix 2.A presents the weather data for the twenty different communities in the young lives survey from 1981 to 2017. Figure 2.A.1 shows the mean monthly rainfall over the 37-year time-span. The figure demonstrates that there is considerable variation in monthly rainfall across communities, with many communities like communities 4 and 5 experiencing one main rainy season in the summer (Meher season from June to September), and other communities experiencing two rainy seasons, a shorter spring rainy season (Belg season from March to May), and a longer summer rainy season. Figure 2.A.2, showing the total annual rainfall for the study communities, demonstrates that there is relatively high volatility in rainfall in most communities, characterised by two severe drought years in 1984 and 2002. Figure 2.A.3 presents the average monthly temperature for communities in the study and shows that temperature is generally at its highest in the spring, and lowest in the winter.

2.3.3 Measuring Droughts

Various indices have been used in the literature to quantify drought such as the Standardised Precipitation Index (SPI), the Standardised Precipitation Evapotranspiration Index (SPEI), Palmer Drought Severity Index, Soil Moisture Deficit Index, and the Surface Water Supply Index. Among these indices, rainfall is the common climate variable for drought assessment and monitoring. The widely used SPI, for example, measures precipitation anomalies for a given time and location and has been recognised as a key drought indicator by the World Meteorological Organisation (WMO, 2016), and a universal meteorological drought index by the Lincoln Declaration on Drought (Hayes et al., 2011). The SPI is commonly chosen over several other drought indices such as the Palmer Drought Severity Index because it serves as a

System version 2 (CFSv2), and in situ precipitation observations (Toté et al., 2015).

better representation of abnormal dryness or wetness, and it is more comparable across regions with different climates.

Despite its widespread acceptance, the SPI has been criticised for solely being based on precipitation. Studies like Ritchie (1998) and Manning et al. (2018) have argued that within the agricultural context, knowing how much water leaves the soil and returns to the atmosphere (evapotranspiration) is of more importance since it is the soil moisture availability (precipitation net of evapotranspiration) that is crucial for the growing of crops, and hence is what determines agricultural droughts (WMO, 2010). To address this concern, the Standardised Precipitation Evapotranspiration Index (SPEI) was developed by Vicente-Serrano et al. (2010). The SPEI, though similar to the SPI, provides a better measure for drought severity by accounting for atmospheric conditions other than precipitation that affect soil evaporative demand, such as temperature, wind speed, and humidity. This is relevant because through accounting for variables like temperature it also considers evapotranspiration, which can consume up to 80% of rainfall (Abramopoulos et al., 1988). Thus, by incorporating evapotranspiration, the SPEI effectively deals with the shortcomings of the SPI to include the importance of soil water availability/water stress on crops.

The SPEI measures drought severity, intensity and duration, and is estimated by first calculating the Potential Evapotranspiration (PET) using the Hargreaves method. The Hargreaves method, proposed by Hargreaves and Allen (2003), is the most commonly used temperature-based method (based on temperature and solar radiation) for calculating PET. It is a method recommended by the FAO as air temperature and solar radiation explain at least 80% of evapotranspiration variability (Hargreaves and Samani, 1982; Priestley and Taylor, 1972; Martí et al., 2015). The Hargreaves method estimate PET as follows:

$$PET = 0.0023 * R_a * (d)^{0.5}(T_{mean} + 17.8) \tag{2.1}$$

where R_a is the mean extra-terrestrial radiation (mm/day) (a function of the location's latitude), d is the temperature difference (mean monthly maximum temperature - mean monthly minimum temperature (°C)), and T_{mean} is the mean monthly temperature (°C).

Following this, the climatic water balance (D) which measures the difference between the precipitation (P) and PET for the month i is calculated:

$$D_i = P_i - PET_i \tag{2.2}$$

This provides a simple measure of the water surplus or deficit for the analyzed month. The calculated D_i values are then aggregated at different time scales (e.g. 1 month, 4 month, 12 month), which is then modelled using a three-parameter log-logistic distribution. The three-parameter log-logistic was chosen to capture deficit values given the likelihood of observing negative climatic water balance values in arid and semi-arid areas. Thus, the Log-logistic distribution was recommended for the SPEI due to its ability to provide a better fit for extreme negative values as well as its ability to adopt different shapes to model the frequencies of the D series at different time scales (Vicente-Serrano et al., 2010).

The probability density function of a three-parameter log-logistic distributed variable is expressed as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left(1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right)^{-2} \tag{2.3}$$

where α, β and γ are scale, shape and origin parameters, respectively, for D values in the range $\gamma > D < \infty$. The Parameters of the log-logistic distribution are obtained using the L-moment procedure.[7] The probability distribution function for the D series, according to the log-logistic distribution, is then given as:

$$F(x) = \left[1+\left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{2.4}$$

With F(x), the SPEI can easily be obtained as the standardized values of F(x) according to the method of Abramowitz and Stegun (1965). For example, following the classical approximation of Abramowitz and Stegun (1965):

$$SPEI = W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \tag{2.5}$$

where:

$$W = \sqrt{-2ln(P)} \quad for\ P \leq 0.5$$

[7]Please refer to Vicente-Serrano et al. (2010) for a detailed analysis of how the parameters and the SPEI index is calculated.

and P is the probability of exceeding a determined D value, P=1-F(x). If P>0.5, then P is replaced by 1-P and the sign of the resultant SPEI is reversed. The constants are $C_0 = 2.515517$, $C_1 = 0.802853$, C_2 =0.010328, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

The average value of the SPEI is 0, and the standard deviation is 1. The SPEI is a standardized variable, and it can therefore be compared with other SPEI values over time and space. Like the SPI, it can be calculated for different times scales (e.g. one, three, twelve, forty-eight months), each representing a specific type of drought such as a metrological drought for a 1-month time scale, an agricultural drought for a 4-6-month time-scale, or a hydrological drought for longer time periods.

The SPEI index can be generated using the SPEI package in R (Beguería et al., 2014). In this paper, we utilise the R SPEI package, and calculate a 4-month SPEI linked to the Meher planting season for the study communities in the Young Lives survey that receive rainfall only in the Meher season, and the 7-month SPEI linked to the Belg and Meher seasons for communities covered in the Young Lives survey that receive rainfall in both seasons. Since households in our sample are interviewed in the harvest season (covering the months of November to January), we identify a drought having had occurred, in a given year and community, if the SPEI value linked to the agricultural season of a given year and community is less than -0.5 standard deviations.[8] Our drought measure is therefore a dummy variable given by:

$$Drought_{c,t} = 1\; if\; (SPEI_{c,t} < -0.5)$$

and 0, otherwise. This allows for a relatively intuitive interpretation of the results.[9]

In Figure 2.A.4 of Appendix 2.A, we plot the percentage of communities in our survey that experience a drought in each given calendar year from 1981 to 2017. The figure generally shows a significant amount of variation in the proportion of communities experiencing droughts across years, with a few years like 1982 and 2015 showing a high prevalence of drought in our sample (approximately 80%), and other years like 1988 and 2001 showing low levels of drought prevalence.

[8] In the sensitivity analysis, we also use other SPEI cut-off values including -0.8, -1, and -2.

[9] The use of dummy variables/cut-offs to classify SPEI drought is done according to the drought literature (McKee et al., 1993; Paulo et al., 2012; Wang et al., 2014; Tirivarombo et al., 2018).

2.3.4 Measuring Educational Outcomes

Due to the multidimensional nature of human capital (Heckman, 2007), we use four different measures of child education as outcome variables. These are school enrolment and years of schooling, which capture the quantity of education, and standardized Peabody Picture Vocabulary Test (PPVT) and Mathematics Achievement test scores, that provide a measure of the quality of education.

The PPVT, originally developed by Dunn (1959), is a widely used age-specific test of receptive vocabulary which seeks to measure a child's ability, and to some extent, predict future individual skills (Duncan et al., 2007). The PPVT is an individually administered and untimed test, which typically takes about 30 minutes to complete. The version employed by the Young Lives (PPVT-III) contains a maximum of 204 questions (17 sections each containing 12 questions) arranged in increasing order of difficulty, with the starting section for each child varying with their age. The child is presented with a word by the examiner and has to match the word with a picture that they feel best represents its meaning. A child's progress through the PPVT test is determined by what are known as the basal item and the ceiling item, and raw scores are then computed by subtracting the number of errors from each child's ceiling item.

Our second measure of educational quality, the Mathematics Achievement Test, measures the basic quantitative ability of a child. It contains a total of 29 questions selected from the Trends in International Mathematics and Science Study (TIMSS) developed by the International Evaluation Association (IEA). The test is timed (20 minutes), without the use of calculators, and includes questions on basic arithmetic such as addition, subtraction, multiplication and division. The score for each individual is calculated as the total number of correctly answered questions. We standardise both the PPVT and Maths scores to have a mean of 0 and a standard deviation of 1.

2.3.5 Descriptive Statistics

Table 2.1 presents the descriptive statistics for the key variables used in our analysis. The sample covers children living in the rural areas of Ethiopia, which constitutes 60% of the total

Table 2.1: Summary Statistics

Variables	Survey Round 1	2	3	4	5	Obs	Mean	Std. Dev	Min	Max
Child Characteristics										
Child's Age (in Months)	✓	✓	✓	✓	✓	2,260	136.01	35.74	86	191
Child's Gender (Female)	✓	✓	✓	✓	✓	2,260	0.46	0.49	0	1
Fraction Enrolled	✓	✓	✓	✓	✓	2,260	0.76	0.43	0	1
Years of Education	✓	✓	✓	✓	✓	2,260	3.40	2.92	0	12
PPVT Score		✓	✓	✓	✓	2,260	47.01	23.99	0	182
Maths Score			✓	✓	✓	2,260	6.41	4.49	0	26
Daily Study Hours		✓	✓	✓	✓	2,260	1.23	1.04	0	6
Child Labour Participation		✓	✓	✓	✓	2,260	0.98	0.12	0	1
Daily Child Labour Hours		✓	✓	✓	✓	2,260	5.11	2.18	0	14
Household Characteristics										
Region:										
Amhara	✓	✓	✓	✓	✓	2,260	0.26	0.43	0	1
Oromia	✓	✓	✓	✓	✓	2,260	0.25	0.43	0	1
SNNP	✓	✓	✓	✓	✓	2,260	0.23	0.41	0	1
Tigray	✓	✓	✓	✓	✓	2,260	0.26	0.44	0	1
Gender of HH Head (Female)	✓	✓	✓	✓	✓	2,260	0.07	0.25	0	1
Father's Education (In Years)	✓	✓	✓	✓	✓	2,260	2.49	3.19	0	17
Mother's Education (In Years)	✓	✓	✓	✓	✓	2,260	1.43	2.49	0	16
Father's Age (Years)	✓	✓	✓	✓	✓	2,260	47.04	9.63	26	89
Mother's Age (Years)	✓	✓	✓	✓	✓	2,260	37.91	7.08	22	64
Wealth Index	✓	✓	✓	✓	✓	2,260	0.30	0.14	0.01	0.78
Wealth Index (Proportion ≤ 0.4)	✓	✓	✓	✓	✓	2,260	0.77	0.42	0	1
HH Size	✓	✓	✓	✓	✓	2,260	6.51	1.74	3	16
HH Food Expenditure Per Capita (Real, Monthly)		✓	✓	✓	✓	2,260	65.07	35.55	9.34	382.41
HH Non-Food Expenditure Per Capita (Real, Monthly)		✓	✓	✓	✓	2,260	41.36	64.92	1.76	1901.08
HH Total Expenditure Per Capita (Real, Monthly)		✓	✓	✓	✓	2,260	103.65	71.54	18.48	1734.53
HH Health Expenditure Per Capita (Real, Monthly)		✓	✓	✓	✓	2,260	1.80	6.30	0	149.35
HH Educational Expenditure Per Capita (Real, Monthly)		✓	✓	✓	✓	2,260	2.17	3.39	0	60.34

sample. Columns (2)-(6) show the rounds for which data is available for each variable, while Columns (7)-(11) present the summary statistics using pooled data from rounds 3-5.

Looking at the household characteristics, the percentage of households living in the rural regions Amhara, Oromia, SNNP, and Tigray are 26%, 25%, 23% and 26%, respectively. The average household is comprised of six members, with approximately 93% of households headed by males. Fathers are on average 47 years old, with approximately 2.49 years of education. Mothers, on the other hand, are much younger and less educated, with an average age and education of 38 years and 1.43 years, respectively. The average per capita household real monthly expenditure is 104 Birr, of which 65 Birr is spent on food items, and the rest on non-food items.[10] The sample is predominantly poor with 77% of households having a wealth index value of less than or equal to 0.4 (Young Lives, 2017).[11]

Next, focusing on child schooling characteristics (our key dependent variables), the fraction of children enrolled in school is very high at 76%, with the average Young Lives child having 3.4 years of schooling. PPVT scores are 47 on average, and Mathematics scores are 6.4 on average. Child labour is a common occurrence in our sample with approximately 98% of children engaging in some sort of child labour, working an average of 5.1 hours a day.[12] The daily average study hours outside of school for each child is 1.23 hours, much less than the amount of time spent on child labour.[13]

2.4 Identification Strategy

2.4.1 Baseline Specification

The primary objective of this study is to identify the causal impact of droughts on child

[10]All monetary values are deflated using monthly Consumer Price Index derived from the Ethiopian Central Statistics Agency, with January 2006 as the base year. The dollar equivalent for real monthly total expenditure, food expenditure and non-food expenditure per capita is approximately \$11.9, \$7.5, and \$4.8, respectively, using the world bank official exchange rate for the 2006 base year (World Bank, 2019).

[11]The wealth index is a variable taking values between 0 and 1, constructed by the Young Lives survey as a weighted average of households' housing quality, access to services, and consumer durables. The Young Lives survey defines a poor household as a household with a wealth index of 0-0.4.

[12]Daily child labour is the sum of the number of hours spent: in paid activity; caring for household members; doing household chores; and domestic tasks including farming.

[13]The average number of hours per day that a child spends in school is 4.79.

educational outcomes. Hence, we begin our empirical analysis by estimating the direct effect of droughts on child educational outcomes using the following baseline model:

$$Y_{ict} = \alpha_i + \beta_1 Drought_{ct} + \beta_2 Drought_{ct-1} + \beta_3 X_{ict} + \beta_4 H_{ict} + \theta\lambda_t + \xi_{ict} \tag{2.6}$$

where Y_{ict} is the outcome variable (school enrolment, years of schooling, PPVT scores and maths scores) for child i, in community/cluster c, at time t. $Drought_{ct}$ and $Drought_{ct-1}$ are SPEI indicators for drought in community c at time t and *t-1*, respectively.[14] X_{ict} is a vector of time varying child characteristics such as child's age. H_{ict} is a vector of time varying household characteristics including household size, parental age, parental level of education, gender of household head,[15] and controls for independent shocks that may have an impact on child educational outcomes such as parental illness and parental divorce.[16] λ_t is a time (season) fixed effect controlling for common trends in weather, and ξ_{ict} is the idiosyncratic error term. α_i is the child fixed effect controlling for all time invariant observables such as the child's sex, community/cluster fixed effects, as well as other time invariant unobservables such as child ability and household resilience, that may be correlated with our outcome and drought measures. With the child fixed effect in Equation (2.6), the coefficients are identified from within-child variations. The standard errors are clustered at the community level to account for spatial correlation in the error term.[17]

Our main coefficients of interest, β_1 and β_2, measure the effect of droughts occurring in periods t and *t-1* on child educational outcomes. Identification of unbiased estimates and causal effects of droughts on educational outcomes (β_1 and β_2) require droughts to be as good as randomly assigned, conditional on observables. The inclusion of rich controls including fixed

[14] As a robustness check we also include additional lags up to period *t-3* in all regressions.

[15] The household characteristics change across rounds in our dataset, however, with very minimal within variation.

[16] The Young Lives Survey also includes information on other potential shocks that may have been experienced by households such as crop failure and the livestock mortality. However, such shocks have not been included in our specifications since they are likely to be as a result of an initial drought, rather than exogenous and independent shocks.

[17] As a robustness check, we wild-cluster bootstrap the standard errors for our linear panel data models using the boottest command in Stata, developed by Roodman et al. (2019), which helps to solve the problem of over-rejection due to few clusters (Cameron and Miller, 2015). The wild-cluster booststrap implemented by the boottest command in Stata is restricted to linear panel data models.

effects in our model ensures that this assumption is met, such that the remaining variation in the drought indices are due to only temporal random fluctuations in weather variables within each locale. Given that Ethiopia is a country heavily reliant on rain-fed agriculture, we expect droughts to have negative impacts on child educational outcomes via reduced agricultural productivity and household income, especially if access to credit is constrained, i.e., we expect β_1 and β_2 in Equation (2.6) to be negative and significant (< 0).

2.4.2 Mechanisms

To identify the possible mechanisms by which droughts may impact child education, we investigate the effect of droughts on a number of variables. These include: (i) parental child investment, measured by real per capita household monthly expenditure on food, education, and health, as well as total expenditure; (ii) child labour participation and labour hours; and (iii) study hours of children outside of school. Equation (2.6) above is adapted to using these three mechanism variables as outcome variables:

$$Y_{ict} = \alpha_i + \beta_1 Drought_{ct} + \beta_2 Drought_{ct-1} + \beta_3 X_{ict} + \beta_4 H_{ict} + \theta\lambda_t + \xi_{ict} \tag{2.7}$$

Given that agricultural households faced with droughts are likely to experience lower agricultural productivity and hence household income, they are likely to make changes to their expenditure, labour, and schooling decisions. Hence, if the coefficients on the drought variables in Equation (2.7) are statistically significant, it would indicate that the effect of droughts on child educational outcomes can be explained (in part) by these changes.

2.4.3 Heterogeneous Effects

The effect of droughts on child educational outcomes may be heterogeneous depending on child or household characteristics. In this study, we examine six sources of heterogeneity which includes heterogeneity in terms of a child's gender, a child's age, educational level of a household head, gender of a household head, age of a household head, and household wealth index. Heterogeneous effects of droughts (if any) are of grave interest and importance because they could be useful in revealing two vital insights: (i) the groups that are most vulnerable to adverse shocks; and (ii) the kinds of ex-ante and ex-post coping strategies that can be employed by households to enhance their resilience and help mitigate any negative impacts of adverse shocks. To this end, we extend our baseline Equation (2.6) to include interaction terms between our drought variables and each dimension of interest.

2.4.4 Buffering Effects

Recent evidence has shown that social protection programs are increasingly becoming relevant in assisting households cope with more frequent and persistent threats to their sources of livelihood (Gilligan et al., 2009; Tafere and Woldehanna, 2012; Hoynes and Schanzenbach, 2018). The rationale behind this is that with regular and predictable cash and food transfers provided from social protection programs, vulnerable households can build better resilience against adverse effects of extreme weather events through investing more in technical skills and know-how and thus preventing detrimental risk-coping mechanisms such as assets depletion, borrowing, and food expenditure and consumption reductions. We examine the role of the Ethiopian Productive Safety Net Programme (PSNP) in mitigating any negative effect of droughts on educational outcomes. The Ethiopian PSNP, introduced in 2005, is a cash transfer programme aimed at protecting the rural poor from acute food insecurity (Welteji et al., 2017). Currently the largest cash transfer programme in Africa, the Ethiopian PSNP involves the provision of cash/food items to food insecure households in exchange for public works (for households with labour capacity), as well as the provision of unconditional cash/food transfers (direct support) for labour-constrained households (Lumbasi, 2018). To assess the effectiveness of the Ethiopian safety net programme in reducing vulnerability among rural households, we adapt our baseline Equation (2.6) to include a dummy variable indicating households' PSNP status in period t, and an interaction term between period t drought and the PSNP indicator:

$$\begin{aligned} Y_{ict} = \alpha_i + \beta_1 Drought_{ct} + \beta_2 Drought_{ct-1} + \beta_3 X_{ict} + \beta_4 H_{ict} + \beta_5 PSNP_{ict} \\ + \beta_6 Drought_{ct} * PSNP_{ict} + \theta\lambda_t + \xi_{ict} \end{aligned} \tag{2.8}$$

where Y_{ict} in the above Equation (2.8) are the outcome variables (measures of child educational outcomes) and mechanism variables (log of real per capita monthly expenditure and consumption, child labour participation and labour and study hours), with all other variables defined as before. Here, our main coefficient of interest, β_6, is expected to be positive and significant if the Ethiopian productive safety net programme is effective in building resilience and protecting vulnerable households from adverse shocks.

2.5 Results

2.5.1 Direct Effect of Droughts on Child Educational Outcomes

Table 2.2 presents the fixed effects estimation results from estimating Equation (2.6) for all four measures of child educational outcomes. As previously mentioned, all regressions control for time and community fixed effect, and all standard errors are adjusted for clustering at the community level.

Beginning with our measures of cognitive skills, presented in columns (1)-(2), we find almost all drought coefficients to be of the expected signs (negative) and significant. Columns (1) and (2) show that children from households that are exposed to a drought in time period t experience a 0.369 and 0.161 standard deviations reduction in PPVT and Mathematics tests scores, respectively. Columns (1) and (2) also show that while there is no lagged effect of droughts on Mathematics, there is a negative and significant impact of period *t-1* drought on PPVT scores, suggesting that droughts have a longer-term impact on language skills. This shows that households may take some time in adapting their coping strategy in the face of droughts and thus, may not be able to fully protect themselves from the lagged effect of droughts. This is consistent with the literature on extreme weather events and welfare that show that the coping mechanisms employed by rural households in developing countries are often ineffective and "time-insensitive" in shielding households from adverse events (Dercon, 2002; Nikoloski et al., 2018). Our results support the findings of Leight et al. (2015) and Aguilar and Vicarelli (2022) who show that children suffer significantly in terms of their cognitive ability when exposed to extreme weather events.

We next examine the effect of droughts on the quantity of schooling, measured as school enrolment and years of education. For school enrolment, we use a random effects Probit model, and for years of education, a Poisson fixed-effect quasi-maximum likelihood estimator (QMLE) for count data is used (Hausman et al., 1984). The FE Poisson estimator is chosen over other count data models such as the Tobit fixed effect as it is considered more robust to violations in distributional assumptions.[18] As indicated in Wooldridge (1999), the Poisson fixed effect estimator remains consistent even under very mild assumptions. Moreover, the estimation of β

[18]The Tobit fixed effects model is also prone to the incidental parameter problem unlike the Poisson fixed effects model (Lancaster, 2000; Santos Silva and Tenreyro, 2022).

Table 2.2: Effect of Droughts on Child Educational Outcomes

	PPVT	Mathematics	Enrolment	Years of Schooling
	(FE)	(FE)	(Probit RE)	(Poisson FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.3697***	-0.1615***	-0.1115	-0.0413
	(0.0961)	(0.0392)	(13.4063)	(0.0546)
SPEI Drought (t-1)	-0.4337***	-0.0035	-0.0365	-0.1334**
	(0.0937)	(0.0549)	(5.5057)	(0.0567)
Child's Age (In Months)	0.0497***	0.0607***	0.0265	0.0325
	(0.0124)	(0.0185)	(5.3089)	(0.0216)
Child's Age-squared	-0.0002***	-0.0002***	-0.0001	-0.0002***
	(0.0001)	(0.0000)	(0.0186)	(0.0000)
Mother's Years of Schooling	0.0631	-0.0365	0.0138	-0.0077
	(0.0405)	(0.0350)	(2.5150)	(0.0348)
Father's Years of Schooling	0.0617***	0.0004	0.0104	0.0021
	(0.0146)	(0.0163)	(1.9872)	(0.0172)
Mother's Age	-0.0156	0.0748*	-0.0259	-0.0169
	(0.0723)	(0.0401)	(5.0868)	(0.0449)
Mother's Age-squared	0.0011	-0.0010	0.0003	-0.0000
	(0.0009)	(0.0007)	(0.0622)	(0.0004)
Father's Age	0.2028***	-0.0232	0.0100	0.0687*
	(0.0586)	(0.0572)	(1.8595)	(0.0402)
Father's Age-squared	-0.0019***	-0.0000	-0.0001	-0.0004
	(0.0006)	(0.0007)	(0.0140)	(0.0004)
Female Head	0.0105	-0.0388	-0.0392	0.0551
	(0.1680)	(0.1228)	(5.3808)	(0.0618)
Household Size	-0.0279	0.0162	0.0047	0.0224*
	(0.0206)	(0.0153)	(0.5899)	(0.0117)
Father's Illness	0.0098	0.2528	-0.0329	-0.0327
	(0.0662)	(0.0514)	(5.8527)	(0.0589)
Mother's Illness	-0.0508	-0.0371	-0.0225	-0.1021**
	(0.0480)	(0.0807)	(2.9178)	(0.0453)
Parental Divorce	-0.0824	-0.2144	-0.0104	0.0198
	(0.1264)	(0.2116)	(1.3434)	(0.0945)
N	2260	2260	2260	1983
r2	0.1182	0.0426	0.3361	0.2331

Note: Column (3) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (3). The pseudo R-squared are provided in columns (3) and (4). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

in the Poisson model is based on the maximum likelihood which does not depend on the E(Y|X) = V(Y|X) assumption. The only condition required for consistency is the correct specification of the conditional mean: E(Y|X) = exp($x|\beta$). As such, it is a fully robust estimator and does not require any additional assumptions concerning the distribution of Y given X (Wooldridge, 1999, 2010). Robust standard errors can also be employed to deal with over-dispersion in the Poisson model resulting from any violation of the mean = variance (E(Y|X) = V(Y|X)) assumption (Wooldridge, 2010).[19]

Looking at schooling outcome results in Table 2.2, Column (3), controlling for the lagged effect of drought, shows no significant impact of droughts on school enrolment. This finding is not particularly surprising given the fact that many sub-Saharan African countries, including Ethiopia, have universal primary education with free school enrolment, and compulsory education until age 16. Hence, it is expected that droughts should have little to no effect on enrolment. Moreover, as previously mentioned, school enrolment is not indicative of human capital accumulation as grade repetition and dropout rates are quite common occurrences in sub-Saharan Africa. Therefore, we also investigate the effect of droughts on children's years of schooling in Table 2.2. Column (4) of the Table (2.2) shows that while a contemporaneous drought has an insignificant effect on years of schooling, a previous year's drought is associated with a 13.3% reduction in years of schooling. When put in context, this corresponds to approximately 23 weeks of schooling compared to the 3-year mean years of schooling in our sample. Our results thus provide evidence that extreme weather events (droughts) come with a cost to the educational outcomes of children from rural Ethiopia.

2.5.2 Mechanisms

Household Expenditure and Consumption

We now examine some of the possible mechanisms that may explain our main findings above. Tables 2.3 and 2.4 present the results for the three mechanism variables estimated using the specification in Equation (2.7). Beginning with our measures of parental investment (food,

[19] We provide the result for over-dispersion test in the years of schooling outcome variable in Table 2.9 of Appendix 2.A, using the "overdisp" command in Stata, developed by Fávero et al. (2020). The results show mild evidence for the existence of over-dispersion in the data. However, as indicated in Wooldridge (1999, 2010), this is accounted for by using robust standard errors.

education, and health expenditure), presented in Table 2.3, our results show that droughts have no significant impact on household per capita food or health expenditure, but they do have a negative and significant impact on education expenditure. With regard to the latter, while there is no significant effect of period *t-1* drought on education expenditure, a contemporaneous drought is associated with a reduction in household per capita education expenditure of approximately 45%. Educational expenses include expenditure on schooling and tuition fees, school uniforms, books, stationery, school transportation, and extra-curricular activities. However, education expenditure is only 2.1% of average total expenditure, whereas food expenditure is 62.8% (see Table 2.1). Overall, these findings indicate that households in rural Ethiopia are more likely to cut down on educational expenses than resort to cutting spending on food or health when faced with droughts. This is consistent with our main findings that show an adverse effect of droughts on child educational outcomes.

Child Labour and Study Hours

As previous research on the welfare impacts of adverse shocks have shown, child labour is a very common coping strategy among rural households in developing countries. To explore this channel, we focus on three dimensions: (1) child labour participation in farming activities, household chores, household caring, and paid activities; (2) the total number of hours spent in these activities; and (3) the total number of hours spent studying outside of school. The results are presented in Table 2.4. Our findings suggests no significant impact of contemporaneous drought at the extensive margin (child labour participation), but a significant impact of a previous year's drought on child labour participation. Column (1) shows that children exposed to a drought in period *t-1* are 2 percentage points more likely to engage in labour activities in period *t*. However, given we have an average participation rate of 98% (from the descriptive Table 2.1), these results should be treated with caution.

At the intensive margin, Table 2.4 provides the results for both the linear fixed-effect model and Poisson Quasi-Maximum Likelihood Estimator (QMLE). The Poisson QMLE accounts for zero-value labour hours in our child labour data (Hausman et al., 1984; Silva and Tenreyro, 2006). As explained in the previous section 2.5.1, the Poisson fixed effects is used due to the robustness of the estimator (Wooldridge, 1999; Silva and Tenreyro, 2006; Wooldridge, 2010).

Table 2.3: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.0064	-0.0083	0.0470	-0.4501***
	(0.0431)	(0.0374)	(0.3345)	(0.1128)
SPEI Drought (t-1)	0.0109	-0.0020	-0.3704	-0.0096
	(0.0597)	(0.0579)	(0.5486)	(0.1465)
Mother's Years of Schooling	0.0005	0.0109	-0.1074	-0.1851
	(0.0253)	(0.0259)	(0.2069)	(0.1143)
Father's Years of Schooling	0.0035	0.0078	-0.1790	0.0572
	(0.0124)	(0.0118)	(0.1163)	(0.0391)
Mother's Age	-0.0162	-0.0076	-0.2340	0.4420***
	(0.0324)	(0.0419)	(0.3216)	(0.1373)
Mother's Age-squared	0.0002	0.0001	0.0024	-0.0059***
	(0.0003)	(0.0004)	(0.0045)	(0.0013)
Father's Age	0.0075	0.0126	-0.0527	0.1706
	(0.0259)	(0.0323)	(0.3541)	(0.1529)
Father's Age-squared	-0.0001	-0.0001	0.0014	-0.0005
	(0.0003)	(0.0003)	(0.0031)	(0.0014)
Female Head	-0.1853***	-0.1780**	1.1659***	0.3568
	(0.0532)	(0.0596)	(0.3414)	(0.3457)
Household Size	-0.0827***	-0.0890***	0.0976	0.0556
	(0.0098)	(0.0142)	(0.1166)	(0.0767)
Father's Illness	-0.0402	-0.0999*	2.3613***	0.1172
	(0.0441)	(0.0481)	(0.5178)	(0.0892)
Mother's Illness	0.0861**	0.0558	1.5822***	0.2530
	(0.0327)	(0.0409)	(0.3947)	(0.1830)
Parental Divorce	0.0714	0.0942	-0.0096	0.2749
	(0.1065)	(0.1126)	(0.9787)	(0.4985)
N	2260	2260	2260	2260
r2	0.0887	0.0790	0.0631	0.1205

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include time fixed effects. Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.4: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE) (1)	Daily Labour Hours (FE) (2)	Daily Labour Hours (Poisson FE) (3)	Daily Study Hours (FE) (4)	Daily Study Hours (Poisson FE) (5)
SPEI Drought (t)	-0.0007	0.3241**	0.0642**	-0.1558**	-0.1596**
	(0.0064)	(0.1442)	(0.0275)	(0.0623)	(0.0644)
SPEI Drought (t-1)	0.0192***	0.4896**	0.0948***	-0.0549	-0.0805
	(0.0061)	(0.1774)	(0.0313)	(0.1079)	(0.0960)
Child's Age (In Months)	0.0037	0.0665	0.0131	-0.0296	-0.0196
	(0.0025)	(0.0626)	(0.0129)	(0.0240)	(0.0290)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0001)
Mother's Years of Schooling	-0.0007	-0.0256	-0.0069	0.2397*	0.1298
	(0.0010)	(0.1521)	(0.0321)	(0.1260)	(0.0793)
Father's Years of Schooling	-0.0007	0.1141**	0.0230**	-0.0218	-0.0176
	(0.0010)	(0.0503)	(0.0091)	(0.0291)	(0.0280)
Mother's Age	-0.0043	-0.0747	-0.0169	-0.0048	0.0276
	(0.0027)	(0.1683)	(0.0304)	(0.0615)	(0.0566)
Mother's Age-squared	0.0000	0.0013	0.0003	0.0003	-0.0001
	(0.0000)	(0.0017)	(0.0003)	(0.0006)	(0.0005)
Father's Age	0.0032	-0.0991	-0.0201	0.0848	0.0549
	(0.0021)	(0.0896)	(0.0174)	(0.0751)	(0.0606)
Father's Age-squared	-0.0000	0.0003	0.0001	-0.0007	-0.0004
	(0.0000)	(0.0008)	(0.0001)	(0.0006)	(0.0005)
Female Head	-0.0114*	-0.2309	-0.0500	-0.1544	-0.0544
	(0.0059)	(0.2830)	(0.0535)	(0.1480)	(0.1328)
Household Size	-0.0011	-0.0690	-0.0138	0.0128	0.0151
	(0.0016)	(0.0540)	(0.0100)	(0.0229)	(0.0173)
Father's Illness	-0.0124**	-0.2129	-0.0416	-0.0846	-0.0858
	(0.0063)	(0.2450)	(0.0444)	(0.0610)	(0.0662)
Mother's Illness	0.0094	0.6249***	0.1222***	-0.0785	-0.1081*
	(0.0080)	(0.1362)	(0.0243)	(0.0884)	(0.0635)
Parental Divorce	-0.0081	-0.3604	-0.0683	0.4652***	0.3230***
	(0.0152)	(0.5596)	(0.1048)	(0.1508)	(0.1067)
N	1464	2260	1995	2260	1942
r2	0.2311	0.0374	0.1210	0.2852	0.1322

Note: Column (1) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (3) and (5).Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ ***. $p < 0.01$.

The coefficients from the Poisson fixed-effect in columns (3) and (5) can be directly interpreted as semi-elasticities (marginal effects). Our findings for child labour hours are generally robust across models, showing positive and significant relationships between droughts and daily labour hours. Column (2) from the linear FE model indicates that children spend longer on non-school related tasks as a result of a drought. Contemporaneous drought increases daily child labour hours by approximately 0.324 hours. This corresponds to an increase in daily labour hours of approximately 19 minutes, signifying a 6% increase in daily labour hours for children relative to the mean daily labour hours in our sample. For the lagged effect of droughts on labour hours, our results indicate a positive and significant coefficient on the drought (*t-1*) variable, thus suggesting a degree of persistence on labour hours such that once increased, a child continues to dedicate more hours to child labour perhaps to make up for lost family income during the year of the drought.

Examining whether child study hours spent outside of school are affected by droughts, Columns (4) and (5) present the results from the linear and the Poisson fixed effects models. Our findings show that drought exposure reduces the amount of time allocated to studying. While droughts in period *t-1* have no significant impact on period *t* study hours, contemporaneous drought reduces child daily study hours by approximately 0.156 hours, which is the equivalent to a 12.6% reduction in the amount of time children spend studying per day relative to the sample mean. One observation from Table 2.4 is that the impact on study hours only lasts one year, thus suggesting that the persistent increase in the hours worked is likely due to a reallocation from one of the other categories of time allocation, such as leisure, time spent in school or time spent sleeping.

2.5.3 Heterogeneous Effects

So far, we have assumed that the effects of droughts on children are homogeneous. However, it may be the case that some children from specific kinds of households are more or less vulnerable to droughts. We test for heterogeneity by child's gender, child's age, education level of the household head, gender of the household head, age of the household head, and household wealth index. In interpreting the interaction terms, it is important to note that the estimated coefficients are only associations due to the potential endogeneity of specific household characteristics. Nonetheless, the inclusion of interaction terms in our specifications is useful in providing meaningful insights in regard to policy implications targeting the most vulnerable group of children.

Gender of the child

Panel 1 of Table 2.5 presents the results from estimating Equation (2.6) including gender interaction terms. Overall, our results provide weak evidence for heterogeneous impacts of droughts by gender, with the exception of the Mathematics measure of cognitive ability. We find that boys exposed to droughts perform worse on their Mathematics test than similarly exposed girls, although this effect is only marginally significant at the 10% significance level. Column (1) shows an additional effect of contemporaneous drought on Maths scores of 0.121 standard deviations for girls over boys. A possible explanation for this is that boys may be required to undertake more non-school activities in times of drought than girls. Future research will look into precisely how children reallocate time after a drought to see whether there is a difference between the sexes in the type of labour hours that are undertaken post-shock.

Age of the child

To understand the role that age has on the effect of droughts on child education, we interact our drought variables with a continuous variable indicating the age (in months) of a child. The results are presented in the second panel of Table 2.5. Our findings suggest that children are equally affected by droughts in terms of their PPVT and Mathematics measures of cognitive ability, as well as enrolment, regardless of age. For years of schooling, however, we find older children to be less adversely impacted by droughts, experiencing an additional effect of 0.5%. This corresponds to a one week increase in schooling compared to younger children. This may be explained by the fact that children mature as they get older and hence are more likely to effectively combine work and school in the face of a drought, thereby resulting in less impaired educational outcomes.

Education level of household head

As a next step, we examine whether the impacts of droughts differ by the educational

Table 2.5: Heterogeneous Effects

	PPVT (FE) (1)	Maths (FE) (2)	Enrolment (Probit RE) (3)	Years of Schooling (Poisson FE) (4)
Panel 1: Child's Gender				
SPEI Drought (t)	-0.4082***	-0.2166***	-0.1059	-0.0582
	(0.0788)	(0.0597)	(4.1094)	(0.0560)
SPEI Drought (t-1)	-0.4856***	-0.0205	-0.0354	-0.1855**
	(0.1046)	(0.0712)	(1.9162)	(0.0815)
SPEI Drought (t)*Female	0.0849	0.1214*	0.0366	0.0383
	(0.0834)	(0.0609)	(1.4465)	(0.0468)
SPEI Drought (t-1)*Female	0.1109	0.0377	0.0349	0.1051
	(0.0762)	(0.0675)	(0.3932)	(0.0725)
Panel 2: Child's Age				
SPEI Drought (t)	-0.1892	-0.5530*	-0.1195	-0.7044
	(0.3216)	(0.2935)	(22.2556)	(0.4893)
SPEI Drought (t-1)	-0.2777	-0.2192	-0.0380	-0.9677***
	(0.4946)	(0.2361)	(6.8671)	(0.3575)
Child's Age (In Months)	0.0477***	0.0641***	0.0288	0.0420**
	(0.0136)	(0.0191)	(6.9021)	(0.0187)
SPEI Drought (t)*Child's Age	-0.0013	0.0028	0.0175	0.0045
	(0.0027)	(0.0021)	(1.9189)	(0.0032)
SPEI Drought (t-1)*Child's Age	-0.0010	0.0014	0.0064	0.0052**
	(0.0038)	(0.0018)	(3.2416)	(0.0023)
Panel 3: Education Level of Household Head				
SPEI Drought (t)	-0.2987*	-0.1293**	-0.1192	-0.1094
	(0.1414)	(0.0501)	(7.3093)	(0.0701)
SPEI Drought (t-1)	-0.4691***	0.0270	-0.0343	-0.2231***
	(0.1407)	(0.0800)	(1.2309)	(0.0822)
Head's Education (In Years)	0.0469***	-0.0070	0.0159	-0.0251
	(0.0151)	(0.0186)	(0.5325)	(0.0175)
SPEI Drought (t)*Head's Education	-0.0345	-0.0107	0.0116	0.0184
	(0.0280)	(0.0167)	(0.6658)	(0.0115)
SPEI Drought (t-1)*Head's Education	0.0228	-0.0097	0.0218	0.0297**
	(0.0258)	(0.0192)	(1.0700)	(0.0134)
Panel 4: Gender of Household Head				
SPEI Drought (t)	-0.3867***	-0.1811***	-0.1069	-0.0426
	(0.0972)	(0.0321)	(17.2217)	(0.0553)
SPEI Drought (t-1)	-0.4355***	-0.0153	-0.0371	-0.1292**
	(0.0869)	(0.0509)	(7.8053)	(0.0593)
Female Head	-0.0946	-0.2396*	-0.0421	0.0840
	(0.3214)	(0.1130)	(5.9754)	(0.0720)
SPEI Drought (t)*Female Head	0.2268	0.2391	0.0076	0.0305
	(0.2391)	(0.1797)	(1.8218)	(0.0610)
SPEI Drought (t-1)*Female Head	0.0135	0.1743	0.0298	-0.0676
	(0.3379)	(0.1045)	(4.7605)	(0.0736)
Panel 5: Age of Household Head				
SPEI Drought (t)	-0.4156**	-0.3308	-0.1082	-0.1096
	(0.1571)	(0.2101)	(0.0849)	(0.1046)
SPEI Drought (t-1)	0.0766	0.0432	-0.0334	-0.0750
	(0.2883)	(0.2972)	(0.0935)	(0.2103)
Age of Household Head	0.0893**	0.0086	-0.0042	0.0015
	(0.0319)	(0.0297)	(0.0060)	(0.0139)
SPEI Drought (t)*Age of Household Head	0.0009	0.0036	-0.0004	0.0014
	(0.0051)	(0.0040)	(0.0041)	(0.0018)
SPEI Drought (t-1)*Age of Household Head	-0.0106	-0.0009	-0.0027	-0.0011
	(0.0067)	(0.0054)	(0.0026)	(0.0034)
Panel 6: Household Wealth Index				
SPEI Drought (t)	-0.5686***	-0.2887*	-0.1071	-0.0817
	(0.1226)	(0.1571)	(0.0852)	(0.0609)
SPEI Drought (t-1)	-0.3516**	0.0264	-0.0415	-0.0452
	(0.1251)	(0.1028)	(0.0945)	(0.0712)
Wealth Index	-0.1004	0.0370	-0.0033	0.1163
	(0.1351)	(0.1102)	(0.0397)	(0.0667)
SPEI Drought (t)*Wealth Index	0.2246	0.1459	-0.0328	0.0447
	(0.1314)	(0.1432)	(0.0937)	(0.0652)
SPEI Drought (t-1)*Wealth Index	-0.0906	-0.0316	-0.0734	-0.1116
	(0.1479)	(0.1097)	(0.0819)	(0.1104)

Note: All regressions include controls for child's age, child's age-squared, parental age, parental education (or the education of household head in panel 3), female household, household size, parental illness, parental divorce, time fixed effects, and an additional community fixed effects in model (3). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ ***. $p < 0.01$.

level of the household head. To do this, we interact the drought measures with a variable indicating the number of years of education of the household head. We find no evidence for heterogeneity by the household head's education, with the exception of years of schooling. The third panel of Table 2.5 shows that children from drought affected households with more educated heads are less adversely affected, and accumulate more years of schooling than children from households with less educated heads. These children on average accumulate 2.9% more schooling (5 additional weeks) compared to their peers from less educated households. A possible explanation for this finding might be that more educated household heads value education more or that it is capturing an income effect where more educated households are able to use accumulated resources to buffer against droughts.

Gender of household head

Next, we investigate whether the gender of the household head is a source of heterogeneity. To do this, we introduce interaction terms between our drought measures and an indicator variable for female headed households in Equation (2.6). Of our sample, 7% are female headed households. The results are presented in Table 2.5. We find no evidence for heterogeneity by gender of household head in our sample, implying that all households, irrespective of the head's gender, are equally affected by droughts.

Age of household head

We next examine the age of the household head as a source of heterogeneity. Our results from Table 2.5, showing the estimates on the interaction terms between drought and the age of the household head indicate no evidence of heterogeneity by household head's age, implying that children from all households, regardless of the age of their household head are equally affected by droughts.

Household Wealth Index

Finally, we investigate the household's wealth index as a source of heterogeneity. Once again, from panel 6 of Table 2.5, we find no evidence for heterogeneity by household wealth index status in our sample, indicating that there is no differential impact of droughts on child educational outcomes by wealth status. It is important to note that however, our sample focuses on rural households and thus, the large majority of them (77%) have very low wealth index values and are classified as poor by the Young Lives.

2.5.4 Buffering Effects

The Ethiopian protective safety net programme may act as a buffer against droughts and protect vulnerable households from adverse events. To investigate its role in reducing vulnerability, we introduce interaction terms in our model specifications. Since households in the survey are asked about their PSNP status in the year of the survey, we limit our interactions to period (t) drought. The results are presented in Tables 2.6-2.8. In general, our findings show weak evidence for the effectiveness of the PSNP in acting as a buffer against droughts. From Tables 2.6-2.8, we see that while the coefficient on the PSNP variable is generally significant in our models, the interaction terms tend to be insignificant, indicating that the programme is not sufficient enough in protecting households from the adverse effects of droughts. The only significant coefficient is found on the child labour participation variable that is marginally significant at the 10% significance level. The result shows that recipients of the PSNP are less likely to enter into child labour as a result of a drought by an additional 0.8 percent compared to non-PSNP recipients.

Overall, our findings are similar to Tafere and Woldehanna (2012), who in their study show little to no effect of the Ethiopian PSNP, thereby indicating its ineffectiveness in reducing risk exposures of households in the face of shocks. Tafere and Woldehanna (2012), in general, argue that the substitution effect for the public work component of the programme induces children to work more hours in paid and unpaid work, and thus dominates the income effect, consequently leading to worse schooling outcomes for some of the participants involved.

2.5.5 Robustness Checks

To establish the robustness of our findings, we present results from estimating various alternate specifications in Appendix 2.B. First, we wild-cluster bootstrap our standard errors for our linear panel data models, and estimate alternative linear models (with wild-cluster

Table 2.6: Buffering Effects: Effect of Droughts on Child Educational Outcomes

	PPVT (FE) (1)	Mathematics (FE) (2)	Enrolment (Probit RE) (3)	Years of Schooling (Poisson FE) (4)
SPEI Drought (t)	-0.3782***	-0.1498**	-0.1068	-0.0128
	(0.1035)	(0.0666)	(0.0750)	(0.0740)
SPEI Drought (t-1)	-0.4273***	-0.0068	-0.0433	-0.1364**
	(0.0910)	(0.0573)	(0.0825)	(0.0601)
PSNP	0.0820	0.0058	0.1011***	0.1377**
	(0.1205)	(0.1244)	(0.0242)	(0.0572)
SPEI Drought (t)*PSNP	0.0499	-0.0401	-0.0619	-0.0771
	(0.1066)	(0.1246)	(0.0865)	(0.0934)
Child's Age (In Months)	0.0519***	0.0607***	0.0295***	0.0358*
	(0.0139)	(0.0181)	(0.0069)	(0.0201)
Child's Age-squared	-0.0002***	-0.0002***	-0.0001***	-0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Mother's Years of Schooling	0.0640	-0.0377	0.0136**	-0.0121
	(0.0425)	(0.0353)	(0.0057)	(0.0349)
Father's Years of Schooling	0.0616***	0.0002	0.0105***	0.0008
	(0.0147)	(0.0165)	(0.0030)	(0.0172)
Mother's Age	-0.0208	0.0771*	-0.0258	-0.0143
	(0.0698)	(0.0389)	(0.0170)	(0.0439)
Mother's Age-squared	0.0011	-0.0010	0.0003	-0.0001
	(0.0009)	(0.0007)	(0.0002)	(0.0004)
Father's Age	0.2013***	-0.0230	0.0108	0.0661*
	(0.0567)	(0.0564)	(0.0099)	(0.0400)
Father's Age-squared	-0.0019***	-0.0000	-0.0001	-0.0004
	(0.0006)	(0.0007)	(0.0001)	(0.0004)
Female Head	0.0037	-0.0377	-0.0472	0.0473
	(0.1662)	(0.1220)	(0.0434)	(0.0598)
Household Size	-0.0297	0.0161	0.0041	0.0189
	(0.0212)	(0.0166)	(0.0052)	(0.0125)
Father's Illness	0.0146	0.2527	-0.0309	-0.0259
	(0.0664)	(0.0531)	(0.0311)	(0.0574)
Mother's Illness	-0.0478	-0.0375	-0.0173	-0.1004**
	(0.0494)	(0.0804)	(0.0201)	(0.0455)
Parental Divorce	-0.0942	-0.2121	-0.0228	0.0113
	(0.1269)	(0.2126)	(0.0484)	(0.0902)
Observations	2,260	2,260	2,260	1,983
R-squared	0.1205	0.0428	0.0221	0.2922

Note: Column (3) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (3). The pseudo R-squared are provided in columns (3) and (4). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ ***. $p < 0.01$.

Table 2.7: Buffering Effects: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.0055	0.0163	-0.1256	-0.3292*
	(0.0507)	(0.0448)	(0.4559)	(0.1612)
SPEI Drought (t-1)	0.0107	-0.0080	-0.3413	-0.0217
	(0.0597)	(0.0584)	(0.5446)	(0.1362)
PSNP	0.0008	0.0317	-0.5009	0.5185*
	(0.0630)	(0.0574)	(0.5627)	(0.2658)
SPEI Drought (t)*PSNP	-0.0029	-0.0781	0.4866	-0.3028
	(0.0433)	(0.0517)	(0.5600)	(0.2343)
Child's Age (In Months)	0.0004	0.0082	-0.0885	-0.1983*
	(0.0259)	(0.0265)	(0.1978)	(0.1102)
Child's Age-squared	0.0034	0.0073	-0.1738	0.0528
	(0.0123)	(0.0119)	(0.1137)	(0.0390)
Mother's Years of Schooling	-0.0161	-0.0037	-0.2507	0.4470***
	(0.0324)	(0.0404)	(0.3342)	(0.1366)
Father's Years of Schooling	0.0002	0.0001	0.0026	-0.0060***
	(0.0003)	(0.0004)	(0.0047)	(0.0013)
Mother's Age	0.0076	0.0128	-0.0496	0.1659
	(0.0258)	(0.0326)	(0.3525)	(0.1514)
Mother's Age-squared	-0.0001	-0.0001	0.0014	-0.0004
	(0.0003)	(0.0003)	(0.0032)	(0.0014)
Father's Age	-0.1853***	-0.1769**	1.1765***	0.3385
	(0.0528)	(0.0594)	(0.3446)	(0.3478)
Father's Age-squared	-0.0827***	-0.0895***	0.1067	0.0457
	(0.0093)	(0.0140)	(0.1148)	(0.0763)
Female Head	-0.0402	-0.0989*	2.3394***	0.1417
	(0.0435)	(0.0473)	(0.5036)	(0.0997)
Household Size	0.0861**	0.0554	1.5773***	0.2614
	(0.0328)	(0.0410)	(0.3958)	(0.1863)
Father's Illness	0.0715	0.0963	0.0075	0.2437
	(0.1081)	(0.1150)	(0.9866)	(0.4944)
Mother's Illness	0.0658	0.0031	1.1581	-0.2286
	(0.1274)	(0.1195)	(0.8238)	(0.4853)
Parental Divorce	0.1130	-0.0263	1.3829	0.0384
	(0.2160)	(0.1795)	(1.5203)	(0.7164)
Observations	2,260	2,260	2,260	2,260
R-squared	0.0887	0.0810	0.0639	0.1246

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include time fixed effects. Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.8: Buffering Effects: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE)	Daily Labour Hours (FE)	Daily Labour Hours (Poisson FE)	Daily Study Hours (FE)	Daily Study Hours (Poisson FE)
	(1)	(2)	(3)	(4)	(5)
SPEI Drought (t)	-0.0012	0.4161**	0.0858**	-0.1526	-0.1320
	(0.0055)	(0.1902)	(0.0351)	(0.0922)	(0.1020)
SPEI Drought (t-1)	0.0168***	0.4671**	0.0897***	-0.0472	-0.0813
	(0.0056)	(0.1735)	(0.0304)	(0.1069)	(0.0996)
PSNP	0.0075**	0.1338	0.0359	0.1875	0.2103*
	(0.0033)	(0.3609)	(0.0611)	(0.1434)	(0.1121)
SPEI Drought (t)*PSNP	-0.0083*	-0.2951	-0.0674	0.0335	-0.0551
	(0.0046)	(0.2854)	(0.0531)	(0.1137)	(0.1482)
Child's Age (In Months)	0.0034	0.0690	0.0141	-0.0247	-0.0132
	(0.0024)	(0.0630)	(0.0132)	(0.0210)	(0.0264)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Mother's Years of Schooling	-0.0006	-0.0352	-0.0096	0.2393*	0.1233
	(0.0010)	(0.1491)	(0.0312)	(0.1233)	(0.0775)
Father's Years of Schooling	-0.0007	0.1122*	0.0229**	-0.0225	-0.0197
	(0.0009)	(0.0517)	(0.0093)	(0.0289)	(0.0279)
Mother's Age	-0.0035	-0.0595	-0.0137	-0.0115	0.0262
	(0.0025)	(0.1659)	(0.0301)	(0.0606)	(0.0546)
Mother's Age-squared	0.0000	0.0011	0.0002	0.0004	-0.0001
	(0.0000)	(0.0016)	(0.0003)	(0.0006)	(0.0005)
Father's Age	0.0030	-0.0990	-0.0208	0.0818	0.0517
	(0.0019)	(0.0879)	(0.0172)	(0.0760)	(0.0617)
Father's Age-squared	-0.0000	0.0003	0.0001	-0.0007	-0.0004
	(0.0000)	(0.0008)	(0.0001)	(0.0006)	(0.0005)
Female Head	-0.0121**	-0.2285	-0.0496	-0.1669	-0.0664
	(0.0057)	(0.2870)	(0.0547)	(0.1437)	(0.1281)
Household Size	-0.0010	-0.0712	-0.0147	0.0088	0.0096
	(0.0015)	(0.0534)	(0.0100)	(0.0198)	(0.0148)
Father's Illness	-0.0116**	-0.2094	-0.0405	-0.0746	-0.0735
	(0.0057)	(0.2435)	(0.0440)	(0.0611)	(0.0643)
Mother's Illness	0.0089	0.6240***	0.1224***	-0.0730	-0.1054
	(0.0073)	(0.1348)	(0.0240)	(0.0899)	(0.0649)
Parental Divorce	-0.0081	-0.3519	-0.0672	0.4442**	0.3001***
	(0.0145)	(0.5735)	(0.1067)	(0.1509)	(0.1037)
Observations	1,464	2,260	1,995	2,260	1,942
R-squared	0.1940	0.2386	0.0312	0.2893	0.2462

Note: Column (1) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (3) and (5). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ ***. $p < 0.01$.

bootstrap standard errors) to solve the problem of over-rejection due to few clusters (Roodman et al., 2019). This is done using the boottest post-estimation command available for linear panel data models in STATA. We present the results in Tables 2.B.1, 2.B.2, and 2.B.3 of Appendix 2.B, with the wild-cluster p-values indicated in the square parenthesis. The findings (level of significance), in general, are robust to the application of the wild-cluster bootstrapping of standard errors, with children from agricultural households negatively impacted by droughts.

Second, we introduce additional drought lag variables (Drought (*t-2*) and Drought (*t-3*)) in all regressions, to test whether the persistent effects of droughts go beyond one period. Tables 2.C.1, 2.C.2, and 2.C.3 of Appendix 2.C generally show significant coefficients on our Drought (*t*) and Drought (*t-1*) variables, but insignificant coefficients on the other lag variables, thereby suggesting no evidence for an extended duration of the drought effect on child educational outcomes.

Third, we re-adjust our models in Equation (2.6) to account for time-varying household controls such as household size, gender of household head, parental illness, and wealth index that may be endogenous to drought, and thus include controls for them from preceding survey rounds. The findings are presented in Tables 2.D.1, 2.D.2, and 2.D.3 of Appendix 2.D. As shown from the tables, our key findings remain unchanged with this alternate specification, with droughts leading to lower cognitive ability test scores and years of schooling of children in rural Ethiopia.

Fourth, we modify our drought variables and use different cut-offs for our SPEI drought indicator. Our SPEI drought variables are reconstructed to take a value of 1 if the SPEI value for the reference agricultural period is less than -0.8, and 0 otherwise. We also use additional SPEI cut-offs of -1 and -2. The results, presented in Appendix 2.E, are all robust to these specifications, where we find similar results to our main specification, with children from agricultural households negatively impacted by droughts.

Fifth, we reconstruct our measure of drought to indicate the number of droughts experienced by households within the past four years. We do this in order to understand whether children from households that experience multiple droughts are more negatively affected. Our findings, presented Tables 2.F.1, 2.F.2, and 2.F.3 of Appendix 2.F, suggest that accumulated droughts over a four-year period result in much larger negative effects. More precisely, experiencing an additional drought causes reductions in PPVT and Mathematics test scores of 0.293 and 0.107 SD, respectively. Children also face reductions in schooling years of about 12% as a result of an additional drought. These finding are explained in terms of children engaging in more daily labour hours (0.36 hours), children allocating less time to daily study activities (-0.178 hours), and agricultural households reducing educational expenditure (35%).

As a sixth robustness check, we estimate a time and place placebo test. To do this, we randomise our drought variable across communities and years in our panel data. This is done using a Fisher type randomisation test for our significantly robust outcome variables (PPVT and Mathematics). This allows us to compute the probability of observing significant estimates within the randomly assigned drought data. The k-density plot showing the estimated t-statistics for drought (t) is presented in Appendix 2.G. From Figures 2.G.1 and 2.G.2, we see that majority of test-statistics are close to zero, suggesting that the initial estimated coefficient of drought (t) shown by the red vertical line is unlikely to be random. In fact, the p-value computing the proportion of datasets in which the test statistic values are as extreme or more extreme than the value of the test statistic computed on the original sample are 0.006 and 0.008 for PPVT and Mathematics, respectively.

Finally, we re-estimate our models using self-reported measures of drought. We do this to show that self-reported measures may be problematic since they are likely to be endogenous (Sohnesen, 2019). Households in the Young Lives Survey are asked about droughts occurring since the last survey round (in the past 3-4 years). We use this measure of drought, taking the value of 1 if a shock is reported, and 0 otherwise. The results are presented in Tables 2.H.1, 2.H.2, and 2.H.3 of Appendix 2.H. We find similar results to using the SPEI indicator only for the PPVT measure of cognitive ability. This finding highlights the aforementioned problems associated with using a self-reported drought measure in that households may misreport droughts depending on their characteristics, thus providing evidence for the superiority of an objective drought measure (SPEI) over a subjective one.

2.6 Conclusion

The role of extreme weather events in shaping the welfare of children has become an increasing focus in the education literature in recent years. In this paper, we draw on a unique and detailed panel data tracking child development outcomes over 15 years in rural Ethiopia to examine the impacts that extreme weather events (droughts) have on child educational outcomes. Merging weather station data with our child level data, we add to the climate and education literature by constructing an exogenous measure for drought (the Standardised Precipitation Evapotranspiration Index) for the various communities in our survey. Employing the child fixed effect model, our study provides evidence for the adverse effect of droughts on child educational outcomes. We find that droughts have negative effects on cognitive ability and years of schooling, but not on enrolment. More specifically, children score significantly lower on their PPVT (-0.36 SD) and Mathematics test (-0.16 SD), as well as accumulate fewer years of schooling (23 weeks reduction) as a result of a drought. These findings can be explained in part, in terms of child labour in that children are more likely to engage in labour activities in periods of droughts with children working 0.32 more hours daily and hence, spending less time studying. Households are also likely to spend less on education, whilst protecting food and health expenditure when exposed to droughts, thus negatively impacting child education.

Our results further provide mild evidence for the presence of heterogeneity in the impact of droughts on child educational outcomes, where we find boys to be more adversely affected than girls with regard to the Mathematics measure of cognitive ability. We also find that younger children and children from less educated households are more adversely affected by droughts. This finding can be explained in terms of boys being more likely to participate in labour activities, and less educated households having fewer sources of income, as well as limited information concerning better agricultural practices that could potentially buffer the lingering effects of droughts. Finally, our study finds the Ethiopian Productive Safety Net Programme to be ineffective in alleviating any negative impacts of droughts on child educational outcomes. In general, our results are similar to the findings of Jensen (2000), Bonjean et al. (2012) and Aguilar and Vicarelli (2022), who show that children suffer significantly in terms of their educational outcomes when exposed to extreme weather events.

Taken together, our results indicate that droughts may act as a key barrier to the schooling outcomes of children among rural households in sub-Saharan Africa. Therefore, policies to address welfare and development in response to droughts need to be targeted towards the most vulnerable group of individuals, children living in poor households. These policies should not only consider investment in children in their critical stages (pre-school period), but continued investment in children in their pre-school years and beyond. Although, Ethiopia, alongside other African countries, have excelled tremendously in getting enrolment rates up, dropout rates and learning quality remain low. As such, policies on education must focus on retention rate and improving access to quality education, especially for the rural poor. Furthermore, safety net policy programmes such as the PSNP must be designed in a more accurate and effective manner that include giving out more handsome payments to rural households and preventing recipient children from taking up additional labour roles that disrupt schooling and learning outcomes in times of financial distress. Such policy design is of considerable importance specifically in areas like rural Ethiopia where droughts are recurrent, and investments in education is low. Additionally, given the large consequences of droughts on welfare, it becomes important for the Ethiopian government to design and implement more pragmatic policies that will assist small-scale farmers in adapting to changing climate conditions. These include planting more drought-resistant crops as well as implementing more efficient agricultural management practices that could help to shield these farmers and their households from income variability and food insecurity.

Appendix

2.A Weather Data

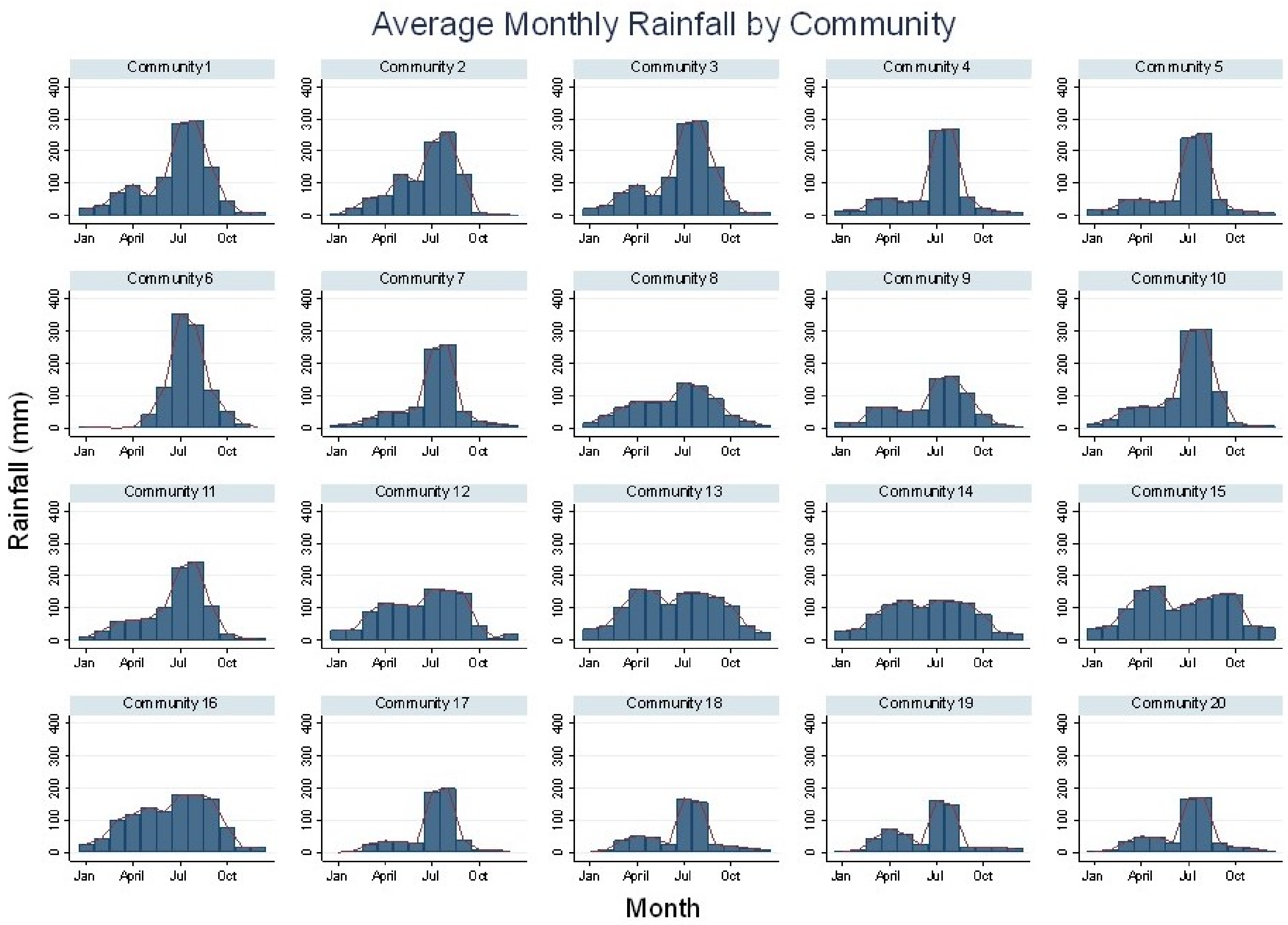

Figure 2.A.1: Mean Monthly Rainfall for the Ethiopia Young Lives Survey Communities (1981-2017).

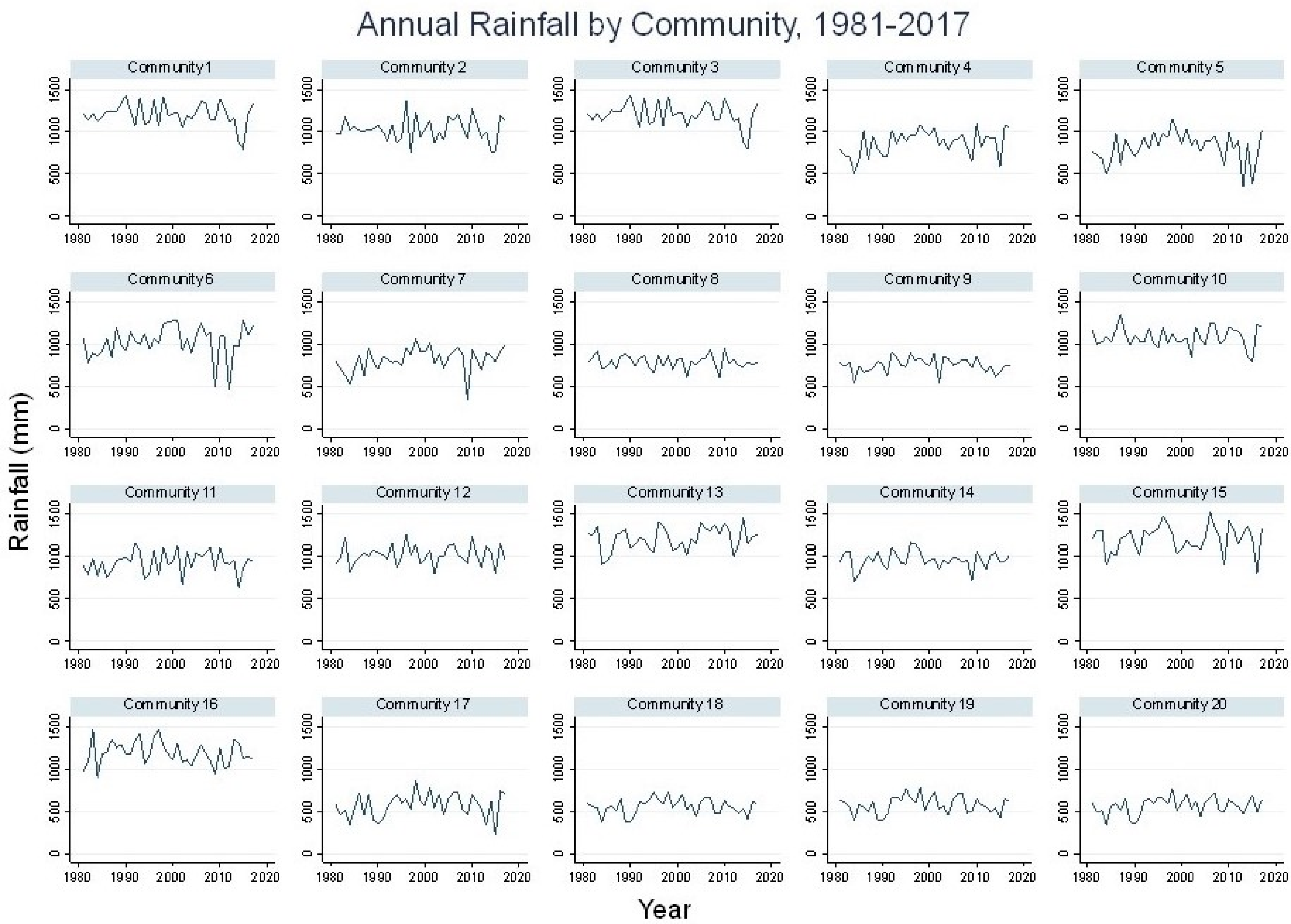

Figure 2.A.2: Total Annual Rainfall for the Ethiopia Young Lives Survey Communities (1981-2017).

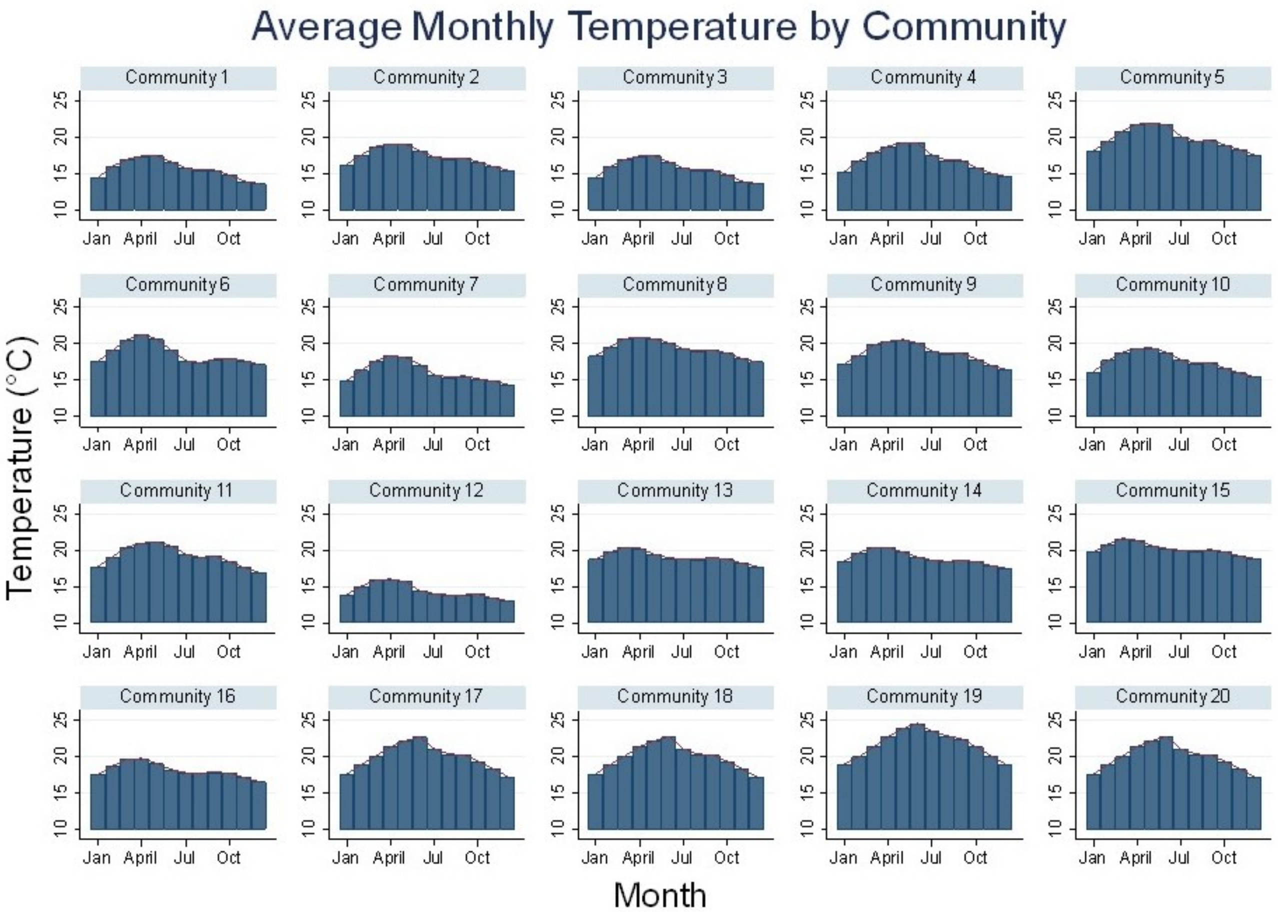

Figure 2.A.3: Mean Monthly Temperature for the Ethiopia Young Lives Survey Communities (1981-2017).

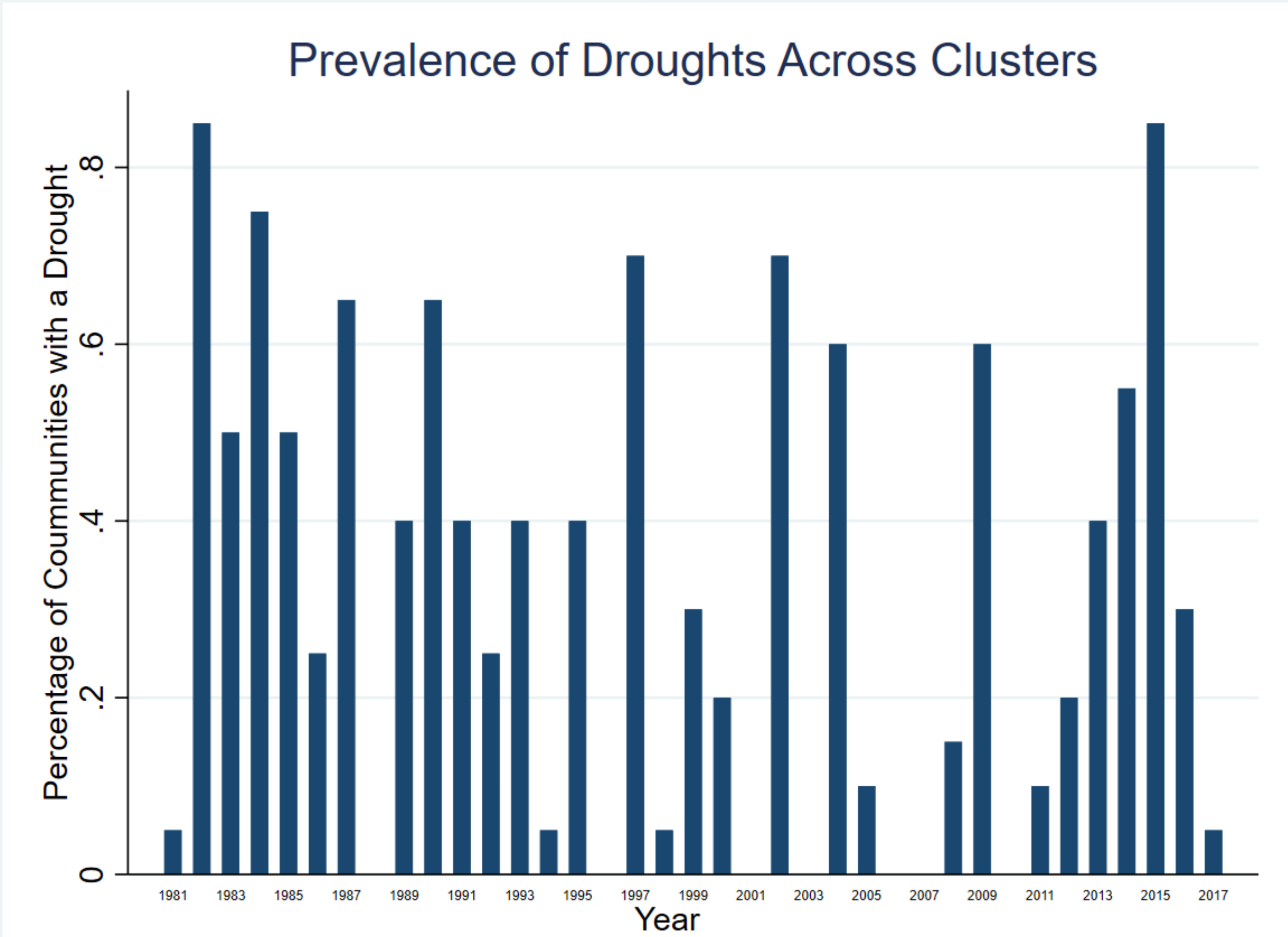

Figure 2.A.4: Graph Showing the Prevalence of Droughts Across Ethiopian Young Lives Survey Communities (1981-2017).

Table 2.9: Test for Overdispersion in Years of Schooling Conditional on Control Variables

Overdispersion test (H0: equidispersion)			Number of Obs = 2,260			
Years of Schooling	Coefficient	Standard Err.	t	P>|t|	[95% Conf.Interval]	
uhat	-0.0614*	0.0332	-1.85	0.065	-0.1266	0.0037

2.B Adjusting For Small Number of Clusters Using the Wild-Cluster Bootstrapping Method

Table 2.B.1: Effect of Droughts on Child Educational Outcomes

	PPVT (FE) (1)	Maths (FE) (2)	Enrollment (Probit RE) (3)	Enrollment (LPM, FE) (4)	Years of Schooling (Poisson FE) (5)	Years of Schooling (FE) (6)
SPEI Drought (t)	-0.3697***	-0.1615***	-0.1115	-0.1039	-0.0413	0.0880
	(0.0023)	(0.0014)	(0.9327)	(0.2342)	(0.4495)	(0.2175)
	[0.0045]	[0.0046]	[.]	[0.3253]	[.]	[0.1221]
SPEI Drought (t-1)	-0.4337***	-0.0035	-0.0365	-0.0361	-0.1334**	-0.3100**
	(0.0006)	(0.9507)	(0.7650)	(0.6809)	(0.0186)	(0.0267)
	[0.0018]	[0.9549]	[.]	[0.7287]	[.]	[0.0421]
Child's Age (In Months)	0.0497***	0.0607***	0.0265	0.0073*	0.0325	-0.0110
	(0.0017)	(0.0066)	(0.3173)	(0.0891)	(0.1322)	(0.9990)
	[0.0100]	[0.0058]	[.]	[0.0901]	[.]	[0.8821]
Child's Age-squared	-0.0002***	-0.0002***	-0.0001	-0.0001*	-0.0002***	-0.0016**
	(0.0017)	(0.0066)	(0.1301)	(0.0514)	(0.0001)	(0.0436)
	[0.0066]	[0.0095]	[.]	[0.0791]	[.]	[0.0491]
Mother's Years of Schooling	0.0631	-0.0365	0.0138	-0.0035	-0.0077	0.1086
	(0.1456)	(0.3178)	(0.2171)	(0.9319)	(0.8254)	(0.2925)
	[0.1438]	[0.2934]	[.]	[0.9369]	[.]	[0.3694]
Father's Years of Schooling	0.0617***	0.0004	0.0104	-0.0023	0.0021	-0.0293
	(0.0011)	(0.9803)	(0.1121)	(0.8387)	(0.9016)	(0.5628)
	[0.0013]	[0.9804]	[.]	[0.8468]	[.]	[0.6186]
Mother's Age	-0.0156	0.0748*	-0.0259	-0.0487	-0.0169	-0.1401
	(0.8324)	(0.0867)	(0.3150)	(0.1647)	(0.7065)	(0.1979)
	[0.8320]	[0.0922]	[.]	[0.1801]	[.]	[0.2482]
Mother's Age-squared	0.0011	-0.0010	0.0003	0.0003	-0.0000	0.0011
	(0.2733)	(0.1885)	(0.1419)	(0.2090)	(0.9205)	(0.2134)
	[0.2980]	[0.1918]	[.]	[0.2072]	[.]	[0.2743]
Father's Age	0.2028**	-0.0232	0.0100	0.0445	0.0687*	0.2889
	(0.0047)	(0.6920)	(0.2503)	(0.1896)	(0.0880)	(0.0503)
	[0.0110]	[0.7104]	[.]	[0.2533]	[.]	[0.1091]
Father's Age-squared	-0.0019**	-0.0000	-0.0001	-0.0004	-0.0004	-0.0015
	(0.0085)	(0.9655)	(0.2299)	(0.1212)	(0.3222)	(0.1965)
	[0.0159]	[0.9677]	[.]	[0.1431]	[.]	[0.2402]
Female Head	0.0105	-0.0388	-0.0392	0.0427	0.0551	0.2621
	(0.9514)	(0.7576)	(0.4346)	(0.5487)	(0.3724)	(0.2167)
	[0.9448]	[0.7669]	[.]	[0.5355]	[.]	[0.2222]
Household Size	-0.0279	0.0162	0.0047	0.0248	0.0224*	-0.0233
	(0.2006)	(0.3105)	(0.4804)	(0.0686)	(0.0565)	(0.3410)
	[0.2272]	[0.3516]	[.]	[0.1131]	[.]	[0.3313]
Father's Illness	0.0098	0.2528	-0.0329	-0.0441	-0.0327	0.2975
	(0.8852)	(0.1014)	(0.3904)	(0.2835)	(0.5793)	(0.1489)
	[0.8914]	[0.1206]	[.]	[0.1131]	[.]	[0.1151]
Mother's Illness	-0.0508	-0.0371	-0.0225	-0.0695	-0.1021**	0.2112
	(0.3114)	(0.6542)	(0.1809)	(0.1053)	(0.0241)	(0.1630)
	[0.3332]	[0.6737]	[.]	[0.1131]	[.]	[0.1952]
Parental Divorce	-0.0824	-0.2144	-0.0104	0.0354	0.0198	0.1100
	(0.5268)	(0.3309)	(0.4789)	(0.7218)	(0.8342)	(0.7995)
	[0.5277]	[0.3568]	[.]	[0.7187]	[.]	[0.7998]
N	2260	2260	2260	2260	1983	2260
r2	0.1182	0.0426	0.3361	0.2258	0.2331	0.3175

Note: Column (3) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (3). The pseudo R-squared are provided in columns (3) and (5). Clustered robust p-values at community level in "()" parentheses. Wild cluster bootstrap p-values are provided for linear models in "[]" parentheses. Significance level denoted using wild cluster bootstrap p-values as * p<0.10 ** p<0.05 *** p<0.01.

Table 2.B.2: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.0064	-0.0083	0.0470	-0.4501***
	(0.8847)	(0.8289)	(0.8905)	(0.0018)
	[0.9040]	[0.8431]	[0.9125]	[0.0082]
SPEI Drought (t-1)	0.0109	-0.0020	-0.3704	-0.0096
	(0.8580)	(0.9734)	(0.5124)	(0.9491)
	[0.8778]	[0.9772]	[0.5608]	[0.9563]
Mother's Years of Schooling	0.0005	0.0109	-0.1074	-0.1851
	(0.9844)	(0.6811)	(0.6132)	(0.1314)
	[0.9864]	[0.7292]	[0.5608]	[0.1218]
Father's Years of Schooling	0.0035	0.0078	-0.1790	0.0572
	(0.7849)	(0.5192)	(0.1498)	(0.1694)
	[0.7848]	[0.5582]	[0.1956]	[0.2250]
Mother's Age	-0.0162	-0.0076	-0.2340	0.4420**
	(0.6259)	(0.8582)	(0.4808)	(0.0074)
	[0.6494]	[0.8645]	[0.4910]	[0.0121]
Mother's Age-squared	0.0002	0.0001	0.0024	-0.0059***
	(0.5613)	(0.7874)	(0.6002)	(0.0009)
	[0.5793]	[0.7988]	[0.6221]	[0.0014]
Father's Age	0.0075	0.0126	-0.0527	0.1706
	(0.7755)	(0.7030)	(0.8842)	(0.2866)
	[0.7765]	[0.7112]	[0.8964]	[0.3169]
Father's Age-squared	-0.0001	-0.0001	0.0014	-0.0005
	(0.7213)	(0.6805)	(0.6562)	(0.7455)
	[0.7363]	[0.6946]	[0.6980]	[0.7672]
Female Head	-0.1853**	-0.1780**	1.1659**	0.3568
	(0.0045)	(0.0114)	(0.0051)	(0.3223)
	[0.0128]	[0.0273]	[0.0166]	[0.3609]
Household Size	-0.0827***	-0.0890***	0.0976	0.0556
	(0.0000)	(0.0000)	(0.4192)	(0.4824)
	[0.0001]	[0.0016]	[0.4325]	[0.5041]
Father's Illness	-0.0402	-0.0999	2.3613***	0.1172
	(0.3797)	(0.0601)	(0.0007)	(0.2131)
	[0.4383]	[0.1012]	[0.0009]	[0.1847]
Mother's Illness	0.0861**	0.0558	1.5822***	0.2530
	(0.0217)	(0.1971)	(0.0017)	(0.1920)
	[0.0458]	[0.2243]	[0.0019]	[0.2093]
Parental Divorce	0.0714	0.0942	-0.0096	0.2749
	(0.5151)	(0.4191)	(0.9923)	(0.5914)
	[0.5219]	[0.4169]	[0.9928]	[0.6104]
N	2260	2260	2260	2260
r2	0.0887	0.0790	0.0631	0.1205

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include time fixed effects. Clustered robust p-values at community level in "()" parentheses. Wild cluster bootstrap p-values in "[]" parentheses. Significance level denoted using wild cluster bootstrap p-values as * p<0.10 ** p<0.05 *** p<0.01.

Table 2.B.3: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE) (1)	Labour Participation (LPM FE) (2)	Daily Labour Hours (FE) (3)	Daily Labour Hours (Poisson FE) (4)	Daily Study Hours (FE) (5)	Daily Study Hours (Poisson FE) (6)
SPEI Drought (t)	-0.0007	-0.0078	0.3241**	0.0642**	-0.1558**	-0.1596**
	(0.9167)	(0.1445)	(0.0441)	(0.0195)	(0.0279)	(0.0132)
	[.]	[0.3213]	[0.0470]	[.]	[0.0258]	[.]
SPEI Drought (t-1)	0.0192***	0.0115**	0.4896**	0.0948***	-0.0549	-0.0805
	(0.0016)	(0.0339)	(0.0173)	(0.0024)	(0.6200)	(0.4017)
	[.]	[0.0421]	[0.0220]	[.]	[0.6646]	[.]
Child's Age (In Months)	0.0037	0.0024	0.0665	0.0131	-0.0296	-0.0196
	(0.1498)	(0.2169)	(0.3087)	(0.3096)	(0.2407)	(0.4991)
	[.]	[0.3764]	[0.4020]	[.]	[0.2359]	[.]
Child's Age-squared	-0.0000	-0.0000**	-0.0001	-0.0000	-0.0001	-0.0001
	(0.1813)	(0.0375)	(0.6000)	(0.5565)	(0.2020)	(0.2276)
	[.]	[0.0400]	[0.6250]	[.]	[0.2263]	[.]
Mother's Years of Schooling	-0.0007	-0.0131	-0.0256	-0.0069	0.2397	0.1298
	(0.4830)	(0.1994)	(0.8689)	(0.8295)	(0.0814)	(0.1016)
	[.]	[0.2611]	[0.8783]	[.]	[0.1493]	[.]
Father's Years of Schooling	-0.0007	0.0034	0.1141*	0.0230**	-0.0218	-0.0176
	(0.4380)	(0.1299)	(0.0426)	(0.0114)	(0.4681)	(0.5285)
	[.]	[0.1330]	[0.0636]	[.]	[0.4909]	[.]
Mother's Age	-0.0043	-0.0049	-0.0747	-0.0169	-0.0048	0.0276
	(0.1162)	(0.1628)	(0.6650)	(0.5776)	(0.9396)	(0.6261)
	[.]	[0.1451]	[0.6760]	[.]	[0.9404]	[.]
Mother's Age-squared	0.0000	0.0000	0.0013	0.0003	0.0003	-0.0001
	(0.2149)	(0.7841)	(0.4605)	(0.3706)	(0.623)	(0.8104)
	[.]	[0.8569]	[0.4713]	[.]	[0.6163]	[.]
Father's Age	0.0032	-0.0015	-0.0991	-0.0201	0.0848	0.0549
	(0.1243)	(0.8783)	(0.2907)	(0.2488)	(0.2808)	(0.3649)
	[.]	[0.8929]	[0.2916]	[.]	[0.2992]	[.]
Father's Age-squared	-0.0000	-0.0000	0.0003	0.0001	-0.0007	-0.0004
	(0.1849)	(0.7460)	(0.7268)	(0.6887)	(0.2474)	(0.4441)
	[.]	[0.7918]	[0.7140]	[.]	[0.2566]	[.]
Female Head	-0.0114*	-0.0127	-0.2309	-0.0500	-0.1544	-0.0544
	(0.0547)	(0.5307)	(0.4304)	(0.3505)	(0.3172)	(0.6822)
	[.]	[0.6046]	[0.4463]	[.]	[0.3638]	[.]
Household Size	-0.0011	-0.0044	-0.0690	-0.0138	0.0128	0.0151
	(0.4912)	(0.1801)	(0.2252)	(0.1672)	(0.5872)	(0.3828)
	[.]	[0.1842]	[0.2791]	[.]	[0.6205]	[.]
Father's Illness	-0.0124**	-0.0264*	-0.2129	-0.0416	-0.0846	-0.0858
	(0.0477)	(0.0590)	(0.4019)	(0.3486)	(0.1906)	(0.1951)
	[.]	[0.0670]	[0.4105]	[.]	[0.1931]	[.]
Mother's Illness	0.0094	0.0171	0.6249***	0.1222***	-0.0785	-0.1081*
	(0.2368)	(0.1036)	(0.0006)	(0.0000)	(0.3918)	(0.0886)
	[.]	[0.1204]	[0.0063]	[.]	[0.4193]	[.]
Parental Divorce	-0.0081	-0.0134	-0.3604	-0.0683	0.4652**	0.3230***
	(0.5936)	(0.7837)	(0.5316)	(0.5147)	(0.0094)	(0.0025)
	[.]	[0.6617]	[0.5499]	[.]	[0.0188]	[.]
N	1464	2260	2260	1995	2260	1942
r2	0.2311	0.1183	0.0374	0.1210	0.2852	0.1322

Note: Column (1) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (4) and (6). Clustered robust p-values at community level in "()" parentheses. Wild cluster bootstrap p-values are provided for linear models in "[]" parentheses. Significance level denoted using wild cluster bootstrap p-values as * p<0.10 ** p<0.05 *** p<0.01.

2.C Controlling For Additional Drought Lags

Table 2.C.1: Effect of Droughts on Child Educational Outcomes

	PPVT	Maths	Enrolment	Years of Schooling
	(FE)	(FE)	(Probit RE)	(Poisson FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.3655**	-0.1635**	-0.1048	-0.0884
	(0.0886)	(0.0382)	(4.3281)	(0.0794)
SPEI Drought (t-1)	-0.4509***	-0.0267	-0.0897	-0.1418***
	(0.0984)	(0.0555)	(3.7777)	(0.0521)
SPEI Drought (t-2)	0.2854	0.0018	-0.1415	-0.1091
	(0.2314)	(0.1014)	(5.8828)	(0.1533)
SPEI Drought (t-3)	-0.1977	-0.1813	-0.2104	-0.2665
	(0.2044)	(0.1058)	(8.5277)	(0.1799)
Child's Age (In Months)	0.0520***	0.0616***	0.0248	0.0357**
	(0.0118)	(0.0175)	(0.9934)	(0.0163)
Child's Age-squared	-0.0002***	-0.0001**	-0.0001	-0.0002***
	(0.0001)	(0.0001)	(0.0032)	(0.0000)
Mother's Years of Schooling	0.0691	-0.0344	0.0134	-0.0071
	(0.0445)	(0.0355)	(0.4598)	(0.0341)
Father's Years of Schooling	0.0603***	0.0002	0.0105	-0.0003
	(0.0170)	(0.0174)	(0.4096)	(0.0175)
Mother's Age	-0.0182	0.0736*	-0.0263	-0.0144
	(0.0719)	(0.0407)	(1.0554)	(0.0473)
Mother's Age-squared	0.0011	-0.0009	0.0003	-0.0000
	(0.0009)	(0.0007)	(0.0129)	(0.0004)
Father's Age	0.1845***	-0.0283	0.0101	0.0606
	(0.0446)	(0.0557)	(0.3799)	(0.0392)
Father's Age-squared	-0.0018***	0.0000	-0.0001	-0.0003
	(0.0005)	(0.0007)	(0.0031)	(0.0004)
Female Head	-0.0030	-0.0478	-0.0441	0.0567
	(0.1738)	(0.1233)	(2.1312)	(0.0562)
Household Size	-0.0216	0.0150	0.0028	0.0166
	(0.0192)	(0.0169)	(0.0860)	(0.0151)
Father's Illness	0.0222	0.2557	-0.0349	-0.0268
	(0.0648)	(0.0538)	(1.1563)	(0.0627)
Mother's Illness	-0.0557	-0.0420	-0.0245	-0.1093**
	(0.0459)	(0.0797)	(0.9279)	(0.0474)
Parental Divorce	-0.0674	-0.2182	-0.0163	0.0046
	(0.1271)	(0.2146)	(0.7377)	(0.0793)
N	2260	2260	2260	1983
r2	0.1383	0.0472	0.1043	0.0132

Note: Column (3) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (3). The pseudo R-squared are provided in columns (3) and (4). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.C.2: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.0115	-0.0095	0.0070	-0.4665***
	(0.0416)	(0.0357)	(0.2891)	(0.1022)
SPEI Drought (t-1)	-0.0014	-0.0022	-0.4901	-0.0658
	(0.0696)	(0.0671)	(0.4765)	(0.1177)
SPEI Drought (t-2)	-0.2207	-0.0811	-1.4928***	-0.5344*
	(0.1242)	(0.0897)	(0.3957)	(0.2717)
SPEI Drought (t-3)	-0.0447	0.0173	-0.5910	-0.3176
	(0.1236)	(0.0946)	(0.3552)	(0.3156)
Mother's Years of Schooling	-0.0020	0.0095	-0.1199	-0.1880*
	(0.0243)	(0.0254)	(0.2269)	(0.1045)
Father's Years of Schooling	0.0043	0.0082	-0.1733	0.0591
	(0.0116)	(0.0113)	(0.1221)	(0.0410)
Mother's Age	-0.0156	-0.0072	-0.2307	0.4427***
	(0.0334)	(0.0420)	(0.3261)	(0.1407)
Mother's Age-squared	0.0002	0.0001	0.0025	-0.0059***
	(0.0003)	(0.0004)	(0.0045)	(0.0014)
Father's Age	0.0162	0.0168	-0.0022	0.1857
	(0.0248)	(0.0307)	(0.3277)	(0.1517)
Father's Age-squared	-0.0002	-0.0002	0.0010	-0.0006
	(0.0002)	(0.0003)	(0.0029)	(0.0014)
Female Head	-0.1848***	-0.1760**	1.1551***	0.3475
	(0.0557)	(0.0600)	(0.3545)	(0.3536)
Household Size	-0.0890***	-0.0911***	0.0529	0.0388
	(0.0068)	(0.0128)	(0.1186)	(0.0740)
Father's Illness	-0.0467	-0.1027*	2.3210***	0.1041
	(0.0440)	(0.0480)	(0.5151)	(0.0882)
Mother's Illness	0.0845**	0.0561	1.5638***	0.2436
	(0.0291)	(0.0395)	(0.4028)	(0.1867)
Parental Divorce	0.0552	0.0887	-0.1231	0.2329
	(0.1157)	(0.1182)	(1.0118)	(0.4863)
N	2260	2260	2260	2260
r2	0.1139	0.0832	0.0725	0.1273

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include time fixed effects. Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.C.3: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE)	Daily Labour Hours (FE)	Daily Labour Hours (Poisson FE)	Daily Study Hours (FE)	Daily Study Hours (Poisson FE)
	(1)	(2)	(3)	(4)	(5)
SPEI Drought (t)	-0.0005	0.3307**	0.0662**	-0.1666**	-0.1835***
	(0.0063)	(0.1471)	(0.0283)	(0.0584)	(0.0684)
SPEI Drought (t-1)	0.0188***	0.5402**	0.1049***	-0.0975	-0.1014
	(0.0062)	(0.2068)	(0.0354)	(0.1165)	(0.0884)
SPEI Drought (t-2)	0.0012	0.1035	0.0183	-0.3466	-0.2313
	(0.0084)	(0.4856)	(0.0825)	(0.2354)	(0.1827)
SPEI Drought (t-3)	-0.0025	0.3707	0.0734	-0.2536	-0.2555
	(0.0091)	(0.4493)	(0.0750)	(0.2254)	(0.1742)
Child's Age (In Months)	0.0037	0.0653	0.0126	-0.0301	-0.0166
	(0.0025)	(0.0618)	(0.0126)	(0.0219)	(0.0234)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Mother's Years of Schooling	-0.0007	-0.0287	-0.0074	0.2381*	0.1259
	(0.0011)	(0.1532)	(0.0319)	(0.1219)	(0.0775)
Father's Years of Schooling	-0.0008	0.1141**	0.0230**	-0.0207	-0.0180
	(0.0010)	(0.0505)	(0.0091)	(0.0276)	(0.0276)
Mother's Age	-0.0043	-0.0728	-0.0168	-0.0048	0.0273
	(0.0027)	(0.1683)	(0.0304)	(0.0612)	(0.0569)
Mother's Age-squared	0.0000	0.0012	0.0003	0.0003	-0.0001
	(0.0000)	(0.0017)	(0.0003)	(0.0006)	(0.0005)
Father's Age	0.0031	-0.0935	-0.0195	0.0933	0.0523
	(0.0020)	(0.0925)	(0.0178)	(0.0742)	(0.0622)
Father's Age-squared	-0.0000	0.0002	0.0001	-0.0008	-0.0004
	(0.0000)	(0.0008)	(0.0001)	(0.0006)	(0.0005)
Female Head	-0.0114*	-0.2138	-0.0446	-0.1626	-0.0513
	(0.0059)	(0.2610)	(0.0483)	(0.1406)	(0.1321)
Household Size	-0.0011	-0.0636	-0.0122	0.0016	0.0043
	(0.0016)	(0.0494)	(0.0091)	(0.0190)	(0.0179)
Father's Illness	-0.0123**	-0.2151	-0.0418	-0.0922	-0.0837
	(0.0060)	(0.2526)	(0.0456)	(0.0678)	(0.0719)
Mother's Illness	0.0095	0.6352***	0.1253***	-0.0861	-0.1180*
	(0.0078)	(0.1371)	(0.0247)	(0.0877)	(0.0640)
Parental Divorce	-0.0082	-0.3454	-0.0655	0.4364**	0.2851***
	(0.0151)	(0.5504)	(0.1032)	(0.1510)	(0.1067)
N	1464	2260	1995	2260	1942
r2	0.0271	0.0400	0.2017	0.2952	0.2013

Note: Column (1) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (3) and (5). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

2.D Controlling For Household Controls From Preceding Rounds

Table 2.D.1: Effect of Droughts on Child Educational Outcomes

	PPVT	Mathematics	Enrolment	Years of Schooling
	(FE)	(FE)	(Probit RE)	(Poisson FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.3653***	-0.1587***	-0.1096	-0.0374
	(0.0951)	(0.0364)	(0.0955)	(0.0520)
SPEI Drought (t-1)	-0.4287***	-0.0045	-0.0404	-0.1386**
	(0.0911)	(0.0546)	(0.0924)	(0.0571)
Child's Age (In Months)	0.0492***	0.0604***	0.0251***	0.0311
	(0.0121)	(0.0180)	(0.0088)	(0.0233)
Child's Age-squared	-0.0002***	-0.0002***	-0.0001***	-0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Mother's Years of Schooling	0.0625	-0.0322	0.0132**	-0.0081
	(0.0387)	(0.0349)	(0.0065)	(0.0353)
Father's Years of Schooling	0.0589***	0.0018	0.0098***	0.0031
	(0.0157)	(0.0161)	(0.0033)	(0.0171)
Mother's Age	-0.0559	0.0754*	-0.0272	-0.0226
	(0.0625)	(0.0353)	(0.0170)	(0.0421)
Mother's Age-squared	0.0016*	-0.0010	0.0003	0.0000
	(0.0008)	(0.0006)	(0.0002)	(0.0004)
Father's Age	0.1953***	-0.0225	0.0094	0.0655
	(0.0594)	(0.0595)	(0.0106)	(0.0413)
Father's Age-squared	-0.0019**	-0.0000	-0.0001	-0.0004
	(0.0006)	(0.0007)	(0.0001)	(0.0004)
Female Head	0.0407	0.0410	-0.0308	0.0833
	(0.1013)	(0.0935)	(0.0521)	(0.0866)
Household Size	0.0351*	0.0128	0.0061	0.0225**
	(0.0174)	(0.0208)	(0.0051)	(0.0093)
Father's Illness	0.0070	0.2541	-0.0347	-0.0274
	(0.0687)	(0.0508)	(0.0302)	(0.0574)
Mother's Illness	-0.0529	-0.0358	-0.0209	-0.0916**
	(0.0479)	(0.0807)	(0.0205)	(0.0422)
Parental Divorce	-0.0672	-0.2333	-0.0307	0.0269
	(0.1332)	(0.1954)	(0.0511)	(0.0996)
Wealth Index	0.2505	0.1907	0.0649	-0.0669
	(0.2663)	(0.3246)	(0.0952)	(0.2841)
Observations	2,253	2,253	2,253	1,980
R-squared	0.1200	0.0427	0.0344	0.2311

Note: Column (3) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (3). The pseudo R-squared are provided in columns (3) and (4). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.D.2: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	-0.0057	-0.0040	0.0023	-0.4473***
	(0.0420)	(0.0402)	(0.3403)	(0.1187)
SPEI Drought (t-1)	0.0100	-0.0012	-0.3817	-0.0161
	(0.0587)	(0.0598)	(0.5349)	(0.1485)
Mother's Years of Schooling	-0.0224	-0.0134	-0.0481	-0.1512
	(0.0270)	(0.0301)	(0.1911)	(0.1136)
Father's Years of Schooling	0.0011	0.0048	-0.1852	0.0545
	(0.0123)	(0.0116)	(0.1087)	(0.0409)
Mother's Age	-0.0695*	-0.0641	-0.0813	0.4466**
	(0.0347)	(0.0422)	(0.3414)	(0.1612)
Mother's Age-squared	0.0009**	0.0009*	0.0004	-0.0061***
	(0.0003)	(0.0004)	(0.0046)	(0.0017)
Father's Age	-0.0026	0.0009	-0.0096	0.1541
	(0.0269)	(0.0357)	(0.3321)	(0.1582)
Father's Age-squared	0.0000	-0.0000	0.0010	-0.0004
	(0.0003)	(0.0004)	(0.0030)	(0.0014)
Female Head	0.1230**	0.1236**	-1.4163**	-0.1149
	(0.0472)	(0.0487)	(0.4881)	(0.1253)
Household Size	0.0001	0.0030	-0.1492	0.0498
	(0.0112)	(0.0102)	(0.1035)	(0.0563)
Father's Illness	-0.0532	-0.1132**	2.3448***	0.1367
	(0.0441)	(0.0488)	(0.4889)	(0.0976)
Mother's Illness	0.0866**	0.0517	1.5425***	0.2753
	(0.0316)	(0.0402)	(0.3952)	(0.1765)
Parental Divorce	0.1137	0.1427	0.0178	0.2643
	(0.1122)	(0.1150)	(0.9981)	(0.5161)
Wealth Index	-0.1132	-0.0039	0.8646	-0.7520
	(0.1603)	(0.1440)	(1.4855)	(0.6763)
Observations	2,253	2,253	2,253	2,253
R-squared	0.0387	0.0229	0.0655	0.1192

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include time fixed effects. Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.D.3: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE) (1)	Daily Labour Hours (FE) (2)	Daily Labour Hours (Poisson FE) (3)	Daily Study Hours (FE) (4)	Daily Study Hours (Poisson FE) (5)
SPEI Drought (t)	0.0009	0.3423**	0.0679**	-0.1589**	-0.1662**
	(0.0064)	(0.1416)	(0.0271)	(0.0597)	(0.0652)
SPEI Drought (t-1)	0.0210***	0.4883**	0.0949***	-0.0616	-0.0812
	(0.0059)	(0.1847)	(0.0330)	(0.1034)	(0.0924)
Child's Age (In Months)	0.0036	0.0646	0.0128	-0.0290	-0.0183
	(0.0024)	(0.0600)	(0.0124)	(0.0236)	(0.0297)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Mother's Years of Schooling	-0.0004	-0.0282	-0.0074	0.2244*	0.1236
	(0.0010)	(0.1574)	(0.0328)	(0.1218)	(0.0786)
Father's Years of Schooling	-0.0004	0.1103**	0.0221**	-0.0158	-0.0144
	(0.0009)	(0.0504)	(0.0092)	(0.0280)	(0.0272)
Mother's Age	-0.0041	-0.1493	-0.0315	0.0344	0.0585
	(0.0026)	(0.1575)	(0.0282)	(0.0665)	(0.0619)
Mother's Age-squared	0.0000	0.0023	0.0005*	-0.0002	-0.0005
	(0.0000)	(0.0015)	(0.0003)	(0.0006)	(0.0006)
Father's Age	0.0030	-0.1078	-0.0216	0.0959	0.0667
	(0.0020)	(0.0878)	(0.0171)	(0.0739)	(0.0576)
Father's Age-squared	-0.0000	0.0004	0.0001	-0.0008	-0.0005
	(0.0000)	(0.0008)	(0.0001)	(0.0006)	(0.0005)
Female Head	-0.0083*	-0.0666	-0.0123	0.1359	0.0930
	(0.0049)	(0.4497)	(0.0903)	(0.1050)	(0.0934)
Household Size	-0.0001	0.0450	0.0092	-0.0488	-0.0359**
	(0.0018)	(0.0524)	(0.0105)	(0.0289)	(0.0150)
Father's Illness	-0.0119**	-0.2354	-0.0464	-0.0895	-0.0870
	(0.0054)	(0.2481)	(0.0453)	(0.0638)	(0.0662)
Mother's Illness	0.0101	0.6030***	0.1180***	-0.0824	-0.1097*
	(0.0075)	(0.1307)	(0.0231)	(0.0799)	(0.0578)
Parental Divorce	-0.0123	-0.3751	-0.0783	0.4646***	0.3126***
	(0.0155)	(0.5934)	(0.1133)	(0.1504)	(0.1184)
Wealth Index	-0.0385***	1.4144	0.2865*	0.1437	0.1094
	(0.0083)	(0.8755)	(0.1661)	(0.4523)	(0.3845)
Observations	1,457	2,253	1,992	2,253	1,939
R-squared	0.1092	0.0395	0.0412	0.2867	0.2213

Note: Column (1) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (3) and (5). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

2.E Using Alternate SPEI Cut-off: < -0.8, < -1, < -2

Table 2.E.1: Effect of Droughts on Child Educational Outcomes

	PPVT	Maths	Enrolment	Years of Schooling
	(FE)	(FE)	(Probit RE)	(Poisson FE)
	(1)	(2)	(3)	(4)
		SPEI Cut-off: < -0.8		
SPEI Drought (t)	-0.1538**	-0.2031***	-0.2297	-0.1528*
	(0.0689)	(0.0465)	(1.5645)	(0.0923)
SPEI Drought (t-1)	-0.3333	-0.0664	-0.1220	-0.2303**
	(0.1918)	(0.0609)	(0.8109)	(0.0962)
Child's Age (In Months)	0.0628***	0.0664***	0.0294	0.0427***
	(0.0102)	(0.0165)	(0.1956)	(0.0133)
Child's Age-squared	-0.0002**	-0.0002**	-0.0001	-0.0002***
	(0.0001)	(0.0001)	(0.0007)	(0.0000)
N	2260	2260	2260	1983
r2	0.0600	0.0441	0.0923	0.1024
		SPEI Cut-off: < -1		
SPEI Drought (t)	-0.2880**	-0.2713***	-0.2524	-0.2727**
	(0.1248)	(0.0686)	(0.8958)	(0.1232)
SPEI Drought (t-1)	-0.4759*	-0.1245*	-0.1621	-0.2721***
	(0.2189)	(0.0667)	(0.5498)	(0.1005)
Child's Age (In Months)	0.0658***	0.0690***	0.0293	0.0471***
	(0.0089)	(0.0169)	(0.0972)	(0.0155)
Child's Age-squared	-0.0002**	-0.0002**	-0.0001	-0.0002***
	(0.0001)	(0.0001)	(0.0004)	(0.0000)
N	2260	2260	2260	1983
r2	0.0708	0.0474	0.0734	0.0351
		SPEI Cut-off: < -2		
SPEI Drought (t)	-0.4321***	-0.2042**	-0.2389	-0.3582*
	(0.1215)	(0.0860)	(3.1636)	(0.1874)
SPEI Drought (t-1)	-0.5819**	-0.0229	-0.0927	-0.2433***
	(0.2204)	(0.0565)	(1.2338)	(0.0813)
Child's Age (In Months)	0.0457***	0.0631***	0.0227	0.0344*
	(0.0114)	(0.0160)	(0.2879)	(0.0186)
Child's Age-squared	-0.0001	-0.0001**	-0.0001	-0.0002***
	(0.0001)	(0.0000)	(0.0008)	(0.0000)
N	2260	2260	2260	1983
r2	0.0960	0.0399	0.1209	0.0617

Note: Column (3) reports the marginal effect from the probit random effect model. Additional controls include parental age, parental education, female household, household size, parental illness, parental divorce, time fixed effects, and additional community fixed effects in model (3). The pseudo R-squared are provided in columns (3) and (4). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.E.2: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
		SPEI Cut-off: < -0.8		
SPEI Drought (t)	0.0752	0.0619	0.2464	-0.4319**
	(0.0465)	(0.0394)	(0.3033)	(0.1768)
SPEI Drought (t-1)	0.1212*	0.0708	0.4034	0.2553
	(0.0637)	(0.0398)	(0.3731)	(0.2224)
N	2260	2260	2260	2260
r2	0.1083	0.0872	0.0636	0.1189
		SPEI Cut-off: < -1		
SPEI Drought (t)	0.1031*	0.0806	0.6066	-0.4658*
	(0.0527)	(0.0495)	(0.3907)	(0.2221)
SPEI Drought (t-1)	0.1518	0.0885	0.3365	0.2944
	(0.0873)	(0.0587)	(0.4693)	(0.2784)
N	2260	2260	2260	2260
r2	0.1078	0.0868	0.0644	0.1202
		SPEI Cut-off: < -2		
SPEI Drought (t)	0.1190*	0.1460*	0.2938	-0.3483
	(0.0660)	(0.0813)	(0.3812)	(0.2872)
SPEI Drought (t-1)	0.0265	0.0290	-0.1609	0.1270
	(0.0480)	(0.0337)	(0.3203)	(0.3207)
N	2260	2260	2260	2260
r2	0.0994	0.0948	0.0626	0.1109

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include parental age, parental education, female household, household size, parental illness, parental divorce and time fixed effects. Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.E.3: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE)	Daily Labour Hours (FE)	Daily Labour Hours (Poisson FE)	Daily Study Hours (FE)	Daily Study Hours (Poisson FE)
	(1)	(2)	(3)	(4)	(5)
SPEI Cut-off: < -0.8					
SPEI Drought (t)	0.0014	0.5671*	0.1107**	-0.3017**	-0.4252***
	(0.0046)	(0.2781)	(0.0492)	(0.1249)	(0.1094)
SPEI Drought (t-1)	0.0014	0.4767	0.0890*	-0.2238	-0.2781**
	(0.0045)	(0.2859)	(0.0467)	(0.1862)	(0.1183)
Child's Age (In Months)	0.0039	0.0497	0.0095	-0.0180	-0.0071
	(0.0026)	(0.0643)	(0.0130)	(0.0218)	(0.0202)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
N	1464	2260	1995	2260	1942
r2	0.0392	0.0438	0.1187	0.2991	0.3210
SPEI Cut-off: < -1					
SPEI Drought (t)	0.0008	0.7601**	0.1428***	-0.3205**	-0.4513***
	(0.0038)	(0.3160)	(0.0544)	(0.1300)	(0.1372)
SPEI Drought (t-1)	0.0013	0.7576**	0.1336***	-0.3808*	-0.3285**
	(0.0071)	(0.3032)	(0.0473)	(0.1976)	(0.1372)
Child's Age (In Months)	0.0039	0.0409	0.0081	-0.0130	-0.0024
	(0.0026)	(0.0653)	(0.0132)	(0.0198)	(0.0209)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001*	-0.0001*
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
N	1464	2260	1995	2260	1942
r2	0.0821	0.0484	0.1937	0.2990	0.2181
SPEI Cut-off: < -2					
SPEI Drought (t)	-0.0071	0.8298**	0.1663***	-0.3236**	-0.5207***
	(0.0061)	(0.3325)	(0.0578)	(0.1129)	(0.1454)
SPEI Drought (t-1)	0.0015	0.5726*	0.1153*	-0.1339	-0.1352
	(0.0078)	(0.3096)	(0.0597)	(0.2009)	(0.1867)
Child's Age (In Months)	0.0039	0.0737	0.0145	-0.0289	-0.0157
	(0.0026)	(0.0659)	(0.0132)	(0.0250)	(0.0264)
Child's Age-squared	-0.0000	-0.0002	-0.0000*	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
N	1464	2260	1995	2260	1942
r2	0.0122	0.0473	0.1921	0.2912	0.3312

Note: Column (1) reports the marginal effect from the probit random effect model. Additional controls include parental age, parental education, female household, household size, parental illness, parental divorce, time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (3) and (5). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

2.F Using an Accumulated Drought Measure For the Past 4 Years

Table 2.F.1: Effect of Droughts on Child Educational Outcomes

	PPVT	Maths	Enrolment	Years of Schooling
	(FE)	(FE)	(Probit RE)	(Poisson FE)
	(1)	(2)	(3)	(4)
Accumulated Drought	-0.2932**	-0.1074**	-0.1204	-0.1165*
	(0.0964)	(0.0397)	(5.4558)	(0.0661)
Child's Age (In Months)	0.0475***	0.0636***	0.0256	0.0315
	(0.0152)	(0.0181)	(1.1303)	(0.0230)
Child's Age-squared	-0.0002**	-0.0002***	-0.0001	-0.0002***
	(0.0001)	(0.0001)	(0.0038)	(0.0000)
Mother's Years of Schooling	0.0543	-0.0359	0.0136	-0.0084
	(0.0489)	(0.0371)	(0.5700)	(0.0340)
Father's Years of Schooling	0.0604***	0.0001	0.0104	0.0026
	(0.0142)	(0.0171)	(0.4271)	(0.0164)
Mother's Age	-0.0176	0.0707*	-0.0258	-0.0112
	(0.0702)	(0.0367)	(1.1455)	(0.0485)
Mother's Age-squared	0.0011	-0.0009	0.0003	-0.0000
	(0.0009)	(0.0007)	(0.0136)	(0.0004)
Father's Age	0.2026***	-0.0191	0.0101	0.0695*
	(0.0576)	(0.0551)	(0.4198)	(0.0408)
Father's Age-squared	-0.0019***	-0.0001	-0.0001	-0.0004
	(0.0006)	(0.0006)	(0.0033)	(0.0004)
Female Head	0.0031	-0.0356	-0.0417	0.0588
	(0.1518)	(0.1262)	(1.8100)	(0.0614)
Household Size	-0.0376	0.0124	0.0035	0.0179
	(0.0232)	(0.0164)	(0.1268)	(0.0117)
Father's Illness	0.0053	0.2547	-0.0344	-0.0390
	(0.0762)	(0.0511)	(1.3750)	(0.0613)
Mother's Illness	-0.0611	-0.0464	-0.0233	-0.1014**
	(0.0691)	(0.0766)	(1.2578)	(0.0480)
Parental Divorce	-0.1242	-0.2149	-0.0151	0.0080
	(0.1353)	(0.2116)	(0.7437)	(0.0824)
N	2260	2260	2260	1983
r2	0.0860	0.0400	0.1643	0.2314

Note: Column (3) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (3). The pseudo R-squared are provided in columns (3) and (4). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.F.2: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
Accumulated Drought	-0.0377	-0.0142	-0.3656	-0.3539**
	(0.0493)	(0.0386)	(0.2345)	(0.1192)
Mother's Years of Schooling	0.0027	0.0114	-0.0980	-0.1789
	(0.0245)	(0.0261)	(0.2031)	(0.1052)
Father's Years of Schooling	0.0042	0.0080	-0.1713	0.0573
	(0.0124)	(0.0119)	(0.1152)	(0.0386)
Mother's Age	-0.0155	-0.0076	-0.2156	0.4328***
	(0.0325)	(0.0416)	(0.3332)	(0.1387)
Mother's Age-squared	0.0002	0.0001	0.0024	-0.0059***
	(0.0003)	(0.0004)	(0.0046)	(0.0014)
Father's Age	0.0095	0.0132	-0.0477	0.1848
	(0.0265)	(0.0323)	(0.3557)	(0.1498)
Father's Age-squared	-0.0001	-0.0001	0.0014	-0.0006
	(0.0003)	(0.0003)	(0.0031)	(0.0014)
Female Head	-0.1884***	-0.1787***	1.1144**	0.3608
	(0.0475)	(0.0574)	(0.3715)	(0.3235)
Household Size	-0.0840***	-0.0895***	0.0850	0.0431
	(0.0088)	(0.0137)	(0.1213)	(0.0779)
Father's Illness	-0.0415	-0.1003*	2.3384***	0.1186
	(0.0458)	(0.0489)	(0.5065)	(0.0788)
Mother's Illness	0.0861**	0.0556	1.6023***	0.2279
	(0.0316)	(0.0404)	(0.3752)	(0.1813)
Parental Divorce	0.0714	0.0938	-0.0593	0.2766
	(0.1051)	(0.1131)	(0.9642)	(0.4976)
N	2260	2260	2260	2260
r2	0.0925	0.0794	0.0649	0.1212

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include time fixed effects. Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.F.3: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE) (1)	Daily Labour Hours (FE) (2)	Daily Labour Hours (Poisson FE) (3)	Daily Study Hours (FE) (4)	Daily Study Hours (Poisson FE) (5)
Accumulated Drought	0.0014	0.3629**	0.0714**	-0.1778**	-0.1680**
	(0.0049)	(0.1622)	(0.0285)	(0.0798)	(0.0726)
Child's Age (In Months)	0.0039	0.0709	0.0138	-0.0279	-0.0157
	(0.0026)	(0.0600)	(0.0122)	(0.0214)	(0.0249)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Mother's Years of Schooling	-0.0008	-0.0205	-0.0057	0.2428*	0.1287*
	(0.0011)	(0.1543)	(0.0320)	(0.1251)	(0.0774)
Father's Years of Schooling	-0.0009	0.1133**	0.0231***	-0.0207	-0.0176
	(0.0011)	(0.0492)	(0.0089)	(0.0284)	(0.0278)
Mother's Age	-0.0047	-0.0779	-0.0172	-0.0056	0.0248
	(0.0030)	(0.1690)	(0.0305)	(0.0599)	(0.0552)
Mother's Age-squared	0.0000	0.0013	0.0003	0.0003	-0.0001
	(0.0000)	(0.0017)	(0.0003)	(0.0006)	(0.0005)
Father's Age	0.0034	-0.1003	-0.0212	0.0905	0.0575
	(0.0022)	(0.0927)	(0.0183)	(0.0750)	(0.0596)
Father's Age-squared	-0.0000	0.0003	0.0001	-0.0008	-0.0004
	(0.0000)	(0.0007)	(0.0001)	(0.0006)	(0.0005)
Female Head	-0.0117*	-0.2110	-0.0445	-0.1602	-0.0495
	(0.0065)	(0.2627)	(0.0491)	(0.1411)	(0.1347)
Household Size	-0.0013	-0.0569	-0.0109	0.0066	0.0072
	(0.0018)	(0.0491)	(0.0091)	(0.0212)	(0.0167)
Father's Illness	-0.0134**	-0.2025	-0.0397	-0.0870	-0.0847
	(0.0062)	(0.2471)	(0.0446)	(0.0659)	(0.0709)
Mother's Illness	0.0101	0.6292***	0.1246***	-0.0848	-0.1156*
	(0.0085)	(0.1495)	(0.0262)	(0.0876)	(0.0618)
Parental Divorce	-0.0097	-0.3106	-0.0579	0.4579**	0.3088***
	(0.0160)	(0.5323)	(0.0997)	(0.1547)	(0.1024)
N	1464	2260	1995	2260	1942
r2	0.2071	0.0370	0.1194	0.2918	0.3911

Note: Column (1) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (3) and (5). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

2.G Fisher Randomisation Test

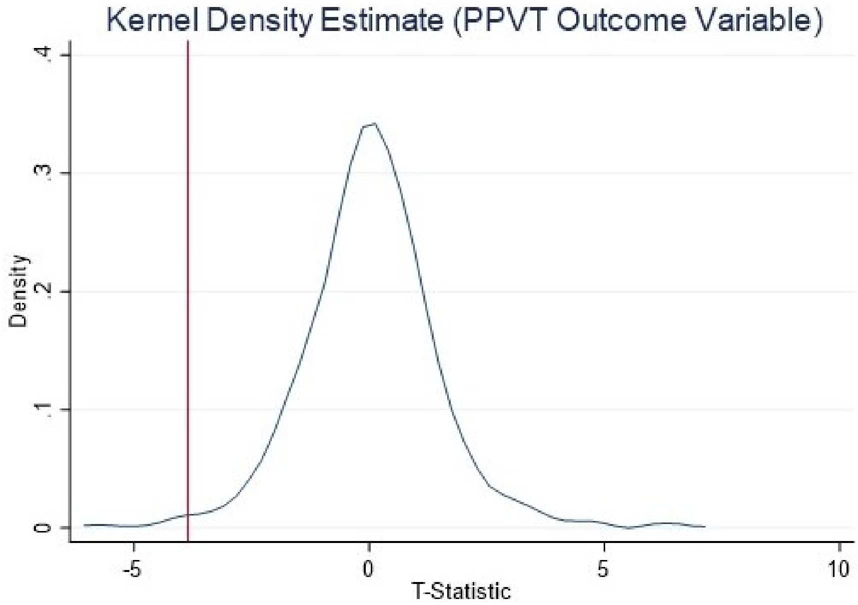

Figure 2.G.1: Fisher Randomisation Test: K-Density Plot Showing the Estimated T-statistics for PPVT Outcome Variable. P-value: 0.006.

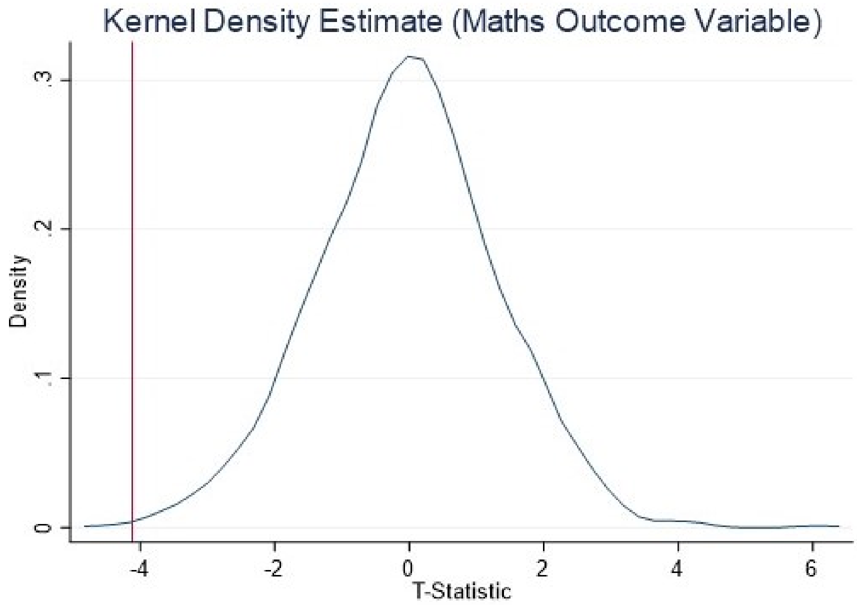

Figure 2.G.2: Fisher Randomisation Test: K-Density Plot Showing the Estimated T-statistics for Maths Outcome Variable. P-value: 0.008.

2.H Using Self Reported Measure of Drought

Table 2.H.1: Effect of Droughts on Child Educational Outcomes

	PPVT	Maths	Enrolment	Years of Schooling
	(FE)	(FE)	(Probit RE)	(Poisson FE)
	(1)	(2)	(3)	(4)
Drought	-0.4887***	0.0055	0.0224	0.0324
	(0.1140)	(0.0516)	(4.3725)	(0.0740)
Child's Age (In Months)	0.0382*	0.0638***	0.0270	0.0335
	(0.0196)	(0.0174)	(4.0068)	(0.0217)
Child's Age-squared	-0.0002*	-0.0001**	-0.0001	-0.0002***
	(0.0001)	(0.0001)	(0.0260)	(0.0000)
Mother's Years of Schooling	0.0379	-0.0419	0.0140	-0.0071
	(0.0501)	(0.0360)	(2.1463)	(0.0363)
Father's Years of Schooling	0.0623***	-0.0024	0.0098	0.0007
	(0.0176)	(0.0175)	(2.1727)	(0.0170)
Mother's Age	-0.0365	0.0674*	-0.0254	-0.0153
	(0.0594)	(0.0350)	(3.9751)	(0.0438)
Mother's Age-squared	0.0013	-0.0009	0.0003	-0.0000
	(0.0008)	(0.0007)	(0.0695)	(0.0004)
Father's Age	0.1927***	-0.0237	0.0090	0.0601
	(0.0556)	(0.0539)	(2.0047)	(0.0429)
Father's Age-squared	-0.0019***	-0.0000	-0.0001	-0.0003
	(0.0006)	(0.0006)	(0.0146)	(0.0004)
Female Head	0.0161	-0.0243	-0.0343	0.0625
	(0.1433)	(0.1133)	(5.7129)	(0.0684)
Household Size	-0.0160	0.0161	0.0041	0.0231**
	(0.0200)	(0.0161)	(0.8047)	(0.0105)
Father's Illness	0.0312	0.2594	-0.0320	-0.0325
	(0.0895)	(0.0531)	(6.2338)	(0.0595)
Mother's Illness	-0.0545	-0.0487	-0.0255	-0.0979*
	(0.0594)	(0.0769)	(3.7810)	(0.0542)
Parental Divorce	-0.0403	-0.2127	-0.0162	-0.0034
	(0.1476)	(0.2034)	(2.9571)	(0.0768)
N	2260	2260	2260	1983
r2	0.1099	0.0314	0.1021	0.2101

Note: Column (3) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (3). The pseudo R-squared are provided in column (3) and (4). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.H.2: Effect of Droughts on Household Expenditure

	Ln(Total Expenditure)	Ln(Food Expenditure)	Ln(Health Expenditure)	Ln(Educational Expenditure)
	(FE)	(FE)	(FE)	(FE)
	(1)	(2)	(3)	(4)
Drought	-0.0289	-0.0359	0.1136	0.0896
	(0.0426)	(0.0335)	(0.2674)	(0.1304)
Mother's Years of Schooling	0.0006	0.0106	-0.1175	-0.1978
	(0.0257)	(0.0250)	(0.2159)	(0.1157)
Father's Years of Schooling	0.0039	0.0083	-0.1813	0.0480
	(0.0126)	(0.0116)	(0.1151)	(0.0392)
Mother's Age	-0.0172	-0.0087	-0.2244	0.4239***
	(0.0341)	(0.0419)	(0.3257)	(0.1352)
Mother's Age-squared	0.0002	0.0001	0.0024	-0.0059***
	(0.0003)	(0.0004)	(0.0045)	(0.0014)
Father's Age	0.0080	0.0127	-0.0638	0.1693
	(0.0268)	(0.0328)	(0.3523)	(0.1470)
Father's Age-squared	-0.0001	-0.0001	0.0015	-0.0004
	(0.0003)	(0.0003)	(0.0031)	(0.0015)
Female Head	-0.1856***	-0.1787***	1.1565***	0.4007
	(0.0499)	(0.0574)	(0.3687)	(0.3534)
Household Size	-0.0821***	-0.0882***	0.0955	0.0537
	(0.0096)	(0.0141)	(0.1157)	(0.0787)
Father's Illness	-0.0391	-0.0987*	2.3510***	0.1313
	(0.0446)	(0.0479)	(0.5241)	(0.0919)
Mother's Illness	0.0861**	0.0562	1.5918***	0.2183
	(0.0335)	(0.0405)	(0.3978)	(0.2018)
Parental Divorce	0.0770	0.0997	-0.0639	0.2752
	(0.1077)	(0.1139)	(0.9754)	(0.5139)
N	2260	2260	2260	2260
r2	0.0897	0.0806	0.0620	0.1067

Note: Zero values in household expenditures are replaced with a value of "0.0001". Additional controls include time fixed effects. Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2.H.3: Effect of Droughts on Child Labour and Study Hours

	Labour Participation (Probit RE) (1)	Daily Labour Hours (FE) (2)	Daily Labour Hours (Poisson FE) (3)	Daily Study Hours (FE) (4)	Daily Study Hours (Poisson FE) (5)
Drought	-0.0000	0.0858	0.0166	0.0346	0.0658
	(0.0028)	(0.2158)	(0.0387)	(0.0980)	(0.0755)
Child's Age (In Months)	0.0039	0.0721	0.0149	-0.0270	-0.0153
	(0.0026)	(0.0640)	(0.0131)	(0.0258)	(0.0293)
Child's Age-squared	-0.0000	-0.0001	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0001)
Mother's Years of Schooling	-0.0008	-0.0002	-0.0020	0.2329*	0.1243
	(0.0011)	(0.1607)	(0.0329)	(0.1241)	(0.0785)
Father's Years of Schooling	-0.0009	0.1198**	0.0247***	-0.0252	-0.0196
	(0.0011)	(0.0519)	(0.0094)	(0.0303)	(0.0281)
Mother's Age	-0.0047	-0.0648	-0.0153	-0.0106	0.0257
	(0.0029)	(0.1621)	(0.0299)	(0.0577)	(0.0501)
Mother's Age-squared	0.0000	0.0012	0.0003	0.0003	-0.0002
	(0.0000)	(0.0016)	(0.0003)	(0.0005)	(0.0005)
Father's Age	0.0034	-0.0853	-0.0178	0.0828	0.0509
	(0.0023)	(0.0915)	(0.0185)	(0.0739)	(0.0577)
Father's Age-squared	-0.0000	0.0002	0.0000	-0.0007	-0.0003
	(0.0000)	(0.0008)	(0.0002)	(0.0006)	(0.0005)
Female Head	-0.0117*	-0.2456	-0.0543	-0.1405	-0.0586
	(0.0065)	(0.2659)	(0.0517)	(0.1490)	(0.1277)
Household Size	-0.0013	-0.0718	-0.0144	0.0121	0.0141
	(0.0018)	(0.0518)	(0.0099)	(0.0218)	(0.0160)
Father's Illness	-0.0134**	-0.2211	-0.0433	-0.0799	-0.0843
	(0.0061)	(0.2544)	(0.0458)	(0.0657)	(0.0691)
Mother's Illness	0.0101	0.6344***	0.1247***	-0.0893	-0.1144*
	(0.0085)	(0.1643)	(0.0280)	(0.0878)	(0.0639)
Parental Divorce	-0.0097	-0.3341	-0.0646	0.4576***	0.3081***
	(0.0159)	(0.5257)	(0.0975)	(0.1451)	(0.0895)
N	1464	2260	1995	2260	1942
r2	0.2911	0.0230	0.0921	0.2798	0.2819

Note: Column (1) reports the marginal effect from the probit random effect model. All models include controls for time fixed effects and additional controls for community fixed effects in model (1). The pseudo R-squared are provided in columns (1), (3) and (5). Clustered robust standard errors at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Chapter 3

The Impact of In-utero Air Pollution on Child Health in Ethiopia

Abstract

This paper examines the effect of fetal exposure to air pollution on early life (health) outcomes of children in Ethiopia. The study combines satellite PM2.5 data and individual-level data to estimate in-utero pollution exposure for each child in our sample and analyses the causal effect of prenatal PM2.5 on health at birth using wind speed as an instrumental variable. Our findings from our IV analysis provide mild evidence for negative effects of air pollution on child health. Whilst we find no significant impact on our child stunting measure (height-for-age), we find that children exposed to PM2.5 during the first trimester are smaller on average, weighing less than their peers of the same age and gender not exposed to polluted air. A unit increase in in-utero PM2.5 Trimester I exposure is seen to lower weight-for-age z-scores by approximately 0.66 standard deviations. We find no effect of PM2.5 during Trimester II and III of pregnancy, thus highlighting the importance of the early stages of pregnancy in fetal growth and development.

3.1 Introduction

Over the past decade research has emphasized the adverse health effects of ambient air pollution. A growing body of evidence has shown that there are severe consequences of air pollution which are not spread evenly across the population. For example, children are considered to be at greater risk than adults owing to a combination of behavioral, environmental and physiological factors (WHO, 2018). Children, particularly during fetal development and early years, are especially vulnerable while their immune systems are still fragile, and their lungs, brains, and organs are still developing (Schwartz, 2004; Korten et al., 2017). According to the World Health Organization (2018), approximately 600,000 children die each year from acute lower respiratory infections caused by polluted air accordingly placing ambient air pollution among the top 5 in mortality risk factors.

Newborns and younger children (0 - 5 years) are uniquely susceptible to air pollution in that they breathe faster than adults, taking in more air per minute, and with it more pollutants (Sly and Flack, 2008). They live closer to the ground, where some pollutants reach peak concentrations, and are also more likely to spend longer periods outdoors engaging in vigorous activities in potentially polluted air (Schwartz, 2004). In the utero, they are vulnerable via their mother's exposure to air pollutants which can pose health risks and burdens that may last a lifetime (Barker et al., 1989; Elder et al., 2020). Although the impacts of air pollution are felt worldwide, the burden of disease attributable to polluted air differ between developed and developing regions, and in most cases argued to be heaviest in developing regions due to a number of reasons. The first of these is that developing regions often lack the resources and technology required to tackle pollution and thus may be less likely to invest in cleaner fuel sources that limit emission (Cesur et al., 2017). Secondly, health is widely seen to be much more delicate in the developing context, and as such small changes in environmental conditions such as pollution could lead to significant changes in health outcomes. Thirdly, coping mechanisms that aid adjustments to changes in environmental conditions including air pollution are often limited in developing regions (Adhvaryu et al., 2019). For these reasons, the impacts of air pollution on health could potentially be more damaging in developing regions (Cesur et al., 2017; Adhvaryu et al., 2019; Heft-Neal et al., 2019).

Despite these known factors associated with the developing world, a few authors such as MacDermott et al. (2019) and Ritchie and Roser (2019) have argued for a minimalist effect in such regions due to the limited industrialising nature of low-income (developing) countries which often puts a cap on industrial activities and thus pollution emissions. The authors argue that developing countries likely to have low industrialisation levels are also likely to have negligible impacts of air pollution on health. Given this lack of consensus in the developing world, understanding the true nature of the relationship between air pollution and health within the developing country context becomes important as it may have significant implications particularly when designing policies that are targeted towards protecting vulnerable children from any adverse impacts of pollution, promoting child welfare and enhancing resilience.

This paper explores the relationship between ambient air pollution and child health outcomes in Ethiopia - a developing country where infant health is fragile with more than 257,000 children under the age of five dying each year, and 120,000 in the neonatal period, thus ranking 32 out of 192 countries in under-five mortality (Abebe, 2020). Health with respect to air pollution in Ethiopia has only until recently become a priority for the Ethiopian government with a fast-rising number of pollution-related deaths averaging more than 50,000 annually (Sanbata et al., 2014). In this paper, we focus on a specific type of air pollutant - particulate matter with an aerodynamic diameter of 2.5μm or less (PM2.5), as it is identified as one of the most harmful strands of air pollutants (WHO, 2020). Unlike other pollutants, PM2.5 originates from both natural sources such as naturally suspended dust, and anthropogenic sources such as fuel combustion from vehicles, firm manufacturing activities, and heat and power generation by households. This makes the PM2.5 a relatively widespread air pollutant, with concentration levels decreasing at a slower pace (Orellano et al., 2020).

Our paper conducts an Ethiopian analysis using district and hourly variation in wind speed as a source of exogenous variation in in-utero PM2.5 exposure to estimate its causal effect on child health. The challenges with uncovering a causal link between air pollution exposure and health have been well established in the economics literature. One of the biggest concerns is that air pollution exposure is rarely randomly assigned across localities and there may be confounding factors unaccounted for that may bias the results. These include mobility and the characteristics of the exposed population. For example, family preferences for clean air or higher income families may be more likely to self-select into regions with better air quality. These families are also likely to invest more in their children such that children who are exposed to lower pollution levels have better health outcomes, causing an upward bias in health estimates. Alternatively, measurement error in air pollution exposure, as well as avoidance behaviour, particularly among individuals most at risk choosing to stay indoors to offset some of the adverse effects of air pollution pose as threats to identification. Inability to account for these factors would understate the effect of pollution on health, causing the overall direction of bias in health estimates to be ambiguous.

Recent attempts to address the issue of omitted confounders and measurement error include studies within the economics literature that use rich data from countries like the US, and quasi-experimental approaches such as fixed effects (Currie and Neidell, 2005) and instrumental variables (Chay and Greenstone, 1999; Friedman et al., 2001; Chay and Greenstone, 2003; Lleras-Muney, 2010; Knittel et al., 2016).[1] One of the first studies to use quasi-experimental design include two similar studies by Chay and Greenstone (1999, 2003) who exploit the exogenous variation in air pollution induced by the 1981-82 recession and the Clean Air Act of 1970, respectively, in the US, to estimate a causal effect of pollution on infant mortality. Comparing pollution levels before and after the natural experiments in affected counties, Chay and Greenstone (1999, 2003) find that both the recession and the Clean Air Act led to sharper reductions in air pollution in some counties than in others, resulting in fewer infant deaths in the counties affected relative to less affected counties. Also using data from the US is Friedman et al. (2001) employing the 1996 summer Olympic games in Atlanta as a source of exogenous variation in ground-level ozone pollution. Friedman et al. (2001) in their study show that efforts to reduce car traffic congestion during the Olympics served as a plausible instrument for air pollution, lowering concentration levels, and thus leading to a reduced event of asthma in children. A more recent study is Knittel et al. (2016) who like Friedman et al. (2001) use shocks in car traffic levels in California city as an instrument for air pollution (PM10, carbon monoxide, and ozone). The authors find shocks in car traffic levels to be a strong predictor for air pollution, with high pollution occurring on days with high traffic levels. Accordingly, Knittel et al. (2016) find large effects of in-utero air pollution (PM10) on infant mortality with a one

[1] The literature review provided in this study is comprehensive and up-to-date. It is conducted using a wide range of databases including Google Scholar, Science Direct, Journal Storage (JSTOR) and EconLit.

unit decrease in PM10 saving approximately 18 lives per 100,000 live births.

Despite the growing literature surrounding the effects of air pollution on health, particularly in showing causality, most of the available evidence on the subject come from the United States and other developed countries. Only relatively few studies in developing countries have been able to use quasi-natural experiments to address the problem of omitted confounders (Jayachandran, 2009; Tanaka, 2015; Cesur et al., 2017; Arceo et al., 2016), with the bulk of the studies focusing on child mortality. For example, Jayachandran (2009), in Indonesia, studies the impact of particulate matter on child mortality using the massive wildfires of 1997 as a source of exogenous variation for pollution. The 1997 wildfire was argued to have induced a massive increase in pollution levels (dust and smoke) across regions of Indonesia, with certain regions affected more than others. Jayachandran (2009) exploits this, using the difference-in-difference strategy to estimate the causal impact of air pollution on child mortality. His results from his analysis show a rise in under-3 (child) mortality of approximately 20% in the regions affected by the wildfire relative to less affected regions. Finding a similar effect in China is Tanaka (2015) using variation in pollution levels (sulfur dioxide) arising from the 1998 regulations on Chinese power plants emissions. Tanaka (2015) finds that the resulting fall in S02 levels due to environmental legislations led to a 20% decline in infant mortality in areas affected relative to less affected areas. In Turkey, Cesur et al. (2017) like Tanaka (2015) uses a similar approach by exploiting differences in the timing of natural gas adoption across Turkish provinces as a source of variation for air pollution. The authors show that the adoption of natural gas across Turkish provinces led to sharp declines in air pollutants (particulate matter and sulfur dioxide), consequently leading to fewer infant deaths (4% reduction) in affected provinces. Finally, Arceo et al. (2016), in Mexico, employ the instrumental variable strategy using the number of thermal inversions as an instrument for PM10 and carbon monoxide (CO) in their study on pollution and infant mortality. The estimates from their IV analysis show that a 1 µg/m3 increase in 24-hour PM10 and a 1 ppb increase in the 8-hour maximum for CO results in 0.23 and 0.0046 weekly infant deaths per 100,000 live births.

A few other studies (Kurata et al., 2020; Liang et al., 2019; Huang et al., 2015; Randeris, 2019) have examined the effect of pollution on child health outcomes such as birth weight, respiratory illness and stunting, however, thus far, the findings have been inconsistent with the majority of the studies failing to address the endogeneity present in the pollution variable. Kurata et al. (2020), for example, study the effect of prenatal PM2.5 exposure on child stunting in Bangladesh using OLS regressions. They find stunting to be prevalent for boys exposed to PM2.5 in utero but not for girls. Liang et al. (2019) in their study on ambient PM2.5 and birth outcomes in China show that PM2.5 exposure is associated with increased risk of preterm birth (1-20%) and low birth weight (18-20%), with the highest risk observed during trimester III of pregnancy. Another study also on China by Huang et al. (2015), however find no significant impact of air pollution (PM10 and NO2) on child health outcomes (preterm birth), but find mild evidence on low birth weight, for which only NO2 in-utero exposure significantly predicts. Unlike the Liang et al. (2019) study, Huang et al. (2015) account for endogeneity using the Beijing 2008 Olympics as a natural experiment. Huang et al. (2015) in their study argue that the 2008 Olympics was a period of tight regulations on pollution to improve air quality including traffic controls, consequently presenting an ideal experiment in examining the link between pollution and child health. In the Philippines, similar evidence for weak effects of ambient air pollution on child health is provided by Randeris (2019). Randeris (2019) in his study finds no significant impact of in-utero PM2.5 exposure on child health outcome; low birth weight.[2] Randeris (2019), however fails to account for endogeneity in his study, potentially creating a bias in health estimates.

Within the context of Africa, very few studies which include Adhvaryu et al. (2019), Foreman (2018) and Heft-Neal et al. (2019) have examined the relationship between ambient air pollution and infant health. Of the three studies listed, only two (Foreman, 2018; Heft-Neal et al., 2019) use exogenous sources of variation for local air pollution levels (PM2.5). Foreman (2018) and Heft-Neal et al. (2019), in a cross-country analysis in West Africa and Africa respectively, leverage variation in air pollution across study countries using dust export from the Bodele Depression (a remote Saharan region responsible for a substantial share of global atmospheric dust). Foreman (2018) and Heft-Neal et al. (2019) argue for the plausibility of this instrument stating its unlikeliness to be correlated with local emission sources and activities. The results from their cross-country analysis on pollution and infant mortality show that

[2] A similar finding is also seen in Europe in Gehring et al. (2011). The study finds preterm birth and birth weight to be unaffected by exposure to air pollution (PM2.5, NO2) during pregnancy for children in the Netherlands.

increases in dust levels arising from changes in the Bodele dust emission results in higher infant mortality of approximately 7-21%. Also finding a negative impact is Adhvaryu et al. (2019). Like Foreman (2018) and Heft-Neal et al. (2019), Adhvaryu et al. (2019) presents a cross-country analysis in Africa (West Africa) on in-utero air pollution (PM2.5) and infant mortality. Their analysis, through the use of Ordinary Least Square (OLS) regressions, show negative but much smaller effects of PM2.5 exposure on infant mortality, with a 10 $\mu g/m^3$ rise in PM2.5 increasing infant mortality by approximately 2.3%.

Our analysis builds on the existing research and makes some important contributions to the literature. First, through the use of satellite measures of PM2.5 combined with a unique panel dataset (Young Lives Survey) tracking children over a 15 year period in Ethiopia, we add to the relatively small body of literature on ambient air pollution and health in Africa, where literature in this region is scarce due to limited data on pollution levels. Our work is closest to Adhvaryu et al. (2019), Foreman (2018) and Heft-Neal et al. (2019) given the study area, however, we stand out from these three studies by focusing on child health outcomes rather than child mortality. We focus on two measures of child health: height-for-age (stunting measure) and weight-for-age (underweight measure), which have consistently been demonstrated to be good predictors of changes in adult health, economic activities and long-term individual well-being (Victora et al., 2008; Campbell et al., 2014; Baird et al., 2016). Our paper examines the impact of in-utero exposure to air pollution on children who are alive in the first year of life and subsequently in the fourth to fifth year in order to identify any short-to-medium run effects of air pollution on the survival cohort. Our paper also makes a contribution through the use of the instrumental variable regression, employing wind speed as a source of exogenous variation for PM2.5. To the best of our knowledge, this is the first study for an African country which addresses the endogeneity issues present while studying the link between air pollution and child health outcomes.

To briefly summarise our findings, our study provides weak evidence for the harmful effects of in-utero air pollution on child health outcomes. We show from our IV analysis that within our preferred model framework which includes seasonal adjustments for PM2.5, exposure to air pollution in utero has little to no effect on child health. The only effect of in-utero PM2.5 on child health outcomes in our study is found on the weight-for-age variable at ages 0-1 for

Trimester 1 level exposure. We find that increases in in-utero PM2.5 of 1 μg/m^3 during trimester 1 of pregnancy causes a reduction in the weight-for-age z-score of approximately 0.66 standard deviations. This finding, though, is marginally significant at the 10% significance level. In our analysis of heterogeneity, our results also provide weak evidence for heterogeneous effects of air pollution by child's gender, mother's level of education, and household area of residence. Our findings indicate a significant effect only for household area of residence, suggesting that children from rural households, with less access to healthcare are more adversely impacted by negative effects of in-utero air pollution.

The rest of this paper is organized as follows. Section 3.2 discusses the data and descriptive statistics; section 3.3 presents the identification strategy employed; section 3.4 discuses the results and robustness checks; and finally, section 3.5 provides the discussions and conclusion.

3.2 Data

3.2.1 Household Data

We use data from the Young Lives survey, an international longitudinal study of 12,000 children growing up in four developing countries (Ethiopia, India, Peru and Vietnam) over 15 years. According to the Young Lives (2019), the overall objective of the survey is "to shed light on the causes and consequences of child poverty, and generate sufficient evidence to enable policymakers design effective poverty alleviation schemes". The survey, which began in 2002, follows two cohorts of children, a younger (the main cohort) and an older cohort. The younger cohort consists of 2,000 children in each country born between May 2001 and May 2002 (between the ages of 6-18 months at the time the first round was conducted), while the older cohort consists of 1,000 children born between January 1994 and May 1995 (ages 7.5-8.5 years during the first round of the survey). The survey has five rounds, 2002, 2006, 2009, 2014 and 2017, when children are approximately one, five, eight, twelve, and fifteen years old in the younger cohort; and eight, twelve, fifteen, nineteen and twenty-two years old in the older cohort. Thus, the younger cohorts are tracked from infancy to their mid-teens and the older cohorts are tracked into adulthood.

In this study we focus on the younger cohort for Ethiopia as it is more relevant in examining the impact of in-utero air pollution on health outcomes in the early stages of a child's life. We limit our analysis to data from rounds 1 and 2 when the children are between 0-5 years, and are argued to be more susceptible to adverse events and health hazards including air pollution (Alderman et al., 2006; Korten et al., 2017).[3] Children in the survey are randomly selected from 20 sentinel sites in the five main regions of Ethiopia which represents for more than 90% of the population.[4] These regions include Addis Ababa, Amhara, Oromia, Southern Nations Nationalities and Peoples' Region (SNNP), and Tigray.

The survey is designed to have three modules - the child module, the household module and the community module. The child module collects information on the index child and the caregiver, providing information on the child's health and well-being, and the caregiver's (mother's) health and well-being during and after pregnancy. Beginning from wave 2, information on the child's educational outcomes, attitude to health and school, perception of how they are seen by others, and their aspirations for the future, is collected. The household module contains information on household members, collecting detailed information on individual labour supply, household consumption and expenditure, household composition, family background, and household asset holdings. The final section of the Young Lives survey, the community module, includes information on the services provided in each community (health and educational services), average wages, price levels and migration flows in and out of a community.

Our study uses two key measures for child health which are provided in the child module of the young lives survey. These include the height-for-age z-score and the weight-for-age z-score measuring the long-run and short-run nutritional status of a child, respectively. The first indicator of health, the height-for-age z-score (HAZ), measures how far (and to what direction) in units of standard deviation, a child's height deviates from the mean height of the age-specific and sex-specific reference population. Children with a HAZ value of less than -2 standard deviations are usually considered to have received insufficient nutrients for a relatively long period and hence stunted. Children with a value less than -3 SD are considered severely stunted. The second indicator of health, weight-for-age z-score (WAZ), measures the distance between

[3]Full information on the health outcomes of the children are only collected in the first two waves of the survey.

[4]The sampling is done on the basis of one child per household.

a child's weight and the mean value of the age-specific and sex-specific reference population (WHO, 2006*a*).[5] Children with a low WAZ value are considered to be underweight (thin). Thinness is often seen to be as a result of a recent food shortage leading to significant weight loss.

We restrict our sample to full-term birth children who are available in both rounds leaving us with a sample size of 1,069 exclusive of missing values in outcome and control variables.[6] It is important to note that outcome variables (health measures) are only available for children who are alive. Given that air pollution also affects the probability of a child's survival, our sample of living children overrepresents children with relatively low in-utero pollution exposure and underrepresents children with high in-utero pollution. Consequently, our estimates should be considered as the lower-bound effect of air pollution on child health.

3.2.2 PM2.5 and Weather Data

Data on air pollution (PM2.5), wind speed, rainfall and temperature are gotten from the Modern-Era Retrospective Analysis for Research and Application - version 2 (MERRA-2), newly released by the NASA's Global Modeling and Assimilation Office in 2017. Based on the NASA's Goddard Earth Observing System-5 (GEOS-5) model and the Goddard Global Ozone Chemistry Aerosol Radiation and Transport (GOCART) model, the gridded data of the MERRA-2 is assimilated with satellite (MODIS, AVHRR and MISR) and ground (AERONET) observations (Gelaro et al., 2017). The Merra-2, in general, is widely known for its high quality and performance relative to other reanalysis data, with studies like Yang and Bright (2020) and Chen et al. (2019) showing the MERRA-2 reanalysis data to be much more accurate than its contemporaries for aerosol estimations and drought predictions. The data is provided on a global scale from 1980 to near-present, in both hourly and monthly formats at a $0.5° \times 0.625°$ (50 km $\times$ 60 km) resolution.

To construct our air pollution (PM2.5) variable, we obtain Aerosol Optical Depth (AOD) data for five major aerosol species (sulfate (S04), organic carbon (OC), black carbon (BC), dust (DUST2.5) and sea-salt (SS2.5) particulate matter with a diameter of less than 2.5 µm) from the M2T1NXAER component of the MERRA-2. Given this, we calculate hourly concentrations

[5] The z-scores are calculated by the Young Lives using the 2006 WHO World Growth Standards.

[6] The sample size before removing missing values in both rounds was 1,331.

of MERRA-2 PM2.5 following Buchard et al. (2016).[7] For wind speed, we utilise hourly u- and v-components of 10-metre wind gotten from the M2T1NXSLV MERRA-2 product. We then calculate the hourly wind speed as $\text{ws} = \sqrt{u^2 + v^2}$. Hourly rainfall and temperature are also obtained from the M2T1NXFLX and M2T1NXSLV components of the MERRA-2, respectively.

We merge our air pollution data and weather data (wind speed, rainfall and temperature) with our household data by overlaying the latitude and longitude data from the centroid of each young lives sampled communities on the gridded pollution and weather datasets, with all households within each community assigned the same level of pollution and weather data. Appendix 3.A presents the air pollution data for the sampled communities in the young lives survey. We explore the spatial variation in average annual PM2.5 for years 2000 to 2017 in Ethiopia by plotting a heat map in Figure 3.A.1. As the figure shows, there is considerable amount of variation in air pollution across regions of Ethiopia. The northern region of the country is heavily impacted by high and dangerous levels of pollution with areas in the north-east recording peak levels of 60μg/m^3 in PM2.5. On the other hand, the southern region of the country has much lower levels of pollution as shown by the lighter shades on the map. The guideline set by the WHO for maintaining safe and healthy standards of pollution is a threshold of 10μg/m^3 in annual PM2.5 levels. We see from Figure 3.A.1 as well as Figure 3.A.2 (which plots the annual PM2.5 for the communities within our study period (2000-2007)) that this guideline is scarcely met, with majority of the communities steadily above the WHO 10μg/m^3 threshold. We also find from Figure 3.A.3 that there is seasonality in PM2.5 trend in Ethiopia. Figure 3.A.3, showing the monthly PM2.5 from January 2000 to December 2007 for our study communities, indicates that PM2.5 mass concentrations are significantly higher during the rainy (wet) season in Ethiopia (known to be from April to September).

To calculate our in-utero pollution exposure measure, we use information on cluster location, month, and birth year of sampled children in the young lives survey. We limit our analysis to those children whose parents report living in their respective clusters for at least 9 months prior to a child's birth date. Our analysis makes use of an average pollution exposure measure, constructed as the average monthly PM2.5 over a 9-month period of gestation.[8]

[7]Buchard et al. (2016) calculates the MERRA-2 PM2.5 using the equation: PM2.5 $= 1.375 \times$ SO4 $+ 1.6 \times$ OC $+$ BC $+$ DUST2.5 $+$ SS2.5.

[8]Our sample excludes children whose parents indicated were born prematurely i.e. we restrict our analysis to full term births only. As robustness checks we use alternate measures of in-utero pollution exposure including

Trimester measures are also computed in our analysis as the mean monthly pollution exposure over three-month periods.

3.2.3 Descriptive Statistics

Table 3.1 presents the descriptive statistics for the key variables used in our analysis. The sample covers children with complete information who are available in both round 1 and round 2 of the young lives survey. Columns 3-6 presents the summary statistics for the first round of the survey when children are approximately one years of age, while columns 7-10 presents the summary statistics for round two when the sampled children are aged 5.

First, looking at the household characteristics, the percentage of households living in the sampled regions, Addis Ababa, Amhara, Oromia, SNNP, and Tigray are 11%, 16%, 21%, 31% and 21%, respectively. The average Young Lives household is comprised of five members in round 1 and six members in round 2, with approximately 98% and 94% of households constituting as male headed in rounds 1 and 2, respectively. Fathers at the time of the first round are on average 37 years old, with approximately 2.75 years of education. Mothers, on the other hand, are much younger and less educated, with an average round 1 age of 28 years and education of 2.01 years. As expected, the average parental age increases by round 2, however, in terms of parental education, we note from Table 3.1 that only fathers accumulate more education (an additional year on average) by the time of the second round of the survey. With regards to households' cooking and heating fuels which are well known to be potential sources of indoor pollution (Kurata et al., 2020), Table 3.1 shows that the most common kinds of fuels used are wood (65-67%), cow dung (17-23%), kerosene (3-6%), and charcoal (3-4%) for cooking; and wood (34-42%), cow dung (7-15%), and charcoal (14-16%) for heating. Fuels such as gas and electricity are fairly uncommon among households in our survey. Table 3.1 shows the households in our survey to be predominantly poor, with 81% in round 1 and 72% in round 2 having a wealth index value of less than or equal to 0.4.[9]

Next, focusing on child health characteristics, the mean height-for-age (HFA) of children

cumulative measures.

[9] The wealth index is a variable taking values between 0 and 1, constructed by the Young Lives survey as a weighted average of households' housing quality, access to services, and consumer durables. The Young Lives survey defines a poor household as a household with a wealth index of 0-0.4 (Young Lives, 2017).

Table 3.1: Summary Statistics

Variables	Obs	Round 1 Mean	Std. Dev.	Min	Max	Round 2 Mean	Std. Dev.	Min	Max
Child Characteristics									
Child's Age (in Months)	1,069	11.56	3.49	6	17	61.59	3.71	54	67
Child's Gender (Female)	1,069	0.47	0.49	0	1	0.47	0.49	0	1
Height-For-Age Z-score	1,069	-1.47	1.91	-5.64	5.24	-1.41	1.12	-5.04	4.59
Fraction Stunted (HFA < -2 SD)	1,069	0.37	0.31	0	1	0.31	0.47	0	1
Weight-For-Age Z-score	1,069	-1.61	1.48	-5.50	2.91	-1.36	0.92	-4.85	3.43
Fraction Underweight (WFA < -2 SD)	1,069	0.41	0.48	0	1	0.24	0.43	0	1
Received BCG Vaccine	1,069	0.71	0.45	0	1	0.93	0.25	0	1
Received Measles Vaccine	1,069	0.57	0.49	0	1	0.95	0.21	0	1
Long Term illness	1,069	0.08	0.28	0	1	0.04	0.21	0	1
Child's Religon:									
Christian	1,069	0.79	0.41	0	1	0.79	0.40	0	1
Muslim	1,069	0.20	0.40	0	1	0.19	0.40	0	1
Other	1,069	0.01	0.10	0	1	0.01	0.09	0	1
Child's Ethnic Group:									
Amhara	1,069	0.23	0.42	0	1	0.21	0.41	0	1
Gurage	1,069	0.09	0.29	0	1	0.09	0.29	0	1
Oromo	1,069	0.20	0.40	0	1	0.20	0.40	0	1
Tigrian	1,069	0.22	0.42	0	1	0.22	0.41	0	1
Other	1,069	0.26	0.44	0	1	0.28	0.45	0	1
Household Characteristics									
Region:									
Addis Ababa	1,069	0.11	0.31	0	1	0.11	0.31	0	1
Amhara	1,069	0.16	0.36	0	1	0.16	0.36	0	1
Oromia	1,069	0.21	0.40	0	1	0.21	0.40	0	1
SNNP	1,069	0.31	0.46	0	1	0.31	0.46	0	1
Tigray	1,069	0.21	0.41	0	1	0.21	0.41	0	1
Gender of HH Head (Female)	1,069	0.02	0.12	0	1	0.06	0.23	0	1
Mother's Education (In Years)	1,069	2.01	3.31	0	16	2.37	3.54	0	16
Father's Education (In Years)	1,069	2.75	3.91	0	16	4.12	4.27	0	16
Mother's Age (Years)	1,069	28.03	6.16	15	50	32.04	6.17	19	54
Father's Age (Years)	1,069	36.89	8.82	19	76	41.01	9.02	23	80
HH Size	1,069	5.89	2.08	3	15	6.39	1.98	3	16
Number of Children Born to Mother	1,069	3.98	2.36	1	11	4.58	2.29	1	12
Type of Cooking Fuel Used:									
Wood	1,069	0.67	0.47	0	1	0.65	0.47	0	1
Kerosene	1,069	0.06	0.23	0	1	0.03	0.16	0	1
Cow Dung	1,069	0.23	0.42	0	1	0.17	0.38	0	1
Charcoal	1,069	0.03	0.18	0	1	0.04	0.19	0	1
Gas and Electricity	1,069	0.004	0.06	0	1	0.03	0.18	0	1
Other	1,069	0.008	0.09	0	1	0.08	0.27	0	1
Type of Heating Fuel Used:									
Wood	1,069	0.42	0.49	0	1	0.34	0.47	0	1
Cow Dung	1,069	0.15	0.35	0	1	0.07	0.26	0	1
Charcoal	1,069	0.16	0.37	0	1	0.14	0.35	0	1
None	1,069	0.26	0.44	0	1	0.38	0.48	0	1
Other	1,069	0.01	0.10	0	1	0.07	0.26	0	1
Wealth Index (Proportion <= 0.4)	1,069	0.81	0.39	0	1	0.72	0.45	0	1
Pollution Exposure:									
Prenatal PM2.5 (Over a 9 month Gestation Period)	1,069	16.51	3.91	9.57	24.54	16.51	3.91	9.57	24.54
First Trimester PM2.5	1,069	16.58	4.99	7.82	28.55	16.58	4.99	7.82	28.55
Second Trimester PM2.5	1,069	16.42	5.08	8.07	28.55	16.42	5.08	8.07	28.55
Third Trimester PM2.5	1,069	16.54	4.96	7.88	28.11	16.54	4.96	7.88	28.11
Postnatal PM2.5 (Average After-Birth PM2.5 Exposure)	1,069	17.46	4.22	10.07	25.43	16.41	3.66	9.86	21.30
Weather Controls									
Prenatal Rainfall (Over a 9 month Gestation Period)	1,069	62.24	24.14	10.12	116.48	62.24	24.14	10.12	116.48
Prenatal Temperature (Over a 9 month Gestation Period)	1,069	18.41	1.96	14.45	22.17	18.41	1.96	14.45	22.17
Postnatal Rainfall (Average After-Birth Exposure)	1,069	58.17	17.31	27.63	122.79	64.23	18.45	32.87	106.07
Postnatal Temperature (Average After-Birth Exposure)	1,069	19.01	1.89	15.11	22.67	18.65	1.92	15.14	21.78

in round 1 of the Young Lives survey is approximately -1.47 standard deviations, with about 37% classified as stunted. In round 2, the height-for-age z-score slightly decreases to a mean of -1.41 SD, showing an improvement in the rate of stunting in sampled children of 6%. The mean weight-for-age (WFA) z-score in our sample is -1.61 SD in round 1, and -1.36 SD in round 2, with approximately 41% and 24% of children having low weight-for-age values (less than -2 SD) and hence underweight in rounds 1 and 2, respectively. From Table 3.1, we see that about 4-8% of children in the young lives survey have at least one long-term illness in rounds 1-2. We also see from the table that the majority of children in the sample have received at least one vaccine between both survey rounds, with about 71-93% receiving the BCG vaccine for Polio, and 57-95% receiving the MMR vaccine for measles.

Finally, Table 3.1 reports summary statistics for our pollution and key weather variables. For our estimation sample, we observe a mean level of prenatal (in-utero) PM2.5 exposure of approximately 16.51µg/m^3. Trimester level in-utero PM2.5 for children in our sample also ranges around the same value - 16.42-16.58µg/m^3. For our weather control variables (rainfall and temperature), Table 3.1 shows a mean monthly value of in-utero rainfall of 62.24mm and in-utero temperature of 18.41°C. Postnatal averages are also indicated in Table 3.1. As at the first survey round, a child in our sample was exposed to an average monthly PM2.5 of 17.46µg/m^3 in the postnatal period. At the second round, Table 3.1 shows postnatal PM2.5 average to be 16.41µg/m^3 in our sample. For our control variable rainfall, we observe average postnatal values of 58.17mm in round 1 and 64.23mm in round 2, whilst for temperature, Table 3.1 shows the corresponding postnatal averages to be 19.01°C and 18.65°C, respectively.

3.3 Empirical Model

The primary objective of this study is to investigate the impact of in-utero exposure to ambient air pollution on child health outcomes. Hence, we begin our analysis by estimating the following baseline model:

$$\begin{aligned} Health_{idmbt} = \alpha + \beta PM2.5^{TrimesterLevel}_{idmbt} + \phi PM2.5^{Postnatal}_{idmbt} + \gamma W_{idmbt} + \delta X_{idmbt} \\ + \eta Z_{idmbt} + \mu_d + \sigma_b + \eta_m + \lambda_t + \xi_{idmbt} \end{aligned} \tag{3.1}$$

where $Health_{idmbt}$ is the health outcome variable (Height-for-Age, Weight-for-Age, stunting and underweight) for child i, born in district d, in month m of year b, with health variables measured at time t. $PM2.5_{idmbt}^{TrimesterLevel}$ is the average measure of trimester level in-utero exposure to PM2.5 concentrations, explained in section 3.2.2. $PM2.5_{idmbt}^{Postnatal}$ is a control for postnatal PM2.5 exposure for child i, born in district d, in month m of year b, calculated as the mean PM2.5 exposure from child's i birth month to child's i survey month. W_{idmbt} is a vector of weather controls such as prenatal and postnatal rainfall and temperature averages. X_{idmbt} is a vector of child characteristics such as child age, child gender, child vaccination status, child long-term illness status, child religion, and child ethnic group. Z_{idmbt} is a vector of household characteristics including parental age, parental level of education, household size, gender of household head, household cooking and heating fuel, and household wealth index. μ_d is the district fixed effect controlling for any unobserved drivers of health that may correlate with PM2.5 over space. σ_b is the year of birth fixed effects controlling for time-specific shocks such as economic crises and disease outbreaks. η_m is the month of birth fixed effect controlling for seasonal variation in birth outcomes. λ_t is the survey date fixed effect controlling for differences in survey timing, and ξ_{idmbt} is the error term. Standard errors are wild-clustered bootstrapped at the community level to account for spatial correlation in the error term.[10]

The coefficient of interest, β, captures the effect of an additional unit of average monthly PM2.5 during each trimester on child health outcomes. A causal interpretation of β in the baseline model would rely on the strong assumption that child health is not correlated with any unobserved maternal or household characteristics. However, if local and transitory unobserved determinants of child health also covary with air pollution levels, the OLS estimator (β) in the baseline model (3.1) will be biased. This is the case if for example families sort into areas with better air quality. Residential sorting arising from family preference or household income hints at endogeneity in prenatal exposure to air pollution (Currie et al., 2009). Moreover, urban areas with high economic activities are often linked to both high pollution levels and better health care. Individuals in these areas are also likely to have similar characteristics such as better education and exposure levels which have positive influence on health outcomes. As a result, failure to account for these variables, including variables such as avoidance behaviour and measurement error would lead to a downward bias in the OLS estimates.

To address these concerns, the instrumental variable regression is used in this paper. We

[10]We bootstrap the standard errors using the boottest command in Stata developed by Roodman et al. (2019) which helps to solve the problem of over-rejection due to few clusters (Cameron and Miller, 2015).

exploit the random variation in ambient air pollution derived from the atmospheric variable, wind speed. Indeed, weather conditions along with local activities can either amplify or mitigate pollution concentrations. For example, wind speed is known to disperse air pollutants, carrying them away from their source, at higher speed levels. As such, there exists a strong negative correlation between wind speed and air pollution. Recent studies (Schlenker and Walker, 2016; Deryugina et al., 2019; Chen, 2019; He et al., 2019) have successfully employed weather conditions, particularly data on wind to instrument for air pollution. For example, Schlenker and Walker (2016) use wind speed and wind direction as instruments for carbon monoxide (CO) in estimating the impact of pollution on respiratory illness. Similarly, Deryugina et al. (2019) use wind direction as a source of exogenous variation in PM2.5 in the explaining its role in medical costs. Chen (2019) utilises ground atmospheric pressure and wind speed as instrumental variables for air pollution in analysing prenatal pollution and its impact on cognitive outcomes. Finally, He et al. (2019) use weather measures including temperature and wind speed as instruments in their study on air pollution and workers' productivity.

Building on these studies, we rely on quasi-experimental variation in PM2.5 induced by wind speed to estimate the causal effect of in-utero air pollution on child health. Our identification assumption is simple and intuitive: changes in wind speed are unrelated to changes in health except through pollution. This is a reasonably valid assumption as there would be no reason to expect maternal behaviours including household sorting resulting directly from movements in wind. To increase the plausibility of this assumption, we flexibly control for other weather variables including temperature and rainfall which have been widely shown in the climate literature to be correlated with PM2.5 (Liu et al., 2020; Palma et al., 2019; Wang and Ogawa, 2015; Tai et al., 2010). We estimate the first stage regression at the highest temporal resolution (hourly concentrations) in order to accurately capture the co-movement between PM2.5 and wind speed:

$$PM2.5_{hdt} = \alpha + \beta_1 WindSpeed_{hdt} + \beta_2 W_{hdt} + \mu_d + \gamma_h + \eta_m + \lambda_t + \xi_{hdt} \tag{3.2}$$

where $PM2.5_{hdt}$ is hourly PM2.5 concentrations in district d for the relevant prenatal time period t in our sample (2000 - 2002). $WindSpeed_{hdt}$ is hourly wind speed in the respective districts d for time period 2000 to 2002. W_{hdt} denotes weather controls which includes hourly temperature and rainfall, the squares of these terms, and the interaction between rainfall and temperature. μ_d is the district fixed effect, γ_h is the hourly fixed effect, η_m is the monthly fixed effect, and λ_t is the yearly fixed effect. Following the first stage, we aggregate the predicted hourly PM2.5 values from Equation (3.2) to daily and monthly averages. We then regress child health outcomes on the predicted average monthly PM2.5 during each trimester period:

$$\begin{aligned} Health_{idmbt} &= \alpha + \beta PM2.5^{TrimesterLevel}_{idmbt} + \phi PM2.5^{Postnatal}_{idmbt} + \gamma W_{idmbt} + \delta X_{idmbt} \\ &+ \eta Z_{idmbt} + \mu_d + \sigma_b + \eta_m + \lambda_t + \xi_{idmbt} \end{aligned} \tag{3.3}$$

where $PM2.5^{TrimesterLevel}_{idmbt}$ is the predicted trimester level PM2.5. All the controls are the same as in Equation (3.1). In this 2sls setup, the coefficient of interest, β, can now be interpreted as the causal effect of in-utero air pollution on child health.

3.4 Results

3.4.1 OLS Results

Table 3.2 presents the OLS estimates for the effect of in-utero air pollution exposure during pregnancy (columns (1)-(4)) and in each trimester of pregnancy (columns (5)-(8)) on child health outcomes. The first panel of Table 3.2 (Panel A) shows the results for the first round of the survey, when the sampled children are between 0-1 years, while the second panel (Panel B) shows the results for the second round of the survey, when the sampled children are 4-5 years old. Looking at the estimated results from Table 3.2, we note that almost all OLS PM2.5 coefficients are statistically insignificant, suggesting that in-utero air pollution exposure has mild effects on our measures of child health outcomes, particularly at ages 0-1. At ages 5, we find the PM2.5 coefficients during Trimester 3 to be statistically significant for the height-for-age and weight-for-age variables. Columns (5) and (6) of Panel B show that an increase in Trimester 3 PM2.5 level exposure of one unit is associated with a reduction in age 5 height-for-age and weight-for-age z-scores of 0.100 and 0.112 standard deviations, respectively. When put in context, this effect corresponds to an approximate 7.1% and 8.2% decrease in height-for-age and weight-for-age, relative to their respective means of -1.41 and -1.36 standard deviations in our sample. In general, although the coefficients as seen in Table 3.2 are small in magnitude and largely insignificant, they must be interpreted with caution due to the existing bias from endogeneity and measurement error highlighted in section 3.3.

Table 3.2: OLS Results Showing the Effect of In-Utero Air Pollution on Child Health

Panel A: Ages 0-1	HFA	WFA	Stunting	Underweight	HFA	WFA	Stunting	Underweight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prenatal PM2.5 Exposure	0.0267	0.0681	-0.0190	-0.0253				
	(0.8180)	(0.2320)	(0.6186)	(0.4951)				
Prenatal PM2.5 Exposure: Trimester 1					0.0053	0.0064	-0.0064	0.0000
					(0.9054)	(0.6999)	(0.6030)	(0.9988)
Prenatal PM2.5 Exposure: Trimester 2					0.0321	0.0269	-0.0126	-0.0120
					(0.4765)	(0.2667)	(0.4677)	(0.4198)
Prenatal PM2.5 Exposure: Trimester 3					0.0592	-0.0192	-0.0233	0.0098
					(0.4035)	(0.4500)	(0.2766)	(0.4927)
Postnatal PM2.5	-0.0898	0.0229	0.0326	-0.0301	0.0813	-0.0447	-0.0200	-0.0061
	(0.6411)	(0.8363)	(0.5730)	(0.5279)	(0.7066)	(0.7059)	(0.7568)	(0.8967)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3149	0.3803	0.2369	0.2975	0.3166	0.3818	0.2387	0.2998
Panel B: Ages 4-5								
Prenatal PM.25 Exposure	-0.0275	-0.0485	0.0150	0.0121				
	(0.7603)	(0.4056)	(0.7343)	(0.7123)				
Prenatal PM2.5 Exposure: Trimester 1					-0.0357	-0.0364	0.0123	0.0048
					(0.3356)	(0.1360)	(0.4762)	(0.6914)
Prenatal PM2.5 Exposure: Trimester 2					-0.0280	-0.0471	0.0071	0.0165
					(0.4993)	(0.1527)	(0.5697)	(0.2614)
Prenatal PM2.5 Exposure: Trimester 3					-0.1006*	-0.1116***	0.0254	0.0253
					(0.0875)	(0.0099)	(0.1530)	(0.1190)
Postnatal PM2.5	-0.1775	-0.4396	0.2588	0.1136	-1.5662	-2.1331**	0.5219	0.6131
	(0.8730)	(0.4816)	(0.5496)	(0.7191)	(0.2961)	(0.0475)	(0.1954)	(0.1934)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.2005	0.1494	0.1400	0.1155	0.2053	0.1563	0.1416	0.1176

Note: Additional controls include all child and household characteristics listed in Equation (3.1), weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey month fixed effect, and community fixed effect (full results shown in Tables 3.B.1 and 3.B.2 of appendix 3.B). Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

3.4.2 IV Results

This section (Tables 3.3-3.5) presents the instrumental variable results for the impact of in-utero PM2.5 pollution on child health outcomes. We start our analysis by including all relevant controls including a seasonal dummy variable adjusting for wet and dry seasons, which we then replace with a more flexible seasonality control (monthly seasonal adjustments for ambient air pollution).

Table 3.3 presents the results for the first stage IV regression. Consistent with other studies that use wind speed as an instrument for pollution, we find a negative and statistically significant relationship between PM2.5 and wind speed. A one unit increase in wind speed is associated with a reduction in PM2.5 concentration of 0.325$\mu g/m^3$. This coefficient slightly decreases to -0.352$\mu g/m^3$ when monthly seasonal controls are included. These findings, presented in Table 3.3, show that indeed wind speed plays a significant role in the dispersion of air pollutants, helping to carry them away from where they are locally produced. The F-statistics for excluded instruments as shown in the table generally exceed the rule of thumb value of 10, thus confirming that wind speed is not a weak instrument.

We next report the results from the second stage IV regression. We present the results separately, with Table 3.4 showing the results without monthly seasonal adjustments for ambient PM2.5, and Table 3.5 showing the results with monthly seasonal adjustments. Panel A of the Tables (3.4 & 3.5) presents the results for children at ages 0-1, while Panel B presents the results for the same group of children at ages 4-5. Beginning with Table 3.4, we find that children exposed to air pollution during pregnancy are generally worse off than their peers not exposed to pollution. The Table (3.4) shows children to be shorter and thinner on average than their peers of the same age and gender. For a 1 $\mu g/m^3$ increase in average monthly in-utero PM2.5 exposure, columns (1)-(2) of Table 3.4 indicate a decrease in height-for-age and weight-for-age z-scores at age 1 of approximately 0.387 and 0.407 standard deviations, respectively. When put into context, this signifies a 25-26% decrease in height-for-age and weight-for-age relative to their respective means of -1.47 and -1.61 standard deviations in our sample. In addition, with regards to the corresponding WHO growth standards for height (in inches) and weight (in kg), a 0.387 SD reduction in HFA in our results corresponds to an approximate decrease in height

Table 3.3: IV First Stage: Regression of Hourly PM2.5 on Hourly Wind speed and other Climate Controls (Prenatal Time Period: 2000 - 2002)

	Without monthly variation in ambient PM2.5	With monthly variation in ambient PM2.5
	PM2.5	PM2.5
	(1)	(2)
Windspeed	-0.3254***	-0.3522***
	(0.0005)	(0.0010)
Rainfall	2.1236	0.4593
	(0.6372)	(0.9115)
Temperature	0.4045***	0.1507
	(0.0090)	(0.3560)
Rainfall*Temperature	0.2556	0.1901
	(0.2538)	(0.3625)
Rainfall_Squared	-1.5358**	-0.7995**
	(0.0135)	(0.0392)
Temperature_Squared	-0.0026	0.0004
	(0.3804)	(0.8744)
F-statistics	15.66	15.58
N	526,080	526,080
r2	0.1877	0.2881

Note: Additional controls include hourly fixed effect, yearly fixed effect, seasonal fixed effect (in column (1)) and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

of 0.36 inches for a 1-year-old boy, and a decrease of 0.39 inches for a 1-year-old girl.[11] In terms of weight-for-age, our findings correspond to about 0.43kg and 0.45kg reductions for the average boy and girl at age 1, respectively.[12] Columns (3)-(4) of the Table (3.4) also provide results for our stunting and underweight measures. Our findings show only our stunting measure to be

[11]A change of 1 standard deviation in the height-for-age z-score at age 1 corresponds to about 2.4cm (0.95 inches) and 2.6cm (1.02 inches) in height for the average boy and girl, respectively (WHO, 2006*b*).

[12]A change of 1 standard deviation in the weight-for-age z-score at age 1 corresponds to about 1.07kg and 1.13kg in weight for the average boy and girl, respectively (WHO, 2006*b*).

Table 3.4: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health Without Monthly Variation in Ambient PM2.5

Panel A: Ages 0-1	HFA	WFA	Stunting	Underweight	HFA	WFA	Stunting	Underweight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prenatal PM2.5 Exposure	-0.3876*	-0.4074***	0.1447*	0.1006				
	(0.0959)	(0.0091)	(0.0905)	(0.1684)				
Prenatal PM2.5 Exposure: Trimester 1					-0.3473	-0.2718*	0.2078***	0.0745
					(0.1258)	(0.0516)	(0.0058)	(0.2503)
Prenatal PM2.5 Exposure: Trimester 2					-0.1115	-0.1343**	0.0588**	0.0305
					(0.1286)	(0.0176)	(0.0290)	(0.2042)
Prenatal PM2.5 Exposure: Trimester 3					-0.2264	-0.2252	0.1906***	0.0525
					(0.3359)	(0.1429)	(0.0077)	(0.3655)
Postnatal PM2.5	-0.0568	-0.0204	0.0359	-0.0201	-0.1231	-0.0431	0.0381	-0.0081
	(0.6306)	(0.8003)	(0.4876)	(0.6233)	(0.3544)	(0.5925)	(0.4671)	(0.8496)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3017	0.3733	0.2270	0.2947	0.3084	0.3753	0.2338	0.2972
Panel B: Ages 4-5								
Prenatal PM2.5 Exposure	-0.1347	-0.1833	0.0332	0.0621				
	(0.4211)	(0.2691)	(0.6193)	(0.3522)				
Prenatal PM2.5 Exposure: Trimester 1					-0.0972	-0.0838	-0.0102	0.0985
					(0.4744)	(0.4490)	(0.7944)	(0.1346)
Prenatal PM2.5 Exposure: Trimester 2					-0.0291	-0.0570	0.0040	0.0233
					(0.5746)	(0.3123)	(0.8567)	(0.3511)
Prenatal PM2.5 Exposure: Trimester 3					-0.0033	-0.0565	-0.0367	0.0838
					(0.9826)	(0.6556)	(0.4355)	(0.2591)
Postnatal PM2.5	0.0401	-0.0978	0.2112	0.0624	0.0146	-0.1062	0.2140	0.0749
	(0.9521)	(0.7640)	(0.2628)	(0.6988)	(0.9849)	(0.7468)	(0.2267)	(0.6576)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.1903	0.1429	0.1343	0.1099	0.1963	0.1437	0.1366	0.1129

Note: Additional controls include all child and household characteristics listed in Equation (3.1), weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, season of birth fixed effect, survey month fixed effect, and community fixed effect (full results shown in Tables 3.B.4 and 3.B.5 of appendix 3.B). Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3.5: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health With Monthly Variation in Ambient PM2.5

Panel A: Ages 0-1	HFA	WFA	Stunting	Underweight	HFA	WFA	Stunting	Underweight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prenatal PM2.5 Exposure	-0.5667	-0.3192	0.6961	0.2648				
	(0.7066)	(0.7400)	(0.2270)	(0.6806)				
Prenatal PM2.5 Exposure: Trimester 1					-0.7687	-0.6613*	0.3477	0.2238
					(0.2325)	(0.0662)	(0.1622)	(0.3965)
Prenatal PM2.5 Exposure: Trimester 2					-0.3741	-0.0872	0.1709	0.0570
					(0.4750)	(0.8184)	(0.3882)	(0.8269)
Prenatal PM2.5 Exposure: Trimester 3					0.1341	0.0883	0.2248	0.0562
					(0.7893)	(0.7814)	(0.2846)	(0.7820)
Postnatal PM2.5	-0.1116	-0.0473	0.0443	-0.0059	-0.1423	-0.0655	0.0448	-0.0030
	(0.3962)	(0.5983)	(0.4714)	(0.8898)	(0.3167)	(0.4876)	(0.4743)	(0.9466)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3150	0.3800	0.2378	0.2972	0.3174	0.3825	0.2389	0.2983
Panel B: Ages 4-5								
Prenatal PM2.5 Exposure	0.7441	0.2148	-0.1559	0.2388				
	(0.5212)	(0.8447)	(0.6619)	(0.6583)				
Prenatal PM2.5 Exposure: Trimester 1					0.4002	-0.0676	-0.0979	0.1409
					(0.4940)	(0.8956)	(0.7466)	(0.6061)
Prenatal PM2.5 Exposure: Trimester 2					0.1358	-0.0380	-0.0157	0.0115
					(0.7512)	(0.9472)	(0.9306)	(0.9631)
Prenatal PM2.5 Exposure: Trimester 3					0.2472	0.1068	-0.0521	0.0830
					(0.5226)	(0.7467)	(0.6068)	(0.6523)
Postnatal PM2.5	-0.0358	-0.1077	0.1625	0.0092	-0.0229	-0.0570	0.1579	0.0211
	(0.9617)	(0.7780)	(0.4361)	(0.9626)	(0.9765)	(0.9036)	(0.4805)	(0.9263)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.2006	0.1490	0.1399	0.1156	0.2011	0.1493	0.1402	0.1164

Note: Additional controls include all child and household characteristics listed in Equation (3.1), weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey month fixed effect, and community fixed effect (full results shown in Tables 3.B.6 and 3.B.7 of appendix 3.B). Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p< 0.05$ *** $p < 0.01$.

significant, indicating that a 1 unit increase in average monthly in-utero PM2.5 exposure increases the probability of stunting by 14.4%.

We further break our analysis into a trimester-specific analysis in Table 3.4. From columns (5)-(8), we find that the negative effect of PM2.5 on child health outcomes mostly occurs during the early stages of pregnancy (Trimesters 1 and 2). For our height-for-age variable, we find no significant impact of PM2.5 exposure on any of the three trimesters of pregnancy. This is not so surprising given the mildly significant coefficient on the average monthly PM2.5 exposure variable during the entire 9 months of pregnancy. For weight-for-age, however, we see from Table 3.4 that Trimesters 1 and 2 PM2.5 exposure are statistically significant. The table shows a reduction of 0.271 and 0.134 standard deviations for a 1 unit increase in average monthly PM2.5 in Trimesters 1 and 2, respectively. This effect corresponds to a 8.3-16.83% reduction in weight-for-age relative to the mean weight-for-age (-1.61) in our sample and about 0.14-0.28kg reduction in weight for an average 1 year old boy and 0.15-0.30kg reduction for an average 1 year old girl in trimesters 1 and 2. We also find from the Table (3.4) that children who are exposed to PM2.5 while in utero (trimesters 1, 2 and 3) are more likely to be stunted, with an increase of 1 $\mu g/m^3$ in average monthly PM2.5 during trimesters 1, 2 and 3 seen to increase the probability of stunting at age 1 by approximately 20%, 6%, and 19%, respectively. In general, our findings from the first panel of Table 3.4 suggests the importance of the early and mid-stages of pregnancy in fetal growth and development. As such, any small changes in the fetal environment such as exposure to harmful chemicals and toxins during this period can cause significant damage to fetal growth and birth outcomes.

In order to examine whether the impact of in-utero PM2.5 exposure diminishes with time, we present the health results on the same group of children at ages 4-5. The results are presented in Panel B of Table 3.4. The results from the table indicate no significant impact of in-utero PM2.5 exposure on child health outcomes at ages 4-5, thus providing weak evidence for a medium run effect of air pollution on health outcomes of children in our sample.

With the inclusion of monthly seasonal adjustments, which is our preferred specification, we find our results as shown in Table 3.5 to change in terms of significance. We note that the majority of our PM2.5 variables lose its significant effect on child health outcomes. The only exception is the PM2.5 trimester 1 coefficient on the weight-for-age variable at age

1. We find that a 1 $\mu g/m^3$ increase in average monthly PM2.5 during trimester 1 reduces weight-for-age z-score at age 1 by approximately 0.661 standard deviations. This effect, though, is mildly significant at the 10% significance level. This finding, together with other insignificant coefficients largely suggests that the effect of PM2.5 pollution in utero has a negligible impact on child health outcomes once seasonality is taken into account. We provide an explanation for this finding which includes two graphs shown in Figures 3.A.4 and 3.A.5 of Appendix 3.A depicting both the monthly variation and predicted monthly variation in PM2.5 during the in-utero period (2000-2002) across our 20 study locations within our survey. We see from the Figures, particularly that of the predicted PM2.5 (Figure 3.A.5) that all 20 locations have the same pattern in monthly PM2.5. The periods of high PM2.5 are identical across all locations, likewise the periods of low PM2.5. Given this, it is clear that the inclusion of monthly seasonal controls is essential, and that these controls pick up the minimal variation in seasonal patterns across study communities in our survey, consequently taking away any impact of PM2.5 on health. A study that finds a similar effect is Kurata et al. (2020) in their analysis of in-utero PM2.5 exposure and child stunting in Bangladesh. The authors who also provide results separately with and without monthly seasonal adjustments show that once monthly seasonal adjustments are taken into account, the effect of ambient air pollution on child health becomes marginally significant.[13]

3.4.3 Heterogeneous Effects

We examine the existence of heterogeneity in the impact of in-utero air pollution on child health outcomes. Heterogeneous effects of air pollution (if any) are of grave interest and importance as they are often useful in revealing (i) the groups that are most vulnerable to the harmful effects of pollution and (ii) the ex-ante and ex-post strategies that could be employed by households to enhance their resilience, and help mitigate the negative impacts of pollution on health. We check for heterogeneity in the impact of in-utero air pollution on child health by the childs' gender, mother's level of education, and household area of residence (rural or urban area). Table 3.6-3.8 provides the results including interaction terms between our average

[13]The difference between Kurata et al. (2020) and our study is that our study accounts for endogeneity in in-utero air pollution.

Table 3.6: Heterogeneity by by Child's Gender

Panel A: Ages 0-1	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	-0.5667	-0.3192	0.6960	0.2648
	(0.7073)	(0.7382)	(0.2304)	(0.6790)
Female	0.2180	0.1209	0.0426	-0.0378
	(0.5912)	(0.7288)	(0.6929)	(0.7993)
Prenatal PM2.5 Exposure*Female	0.0039	0.0008	-0.0079	-0.0001
	(0.8776)	(0.9658)	(0.2368)	(0.9871)
Postnatal PM2.5	-0.1108	-0.0472	0.0427	-0.0059
	(0.4001)	(0.6143)	(0.4868)	(0.8950)
Child's Age (in Months)	-0.8032**	-0.4960	0.0915	0.1244
	(0.0452)	(0.2237)	(0.5143)	(0.4960)
Child's Age-squared	0.0230**	0.0142	-0.0015	-0.0045
	(0.0414)	(0.2840)	(0.6793)	(0.4810)
N	1069	1069	1069	1069
r2	0.3150	0.3800	0.2387	0.2972
First Stage F-statistics	15.58	15.58	15.58	15.58
Panel B: Ages 4-5				
Prenatal PM2.5 Exposure	0.7489	0.2352	-0.1536	0.2272
	(0.5228)	(0.8312)	(0.6727)	(0.6727)
Female	0.1704	0.1701	-0.0114	-0.0987
	(0.4313)	(0.5319)	(0.9122)	(0.2809)
Prenatal PM2.5 Exposure*Female	-0.0034	-0.0145	-0.0016	0.0083
	(0.7767)	(0.3423)	(0.8020)	(0.1657)
Postnatal PM2.5	-0.0406	-0.1282	0.1602	0.0209
	(0.9561)	(0.7465)	(0.4552)	(0.9161)
Child's Age (in Months)	-0.3134	-0.2094	0.1056	0.0997
	(0.4188)	(0.6008)	(0.5969)	(0.5793)
Child's Age-squared	0.0032	0.0021	-0.0012	-0.0008
	(0.3178)	(0.4741)	(0.4927)	(0.5475)
N	1069	1069	1069	1069
r2	0.2007	0.1499	0.1399	0.1169
First Stage F-statistics	15.58	15.58	15.58	15.58

Note: Additional controls include all child and household characteristics listed in Equation (3.1), weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey month fixed effect, and community fixed effect (full results shown in Tables 3.B.9 and 3.B.10 of appendix 3.B). Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3.7: Heterogeneity by Mother's Years of Education

Panel A: Ages 0-1	HFA	WFA	Stunting	Underweight
	(1)	(2)	(3)	(4)
Prenatal PM2.5 Exposure	-0.5933	-0.3104	0.7066	0.2592
	(0.6913)	(0.7478)	(0.2259)	(0.6837)
Mother's Years of Schooling	0.0266	-0.0160	-0.0061	0.0105
	(0.7335)	(0.7285)	(0.8082)	(0.6045)
Prenatal PM2.5 Exposure*Mother's Years of Schooling	-0.0014	0.0004	0.0005	-0.0003
	(0.7945)	(0.9007)	(0.7802)	(0.8551)
Postnatal PM2.5	-0.1157	-0.0460	0.0459	-0.0067
	(0.3893)	(0.6271)	(0.4472)	(0.8762)
Child's Age (in Months)	-0.8105**	-0.4947	0.0974	0.1234
	(0.0430)	(0.2184)	(0.4979)	(0.4950)
Child's Age-squared	0.0231**	0.0142	-0.0015	-0.0044
	(0.0408)	(0.2864)	(0.6931)	(0.4847)
Female	0.2820**	0.1344	-0.0885***	-0.0398
	(0.0094)	(0.1117)	(0.0011)	(0.2194)
N	1069	1069	1069	1069
r2	0.3150	0.3800	0.2379	0.2973
First Stage F-statistics	15.58	15.58	15.58	15.58
Panel B: Ages 4-5				
Prenatal PM2.5 Exposure	0.6826	0.1455	-0.1118	0.2827
	(0.5663)	(0.8978)	(0.7674)	(0.6164)
Mother's Years of Schooling	0.0548	0.0445	-0.0310	-0.0308
	(0.3713)	(0.5460)	(0.0918)	(0.1467)
Prenatal PM2.5 Exposure*Mother's Years of Schooling	-0.0024	-0.0027	0.0017	0.0017
	(0.5058)	(0.5023)	(0.1035)	(0.1928)
Postnatal PM2.5	-0.0485	-0.1220	0.1716	0.0182
	(0.9485)	(0.7539)	(0.4044)	(0.9263)
Child's Age (in Months)	-0.3009	-0.1655	0.1081	0.0744
	(0.4401)	(0.6664)	(0.6011)	(0.6723)
Child's Age-squared	0.0031	0.0017	-0.0012	-0.0006
	(0.3334)	(0.5392)	(0.4919)	(0.6417)
Female	0.1140*	-0.0700	-0.0386	0.0387
	(0.0778)	(0.3156)	(0.2108)	(0.2492)
N	1069	1069	1069	1069
r2	0.2012	0.1500	0.1414	0.1174
First Stage F-statistics	15.58	15.58	15.58	15.58

Note: Additional controls include all child and household characteristics listed in Equation (3.1), weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey month fixed effect, and community fixed effect (full results shown in Tables 3.B.11 and 3.B.12 of appendix 3.B). Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p< 0.05$ *** $p < 0.01$.

Table 3.8: Heterogeneity by Household Area of Residence

Panel A: Ages 0-1	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	-0.6201	-0.3120	0.4665	-0.0082
	(0.6635)	(0.7653)	(0.3340)	(0.9904)
Rural Area	0.7399	0.0185	-3.1777	-1.2272
	(0.9245)	(0.9969)	(0.2248)	(0.6884)
Prenatal PM2.5 Exposure*Rural Area	0.0114	-0.0015	0.0490	0.0582*
	(0.9407)	(0.9758)	(0.1669)	(0.0616)
Postnatal PM2.5	-0.1157	-0.0468	0.0265	-0.0270
	(0.4016)	(0.6128)	(0.6680)	(0.5712)
Child's Age (in Months)	-0.8087**	-0.4960	0.0798	0.1061
	(0.0482)	(0.2188)	(0.5565)	(0.5382)
Child's Age-squared	0.0230**	0.0142	-0.0010	-0.0039
	(0.0457)	(0.2840)	(0.7853)	(0.5225)
Female	0.2821***	0.1343	-0.0893***	-0.0405
	(0.0090)	(0.1104)	(0.0010)	(0.2016)
N	1069	1069	1069	1069
r2	0.3150	0.3800	0.2396	0.2997
First Stage F-statistics	15.58	15.58	15.58	15.58
Panel B: Ages 4-5				
Prenatal PM2.5 Exposure	0.1698	-0.3571	0.1715	0.3771
	(0.8956)	(0.7750)	(0.6344)	(0.5350)
Rural Area	-1.1424	-0.2781	0.1735	-0.3554
	(0.4673)	(0.8314)	(0.7999)	(0.5445)
Prenatal PM2.5 Exposure*Rural Area	0.0765	0.0799	-0.0457	-0.0212
	(0.1683)	(0.2383)	(0.1030)	(0.4606)
Postnatal PM2.5	-0.0432	-0.1141	0.1662	0.0103
	(0.9560)	(0.7634)	(0.3862)	(0.9565)
Child's Age (in Months)	-0.3365	-0.2077	0.1323	0.0891
	(0.4264)	(0.5905)	(0.5557)	(0.6288)
Child's Age-squared	0.0035	0.0021	-0.0014	-0.0007
	(0.3286)	(0.4635)	(0.4564)	(0.6006)
Female	0.1117*	-0.0729	-0.0369	0.0398
	(0.0799)	(0.2927)	(0.2219)	(0.2333)
N	1069	1069	1069	1069
r2	0.2016	0.1515	0.1430	0.1182
First Stage F-statistics	15.58	15.58	15.58	15.58

Note: Additional controls include all child and household characteristics listed in Equation (3.1), weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey month fixed effect, and community fixed effect (full results shown in Tables 3.B.13 and 3.B.14 of appendix 3.B). Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted as * $p < 0.10$ ** $p< 0.05$ *** $p < 0.01$.

monthly in-utero PM2.5 variable and each dimension of interest. In general, our findings provide weak evidence for the existence of heterogeneous effects in our sample. We find only the interaction term on household area of residence for the age 1 underweight variable to be marginally significant, thus suggesting that children in rural areas who are likely to have less access to information and good quality health care are more adversely impacted from the negative effects of ambient air pollution on health.

3.4.4 Robustness Checks

To check the robustness of our findings, we present results from alternative sets of specifications in Appendix 3.C. First, we modify our instrument to a dummy variable indicating relatively high levels of wind speed (≥ 3 m s^{-1}). This modification is in line with several studies that have shown relatively low pollution levels at wind speed levels usually greater than or equal to 2-3 m s^{-1} (Xu et al., 2018; Kountouris, 2020). Tables 3.C.1, 3.C.2, and 3.C.3 presents the IV results using this new indicator variable for wind speed. The results from our first stage are fairly robust, with wind speed levels of 3 m s^{-1} or more causing a significant reduction in PM2.5 of approximately 0.83 μg/m^3. The F-statistics are also above the threshold of 10, indicating that wind speed is not a weak instrument. Appendix 3.C also indicates fairly similar results for the IV second stage. We find in-utero PM2.5 exposure to have a marginally significant effect on health (weight-for-age), with a 1 μg/m^3 increase in average Trimester 1 level PM2.5 reducing weight-for-age z-score by 1.03 standard deviations.

As our second robustness check, we use a slightly different variable for in-utero PM2.5 exposure. We measure monthly PM2.5 exposure using a cumulative measure, constructed as the sum of the average daily PM2.5 exposure for each given month within the 9 months period of gestation. This new measure as opposed to the average daily PM2.5 does not ignore significant amount of variation in daily PM2.5 through averaging out extremely high and low pollution days. We provide the results using this alternate PM2.5 measure in Tables 3.D.2 and 3.D.3 of Appendix 3.D. In general, the results show mildly significant effects of in-utero PM2.5 on child health outcomes. We find that an increase in cumulative PM2.5 exposure during the 9 month pregnancy period increases the probability of stunting by 0.3%. For the trimester analysis, we find only Trimester 1 PM2.5 level to be significant, with a 1 μg/m^3 increase in cumulative

Trimester 1 PM2.5 reducing height-for-age z-score at age 1 by 0.013 standard deviations and increasing the probability of stunting by 0.4%. These findings, however, are significant at the 10% significance level. We find no significant effect on the weight-for-age or the underweight measure, suggesting a weak overall effect of in-utero air pollution on child health.

As our final robustness check, we use a longer gestation period, using a full year of exposure before birth (Adhvaryu et al., 2019). The results are presented in Tables 3.E.2 and 3.E.3 of Appendix 3.E. Again, we find similar results to our main specification, with children exposed to polluted air in utero not affected in their height-for-age or weight-for-age. The Tables 3.E.2 and 3.E.3 show statistically insignificant coefficients on all PM2.5 variables at both age 1 and age 5, suggesting that in-utero air pollution has no short run or medium run effect on health outcomes of children in our sample.

3.5 Discussion and Conclusion

This study has analysed the impact of ambient air pollution on child health in a developing country, Ethiopia, where infant health is fragile and air pollution levels are above the safety standards. By combining satellite PM2.5 data and individual-level data, we are able to assign in-utero pollution measures to each child in our sample and estimate the causal effect of PM2.5 exposure during pregnancy on child health using wind speed as an instrumental variable.

Overall, our IV regression analysis provides weak evidence for the harmful effects of air pollution on child health outcomes. We show that within our preferred model specification which incorporates monthly adjustments for seasonality in our pollution variable, exposure to ambient air pollution has little to no effect on child health. From the results tables, we note that most of the harmful effects initially found diminishes once monthly fixed effects are included. This finding highlights the importance of controlling for seasonal patterns in examining the relationship between PM2.5 and child health outcomes. When we compare to the literature on in-utero air pollution and health outcomes, our finding is not particularly uncommon, as few studies like Kurata et al. (2020), Huang et al. (2015), and Gehring et al. (2011) have shown similar findings on child health. It is important to note, however, that some of these studies are not directly comparable due to differences in study indicators such pollution variable measures or health outcome measures. Nevertheless, they are relevant in giving vital insights into the general impact of air pollution in utero on child health.

Among the three studies listed, the most relevant to our study is Kurata et al. (2020) who undertaking a similar empirical procedure to ours, show that the effects of in-utero PM2.5 exposure on child health (stunting) is mild and marginally significant at the 10% significance level. Although our study differs from this study given that we account for endogeneity using instrumental variables, we have a number of limitations to our study which may have played a role in our marginally significant findings.

Our first limitation is our relatively small sample size. A number of studies that have analysed the relationship between air pollution and birth outcomes use hospital data containing hundreds of live births. For example, Ha et al. (2014) in Florida, USA, uses data on 445,085 live births in examining the adverse effects of in-utero air pollution on child health. Likewise, Liang et al. (2019) with a sample of 1,455,066 children derived from the Chinese birth registry, and Palma et al. (2019) in Italy using live birth data on 3,400,000 children. This is also applicable to cross-country studies such as Adhvaryu et al. (2019); Foreman (2018) and Heft-Neal et al. (2019) that use a wide range of countries within Africa, and as a result have a sample sizes varying from approximately 517,000 to 956,000 children. Having a relatively smaller sample size as in the case of our study with children who are born during the same time period (2001-2002) comes at a cost of much more limited variation in our data, particularly in our in-utero air pollution variable. Moreover, focusing on a single country like Ethiopia, which has very similar patterns in PM2.5 across regions, and very low pollution levels on average relative to other study countries like China or India, could be an explanation for the absence of an effect in the present study. In general, although our study shows in-utero PM2.5 levels for our Ethiopian sample (mean: 16 $\mu g/m^3$; standard deviation: 4) to be higher than the WHO health standard of 10 $\mu g/m^3$, it remains significantly lower than levels found in other studies like Qian et al. (2016) and Singh et al. (2019) that show mean values of in-utero PM2.5 of 71 and 54 $\mu g/m^3$; and standard deviations of 14 and 31 for China and India, respectively. Given this, future research that estimate the impacts of air pollution in Ethiopia may need to use a larger study sample, as well as better pollution data with a much higher spatial resolution in order to be able to accurately individualise air pollution estimates, consequently allowing for wider variation within the estimation sample.

Another potential explanation for the mild effects of in-utero air pollution on child health outcomes found in our study is the idea that our results represent lower-bound estimates as mentioned in section 3.2.1. As evidenced in the literature, air pollution exposure in utero have negative impacts on child mortality (Adhvaryu et al. (2019); Foreman (2018) and Heft-Neal et al. (2019)). This finding could imply that the majority of children who are alive with health data are likely to have experienced much lower levels of in-utero air pollution, thus creating a survival bias that might underestimate the true association between ambient air pollution and child health. Given that the young lives survey has limited information on still births and infant mortality, further research with more detailed datasets may be useful in investigating the existence and magnitude of the potential estimation bias.

Overall, we cannot conclude from the absence of an effect in our study that there is no association between in-utero air pollution and child health outcomes due to the limitations present. Our findings call for further research particularly within the African context where data on air pollution having characteristics of both high spatial and temporal resolution is scarce. The implementation of higher quality datasets for both air pollution and health outcomes will help to give further insight into the true nature of the relationship between ambient air pollution and child health.

Appendix

3.A PM2.5 Data

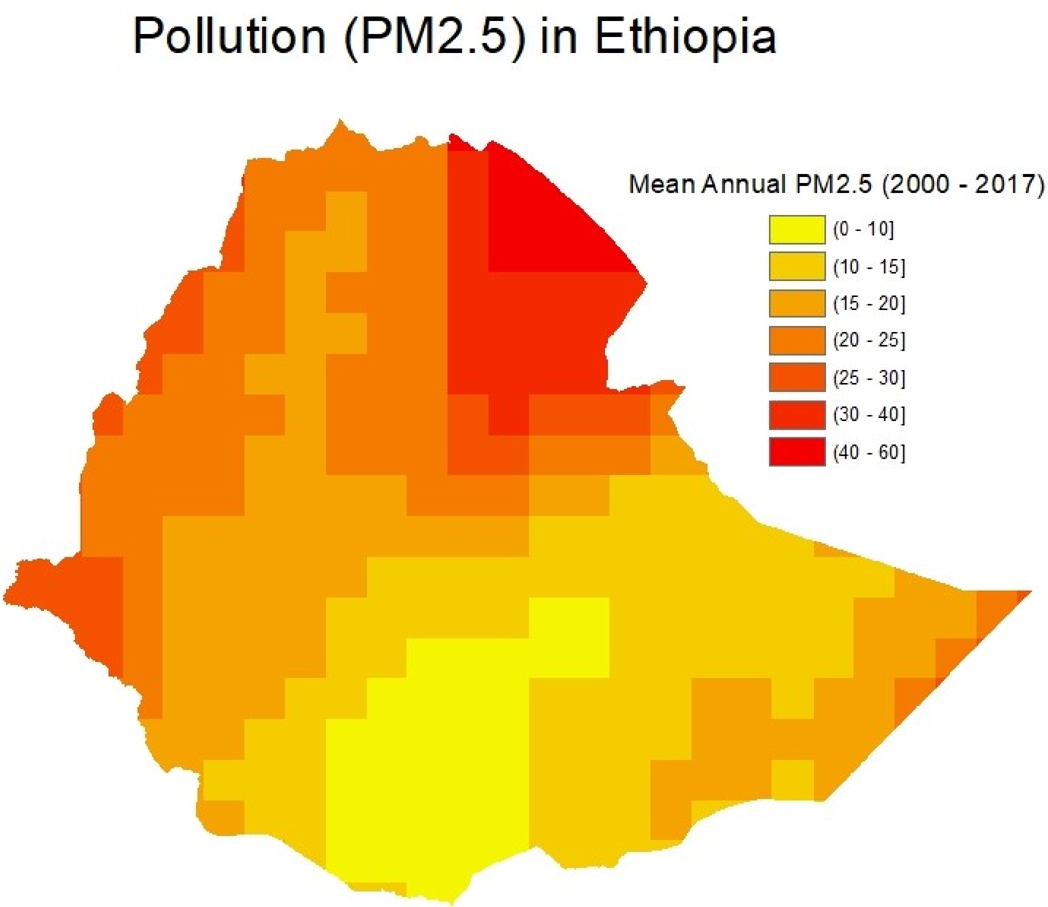

Figure 3.A.1: Spatial Variation in Mean Annual PM2.5 in Ethiopia.

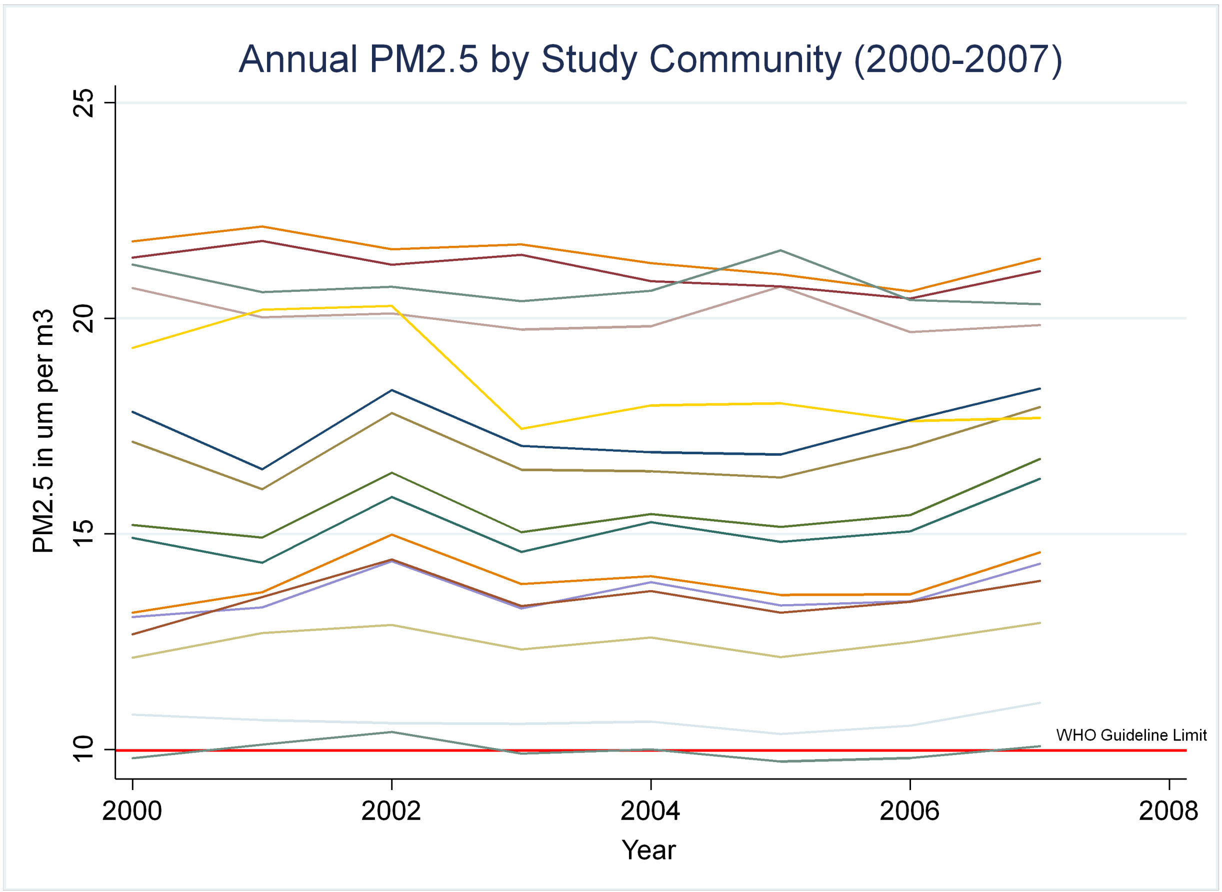

Figure 3.A.2: Annual PM2.5 for the Ethiopian Young Lives Survey Study Communities (2000-2007).

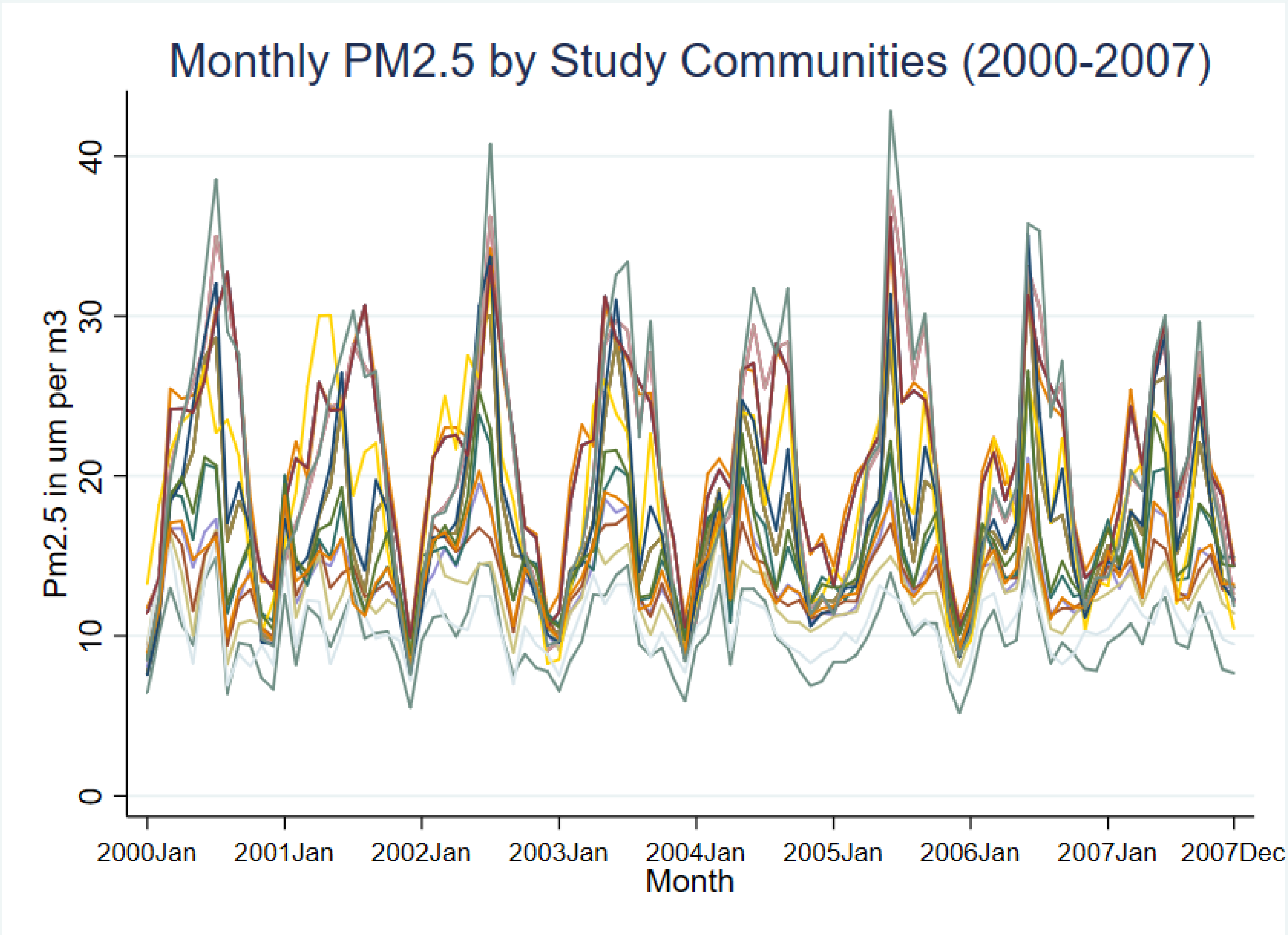

Figure 3.A.3: Monthly PM2.5 for the Ethiopian Young Lives Survey Study Communities (2000-2007).

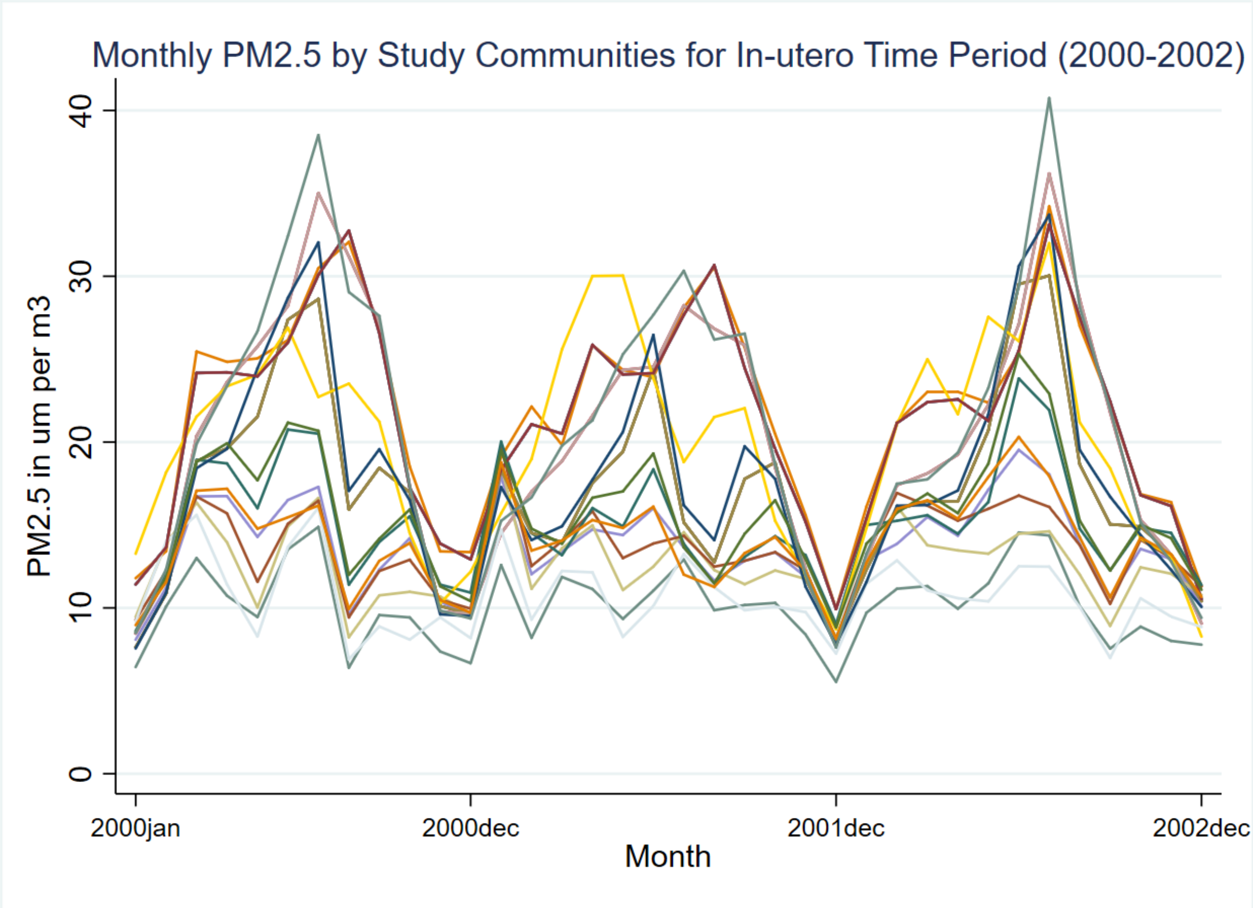

Figure 3.A.4: Monthly PM2.5 for the Ethiopian Young Lives Survey Study Communities for In-utero Time Period (2000-2002).

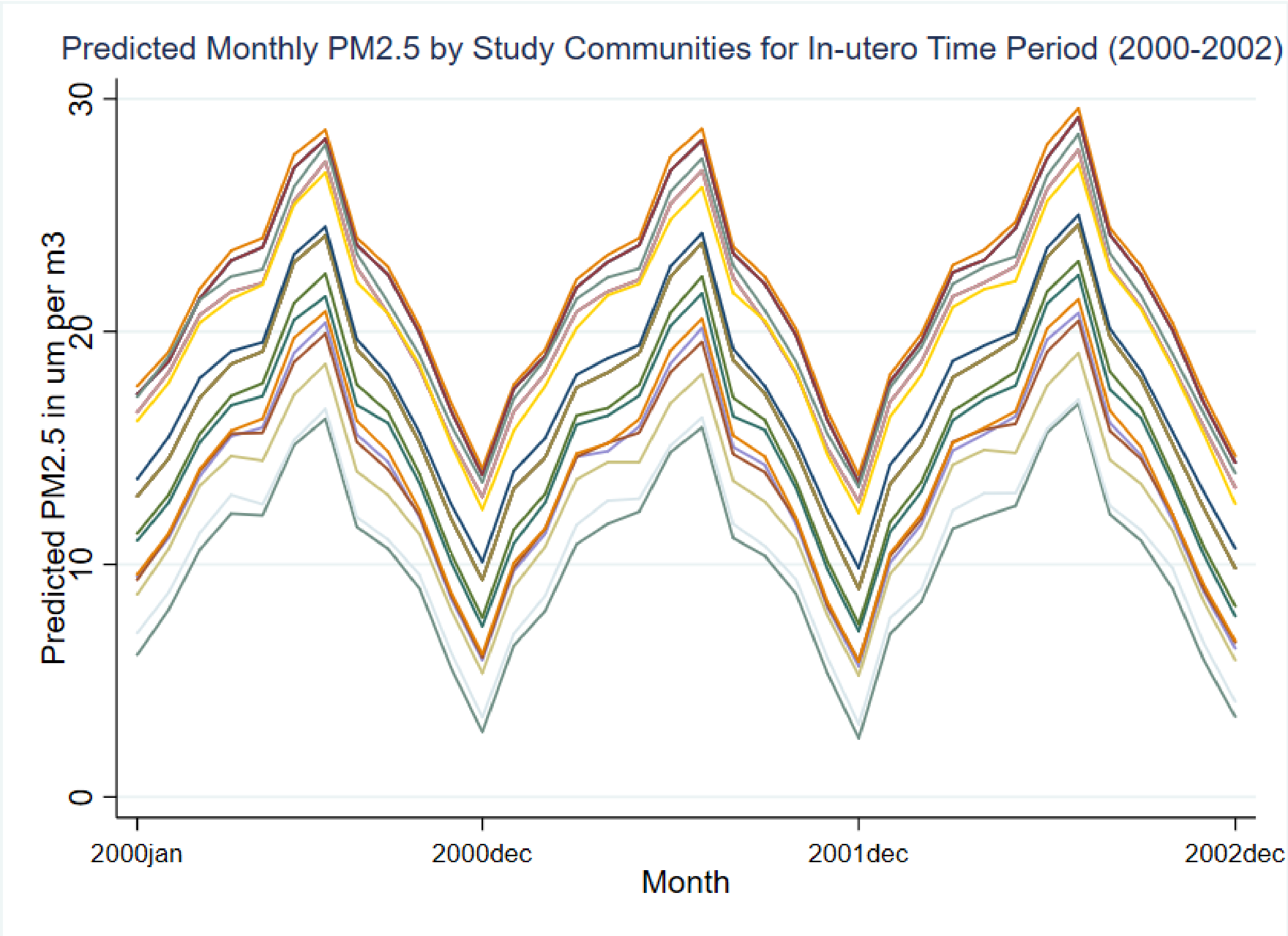

Figure 3.A.5: Predicted Monthly PM2.5 for the Ethiopian Young Lives Survey Study Communities for In-utero Time Period (2000-2002).

3.B Regression Results Showing All Additional Controls

Table 3.B.1: OLS Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 0-1 Years

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	0.0267	0.0681	-0.0190	-0.0253				
	(0.8180)	(0.2320)	(0.6186)	(0.4951)				
Prenatal PM2.5 Exposure: Trimester 1					0.0053	0.0064	-0.0064	0.0000
					(0.9054)	(0.6999)	(0.6030)	(0.9988)
Prenatal PM2.5 Exposure: Trimester 2					0.0321	0.0269	-0.0126	-0.0120
					(0.4765)	(0.2667)	(0.4677)	(0.4198)
Prenatal PM2.5 Exposure: Trimester 3					0.0592	-0.0192	-0.0233	0.0098
					(0.4035)	(0.4500)	(0.2766)	(0.4927)
Postnatal PM2.5	-0.0898	0.0229	0.0326	-0.0301	0.0813	-0.0447	-0.0200	-0.0061
	(0.6411)	(0.8363)	(0.5730)	(0.5279)	(0.7066)	(0.7059)	(0.7568)	(0.8967)
Child's Age (in Months)	-0.7588*	-0.4096	0.0542	0.0881	-0.6922	-0.4339	0.0339	0.0965
	(0.0714)	(0.2882)	(0.6303)	(0.5988)	(0.1184)	(0.2959)	(0.7669)	(0.5712)
Child's Age-squared	0.0211	0.0107	0.0001	-0.0030	0.0209	0.0106	0.0002	-0.0029
	(0.1183)	(0.4292)	(0.9637)	(0.6229)	(0.1257)	(0.4427)	(0.9463)	(0.6371)
Female	0.2801***	0.1312	-0.0864***	-0.0383	0.2876***	0.1305	-0.0886***	-0.0384
	(0.0084)	(0.1176)	(0.0020)	(0.2271)	(0.0084)	(0.1185)	(0.0009)	(0.2230)
Female Head	0.0572	0.0278	-0.0593	-0.0355	0.0375	0.0335	-0.0534	-0.0372
	(0.8575)	(0.8972)	(0.4978)	(0.6679)	(0.9035)	(0.8829)	(0.5487)	(0.6459)
Mother's Age	-0.0223	-0.0066	0.0126	0.0019	-0.0265	-0.0056	0.0138	0.0017
	(0.6483)	(0.8343)	(0.3827)	(0.8812)	(0.5948)	(0.8547)	(0.3445)	(0.8984)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001	0.0007	0.0004	-0.0002	-0.0001
	(0.4288)	(0.4432)	(0.3459)	(0.7721)	(0.4015)	(0.4475)	(0.3140)	(0.7787)
Father's Age	0.0107	0.0051	-0.0088	0.0064	0.0146	0.0033	-0.0100	0.0070
	(0.6547)	(0.8445)	(0.4878)	(0.6111)	(0.5689)	(0.8938)	(0.4380)	(0.5680)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001	-0.0003	-0.0001	0.0001	-0.0001
	(0.3903)	(0.7510)	(0.4545)	(0.6363)	(0.3485)	(0.7946)	(0.4257)	(0.5969)
Mother's Years of Schooling	0.0050	-0.0090	0.0022	0.0060	0.0044	-0.0088	0.0024	0.0059
	(0.8326)	(0.3818)	(0.7187)	(0.3110)	(0.8586)	(0.4022)	(0.6743)	(0.3228)
Father's Years of Schooling	0.0201	0.0163	-0.0107**	-0.0049	0.0191	0.0173	-0.0103**	-0.0053
	(0.2202)	(0.1559)	(0.0197)	(0.3336)	(0.2700)	(0.1392)	(0.0265)	(0.2925)
BCG Vaccine	0.1348	0.0758	0.0135	0.0171	0.1164	0.0839	0.0192	0.0140
	(0.2328)	(0.4588)	(0.7522)	(0.6490)	(0.3230)	(0.4225)	(0.6570)	(0.7194)
Measles Vaccine	0.3835***	0.2132**	-0.0903*	-0.0949*	0.3975***	0.2142**	-0.0942*	-0.0963*
	(0.0013)	(0.0222)	(0.0969)	(0.0600)	(0.0004)	(0.0216)	(0.0783)	(0.0576)
Household Size	0.0710	0.0656***	-0.0269*	-0.0287***	0.0693	0.0680***	-0.0262*	-0.0298***
	(0.1335)	(0.0038)	(0.0547)	(0.0038)	(0.1510)	(0.0036)	(0.0596)	(0.0036)
Number of Children born to Mother	-0.0789*	-0.1086**	0.0314**	0.0384***	-0.0766	-0.1119**	0.0306**	0.0400***
	(0.0992)	(0.0120)	(0.0385)	(0.0088)	(0.1041)	(0.0101)	(0.0402)	(0.0078)
Wealth Index	1.9988***	1.9003***	-0.5790**	-0.7320***	2.0297***	1.8644***	-0.5901**	-0.7157***
	(0.0048)	(0.0002)	(0.0247)	(0.0001)	(0.0047)	(0.0000)	(0.0213)	(0.0000)
Child's Religion: Christian	0.1402	0.0935	-0.0096	-0.0034	0.1408	0.0884	-0.0101	-0.0009
	(0.3707)	(0.2986)	(0.8958)	(0.9790)	(0.3590)	(0.3337)	(0.8906)	(0.9947)
Child's Religion: Other	0.5071	0.3407	-0.1894	-0.1294	0.5074	0.3365	-0.1898	-0.1273
	(0.3618)	(0.3272)	(0.2855)	(0.5836)	(0.3670)	(0.3268)	(0.2926)	(0.5804)
Child's Ethnic Group: Gurage	0.4788	0.5062**	-0.0973	-0.0539	0.4716	0.4847**	-0.0967	-0.0426
	(0.3167)	(0.0278)	(0.7067)	(0.6626)	(0.3212)	(0.0317)	(0.7382)	(0.7168)
Child's Ethnic Group: Oromo	-0.5104	-0.0969	0.1395	0.0827	-0.5118	-0.1027	0.1395	0.0858
	(0.1455)	(0.8425)	(0.1336)	(0.3020)	(0.1641)	(0.8290)	(0.1534)	(0.2757)
Child's Ethnic Group: Tigrian	-0.5345*	-0.2743	0.1911*	0.1073	-0.5486*	-0.2621	0.1959*	0.1019
	(0.0682)	(0.4328)	(0.0779)	(0.4856)	(0.0602)	(0.4579)	(0.0651)	(0.5093)
Child's Ethnic Group: Other	-0.6514**	-0.1205	0.1499*	0.0592	-0.6700**	-0.1060	0.1561*	0.0530
	(0.0481)	(0.6310)	(0.0986)	(0.5256)	(0.0434)	(0.6660)	(0.0971)	(0.5576)
Long Term Illness	-0.0704	-0.1490	0.0204	0.0720	-0.0802	-0.1383	0.0238	0.0672
	(0.7649)	(0.1352)	(0.8044)	(0.1555)	(0.7274)	(0.1713)	(0.7672)	(0.1949)
Cooking Fuel Used: Wood	0.3982	0.3282**	-0.0702	-0.0804*	0.4108*	0.3183**	-0.0744	-0.0761*
	(0.1573)	(0.0112)	(0.2195)	(0.0867)	(0.1536)	(0.0108)	(0.2104)	(0.0898)
Cooking Fuel Used: Kerosene	-0.1250	0.0824	0.0284	-0.0188	-0.1178	0.0656	0.0253	-0.0108
	(0.7243)	(0.7317)	(0.8479)	(0.8526)	(0.7482)	(0.7716)	(0.8715)	(0.9121)
Cooking Fuel Used: Charcoal	0.1698	0.1426	-0.0147	-0.0457	0.1951	0.1382	-0.0222	-0.0450
	(0.3686)	(0.5911)	(0.8548)	(0.6820)	(0.3382)	(0.5991)	(0.7989)	(0.6932)
Cooking Fuel Used: Gas/Electricity	0.1441	-0.4778	-0.1116	0.1122	0.1986	-0.5056	-0.1288	0.1230
	(0.8682)	(0.4115)	(0.7084)	(0.5412)	(0.8330)	(0.3650)	(0.6906)	(0.4897)
Cooking Fuel Used: Other	0.0516	-0.4569	0.1507	0.2334	0.0982	-0.4748	0.1364	0.2396
	(0.9299)	(0.2585)	(0.3616)	(0.1755)	(0.8709)	(0.2356)	(0.4214)	(0.1754)
Heating Fuel Used: Wood	-0.0586	0.0143	-0.0466	-0.0436	-0.0768	0.0220	-0.0409	-0.0464
	(0.6900)	(0.8958)	(0.2761)	(0.6065)	(0.6213)	(0.8427)	(0.3273)	(0.5817)
Heating Fuel Used: Charcoal	-0.4778**	-0.2467	0.0495	0.0016	-0.5142**	-0.2380	0.0603	-0.0006
	(0.0237)	(0.2648)	(0.3360)	(0.9887)	(0.0113)	(0.2888)	(0.2733)	(0.9938)
Heating Fuel Used: None	-0.0060	-0.0444	-0.1308**	-0.0806	-0.0220	-0.0312	-0.1254**	-0.0863
	(0.9726)	(0.7951)	(0.0156)	(0.3723)	(0.9018)	(0.8503)	(0.0241)	(0.3259)
Heating Fuel Used: Other	-0.8107*	-0.4602**	0.0196	0.1288	-0.8543**	-0.4360**	0.0335	0.1191
	(0.0524)	(0.0300)	(0.8929)	(0.6075)	(0.0449)	(0.0426)	(0.8389)	(0.6653)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3149	0.3803	0.2369	0.2975	0.3166	0.3818	0.2387	0.2998

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3.B.2: OLS Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 4-5 Years

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-0.0275	-0.0485	0.0150	0.0121				
	(0.7603)	(0.4056)	(0.7343)	(0.7123)				
Prenatal PM2.5 Exposure: Trimester 1					-0.0357	-0.0364	0.0123	0.0048
					(0.3356)	(0.1360)	(0.4762)	(0.6914)
Prenatal PM2.5 Exposure: Trimester 2					-0.0280	-0.0471	0.0071	0.0165
					(0.4993)	(0.1527)	(0.5697)	(0.2614)
Prenatal PM2.5 Exposure: Trimester 3					-0.1006*	-0.1116***	0.0254	0.0253
					(0.0875)	(0.0099)	(0.1530)	(0.1190)
Postnatal PM2.5	-0.1775	-0.4396	0.2588	0.1136	-1.5662	-2.1331**	0.5219	0.6131
	(0.8730)	(0.4816)	(0.5496)	(0.7191)	(0.2961)	(0.0475)	(0.1954)	(0.1934)
Child's Age (in Months)	-0.3194	-0.2283	0.1260	0.0999	-0.7516	-0.6730	0.2233	0.1956
	(0.4424)	(0.5590)	(0.5208)	(0.5847)	(0.1470)	(0.1040)	(0.3592)	(0.2510)
Child's Age-squared	0.0033	0.0022	-0.0014	-0.0008	0.0062	0.0051*	-0.0020	-0.0014
	(0.3120)	(0.4308)	(0.4043)	(0.5536)	(0.1341)	(0.0729)	(0.3139)	(0.2899)
Female	0.1153*	-0.0680	-0.0392	0.0384	0.1140*	-0.0706	-0.0391	0.0395
	(0.0736)	(0.3185)	(0.2007)	(0.2412)	(0.0717)	(0.3169)	(0.1914)	(0.2424)
Female Head	-0.2425	-0.2288*	0.0936*	0.0733	-0.2511	-0.2384*	0.0953*	0.0758
	(0.1414)	(0.0519)	(0.0599)	(0.3573)	(0.1485)	(0.0510)	(0.0620)	(0.3552)
Mother's Age	-0.0940*	-0.0347	0.0101	-0.0086	-0.0940*	-0.0337	0.0103	-0.0094
	(0.0583)	(0.3968)	(0.6408)	(0.6808)	(0.0629)	(0.4079)	(0.6356)	(0.6495)
Mother's Age-squared	0.0016**	0.0007	-0.0002	0.0001	0.0016**	0.0007	-0.0002	0.0001
	(0.0387)	(0.2649)	(0.6123)	(0.7831)	(0.0410)	(0.2826)	(0.5903)	(0.7556)
Father's Age	0.0578**	0.0091	-0.0073	0.0046	0.0560**	0.0072	-0.0070	0.0051
	(0.0253)	(0.7626)	(0.5850)	(0.7810)	(0.0249)	(0.8136)	(0.5942)	(0.7618)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0329)	(0.7118)	(0.5158)	(0.8692)	(0.0298)	(0.7459)	(0.5112)	(0.8424)
Mother's Years of Schooling	0.0161	0.0009	-0.0032	-0.0032	0.0180	0.0030	-0.0036	-0.0037
	(0.1919)	(0.9447)	(0.6943)	(0.5325)	(0.1578)	(0.8174)	(0.6563)	(0.4737)
Father's Years of Schooling	0.0166	0.0123	-0.0118*	-0.0061	0.0156	0.0110	-0.0116*	-0.0058
	(0.1253)	(0.2459)	(0.0573)	(0.1084)	(0.1539)	(0.2978)	(0.0581)	(0.1183)
BCG Vaccine	0.1469	0.1051	-0.1149	-0.0008	0.1632	0.1214	-0.1187	-0.0040
	(0.4246)	(0.4786)	(0.1446)	(0.9935)	(0.3633)	(0.4108)	(0.1301)	(0.9646)
Measles Vaccine	0.1929	0.2295	0.0043	-0.1172	0.1784	0.2176	0.0082	-0.1162
	(0.3204)	(0.2180)	(0.9681)	(0.2602)	(0.3306)	(0.2229)	(0.9312)	(0.2710)
Household Size	0.0114	-0.0180	0.0029	0.0091	0.0151	-0.0141	0.0020	0.0082
	(0.4313)	(0.3968)	(0.7730)	(0.2928)	(0.3236)	(0.4999)	(0.8433)	(0.3413)
Number of Children born to Mother	-0.0469	-0.0113	-0.0013	0.0005	-0.0494	-0.0139	-0.0007	0.0010
	(0.1540)	(0.7064)	(0.9239)	(0.9666)	(0.1426)	(0.6431)	(0.9584)	(0.9374)
Wealth Index	0.9992*	0.7634	-0.3930*	-0.3915**	0.9772*	0.7401	-0.3882*	-0.3861**
	(0.0693)	(0.1023)	(0.0574)	(0.0309)	(0.0717)	(0.1139)	(0.0568)	(0.0338)
Child's Religion: Christian	0.0912	0.1101	0.0244	-0.0246	0.0946	0.1157	0.0240	-0.0269
	(0.6394)	(0.3722)	(0.7848)	(0.5938)	(0.6287)	(0.3601)	(0.7912)	(0.5684)
Child's Religion: Other	0.2967	0.0401	-0.1369	-0.0617	0.3035	0.0395	-0.1398	-0.0577
	(0.4811)	(0.7462)	(0.3706)	(0.4435)	(0.4716)	(0.7327)	(0.3594)	(0.4290)
Child's Ethnic Group: Gurage	0.6041	0.4674	-0.1302	-0.2100	0.5747	0.4470	-0.1217	-0.2107
	(0.1519)	(0.1152)	(0.3197)	(0.1975)	(0.1650)	(0.1233)	(0.3326)	(0.1858)
Child's Ethnic Group: Oromo	0.2177	0.2402*	0.0323	-0.0303	0.2137	0.2351*	0.0330	-0.0288
	(0.2491)	(0.0500)	(0.7924)	(0.5999)	(0.2595)	(0.0654)	(0.7957)	(0.6209)
Child's Ethnic Group: Tigrian	0.0057	-0.0293	-0.0236	0.0347	0.0599	0.0056	-0.0397	0.0378
	(0.9675)	(0.8887)	(0.9188)	(0.7337)	(0.7224)	(0.9873)	(0.8732)	(0.7326)
Child's Ethnic Group: Other	-0.0007	0.2463**	0.0497	-0.0523	0.0071	0.2523**	0.0476	-0.0526
	(0.9971)	(0.0420)	(0.5605)	(0.3106)	(0.9717)	(0.0241)	(0.5806)	(0.2723)
Long Term Illness	-0.2521**	-0.1428	0.1121	0.0680	-0.2424**	-0.1349	0.1095*	0.0674
	(0.0458)	(0.3455)	(0.1051)	(0.2757)	(0.0437)	(0.3669)	(0.0999)	(0.2774)
Cooking Fuel Used: Wood	-0.0134	0.2095	0.0579	-0.1041*	-0.0227	0.2052	0.0609	-0.1059*
	(0.8876)	(0.2101)	(0.3473)	(0.0776)	(0.8085)	(0.2069)	(0.3010)	(0.0575)
Cooking Fuel Used: Kerosene	0.0449	0.3352	0.1694	-0.0776	0.0016	0.3048	0.1818	-0.0783
	(0.9322)	(0.2567)	(0.3213)	(0.5097)	(0.9977)	(0.3132)	(0.3069)	(0.5073)
Cooking Fuel Used: Charcoal	0.1517	0.2732	0.0792	-0.1204	0.1390	0.2603	0.0821	-0.1177
	(0.7579)	(0.2991)	(0.4384)	(0.3012)	(0.7599)	(0.3188)	(0.4329)	(0.3054)
Cooking Fuel Used: Gas/Electricity	0.0117	0.2930	0.1600	-0.1085	-0.0333	0.2614	0.1729	-0.1093
	(0.9650)	(0.1869)	(0.1858)	(0.2466)	(0.9035)	(0.2178)	(0.1552)	(0.2477)
Cooking Fuel Used: Other	0.0728	0.1837	0.0620	-0.0516	0.0559	0.1729	0.0670	-0.0526
	(0.6363)	(0.2501)	(0.5015)	(0.3863)	(0.7089)	(0.2582)	(0.4713)	(0.3688)
Heating Fuel Used: Wood	0.2084	-0.1080	-0.0679	0.0166	0.2373	-0.0851	-0.0757	0.0152
	(0.2599)	(0.5864)	(0.2872)	(0.8136)	(0.1898)	(0.6446)	(0.2243)	(0.8232)
Heating Fuel Used: Charcoal	0.1449	0.0353	-0.0813	-0.0127	0.1795	0.0649	-0.0902	-0.0161
	(0.4173)	(0.8755)	(0.4549)	(0.8863)	(0.2929)	(0.7681)	(0.3997)	(0.8605)
Heating Fuel Used: None	0.1987	-0.0712	-0.1147	0.0076	0.2243	-0.0502	-0.1215	0.0058
	(0.2323)	(0.7275)	(0.1885)	(0.9216)	(0.1715)	(0.8063)	(0.1653)	(0.9446)
Heating Fuel Used: Other	0.0650	-0.1796	0.0433	0.0334	0.0824	-0.1670	0.0384	0.0334
	(0.5708)	(0.2849)	(0.7150)	(0.6057)	(0.4709)	(0.3072)	(0.7469)	(0.6112)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.2005	0.1494	0.1400	0.1155	0.2053	0.1563	0.1416	0.1176

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.3: IV First Stage: Regression of Hourly PM2.5 on Hourly Wind speed and other Climate Controls (Prenatal Time Period: 2000 - 2002)

	Without monthly variation in ambient PM2.5	With monthly variation in ambient PM2.5
	PM2.5	PM2.5
	(1)	(2)
Windspeed	-0.3254***	-0.3522***
	(0.0005)	(0.0010)
Rainfall	2.1236	0.4593
	(0.6372)	(0.9115)
Temperature	0.4045***	0.1507
	(0.0090)	(0.3560)
Rainfall*Temperature	0.2556	0.1901
	(0.2538)	(0.3625)
Rainfall_Squared	-1.5358**	-0.7995**
	(0.0135)	(0.0392)
Temperature_Squared	-0.0026	0.0004
	(0.3804)	(0.8744)
F-statistics	15.66	15.58
N	526,080	526,080
r2	0.1877	0.2881

Note: Additional controls include hourly fixed effect, yearly fixed effect, seasonal fixed effect (in column (1)) and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.4: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 0-1, Without Monthly Variation in Ambient PM2.5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-0.3876*	-0.4074***	0.1447*	0.1006				
	(0.0959)	(0.0091)	(0.0905)	(0.1684)				
Prenatal PM2.5 Exposure: Trimester 1					-0.3473	-0.2718*	0.2078***	0.0745
					(0.1258)	(0.0516)	(0.0058)	(0.2503)
Prenatal PM2.5 Exposure: Trimester 2					-0.1115	-0.1343**	0.0588**	0.0305
					(0.1286)	(0.0176)	(0.0290)	(0.2042)
Prenatal PM2.5 Exposure: Trimester 3					-0.2264	-0.2252	0.1906***	0.0525
					(0.3359)	(0.1429)	(0.0077)	(0.3655)
Postnatal PM2.5	-0.0568	-0.0204	0.0359	-0.0201	-0.1231	-0.0431	0.0381	-0.0081
	(0.6306)	(0.8003)	(0.4876)	(0.6233)	(0.3544)	(0.5925)	(0.4671)	(0.8496)
Child's Age (in Months)	-0.3314	-0.3762	-0.0729	0.1086	-0.5970**	-0.5094**	0.0411	0.1576
	(0.1565)	(0.1065)	(0.1916)	(0.3210)	(0.0215)	(0.0424)	(0.5575)	(0.1312)
Child's Age-squared	0.0105	0.0123	0.0028	-0.0040	0.0220**	0.0180*	-0.0018	-0.0061
	(0.2553)	(0.2020)	(0.2044)	(0.3907)	(0.0217)	(0.0738)	(0.5012)	(0.1731)
Female	0.2628**	0.1266	-0.0822***	-0.0367	0.2772**	0.1331	-0.0865***	-0.0394
	(0.0108)	(0.1119)	(0.0025)	(0.2266)	(0.0098)	(0.1082)	(0.0014)	(0.2143)
Female Head	0.0026	-0.0039	-0.0442	-0.0245	0.0416	0.0116	-0.0508	-0.0316
	(0.9933)	(0.9882)	(0.6197)	(0.7655)	(0.8948)	(0.9632)	(0.5528)	(0.7013)
Mother's Age	-0.0159	-0.0042	0.0110	0.0015	-0.0194	-0.0055	0.0113	0.0022
	(0.7522)	(0.8902)	(0.4715)	(0.9147)	(0.6934)	(0.8498)	(0.4444)	(0.8682)
Mother's Age-squared	0.0006	0.0004	-0.0002	-0.0001	0.0006	0.0004	-0.0002	-0.0001
	(0.4559)	(0.4562)	(0.4001)	(0.7754)	(0.4493)	(0.4436)	(0.3782)	(0.7697)
Father's Age	0.0113	0.0053	-0.0096	0.0063	0.0121	0.0054	-0.0092	0.0061
	(0.6603)	(0.8334)	(0.4721)	(0.6158)	(0.6250)	(0.8254)	(0.4576)	(0.6276)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001	-0.0003	-0.0001	0.0001	-0.0001
	(0.4114)	(0.7604)	(0.4486)	(0.6507)	(0.3960)	(0.7598)	(0.4421)	(0.6488)
Mother's Years of Schooling	0.0037	-0.0089	0.0025	0.0063	0.0066	-0.0077	0.0018	0.0058
	(0.8726)	(0.3781)	(0.6671)	(0.2759)	(0.7886)	(0.4427)	(0.7573)	(0.3186)
Father's Years of Schooling	0.0191	0.0160	-0.0102**	-0.0053	0.0157	0.0147	-0.0099**	-0.0047
	(0.2242)	(0.1313)	(0.0215)	(0.2587)	(0.3346)	(0.1932)	(0.0276)	(0.3353)
BCG Vaccine	0.1231	0.0649	0.0147	0.0190	0.1303	0.0681	0.0125	0.0177
	(0.2513)	(0.5146)	(0.7233)	(0.6016)	(0.2451)	(0.5069)	(0.7669)	(0.6286)
Measles Vaccine	0.3794***	0.2069**	-0.0892*	-0.0974**	0.3804***	0.2089**	-0.0933*	-0.0976*
	(0.0006)	(0.0311)	(0.0874)	(0.0498)	(0.0009)	(0.0318)	(0.0900)	(0.0518)
Household Size	0.0651	0.0641***	-0.0249*	-0.0276***	0.0711	0.0666***	-0.0263*	-0.0287***
	(0.1573)	(0.0039)	(0.0595)	(0.0047)	(0.1442)	(0.0028)	(0.0594)	(0.0034)
Number of Children born to Mother	-0.0772	-0.1085**	0.0305**	0.0379**	-0.0801*	-0.1097***	0.0311**	0.0384***
	(0.1001)	(0.0110)	(0.0443)	(0.0103)	(0.0973)	(0.0099)	(0.0468)	(0.0081)
Wealth Index	2.0515***	1.9024***	-0.5964**	-0.7283***	2.0395***	1.8932***	-0.5835**	-0.7259***
	(0.0030)	(0.0000)	(0.0206)	(0.0001)	(0.0041)	(0.0000)	(0.0239)	(0.0000)
Child's Religion: Christian	0.1325	0.0894	-0.0145	-0.0037	0.1459	0.0932	-0.0130	-0.0061
	(0.4383)	(0.3106)	(0.8570)	(0.9754)	(0.3578)	(0.2743)	(0.8670)	(0.9637)
Child's Religion: Other	0.4804	0.3135	-0.1866	-0.1270	0.4771	0.3100	-0.1806	-0.1263
	(0.3791)	(0.3636)	(0.2868)	(0.5730)	(0.3427)	(0.3191)	(0.2892)	(0.5440)
Child's Ethnic Group: Gurage	0.5308	0.5271**	-0.1175	-0.0712	0.4868	0.5099**	-0.1109	-0.0632
	(0.3107)	(0.0282)	(0.6258)	(0.5750)	(0.3201)	(0.0329)	(0.6226)	(0.6097)
Child's Ethnic Group: Oromo	-0.4898	-0.0816	0.1370	0.0787	-0.5058	-0.0887	0.1416	0.0816
	(0.1832)	(0.8684)	(0.1520)	(0.3294)	(0.1719)	(0.8607)	(0.1388)	(0.3169)
Child's Ethnic Group: Tigrian	-0.4895	-0.2647	0.1736	0.0996	-0.5203*	-0.2783	0.1822	0.1053
	(0.1199)	(0.4992)	(0.1195)	(0.5157)	(0.0892)	(0.4849)	(0.1050)	(0.4821)
Child's Ethnic Group: Other	-0.6210*	-0.1076	0.1467	0.0529	-0.6597*	-0.1238	0.1552	0.0600
	(0.0612)	(0.6727)	(0.1165)	(0.5513)	(0.0571)	(0.6324)	(0.1122)	(0.5205)
Long Term Illness	-0.0658	-0.1480	0.0204	0.0716	-0.0664	-0.1469	0.0172	0.0717
	(0.7837)	(0.1378)	(0.8118)	(0.1577)	(0.7778)	(0.1324)	(0.8287)	(0.1535)
Cooking Fuel Used: Wood	0.3678	0.2970**	-0.0704	-0.0812*	0.3679	0.2976**	-0.0718	-0.0813*
	(0.1629)	(0.0167)	(0.2097)	(0.0801)	(0.1774)	(0.0155)	(0.2061)	(0.0762)
Cooking Fuel Used: Kerosene	-0.1502	0.0676	0.0313	-0.0152	-0.1198	0.0806	0.0237	-0.0208
	(0.6563)	(0.7744)	(0.8219)	(0.8832)	(0.7179)	(0.7239)	(0.8691)	(0.8398)
Cooking Fuel Used: Charcoal	0.1518	0.1246	-0.0171	-0.0457	0.1488	0.1221	-0.0134	-0.0451
	(0.4166)	(0.6286)	(0.8378)	(0.6891)	(0.4178)	(0.6177)	(0.8770)	(0.6841)
Cooking Fuel Used: Gas/Electricity	0.0682	-0.4679	-0.0936	0.1238	0.1812	-0.4226	-0.1140	0.1032
	(0.9265)	(0.4379)	(0.7458)	(0.5110)	(0.8281)	(0.4665)	(0.7026)	(0.5613)
Cooking Fuel Used: Other	-0.0555	-0.5113	0.1750	0.2468	-0.0123	-0.4987	0.1791	0.2390
	(0.9320)	(0.2089)	(0.2708)	(0.1274)	(0.9853)	(0.2253)	(0.2649)	(0.1573)
Heating Fuel Used: Wood	-0.0834	0.0026	-0.0388	-0.0372	-0.0632	0.0126	-0.0472	-0.0409
	(0.5423)	(0.9803)	(0.3103)	(0.6489)	(0.6338)	(0.9102)	(0.2164)	(0.6306)
Heating Fuel Used: Charcoal	-0.4677**	-0.2294	0.0537	0.0085	-0.4303*	-0.2101	0.0361	0.0015
	(0.0291)	(0.2743)	(0.2789)	(0.9310)	(0.0564)	(0.3335)	(0.4849)	(0.9863)
Heating Fuel Used: None	-0.0136	-0.0321	-0.1225**	-0.0784	0.0034	-0.0224	-0.1326**	-0.0816
	(0.9332)	(0.8465)	(0.0136)	(0.3810)	(0.9845)	(0.8942)	(0.0123)	(0.3568)
Heating Fuel Used: Other	-0.7850	-0.4428*	0.0179	0.1296	-0.7648	-0.4236*	-0.0133	0.1257
	(0.0635)	(0.0575)	(0.8991)	(0.6288)	(0.0629)	(0.0518)	(0.9319)	(0.6184)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3017	0.3733	0.2270	0.2947	0.3084	0.3753	0.2338	0.2972

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, season of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.5: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 4-5, Without Monthly Variation in Ambient PM2.5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-0.1347	-0.1833	0.0332	0.0621				
	(0.4211)	(0.2691)	(0.6193)	(0.3522)				
Prenatal PM2.5 Exposure: Trimester 1					-0.0972	-0.0838	-0.0102	0.0985
					(0.4744)	(0.4490)	(0.7944)	(0.1346)
Prenatal PM2.5 Exposure: Trimester 2					-0.0291	-0.0570	0.0040	0.0233
					(0.5746)	(0.3123)	(0.8567)	(0.3511)
Prenatal PM2.5 Exposure: Trimester 3					-0.0033	-0.0565	-0.0367	0.0838
					(0.9826)	(0.6556)	(0.4355)	(0.2591)
Postnatal PM2.5	0.0401	-0.0978	0.2112	0.0624	0.0146	-0.1062	0.2140	0.0749
	(0.9521)	(0.7640)	(0.2628)	(0.6988)	(0.9849)	(0.7468)	(0.2267)	(0.6576)
Child's Age (in Months)	-0.0445	0.0498	0.0828	-0.0939	-0.1373	0.0130	0.0621	0.0110
	(0.9159)	(0.9015)	(0.7319)	(0.6557)	(0.7559)	(0.9727)	(0.8028)	(0.9510)
Child's Age-squared	0.0003	-0.0004	-0.0007	0.0008	0.0012	-0.0001	-0.0006	-0.0001
	(0.9327)	(0.8931)	(0.7158)	(0.6444)	(0.7407)	(0.9787)	(0.7625)	(0.9722)
Female	0.1070*	-0.0696	-0.0394	0.0382	0.1123*	-0.0679	-0.0406	0.0366
	(0.0889)	(0.3085)	(0.1948)	(0.2412)	(0.0799)	(0.3317)	(0.1886)	(0.2758)
Female Head	-0.2486	-0.2472**	0.0983**	0.0773	-0.2362	-0.2433**	0.0965*	0.0722
	(0.1269)	(0.0351)	(0.0443)	(0.3216)	(0.1636)	(0.0436)	(0.0517)	(0.3603)
Mother's Age	-0.0915*	-0.0284	0.0090	-0.0105	-0.0928*	-0.0288	0.0092	-0.0101
	(0.0724)	(0.4855)	(0.6795)	(0.6155)	(0.0663)	(0.4614)	(0.6700)	(0.6245)
Mother's Age-squared	0.0016**	0.0006	-0.0002	0.0001	0.0016**	0.0006	-0.0002	0.0001
	(0.0456)	(0.3241)	(0.6138)	(0.7359)	(0.0427)	(0.3268)	(0.5993)	(0.7456)
Father's Age	0.0584**	0.0097	-0.0073	0.0049	0.0566**	0.0092	-0.0066	0.0048
	(0.0198)	(0.7540)	(0.6065)	(0.7677)	(0.0245)	(0.7744)	(0.6355)	(0.7800)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0266)	(0.7020)	(0.5297)	(0.8634)	(0.0332)	(0.7082)	(0.5545)	(0.8751)
Mother's Years of Schooling	0.0164	0.0024	-0.0033	-0.0036	0.0169	0.0025	-0.0034	-0.0038
	(0.2300)	(0.8525)	(0.6928)	(0.4892)	(0.2000)	(0.8471)	(0.6809)	(0.4746)
Father's Years of Schooling	0.0160	0.0112	-0.0113*	-0.0056	0.0156	0.0111	-0.0111*	-0.0057
	(0.1527)	(0.3080)	(0.0804)	(0.1407)	(0.1604)	(0.3167)	(0.0792)	(0.1562)
BCG Vaccine	0.1639	0.1059	-0.1170	-0.0011	0.1648	0.1060	-0.1178	-0.0003
	(0.3805)	(0.4718)	(0.1184)	(0.9904)	(0.3883)	(0.4849)	(0.1192)	(0.9979)
Measles Vaccine	0.2084	0.2435	-0.0053	-0.1237	0.1979	0.2407	-0.0011	-0.1244
	(0.2973)	(0.1887)	(0.9580)	(0.2388)	(0.2957)	(0.1918)	(0.9908)	(0.2400)
Household Size	0.0143	-0.0178	0.0028	0.0092	0.0150	-0.0176	0.0027	0.0090
	(0.2625)	(0.3732)	(0.7775)	(0.2931)	(0.2810)	(0.3888)	(0.7872)	(0.3223)
Number of Children born to Mother	-0.0526	-0.0137	0.0005	0.0018	-0.0504	-0.0131	-0.0001	0.0014
	(0.1183)	(0.6503)	(0.9719)	(0.8881)	(0.1359)	(0.6604)	(0.9975)	(0.9215)
Wealth Index	1.0289*	0.7921*	-0.4056*	-0.4073**	1.0453**	0.7962*	-0.4135**	-0.4037**
	(0.0583)	(0.0919)	(0.0597)	(0.0245)	(0.0495)	(0.0879)	(0.0496)	(0.0241)
Child's Religion: Christian	0.0939	0.1130	0.0292	-0.0221	0.0968	0.1136	0.0272	-0.0202
	(0.6188)	(0.3622)	(0.7194)	(0.6196)	(0.6136)	(0.3619)	(0.7443)	(0.6501)
Child's Religion: Other	0.3331	0.0496	-0.1506	-0.0687	0.3207	0.0456	-0.1491	-0.0628
	(0.4703)	(0.6893)	(0.3352)	(0.4363)	(0.4991)	(0.6993)	(0.3329)	(0.4484)
Child's Ethnic Group: Gurage	0.6519	0.4996	-0.1379	-0.2242	0.6216	0.4909	-0.1290	-0.2202
	(0.1595)	(0.1010)	(0.2997)	(0.1595)	(0.1673)	(0.1023)	(0.3137)	(0.1554)
Child's Ethnic Group: Oromo	0.2517	0.2736*	0.0233	-0.0417	0.2480	0.2725*	0.0244	-0.0412
	(0.2088)	(0.0522)	(0.8471)	(0.5014)	(0.2236)	(0.0530)	(0.8458)	(0.5023)
Child's Ethnic Group: Tigrian	-0.0019	-0.0005	-0.0194	0.0303	0.0046	0.0010	-0.0230	0.0329
	(0.9927)	(0.9986)	(0.9296)	(0.7655)	(0.9777)	(0.9966)	(0.9131)	(0.7443)
Child's Ethnic Group: Other	0.0290	0.2792**	0.0398	-0.0628	0.0168	0.2756**	0.0430	-0.0606
	(0.8986)	(0.0278)	(0.6361)	(0.2165)	(0.9387)	(0.0266)	(0.6135)	(0.2249)
Long Term Illness	-0.2468**	-0.1492	0.1129	0.0708	-0.2512**	-0.1505	0.1139*	0.0718
	(0.0492)	(0.3250)	(0.1055)	(0.2628)	(0.0452)	(0.3204)	(0.0994)	(0.2415)
Cooking Fuel Used: Wood	-0.0198	0.2004	0.0588	-0.1024*	-0.0225	0.1998	0.0605	-0.1037*
	(0.8250)	(0.2493)	(0.3512)	(0.0883)	(0.8239)	(0.2498)	(0.3422)	(0.0768)
Cooking Fuel Used: Kerosene	0.0203	0.3325	0.1655	-0.0695	0.0337	0.3375	0.1670	-0.0817
	(0.9590)	(0.2595)	(0.3636)	(0.5547)	(0.9448)	(0.2583)	(0.3443)	(0.4850)
Cooking Fuel Used: Charcoal	0.1159	0.2511	0.0828	-0.1130	0.1267	0.2547	0.0819	-0.1189
	(0.7867)	(0.3111)	(0.4465)	(0.2975)	(0.7839)	(0.3150)	(0.4678)	(0.2784)
Cooking Fuel Used: Gas/Electricity	-0.0486	0.2583	0.1634	-0.0958	-0.0177	0.2678	0.1569	-0.1051
	(0.8746)	(0.2345)	(0.2103)	(0.3622)	(0.9548)	(0.2252)	(0.2284)	(0.2881)
Cooking Fuel Used: Other	0.0603	0.1726	0.0637	-0.0508	0.0662	0.1748	0.0644	-0.0562
	(0.6971)	(0.2678)	(0.5090)	(0.4020)	(0.6774)	(0.2780)	(0.4948)	(0.3438)
Heating Fuel Used: Wood	0.2004	-0.1046	-0.0685	0.0154	0.2182	-0.0996	-0.0740	0.0136
	(0.2440)	(0.6028)	(0.3129)	(0.8257)	(0.2038)	(0.6133)	(0.2687)	(0.8430)
Heating Fuel Used: Charcoal	0.1467	0.0340	-0.0824	-0.0122	0.1666	0.0400	-0.0870	-0.0172
	(0.4115)	(0.8909)	(0.4573)	(0.8940)	(0.3383)	(0.8710)	(0.4361)	(0.8515)
Heating Fuel Used: None	0.2100	-0.0568	-0.1218	-0.0007	0.2138	-0.0558	-0.1232	-0.0007
	(0.1666)	(0.7853)	(0.1697)	(0.9913)	(0.1639)	(0.7812)	(0.1631)	(0.9925)
Heating Fuel Used: Other	0.0632	-0.1711	0.0400	0.0315	0.0831	-0.1652	0.0348	0.0277
	(0.5364)	(0.2609)	(0.7397)	(0.6234)	(0.4524)	(0.2888)	(0.7744)	(0.6640)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.1903	0.1429	0.1343	0.1099	0.1963	0.1437	0.1366	0.1129

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, season of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.6: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 0-1, With Monthly Variation in Ambient PM2.5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-0.5667	-0.3192	0.6961	0.2648				
	(0.7066)	(0.7400)	(0.2270)	(0.6806)				
Prenatal PM2.5 Exposure: Trimester 1					-0.7687	-0.6613*	0.3477	0.2238
					(0.2325)	(0.0662)	(0.1622)	(0.3965)
Prenatal PM2.5 Exposure: Trimester 2					-0.3741	-0.0872	0.1709	0.0570
					(0.4750)	(0.8184)	(0.3882)	(0.8269)
Prenatal PM2.5 Exposure: Trimester 3					0.1341	0.0883	0.2248	0.0562
					(0.7893)	(0.7814)	(0.2846)	(0.7820)
Postnatal PM2.5	-0.1116	-0.0473	0.0443	-0.0059	-0.1423	-0.0655	0.0448	-0.0030
	(0.3962)	(0.5983)	(0.4714)	(0.8898)	(0.3167)	(0.4876)	(0.4743)	(0.9466)
Child's Age (in Months)	-0.8051**	-0.4964	0.0953	0.1245	-0.4523	-0.2102	0.0506	0.0615
	(0.0437)	(0.2172)	(0.5020)	(0.4963)	(0.1408)	(0.5429)	(0.6786)	(0.6874)
Child's Age-squared	0.0229**	0.0142	-0.0014	-0.0045	0.0125	0.0052	0.0002	-0.0024
	(0.0418)	(0.2899)	(0.7140)	(0.4884)	(0.1834)	(0.6542)	(0.9603)	(0.6831)
Female	0.2823***	0.1343	-0.0886***	-0.0398	0.2724**	0.1257	-0.0871***	-0.0378
	(0.0073)	(0.1070)	(0.0017)	(0.2193)	(0.0108)	(0.1335)	(0.0010)	(0.2423)
Female Head	0.0516	0.0167	-0.0545	-0.0309	0.0538	0.0161	-0.0536	-0.0304
	(0.8718)	(0.9399)	(0.5322)	(0.7079)	(0.8561)	(0.9474)	(0.5328)	(0.7173)
Mother's Age	-0.0230	-0.0073	0.0133	0.0023	-0.0280	-0.0104	0.0134	0.0028
	(0.6382)	(0.8106)	(0.3671)	(0.8565)	(0.5870)	(0.7345)	(0.3739)	(0.8290)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001	0.0008	0.0005	-0.0002	-0.0001
	(0.4247)	(0.4270)	(0.3313)	(0.7530)	(0.4065)	(0.3954)	(0.3279)	(0.7415)
Father's Age	0.0109	0.0052	-0.0090	0.0063	0.0135	0.0068	-0.0091	0.0060
	(0.6487)	(0.8441)	(0.4732)	(0.6165)	(0.5687)	(0.7858)	(0.4473)	(0.6367)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001	-0.0003	-0.0001	0.0001	-0.0001
	(0.3869)	(0.7548)	(0.4402)	(0.6410)	(0.3390)	(0.7133)	(0.4240)	(0.6581)
Mother's Years of Schooling	0.0049	-0.0088	0.0024	0.0060	0.0062	-0.0075	0.0020	0.0056
	(0.8368)	(0.3870)	(0.7067)	(0.3073)	(0.8080)	(0.4599)	(0.7322)	(0.3386)
Father's Years of Schooling	0.0205	0.0169	-0.0111**	-0.0051	0.0203	0.0169	-0.0111**	-0.0052
	(0.2109)	(0.1388)	(0.0191)	(0.3000)	(0.2187)	(0.1370)	(0.0196)	(0.2893)
BCG Vaccine	0.1327	0.0747	0.0161	0.0180	0.1243	0.0706	0.0158	0.0185
	(0.2303)	(0.4669)	(0.7065)	(0.6348)	(0.2609)	(0.5004)	(0.7123)	(0.6302)
Measles Vaccine	0.3838***	0.2115**	-0.0911*	-0.0946*	0.3872***	0.2141**	-0.0914*	-0.0951**
	(0.0013)	(0.0204)	(0.0867)	(0.0572)	(0.0003)	(0.0125)	(0.0919)	(0.0481)
Household Size	0.0705	0.0652***	-0.0262*	-0.0284***	0.0699	0.0655***	-0.0265*	-0.0286***
	(0.1496)	(0.0053)	(0.0718)	(0.0043)	(0.1564)	(0.0049)	(0.0733)	(0.0052)
Number of Children born to Mother	-0.0783	-0.1080**	0.0308**	0.0381***	-0.0767	-0.1070**	0.0308**	0.0379***
	(0.1054)	(0.0128)	(0.0466)	(0.0083)	(0.1050)	(0.0100)	(0.0448)	(0.0071)
Wealth Index	1.9980***	1.8963***	-0.5790**	-0.7308***	1.9943***	1.8808***	-0.5722**	-0.7254***
	(0.0048)	(0.0002)	(0.0254)	(0.0001)	(0.0055)	(0.0000)	(0.0262)	(0.0000)
Child's Religion: Christian	0.1399	0.0992	-0.0078	-0.0047	0.1494	0.1040	-0.0076	-0.0053
	(0.3952)	(0.2837)	(0.9207)	(0.9693)	(0.3522)	(0.2538)	(0.9201)	(0.9658)
Child's Religion: Other	0.5034	0.3400	-0.1845	-0.1280	0.5144	0.3400	-0.1815	-0.1266
	(0.3633)	(0.3177)	(0.2883)	(0.5901)	(0.3509)	(0.3075)	(0.3012)	(0.5867)
Child's Ethnic Group: Gurage	0.4802	0.5159**	-0.0968	-0.0568	0.4587	0.5053**	-0.0975	-0.0556
	(0.3082)	(0.0272)	(0.7184)	(0.6535)	(0.3260)	(0.0308)	(0.7059)	(0.6621)
Child's Ethnic Group: Oromo	-0.5107	-0.0939	0.1407	0.0821	-0.5080	-0.0930	0.1410	0.0821
	(0.1402)	(0.8496)	(0.1261)	(0.3069)	(0.1478)	(0.8623)	(0.1245)	(0.3122)
Child's Ethnic Group: Tigrian	-0.5362*	-0.2742	0.1934*	0.1078	-0.5296*	-0.2599	0.1881	0.1032
	(0.0666)	(0.4445)	(0.0636)	(0.4960)	(0.0638)	(0.5073)	(0.0813)	(0.5256)
Child's Ethnic Group: Other	-0.6532**	-0.1188	0.1528*	0.0594	-0.6476**	-0.1158	0.1528*	0.0590
	(0.0456)	(0.6332)	(0.0939)	(0.5225)	(0.0468)	(0.6459)	(0.0964)	(0.5297)
Long Term Illness	-0.0690	-0.1510	0.0179	0.0720	-0.0752	-0.1519	0.0166	0.0716
	(0.7713)	(0.1298)	(0.8291)	(0.1520)	(0.7506)	(0.1287)	(0.8429)	(0.1559)
Cooking Fuel Used: Wood	0.3976	0.3280**	-0.0695	-0.0801*	0.3900	0.3232**	-0.0692	-0.0793*
	(0.1564)	(0.0107)	(0.2223)	(0.0864)	(0.1623)	(0.0141)	(0.2247)	(0.0862)
Cooking Fuel Used: Kerosene	-0.1264	0.0820	0.0303	-0.0183	-0.1307	0.0778	0.0312	-0.0172
	(0.7225)	(0.7351)	(0.8391)	(0.8582)	(0.7186)	(0.7504)	(0.8352)	(0.8673)
Cooking Fuel Used: Charcoal	0.1720	0.1460	-0.0168	-0.0473	0.1641	0.1371	-0.0145	-0.0449
	(0.3701)	(0.5903)	(0.8374)	(0.6738)	(0.3919)	(0.5987)	(0.8608)	(0.6902)
Cooking Fuel Used: Gas/Electricity	0.1449	-0.4744	-0.1117	0.1111	0.1353	-0.4947	-0.1042	0.1176
	(0.8666)	(0.4156)	(0.7100)	(0.5475)	(0.8726)	(0.4021)	(0.7148)	(0.5254)
Cooking Fuel Used: Other	0.0536	-0.4560	0.1482	0.2325	0.1313	-0.4082	0.1460	0.2244
	(0.9289)	(0.2629)	(0.3579)	(0.1767)	(0.8196)	(0.3591)	(0.3806)	(0.2016)
Heating Fuel Used: Wood	-0.0602	0.0112	-0.0451	-0.0423	-0.0733	0.0091	-0.0478	-0.0432
	(0.6847)	(0.9155)	(0.2792)	(0.6244)	(0.6324)	(0.9344)	(0.2508)	(0.6210)
Heating Fuel Used: Charcoal	-0.4772**	-0.2512	0.0476	0.0025	-0.5042**	-0.2612	0.0450	0.0028
	(0.0287)	(0.2482)	(0.3596)	(0.9799)	(0.0211)	(0.2315)	(0.3979)	(0.9751)
Heating Fuel Used: None	-0.0033	-0.0436	-0.1342**	-0.0817	-0.0210	-0.0525	-0.1347***	-0.0806
	(0.9849)	(0.7984)	(0.0123)	(0.3632)	(0.9032)	(0.7631)	(0.0124)	(0.3665)
Heating Fuel Used: Other	-0.8084*	-0.4705**	0.0138	0.1305	-0.8426*	-0.4533**	-0.0042	0.1196
	(0.0518)	(0.0293)	(0.9203)	(0.6080)	(0.0558)	(0.0456)	(0.9794)	(0.6015)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3150	0.3800	0.2378	0.2972	0.3174	0.3825	0.2389	0.2983

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.7: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 4-5, With Monthly Variation in Ambient PM2.5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	0.7441	0.2148	-0.1559	0.2388				
	(0.5212)	(0.8447)	(0.6619)	(0.6583)				
Prenatal PM2.5 Exposure: Trimester 1					0.4002	-0.0676	-0.0979	0.1409
					(0.4940)	(0.8956)	(0.7466)	(0.6061)
Prenatal PM2.5 Exposure: Trimester 2					0.1358	-0.0380	-0.0157	0.0115
					(0.7512)	(0.9472)	(0.9306)	(0.9631)
Prenatal PM2.5 Exposure: Trimester 3					0.2472	0.1068	-0.0521	0.0830
					(0.5226)	(0.7467)	(0.6068)	(0.6523)
Postnatal PM2.5	-0.0358	-0.1077	0.1625	0.0092	-0.0229	-0.0570	0.1579	0.0211
	(0.9617)	(0.7780)	(0.4361)	(0.9626)	(0.9765)	(0.9036)	(0.4805)	(0.9263)
Child's Age (in Months)	-0.3039	-0.1688	0.1102	0.0765	-0.3789	-0.0348	0.1320	0.0534
	(0.4390)	(0.6567)	(0.5784)	(0.6612)	(0.4505)	(0.9203)	(0.6258)	(0.7954)
Child's Age-squared	0.0032	0.0017	-0.0012	-0.0006	0.0038	0.0008	-0.0014	-0.0004
	(0.3164)	(0.5257)	(0.4604)	(0.6277)	(0.3390)	(0.7406)	(0.4999)	(0.7826)
Female	0.1139*	-0.0700	-0.0385	0.0388	0.1146*	-0.0710	-0.0387	0.0390
	(0.0792)	(0.3092)	(0.2148)	(0.2386)	(0.0756)	(0.3067)	(0.2042)	(0.2445)
Female Head	-0.2447	-0.2290*	0.0939*	0.0724	-0.2470	-0.2303**	0.0947*	0.0711
	(0.1397)	(0.0528)	(0.0600)	(0.3646)	(0.1426)	(0.0486)	(0.0585)	(0.3733)
Mother's Age	-0.0934*	-0.0346	0.0100	-0.0084	-0.0941*	-0.0347	0.0102	-0.0088
	(0.0625)	(0.3978)	(0.6485)	(0.6871)	(0.0585)	(0.3879)	(0.6422)	(0.6692)
Mother's Age-squared	0.0016**	0.0007	-0.0002	0.0001	0.0016**	0.0007	-0.0002	0.0001
	(0.0421)	(0.2640)	(0.6144)	(0.7931)	(0.0385)	(0.2693)	(0.5967)	(0.7810)
Father's Age	0.0572**	0.0088	-0.0072	0.0045	0.0577**	0.0078	-0.0073	0.0047
	(0.0283)	(0.7729)	(0.5901)	(0.7845)	(0.0227)	(0.7975)	(0.5765)	(0.7781)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0357)	(0.7222)	(0.5188)	(0.8756)	(0.0291)	(0.7229)	(0.5027)	(0.8715)
Mother's Years of Schooling	0.0160	0.0007	-0.0031	-0.0031	0.0154	0.0005	-0.0030	-0.0034
	(0.1889)	(0.9571)	(0.6972)	(0.5313)	(0.1994)	(0.9669)	(0.7141)	(0.4859)
Father's Years of Schooling	0.0165	0.0123	-0.0118*	-0.0062	0.0165	0.0120	-0.0118*	-0.0062
	(0.1285)	(0.2471)	(0.0568)	(0.1096)	(0.1326)	(0.2610)	(0.0535)	(0.1098)
BCG Vaccine	0.1530	0.1084	-0.1165	0.0004	0.1545	0.1070	-0.1170	0.0010
	(0.4200)	(0.4786)	(0.1395)	(0.9965)	(0.4231)	(0.4951)	(0.1413)	(0.9911)
Measles Vaccine	0.1882	0.2263	0.0057	-0.1177	0.1834	0.2291	0.0072	-0.1198
	(0.3324)	(0.2334)	(0.9552)	(0.2608)	(0.3432)	(0.2230)	(0.9394)	(0.2591)
Household Size	0.0117	-0.0179	0.0028	0.0092	0.0109	-0.0176	0.0030	0.0088
	(0.4261)	(0.3961)	(0.7784)	(0.2950)	(0.4513)	(0.4123)	(0.7636)	(0.3227)
Number of Children born to Mother	-0.0470	-0.0117	-0.0012	0.0006	-0.0468	-0.0118	-0.0013	0.0007
	(0.1520)	(0.6974)	(0.9278)	(0.9596)	(0.1561)	(0.6915)	(0.9277)	(0.9563)
Wealth Index	0.9930*	0.7682*	-0.3932*	-0.3968**	0.9935*	0.7825*	-0.3935*	-0.3950**
	(0.0717)	(0.0974)	(0.0607)	(0.0283)	(0.0734)	(0.0944)	(0.0556)	(0.0354)
Child's Religion: Christian	0.0937	0.1069	0.0248	-0.0217	0.0942	0.1096	0.0246	-0.0212
	(0.6292)	(0.3699)	(0.7708)	(0.6295)	(0.6298)	(0.3606)	(0.7772)	(0.6376)
Child's Religion: Other	0.2948	0.0354	-0.1356	-0.0602	0.2946	0.0406	-0.1356	-0.0597
	(0.4931)	(0.7761)	(0.3655)	(0.4763)	(0.4942)	(0.7470)	(0.3497)	(0.4519)
Child's Ethnic Group: Gurage	0.6031	0.4670	-0.1300	-0.2103	0.6006	0.4614	-0.1291	-0.2121
	(0.1607)	(0.1245)	(0.3234)	(0.1984)	(0.1699)	(0.1290)	(0.3270)	(0.1972)
Child's Ethnic Group: Oromo	0.2178	0.2467**	0.0308	-0.0336	0.2175	0.2455**	0.0309	-0.0339
	(0.2523)	(0.0408)	(0.8008)	(0.5669)	(0.2342)	(0.0414)	(0.8026)	(0.5857)
Child's Ethnic Group: Tigrian	0.0017	-0.0320	-0.0224	0.0342	0.0005	-0.0256	-0.0221	0.0343
	(0.9914)	(0.8769)	(0.9234)	(0.7410)	(0.9967)	(0.9001)	(0.9189)	(0.7469)
Child's Ethnic Group: Other	0.0029	0.2499**	0.0484	-0.0525	0.0025	0.2471**	0.0485	-0.0530
	(0.9894)	(0.0341)	(0.5698)	(0.3159)	(0.9914)	(0.0347)	(0.5738)	(0.3159)
Long Term Illness	-0.2463**	-0.1392	0.1105	0.0689	-0.2489**	-0.1388	0.1113*	0.0676
	(0.0441)	(0.3612)	(0.1019)	(0.2764)	(0.0457)	(0.3578)	(0.0972)	(0.2828)
Cooking Fuel Used: Wood	-0.0110	0.2102	0.0573	-0.1034*	-0.0124	0.2090	0.0578	-0.1042*
	(0.9075)	(0.2090)	(0.3626)	(0.0808)	(0.9007)	(0.2198)	(0.3674)	(0.0731)
Cooking Fuel Used: Kerosene	0.0517	0.3408	0.1671	-0.0773	0.0492	0.3310	0.1680	-0.0797
	(0.9208)	(0.2484)	(0.3333)	(0.5085)	(0.9276)	(0.2752)	(0.3365)	(0.4991)
Cooking Fuel Used: Charcoal	0.1530	0.2720	0.0793	-0.1191	0.1541	0.2673	0.0790	-0.1191
	(0.7464)	(0.3057)	(0.4428)	(0.3068)	(0.7569)	(0.3072)	(0.4528)	(0.2921)
Cooking Fuel Used: Gas/Electricity	0.0207	0.2983	0.1575	-0.1070	0.0283	0.2953	0.1552	-0.1036
	(0.9413)	(0.1821)	(0.2009)	(0.2572)	(0.9227)	(0.1817)	(0.2033)	(0.2572)
Cooking Fuel Used: Other	0.0701	0.1836	0.0624	-0.0528	0.0686	0.1814	0.0629	-0.0538
	(0.6514)	(0.2569)	(0.4995)	(0.3753)	(0.6584)	(0.2595)	(0.4980)	(0.3679)
Heating Fuel Used: Wood	0.2071	-0.1116	-0.0669	0.0179	0.2096	-0.1146	-0.0676	0.0188
	(0.2650)	(0.5792)	(0.3021)	(0.8026)	(0.2571)	(0.5736)	(0.3031)	(0.7896)
Heating Fuel Used: Charcoal	0.1455	0.0358	-0.0815	-0.0127	0.1437	0.0329	-0.0809	-0.0139
	(0.4113)	(0.8750)	(0.4489)	(0.8851)	(0.4189)	(0.8868)	(0.4583)	(0.8831)
Heating Fuel Used: None	0.1983	-0.0729	-0.1143	0.0083	0.1980	-0.0759	-0.1141	0.0078
	(0.2346)	(0.7221)	(0.1933)	(0.9161)	(0.2321)	(0.7149)	(0.1968)	(0.9263)
Heating Fuel Used: Other	0.0657	-0.1786	0.0430	0.0332	0.0623	-0.1792	0.0441	0.0314
	(0.5602)	(0.2887)	(0.7138)	(0.6071)	(0.5875)	(0.2852)	(0.7140)	(0.6279)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.2006	0.1490	0.1399	0.1156	0.2011	0.1493	0.1402	0.1164

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.8: Heterogeneous Effects: IV First Stage: Regression of Hourly PM2.5 on Hourly Wind speed and other Climate Controls (Prenatal Time Period: 2000 - 2002)

	PM2.5 (1)
Windspeed	-0.3522*** (0.0010)
Rainfall	0.4593 (0.9115)
Temperature	0.1507 (0.3560)
Rainfall*Temperature	0.1901 (0.3625)
Rainfall_Squared	-0.7995** (0.0392)
Temperature_Squared	0.0004 (0.8744)
F-statistics	15.58
N	526,080
r2	0.2881

Note: Additional controls include hourly fixed effect, monthly fixed effect, yearly fixed effect and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.9: IV Second Stage: Heterogeneity by Child's Gender at Ages 0-1

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	-0.5667	-0.3192	0.6960	0.2648
	(0.7073)	(0.7382)	(0.2304)	(0.6790)
Female	0.2180	0.1209	0.0426	-0.0378
	(0.5912)	(0.7288)	(0.6929)	(0.7993)
Prenatal PM2.5 Exposure*Female	0.0039	0.0008	-0.0079	-0.0001
	(0.8776)	(0.9658)	(0.2368)	(0.9871)
Postnatal PM2.5	-0.1108	-0.0472	0.0427	-0.0059
	(0.4001)	(0.6143)	(0.4868)	(0.8950)
Child's Age (in Months)	-0.8032**	-0.4960	0.0915	0.1244
	(0.0452)	(0.2237)	(0.5143)	(0.4960)
Child's Age-squared	0.0230**	0.0142	-0.0015	-0.0045
	(0.0414)	(0.2840)	(0.6793)	(0.4810)
Female Head	0.0526	0.0169	-0.0566	-0.0310
	(0.8666)	(0.9400)	(0.5315)	(0.7124)
Mother's Age	-0.0227	-0.0073	0.0126	0.0023
	(0.6494)	(0.8073)	(0.3942)	(0.8484)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001
	(0.4269)	(0.4201)	(0.3472)	(0.7522)
Father's Age	0.0108	0.0051	-0.0087	0.0063
	(0.6420)	(0.8337)	(0.4783)	(0.6216)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001
	(0.3822)	(0.7457)	(0.4287)	(0.6448)
Mother's Years of Schooling	0.0049	-0.0088	0.0025	0.0060
	(0.8373)	(0.3743)	(0.6867)	(0.3022)
Father's Years of Schooling	0.0205	0.0169	-0.0110**	-0.0051
	(0.2137)	(0.1401)	(0.0200)	(0.3006)
BCG Vaccine	0.1330	0.0748	0.0154	0.0180
	(0.2300)	(0.4640)	(0.7157)	(0.6361)
Measles Vaccine	0.3843***	0.2117**	-0.0921*	-0.0946*
	(0.0011)	(0.0234)	(0.0854)	(0.0587)
Household Size	0.0703	0.0652***	-0.0259*	-0.0284***
	(0.1619)	(0.0054)	(0.0768)	(0.0055)
Number of Children born to Mother	-0.0782	-0.1079**	0.0305**	0.0381***
	(0.1092)	(0.0127)	(0.0487)	(0.0085)
Wealth Index	2.0033***	1.8974***	-0.5897**	-0.7310***
	(0.0049)	(0.0000)	(0.0214)	(0.0000)
Child's Religion: Christian	0.1402	0.0992	-0.0084	-0.0047
	(0.3927)	(0.2825)	(0.9119)	(0.9693)
Child's Religion: Other	0.5087	0.3411	-0.1953	-0.1282
	(0.3569)	(0.3001)	(0.2642)	(0.5782)
Child's Ethnic Group: Gurage	0.4808	0.5160**	-0.0980	-0.0568
	(0.3104)	(0.0290)	(0.7137)	(0.6474)
Child's Ethnic Group: Oromo	-0.5103	-0.0938	0.1399	0.0821
	(0.1410)	(0.8442)	(0.1271)	(0.3000)
Child's Ethnic Group: Tigrian	-0.5364*	-0.2743	0.1939*	0.1078
	(0.0667)	(0.4577)	(0.0646)	(0.4970)
Child's Ethnic Group: Other	-0.6518**	-0.1185	0.1499*	0.0593
	(0.0460)	(0.6373)	(0.0969)	(0.5228)
Long Term Illness	-0.0686	-0.1509	0.0171	0.0720
	(0.7746)	(0.1255)	(0.8393)	(0.1516)
Cooking Fuel Used: Wood	0.3983	0.3281***	-0.0710	-0.0801*
	(0.1548)	(0.0078)	(0.2187)	(0.0814)
Cooking Fuel Used: Kerosene	-0.1269	0.0819	0.0313	-0.0182
	(0.7177)	(0.7279)	(0.8326)	(0.8546)
Cooking Fuel Used: Charcoal	0.1703	0.1457	-0.0135	-0.0472
	(0.3852)	(0.5923)	(0.8664)	(0.6830)
Cooking Fuel Used: Gas/Electricity	0.1424	-0.4749	-0.1066	0.1112
	(0.8742)	(0.4107)	(0.7276)	(0.5393)
Cooking Fuel Used: Other	0.0529	-0.4562	0.1497	0.2325
	(0.9275)	(0.2611)	(0.3454)	(0.1687)
Heating Fuel Used: Wood	-0.0598	0.0113	-0.0459	-0.0423
	(0.6958)	(0.9119)	(0.2470)	(0.6135)
Heating Fuel Used: Charcoal	-0.4773**	-0.2512	0.0477	0.0025
	(0.0243)	(0.2335)	(0.3360)	(0.9762)
Heating Fuel Used: None	-0.0017	-0.0432	-0.1375**	-0.0817
	(0.9915)	(0.8090)	(0.0116)	(0.3547)
Heating Fuel Used: Other	-0.8076*	-0.4703**	0.0121	0.1305
	(0.0503)	(0.0298)	(0.9305)	(0.6046)
N	1069	1069	1069	1069
r2	0.3150	0.3800	0.2387	0.2972

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.10: IV Second Stage: Heterogeneity by Child's Gender at Ages 4-5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	0.7489	0.2352	-0.1536	0.2272
	(0.5228)	(0.8312)	(0.6727)	(0.6727)
Female	0.1704	0.1701	-0.0114	-0.0987
	(0.4313)	(0.5319)	(0.9122)	(0.2809)
Prenatal PM2.5 Exposure*Female	-0.0034	-0.0145	-0.0016	0.0083
	(0.7767)	(0.3423)	(0.8020)	(0.1657)
Postnatal PM2.5	-0.0406	-0.1282	0.1602	0.0209
	(0.9561)	(0.7465)	(0.4552)	(0.9161)
Child's Age (in Months)	-0.3134	-0.2094	0.1056	0.0997
	(0.4188)	(0.6008)	(0.5969)	(0.5793)
Child's Age-squared	0.0032	0.0021	-0.0012	-0.0008
	(0.3178)	(0.4741)	(0.4927)	(0.5475)
Female Head	-0.2447	-0.2290**	0.0939*	0.0724
	(0.1391)	(0.0496)	(0.0605)	(0.3662)
Mother's Age	-0.0934*	-0.0343	0.0100	-0.0086
	(0.0665)	(0.4157)	(0.6532)	(0.6900)
Mother's Age-squared	0.0016**	0.0007	-0.0002	0.0001
	(0.0453)	(0.2712)	(0.6052)	(0.7809)
Father's Age	0.0572**	0.0089	-0.0071	0.0044
	(0.0260)	(0.7689)	(0.6019)	(0.7922)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0364)	(0.7170)	(0.5123)	(0.8797)
Mother's Years of Schooling	0.0160	0.0010	-0.0031	-0.0033
	(0.1877)	(0.9337)	(0.6994)	(0.5085)
Father's Years of Schooling	0.0165	0.0125	-0.0117*	-0.0063*
	(0.1286)	(0.2456)	(0.0618)	(0.0984)
BCG Vaccine	0.1549	0.1163	-0.1156	-0.0041
	(0.4157)	(0.4543)	(0.1351)	(0.9665)
Measles Vaccine	0.1874	0.2231	0.0054	-0.1159
	(0.3329)	(0.2490)	(0.9545)	(0.2720)
Household Size	0.0115	-0.0185	0.0027	0.0095
	(0.4231)	(0.3755)	(0.7814)	(0.2849)
Number of Children born to Mother	-0.0470	-0.0116	-0.0012	0.0006
	(0.1584)	(0.6875)	(0.9318)	(0.9605)
Wealth Index	0.9895*	0.7531*	-0.3949*	-0.3882**
	(0.0730)	(0.0986)	(0.0615)	(0.0338)
Child's Religion: Christian	0.0933	0.1053	0.0246	-0.0208
	(0.6341)	(0.3850)	(0.7777)	(0.6417)
Child's Religion: Other	0.2926	0.0262	-0.1366	-0.0549
	(0.4968)	(0.8400)	(0.3614)	(0.5129)
Child's Ethnic Group: Gurage	0.6056	0.4779	-0.1287	-0.2166
	(0.1528)	(0.1073)	(0.3242)	(0.1706)
Child's Ethnic Group: Oromo	0.2197	0.2546**	0.0317	-0.0381
	(0.2507)	(0.0343)	(0.7997)	(0.5091)
Child's Ethnic Group: Tigrian	0.0048	-0.0189	-0.0210	0.0267
	(0.9741)	(0.9334)	(0.9275)	(0.7905)
Child's Ethnic Group: Other	0.0048	0.2580**	0.0493	-0.0572
	(0.9836)	(0.0319)	(0.5654)	(0.2519)
Long Term Illness	-0.2453**	-0.1350	0.1109*	0.0665
	(0.0437)	(0.3806)	(0.0955)	(0.2933)
Cooking Fuel Used: Wood	-0.0105	0.2123	0.0576	-0.1046*
	(0.9103)	(0.2222)	(0.3539)	(0.0854)
Cooking Fuel Used: Kerosene	0.0522	0.3427	0.1673	-0.0784
	(0.9137)	(0.2449)	(0.3256)	(0.4994)
Cooking Fuel Used: Charcoal	0.1547	0.2793	0.0801	-0.1233
	(0.7357)	(0.2848)	(0.4257)	(0.2774)
Cooking Fuel Used: Gas/Electricity	0.0201	0.2960	0.1572	-0.1057
	(0.9411)	(0.1807)	(0.2145)	(0.2537)
Cooking Fuel Used: Other	0.0711	0.1878	0.0629	-0.0552
	(0.6451)	(0.2444)	(0.4955)	(0.3554)
Heating Fuel Used: Wood	0.2043	-0.1236	-0.0682	0.0248
	(0.2575)	(0.5425)	(0.2875)	(0.7221)
Heating Fuel Used: Charcoal	0.1433	0.0264	-0.0825	-0.0073
	(0.4128)	(0.9110)	(0.4466)	(0.9322)
Heating Fuel Used: None	0.1962	-0.0818	-0.1153	0.0134
	(0.2223)	(0.6893)	(0.1823)	(0.8618)
Heating Fuel Used: Other	0.0613	-0.1975	0.0409	0.0440
	(0.6005)	(0.2527)	(0.7248)	(0.4990)
N	1069	1069	1069	1069
r2	0.2007	0.1499	0.1399	0.1169

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.11: IV Second Stage: Heterogeneity by Mother's Level of Education at Ages 0-1

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	-0.5933	-0.3104	0.7066	0.2592
	(0.6913)	(0.7478)	(0.2259)	(0.6837)
Mother's Years of Schooling	0.0266	-0.0160	-0.0061	0.0105
	(0.7335)	(0.7285)	(0.8082)	(0.6045)
Prenatal PM2.5 Exposure*Mother's Years of Schooling	-0.0014	0.0004	0.0005	-0.0003
	(0.7945)	(0.9007)	(0.7802)	(0.8551)
Postnatal PM2.5	-0.1157	-0.0460	0.0459	-0.0067
	(0.3893)	(0.6271)	(0.4472)	(0.8762)
Child's Age (in Months)	-0.8105**	-0.4947	0.0974	0.1234
	(0.0430)	(0.2184)	(0.4979)	(0.4950)
Child's Age-squared	0.0231**	0.0142	-0.0015	-0.0044
	(0.0408)	(0.2864)	(0.6931)	(0.4847)
Female	0.2820***	0.1344	-0.0885***	-0.0398
	(0.0094)	(0.1117)	(0.0011)	(0.2194)
Female Head	0.0586	0.0144	-0.0573	-0.0295
	(0.8509)	(0.9522)	(0.5284)	(0.7196)
Mother's Age	-0.0240	-0.0070	0.0137	0.0021
	(0.6295)	(0.8188)	(0.3604)	(0.8717)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001
	(0.4159)	(0.4382)	(0.3112)	(0.7733)
Father's Age	0.0110	0.0051	-0.0090	0.0063
	(0.6418)	(0.8353)	(0.4560)	(0.6199)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001
	(0.3826)	(0.7537)	(0.4344)	(0.6422)
Father's Years of Schooling	0.0204	0.0169	-0.0110**	-0.0052
	(0.2126)	(0.1410)	(0.0196)	(0.2935)
BCG Vaccine	0.1313	0.0752	0.0167	0.0177
	(0.2174)	(0.4608)	(0.6859)	(0.6355)
Measles Vaccine	0.3836***	0.2116**	-0.0910*	-0.0946*
	(0.0008)	(0.0220)	(0.0909)	(0.0587)
Household Size	0.0709	0.0651***	-0.0264*	-0.0283***
	(0.1556)	(0.0052)	(0.0705)	(0.0056)
Number of Children born to Mother	-0.0785	-0.1079**	0.0309**	0.0381***
	(0.1056)	(0.0126)	(0.0460)	(0.0085)
Wealth Index	1.9967***	1.8968***	-0.5784**	-0.7311***
	(0.0038)	(0.0000)	(0.0215)	(0.0000)
Child's Religion: Christian	0.1399	0.0992	-0.0078	-0.0047
	(0.3941)	(0.2837)	(0.9180)	(0.9696)
Child's Religion: Other	0.5103	0.3377	-0.1872	-0.1266
	(0.3441)	(0.3138)	(0.2787)	(0.6066)
Child's Ethnic Group: Gurage	0.4783	0.5165**	-0.0961	-0.0572
	(0.3102)	(0.0276)	(0.7202)	(0.6443)
Child's Ethnic Group: Oromo	-0.5058	-0.0955	0.1388	0.0831
	(0.1445)	(0.8422)	(0.1323)	(0.2947)
Child's Ethnic Group: Tigrian	-0.5286*	-0.2767	0.1904*	0.1094
	(0.0655)	(0.4522)	(0.0687)	(0.5070)
Child's Ethnic Group: Other	-0.6422**	-0.1225	0.1484**	0.0617
	(0.0421)	(0.6248)	(0.0894)	(0.5015)
Long Term Illness	-0.0678	-0.1514	0.0174	0.0723
	(0.7762)	(0.1255)	(0.8356)	(0.1551)
Cooking Fuel Used: Wood	0.3949	0.3289***	-0.0685	-0.0807*
	(0.1486)	(0.0070)	(0.2108)	(0.0723)
Cooking Fuel Used: Kerosene	-0.1284	0.0827	0.0311	-0.0187
	(0.7126)	(0.7219)	(0.8335)	(0.8523)
Cooking Fuel Used: Charcoal	0.1714	0.1462	-0.0166	-0.0474
	(0.3755)	(0.5938)	(0.8361)	(0.6801)
Cooking Fuel Used: Gas/Electricity	0.1489	-0.4757	-0.1132	0.1120
	(0.8721)	(0.4137)	(0.7183)	(0.5374)
Cooking Fuel Used: Other	0.0518	-0.4554	0.1489	0.2321
	(0.9309)	(0.2653)	(0.3627)	(0.1737)
Heating Fuel Used: Wood	-0.0589	0.0108	-0.0456	-0.0420
	(0.6958)	(0.9180)	(0.2626)	(0.6181)
Heating Fuel Used: Charcoal	-0.4725**	-0.2528	0.0457	0.0035
	(0.0238)	(0.2285)	(0.3600)	(0.9700)
Heating Fuel Used: None	-0.0033	-0.0436	-0.1343***	-0.0817
	(0.9854)	(0.8087)	(0.0135)	(0.3618)
Heating Fuel Used: Other	-0.8067*	-0.4710**	0.0132	0.1309
	(0.0515)	(0.0303)	(0.9268)	(0.6054)
N	1069	1069	1069	1069
r2	0.3150	0.3800	0.2379	0.2973

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.12: IV Second Stage: Heterogeneity by Mother's Level of Education at Ages 4-5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	0.6826	0.1455	-0.1118	0.2827
	(0.5663)	(0.8978)	(0.7674)	(0.6164)
Mother's Years of Schooling	0.0548	0.0445	-0.0310	-0.0308
	(0.3713)	(0.5460)	(0.0918)	(0.1467)
Prenatal PM2.5 Exposure*Mother's Years of Schooling	-0.0024	-0.0027	0.0017	0.0017
	(0.5058)	(0.5023)	(0.1035)	(0.1928)
Postnatal PM2.5	-0.0485	-0.1220	0.1716	0.0182
	(0.9485)	(0.7539)	(0.4044)	(0.9263)
Child's Age (in Months)	-0.3009	-0.1655	0.1081	0.0744
	(0.4401)	(0.6664)	(0.6011)	(0.6723)
Child's Age-squared	0.0031	0.0017	-0.0012	-0.0006
	(0.3334)	(0.5392)	(0.4919)	(0.6417)
Female	0.1140*	-0.0700	-0.0386	0.0387
	(0.0778)	(0.3156)	(0.2108)	(0.2492)
Female Head	-0.2393	-0.2229*	0.0901*	0.0685
	(0.1462)	(0.0566)	(0.0707)	(0.3939)
Mother's Age	-0.0955*	-0.0370	0.0115	-0.0069
	(0.0526)	(0.3308)	(0.5919)	(0.7396)
Mother's Age-squared	0.0016**	0.0007	-0.0002	0.0001
	(0.0350)	(0.2234)	(0.5597)	(0.8391)
Father's Age	0.0570**	0.0086	-0.0071	0.0046
	(0.0297)	(0.7821)	(0.6026)	(0.7866)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0362)	(0.7101)	(0.5220)	(0.8741)
Father's Years of Schooling	0.0167	0.0125	-0.0119*	-0.0063
	(0.1290)	(0.2447)	(0.0623)	(0.1090)
BCG Vaccine	0.1494	0.1042	-0.1139	0.0030
	(0.4344)	(0.5011)	(0.1456)	(0.9733)
Measles Vaccine	0.1785	0.2154	0.0127	-0.1108
	(0.3555)	(0.2517)	(0.8957)	(0.2814)
Household Size	0.0123	-0.0172	0.0024	0.0087
	(0.4104)	(0.4115)	(0.8160)	(0.3299)
Number of Children born to Mother	-0.0463	-0.0109	-0.0017	0.0001
	(0.1657)	(0.7084)	(0.9026)	(0.9917)
Wealth Index	0.9908*	0.7656*	-0.3916*	-0.3952**
	(0.0714)	(0.0921)	(0.0580)	(0.0269)
Child's Religion: Christian	0.0931	0.1062	0.0252	-0.0213
	(0.6327)	(0.3772)	(0.7784)	(0.6304)
Child's Religion: Other	0.2827	0.0217	-0.1269	-0.0516
	(0.4937)	(0.8737)	(0.3992)	(0.5427)
Child's Ethnic Group: Gurage	0.6026	0.4665	-0.1297	-0.2100
	(0.1564)	(0.1161)	(0.3241)	(0.2027)
Child's Ethnic Group: Oromo	0.2217	0.2511**	0.0280	-0.0364
	(0.2547)	(0.0322)	(0.8281)	(0.5363)
Child's Ethnic Group: Tigrian	0.0120	-0.0205	-0.0298	0.0269
	(0.9398)	(0.9308)	(0.8974)	(0.8200)
Child's Ethnic Group: Other	0.0088	0.2565**	0.0442	-0.0567
	(0.9691)	(0.0220)	(0.5981)	(0.2572)
Long Term Illness	-0.2506**	-0.1440	0.1136*	0.0719
	(0.0441)	(0.3546)	(0.0881)	(0.2545)
Cooking Fuel Used: Wood	-0.0086	0.2130	0.0556	-0.1051*
	(0.9275)	(0.2223)	(0.3900)	(0.0836)
Cooking Fuel Used: Kerosene	0.0557	0.3453	0.1643	-0.0801
	(0.9077)	(0.2534)	(0.3425)	(0.4956)
Cooking Fuel Used: Charcoal	0.1586	0.2782	0.0753	-0.1231
	(0.7275)	(0.3189)	(0.4902)	(0.3043)
Cooking Fuel Used: Gas/Electricity	0.0348	0.3143	0.1473	-0.1171
	(0.8977)	(0.1610)	(0.2392)	(0.2138)
Cooking Fuel Used: Other	0.0693	0.1827	0.0630	-0.0523
	(0.6560)	(0.2557)	(0.5034)	(0.3697)
Heating Fuel Used: Wood	0.2059	-0.1130	-0.0660	0.0188
	(0.2650)	(0.5718)	(0.3038)	(0.7855)
Heating Fuel Used: Charcoal	0.1453	0.0356	-0.0814	-0.0126
	(0.4181)	(0.8782)	(0.4571)	(0.8903)
Heating Fuel Used: None	0.1964	-0.0751	-0.1129	0.0097
	(0.2305)	(0.7132)	(0.1935)	(0.9030)
Heating Fuel Used: Other	0.0649	-0.1795	0.0436	0.0338
	(0.5747)	(0.2802)	(0.7075)	(0.6078)
N	1069	1069	1069	1069
r2	0.2012	0.1500	0.1414	0.1174

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * $p < 0.10$ **$p<0.05$ ***$p < 0.01$.

Table 3.B.13: IV Second Stage: Heterogeneity by Household Area of Residence at Ages 0-1

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	-0.6201	-0.3120	0.4665	-0.0082
	(0.6635)	(0.7653)	(0.3340)	(0.9904)
Rural Area	0.7399	0.0185	-3.1777	-1.2272
	(0.9245)	(0.9969)	(0.2248)	(0.6884)
Prenatal PM2.5 Exposure*Rural Area	0.0114	-0.0015	0.0490	0.0582*
	(0.9407)	(0.9758)	(0.1669)	(0.0616)
Postnatal PM2.5	-0.1157	-0.0468	0.0265	-0.0270
	(0.4016)	(0.6128)	(0.6680)	(0.5712)
Child's Age (in Months)	-0.8087**	-0.4960	0.0798	0.1061
	(0.0482)	(0.2188)	(0.5565)	(0.5382)
Child's Age-squared	0.0230**	0.0142	-0.0010	-0.0039
	(0.0457)	(0.2840)	(0.7853)	(0.5225)
Female	0.2821***	0.1343	-0.0893***	-0.0405
	(0.0090)	(0.1104)	(0.0010)	(0.2016)
Female Head	0.0513	0.0167	-0.0559	-0.0326
	(0.8695)	(0.9391)	(0.5409)	(0.6760)
Mother's Age	-0.0231	-0.0073	0.0127	0.0016
	(0.6418)	(0.8094)	(0.3914)	(0.8989)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001
	(0.4250)	(0.4280)	(0.3374)	(0.7916)
Father's Age	0.0112	0.0051	-0.0080	0.0075
	(0.6239)	(0.8398)	(0.5003)	(0.5679)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001
	(0.3620)	(0.7585)	(0.4691)	(0.5948)
Mother's Years of Schooling	0.0050	-0.0088	0.0026	0.0063
	(0.8405)	(0.3795)	(0.6522)	(0.2810)
Father's Years of Schooling	0.0204	0.0169	-0.0114**	-0.0055
	(0.2105)	(0.1395)	(0.0152)	(0.2564)
BCG Vaccine	0.1320	0.0748	0.0131	0.0144
	(0.2253)	(0.4747)	(0.7547)	(0.7076)
Measles Vaccine	0.3845***	0.2114**	-0.0879	-0.0908*
	(0.0011)	(0.0223)	(0.1044)	(0.0600)
Household Size	0.0706	0.0652**	-0.0259*	-0.0280***
	(0.1586)	(0.0045)	(0.0696)	(0.0036)
Number of Children born to Mother	-0.0786	-0.1079**	0.0296**	0.0366***
	(0.1052)	(0.0131)	(0.0487)	(0.0125)
Wealth Index	1.9966***	1.8965***	-0.5850**	-0.7380***
	(0.0055)	(0.0000)	(0.0206)	(0.0000)
Child's Religion: Christian	0.1401	0.0991	-0.0071	-0.0039
	(0.3980)	(0.2826)	(0.9243)	(0.9748)
Child's Religion: Other	0.5028	0.3401	-0.1873	-0.1313
	(0.3615)	(0.3119)	(0.2890)	(0.5568)
Child's Ethnic Group: Gurage	0.4811	0.5158**	-0.0930	-0.0523
	(0.3075)	(0.0288)	(0.6837)	(0.6484)
Child's Ethnic Group: Oromo	-0.5091	-0.0941	0.1475	0.0903
	(0.1436)	(0.8487)	(0.1153)	(0.2807)
Child's Ethnic Group: Tigrian	-0.5348*	-0.2744	0.1991*	0.1146
	(0.0680)	(0.4469)	(0.0717)	(0.4303)
Child's Ethnic Group: Other	-0.6519**	-0.1190	0.1582*	0.0659
	(0.0452)	(0.6338)	(0.0831)	(0.4901)
Long Term Illness	-0.0695	-0.1510	0.0157	0.0694
	(0.7737)	(0.1300)	(0.8532)	(0.1632)
Cooking Fuel Used: Wood	0.3969	0.3281***	-0.0727	-0.0839*
	(0.1512)	(0.0092)	(0.1976)	(0.0598)
Cooking Fuel Used: Kerosene	-0.1247	0.0818	0.0376	-0.0096
	(0.7200)	(0.7240)	(0.7869)	(0.9114)
Cooking Fuel Used: Charcoal	0.1716	0.1460	-0.0184	-0.0491
	(0.3759)	(0.5910)	(0.8056)	(0.6635)
Cooking Fuel Used: Gas/Electricity	0.1505	-0.4751	-0.0875	0.1399
	(0.8664)	(0.4134)	(0.7416)	(0.4268)
Cooking Fuel Used: Other	0.0495	-0.4555	0.1304	0.2113
	(0.9395)	(0.2673)	(0.4410)	(0.2191)
Heating Fuel Used: Wood	-0.0594	0.0111	-0.0420	-0.0385
	(0.6992)	(0.9163)	(0.3062)	(0.6390)
Heating Fuel Used: Charcoal	-0.4774**	-0.2512	0.0469	0.0017
	(0.0247)	(0.2340)	(0.3521)	(0.9840)
Heating Fuel Used: None	-0.0035	-0.0435	-0.1351**	-0.0827
	(0.9835)	(0.8073)	(0.0162)	(0.3555)
Heating Fuel Used: Other	-0.8095**	-0.4703**	0.0091	0.1249
	(0.0498)	(0.0289)	(0.9500)	(0.6181)
N	1069	1069	1069	1069
r2	0.3150	0.3800	0.2396	0.2997

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.B.14: IV Second Stage: Heterogeneity by Household Area of Residence at Ages 4-5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)
Prenatal PM2.5 Exposure	0.1698	-0.3571	0.1715	0.3771
	(0.8956)	(0.7750)	(0.6344)	(0.5350)
Rural Area	-1.1424	-0.2781	0.1735	-0.3554
	(0.4673)	(0.8314)	(0.7999)	(0.5445)
Prenatal PM2.5 Exposure*Rural Area	0.0765	0.0799	-0.0457	-0.0212
	(0.1683)	(0.2383)	(0.1030)	(0.4606)
Postnatal PM2.5	-0.0432	-0.1141	0.1662	0.0103
	(0.9560)	(0.7634)	(0.3862)	(0.9565)
Child's Age (in Months)	-0.3365	-0.2077	0.1323	0.0891
	(0.4264)	(0.5905)	(0.5557)	(0.6288)
Child's Age-squared	0.0035	0.0021	-0.0014	-0.0007
	(0.3286)	(0.4635)	(0.4564)	(0.6006)
Female	0.1117*	-0.0729	-0.0369	0.0398
	(0.0799)	(0.2927)	(0.2219)	(0.2333)
Female Head	-0.2478	-0.2450**	0.1028*	0.0826
	(0.1509)	(0.0461)	(0.0607)	(0.3142)
Mother's Age	-0.0914*	-0.0314	0.0082	-0.0098
	(0.0609)	(0.4286)	(0.7053)	(0.6282)
Mother's Age-squared	0.0016**	0.0006	-0.0001	0.0001
	(0.0406)	(0.2908)	(0.6479)	(0.7404)
Father's Age	0.0580**	0.0101	-0.0079	0.0039
	(0.0258)	(0.7445)	(0.5468)	(0.8166)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0315)	(0.6773)	(0.4743)	(0.9094)
Mother's Years of Schooling	0.0169	0.0024	-0.0041	-0.0039
	(0.1705)	(0.8530)	(0.6131)	(0.4266)
Father's Years of Schooling	0.0160	0.0113	-0.0112*	-0.0057
	(0.1450)	(0.2976)	(0.0667)	(0.1212)
BCG Vaccine	0.1527	0.1041	-0.1142	0.0034
	(0.4314)	(0.5182)	(0.1536)	(0.9722)
Measles Vaccine	0.1905	0.2292	0.0041	-0.1187
	(0.3068)	(0.2194)	(0.9626)	(0.2695)
Household Size	0.0105	-0.0200	0.0040	0.0101
	(0.5014)	(0.3619)	(0.7010)	(0.2467)
Number of Children born to Mother	-0.0478	-0.0119	-0.0010	0.0004
	(0.1592)	(0.6880)	(0.9419)	(0.9749)
Wealth Index	0.9804*	0.7779*	-0.3984*	-0.4102**
	(0.0778)	(0.0879)	(0.0565)	(0.0244)
Child's Religion: Christian	0.0977	0.1099	0.0230	-0.0220
	(0.6155)	(0.3507)	(0.8006)	(0.6293)
Child's Religion: Other	0.2897	0.0281	-0.1314	-0.0573
	(0.5276)	(0.8125)	(0.4171)	(0.4666)
Child's Ethnic Group: Gurage	0.6253	0.4900	-0.1431	-0.2163
	(0.1665)	(0.1192)	(0.3378)	(0.1939)
Child's Ethnic Group: Oromo	0.2229	0.2448**	0.0317	-0.0298
	(0.2425)	(0.0430)	(0.8066)	(0.6183)
Child's Ethnic Group: Tigrian	0.0335	-0.0028	-0.0393	0.0283
	(0.8458)	(0.9915)	(0.8653)	(0.8082)
Child's Ethnic Group: Other	0.0093	0.2559**	0.0449	-0.0538
	(0.9655)	(0.0309)	(0.6065)	(0.2917)
Long Term Illness	-0.2489*	-0.1408	0.1114*	0.0688
	(0.0373)	(0.3443)	(0.0896)	(0.2789)
Cooking Fuel Used: Wood	-0.0127	0.2058	0.0598	-0.1010*
	(0.9005)	(0.2272)	(0.3363)	(0.0933)
Cooking Fuel Used: Kerosene	0.0447	0.3260	0.1755	-0.0699
	(0.9354)	(0.2654)	(0.3321)	(0.5394)
Cooking Fuel Used: Charcoal	0.1657	0.2859	0.0713	-0.1232
	(0.7385)	(0.2782)	(0.4829)	(0.2839)
Cooking Fuel Used: Gas/Electricity	0.0123	0.2801	0.1678	-0.0978
	(0.9662)	(0.1969)	(0.1863)	(0.2863)
Cooking Fuel Used: Other	0.0604	0.1696	0.0704	-0.0472
	(0.6959)	(0.2814)	(0.4587)	(0.4243)
Heating Fuel Used: Wood	0.2091	-0.1090	-0.0683	0.0170
	(0.2606)	(0.5869)	(0.2849)	(0.8120)
Heating Fuel Used: Charcoal	0.1455	0.0390	-0.0833	-0.0151
	(0.4018)	(0.8651)	(0.4350)	(0.8705)
Heating Fuel Used: None	0.1992	-0.0726	-0.1145	0.0085
	(0.2277)	(0.7245)	(0.1876)	(0.9190)
Heating Fuel Used: Other	0.0729	-0.1684	0.0372	0.0293
	(0.5287)	(0.3091)	(0.7541)	(0.6481)
N	1069	1069	1069	1069
r2	0.2016	0.1515	0.1430	0.1182

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

3.C Using a Dummy Variable for Wind Speed

Table 3.C.1: IV First Stage: Regression of Hourly PM2.5 on Hourly Wind speed and other Climate Controls (Prenatal Time Period: 2000 - 2002)

	PM2.5
	(1)
Windspeed	-0.8309***
	(0.0003)
Rainfall	0.2794
	(0.9476)
Temperature	0.1447
	(0.3781)
Rainfall*Temperature	0.2054
	(0.3225)
Rainfall_Squared	-0.8307**
	(0.0344)
Temperature_Squared	0.0005
	(0.8650)
F-statistics	14.79
N	526,080
r2	0.3115

Note: Additional controls include hourly fixed effect, monthly fixed effect, yearly fixed effect and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.C.2: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 0-1

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-0.0805	-1.0579	0.6664	0.4662				
	(0.9672)	(0.4990)	(0.3195)	(0.5845)				
Prenatal PM2.5 Exposure: Trimester 1					-0.8808	-1.0317*	0.3556	0.3206
					(0.2659)	(0.0760)	(0.2305)	(0.3704)
Prenatal PM2.5 Exposure: Trimester 2					-0.2197	-0.3133	0.1276	0.1159
					(0.7420)	(0.6092)	(0.5911)	(0.7405)
Prenatal PM2.5 Exposure: Trimester 3					0.3558	-0.0893	0.1889	0.0977
					(0.6038)	(0.8620)	(0.4255)	(0.7162)
Postnatal PM2.5	-0.1183	-0.0426	0.0477	-0.0064	-0.1375	-0.0521	0.0470	-0.0049
	(0.3710)	(0.6382)	(0.4406)	(0.8796)	(0.3266)	(0.5807)	(0.4520)	(0.9094)
Child's Age (in Months)	-0.7911**	-0.5103	0.0903	0.1272	-0.3519	-0.1788	0.0332	0.0493
	(0.0429)	(0.2099)	(0.5097)	(0.4893)	(0.2293)	(0.6012)	(0.7795)	(0.7418)
Child's Age-squared	0.0224**	0.0146	-0.0012	-0.0045	0.0095	0.0045	0.0007	-0.0021
	(0.0430)	(0.2834)	(0.7425)	(0.4861)	(0.3227)	(0.6960)	(0.8327)	(0.7182)
Female	0.2811***	0.1348	-0.0878***	-0.0397	0.2699**	0.1257	-0.0860***	-0.0375
	(0.0078)	(0.1063)	(0.0017)	(0.2178)	(0.0117)	(0.1361)	(0.0012)	(0.2470)
Female Head	0.0529	0.0137	-0.0540	-0.0300	0.0492	0.0096	-0.0527	-0.0288
	(0.8681)	(0.9470)	(0.5352)	(0.7185)	(0.8680)	(0.9670)	(0.5378)	(0.7341)
Mother's Age	-0.0226	-0.0078	0.0132	0.0024	-0.0286	-0.0115	0.0134	0.0032
	(0.6453)	(0.7961)	(0.3713)	(0.8492)	(0.5825)	(0.7087)	(0.3768)	(0.8098)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001	0.0008	0.0005	-0.0002	-0.0001
	(0.4296)	(0.4163)	(0.3359)	(0.7459)	(0.4091)	(0.3815)	(0.3308)	(0.7254)
Father's Age	0.0107	0.0054	-0.0089	0.0062	0.0141	0.0074	-0.0091	0.0058
	(0.6561)	(0.8384)	(0.4777)	(0.6184)	(0.5538)	(0.7693)	(0.4497)	(0.6459)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001	-0.0003	-0.0001	0.0001	-0.0001
	(0.3931)	(0.7452)	(0.4456)	(0.6449)	(0.3280)	(0.6929)	(0.4284)	(0.6687)
Mother's Years of Schooling	0.0051	-0.0091	0.0024	0.0061	0.0064	-0.0078	0.0020	0.0057
	(0.8332)	(0.3734)	(0.7061)	(0.3047)	(0.8013)	(0.4444)	(0.7380)	(0.3357)
Father's Years of Schooling	0.0203	0.0171	-0.0110**	-0.0052	0.0203	0.0171	-0.0111**	-0.0052
	(0.2153)	(0.1372)	(0.0192)	(0.2994)	(0.2177)	(0.1341)	(0.0201)	(0.2906)
BCG Vaccine	0.1346	0.0728	0.0154	0.0184	0.1263	0.0686	0.0152	0.0190
	(0.2193)	(0.4764)	(0.7179)	(0.6238)	(0.2500)	(0.5109)	(0.7253)	(0.6192)
Measles Vaccine	0.3827***	0.2126**	-0.0907*	-0.0948*	0.3858***	0.2141**	-0.0906*	-0.0950**
	(0.0012)	(0.0193)	(0.0902)	(0.0558)	(0.0003)	(0.0120)	(0.0996)	(0.0469)
Household Size	0.0710	0.0650***	-0.0265*	-0.0284***	0.0704	0.0649***	-0.0267*	-0.0285***
	(0.1421)	(0.0054)	(0.0648)	(0.0044)	(0.1501)	(0.0049)	(0.0654)	(0.0052)
Number of Children born to Mother	-0.0787	-0.1079**	0.0311**	0.0381***	-0.0765	-0.1063**	0.0309**	0.0378***
	(0.1023)	(0.0129)	(0.0427)	(0.0083)	(0.1036)	(0.0100)	(0.0411)	(0.0072)
Wealth Index	1.9970***	1.8951***	-0.5773**	-0.7300***	1.9882***	1.8786***	-0.5698**	-0.7246***
	(0.0046)	(0.0002)	(0.0258)	(0.0001)	(0.0053)	(0.0000)	(0.0265)	(0.0000)
Child's Religion: Christian	0.1427	0.0964	-0.0088	-0.0042	0.1559	0.1046	-0.0093	-0.0058
	(0.3845)	(0.3019)	(0.9103)	(0.9720)	(0.3269)	(0.2558)	(0.9012)	(0.9641)
Child's Religion: Other	0.5074	0.3368	-0.1863	-0.1275	0.5172	0.3372	-0.1831	-0.1265
	(0.3600)	(0.3212)	(0.2866)	(0.5853)	(0.3458)	(0.2990)	(0.3015)	(0.5769)
Child's Ethnic Group: Gurage	0.4830	0.5143**	-0.0984	-0.0567	0.4648	0.5059**	-0.0995	-0.0556
	(0.3067)	(0.0273)	(0.7108)	(0.6554)	(0.3258)	(0.0312)	(0.6960)	(0.6624)
Child's Ethnic Group: Oromo	-0.5090	-0.0953	0.1399	0.0823	-0.5043	-0.0932	0.1403	0.0821
	(0.1412)	(0.8464)	(0.1266)	(0.3054)	(0.1482)	(0.8626)	(0.1259)	(0.3111)
Child's Ethnic Group: Tigrian	-0.5341*	-0.2745	0.1917*	0.1075	-0.5236*	-0.2599	0.1860	0.1030
	(0.0683)	(0.4425)	(0.0700)	(0.4973)	(0.0709)	(0.5124)	(0.0897)	(0.5307)
Child's Ethnic Group: Other	-0.6504**	-0.1206	0.1512*	0.0595	-0.6468**	-0.1190	0.1514*	0.0593
	(0.0463)	(0.6279)	(0.0960)	(0.5202)	(0.0467)	(0.6378)	(0.0971)	(0.5250)
Long Term Illness	-0.0716	-0.1491	0.0192	0.0718	-0.0797	-0.1526	0.0185	0.0722
	(0.7626)	(0.1349)	(0.8168)	(0.1562)	(0.7335)	(0.1261)	(0.8242)	(0.1529)
Cooking Fuel Used: Wood	0.3982	0.3276**	-0.0698	-0.0801*	0.3920	0.3240**	-0.0697	-0.0794*
	(0.1562)	(0.0106)	(0.2208)	(0.0874)	(0.1607)	(0.0146)	(0.2219)	(0.0860)
Cooking Fuel Used: Kerosene	-0.1249	0.0808	0.0296	-0.0181	-0.1281	0.0786	0.0299	-0.0176
	(0.7247)	(0.7405)	(0.8428)	(0.8619)	(0.7210)	(0.7502)	(0.8419)	(0.8648)
Cooking Fuel Used: Charcoal	0.1710	0.1475	-0.0168	-0.0477	0.1635	0.1400	-0.0147	-0.0456
	(0.3683)	(0.5902)	(0.8381)	(0.6725)	(0.3846)	(0.5961)	(0.8590)	(0.6853)
Cooking Fuel Used: Gas/Electricity	0.1457	-0.4738	-0.1127	0.1107	0.1358	-0.4915	-0.1048	0.1165
	(0.8664)	(0.4195)	(0.7086)	(0.5519)	(0.8703)	(0.4077)	(0.7129)	(0.5321)
Cooking Fuel Used: Other	0.0515	-0.4577	0.1511	0.2337	0.1326	-0.4097	0.1492	0.2246
	(0.9289)	(0.2606)	(0.3532)	(0.1725)	(0.8167)	(0.3600)	(0.3782)	(0.2007)
Heating Fuel Used: Wood	-0.0597	0.0114	-0.0457	-0.0425	-0.0687	0.0114	-0.0490	-0.0436
	(0.6902)	(0.9137)	(0.2764)	(0.6234)	(0.6496)	(0.9201)	(0.2417)	(0.6164)
Heating Fuel Used: Charcoal	-0.4798**	-0.2476	0.0478	0.0016	-0.5030**	-0.2555	0.0447	0.0019
	(0.0274)	(0.2530)	(0.3527)	(0.9871)	(0.0193)	(0.2366)	(0.3900)	(0.9839)
Heating Fuel Used: None	-0.0060	-0.0407	-0.1334**	-0.0823	-0.0220	-0.0482	-0.1343***	-0.0812
	(0.9731)	(0.8103)	(0.0122)	(0.3594)	(0.8987)	(0.7800)	(0.0113)	(0.3630)
Heating Fuel Used: Other	-0.8156*	-0.4634**	0.0164	0.1292	-0.8332*	-0.4420*	-0.0037	0.1185
	(0.0504)	(0.0297)	(0.9079)	(0.6117)	(0.0686)	(0.0503)	(0.9836)	(0.6024)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3149	0.3801	0.2372	0.2973	0.3181	0.3830	0.2386	0.2986

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * $p < 0.10$ **$p < 0.05$ ***$p < 0.01$.

Table 3.C.3: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 4-5

	HFA	WFA	Stunting	Underweight	HFA	WFA	Stunting	Underweight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prenatal PM2.5 Exposure	0.7016	-0.1588	-0.3603	0.5482				
	(0.6777)	(0.9085)	(0.4504)	(0.4672)				
Prenatal PM2.5 Exposure: Trimester 1					0.3881	-0.2449	-0.1480	0.2608
					(0.5784)	(0.7031)	(0.6419)	(0.4391)
Prenatal PM2.5 Exposure: Trimester 2					0.1233	-0.1747	-0.0599	0.1095
					(0.8364)	(0.8012)	(0.7708)	(0.7388)
Prenatal PM2.5 Exposure: Trimester 3					0.1856	0.0004	-0.1104	0.1579
					(0.7478)	(0.9992)	(0.4316)	(0.5096)
Postnatal PM2.5	-0.0158	-0.0836	0.1691	-0.0008	-0.0329	-0.0218	0.1659	-0.0068
	(0.9846)	(0.8280)	(0.4045)	(0.9965)	(0.9682)	(0.9642)	(0.4526)	(0.9753)
Child's Age (in Months)	-0.2873	-0.1614	0.1082	0.0795	-0.3933	-0.0069	0.1239	0.0273
	(0.4663)	(0.6758)	(0.5900)	(0.6411)	(0.4215)	(0.9839)	(0.6431)	(0.8965)
Child's Age-squared	0.0030	0.0017	-0.0012	-0.0007	0.0038	0.0006	-0.0014	-0.0003
	(0.3375)	(0.5402)	(0.4724)	(0.6069)	(0.3261)	(0.7995)	(0.5089)	(0.8662)
Female	0.1143*	-0.0700	-0.0387	0.0389	0.1152*	-0.0709	-0.0388	0.0394
	(0.0771)	(0.3094)	(0.2130)	(0.2375)	(0.0730)	(0.3079)	(0.2024)	(0.2408)
Female Head	-0.2440	-0.2279*	0.0943*	0.0718	-0.2453	-0.2299**	0.0951*	0.0709
	(0.1409)	(0.0542)	(0.0593)	(0.3676)	(0.1472)	(0.0488)	(0.0582)	(0.3715)
Mother's Age	-0.0935*	-0.0349	0.0099	-0.0082	-0.0939*	-0.0351	0.0100	-0.0084
	(0.0630)	(0.3960)	(0.6520)	(0.6952)	(0.0597)	(0.3845)	(0.6507)	(0.6785)
Mother's Age-squared	0.0016**	0.0007	-0.0002	0.0001	0.0016**	0.0007	-0.0002	0.0001
	(0.0424)	(0.2612)	(0.6214)	(0.8043)	(0.0391)	(0.2693)	(0.6063)	(0.7970)
Father's Age	0.0572**	0.0090	-0.0071	0.0044	0.0580**	0.0079	-0.0072	0.0048
	(0.0282)	(0.7676)	(0.5962)	(0.7934)	(0.0227)	(0.7947)	(0.5857)	(0.7773)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0361)	(0.7170)	(0.5246)	(0.8852)	(0.0295)	(0.7188)	(0.5108)	(0.8703)
Mother's Years of Schooling	0.0160	0.0007	-0.0032	-0.0031	0.0156	0.0005	-0.0030	-0.0034
	(0.1879)	(0.9593)	(0.6958)	(0.5373)	(0.1948)	(0.9717)	(0.7105)	(0.5014)
Father's Years of Schooling	0.0165	0.0123	-0.0117*	-0.0062	0.0166	0.0121	-0.0117*	-0.0062
	(0.1312)	(0.2469)	(0.0569)	(0.1097)	(0.1328)	(0.2562)	(0.0556)	(0.1108)
BCG Vaccine	0.1517	0.1060	-0.1174	0.0018	0.1526	0.1050	-0.1176	0.0023
	(0.4257)	(0.4888)	(0.1355)	(0.9852)	(0.4269)	(0.5042)	(0.1367)	(0.9800)
Measles Vaccine	0.1898	0.2277	0.0059	-0.1180	0.1848	0.2312	0.0073	-0.1207
	(0.3291)	(0.2289)	(0.9546)	(0.2584)	(0.3385)	(0.2166)	(0.9390)	(0.2527)
Household Size	0.0115	-0.0180	0.0028	0.0091	0.0109	-0.0175	0.0030	0.0088
	(0.4303)	(0.3959)	(0.7760)	(0.2988)	(0.4521)	(0.4168)	(0.7690)	(0.3274)
Number of Children born to Mother	-0.0470	-0.0117	-0.0012	0.0007	-0.0468	-0.0118	-0.0013	0.0007
	(0.1523)	(0.6971)	(0.9262)	(0.9569)	(0.1558)	(0.6905)	(0.9284)	(0.9558)
Wealth Index	0.9983*	0.7725*	-0.3927*	-0.3976**	0.9943*	0.7875*	-0.3935*	-0.3990**
	(0.0699)	(0.0972)	(0.0608)	(0.0285)	(0.0715)	(0.0952)	(0.0544)	(0.0343)
Child's Religion: Christian	0.0919	0.1046	0.0241	-0.0208	0.0905	0.1085	0.0240	-0.0213
	(0.6377)	(0.3808)	(0.7766)	(0.6484)	(0.6451)	(0.3718)	(0.7817)	(0.6385)
Child's Religion: Other	0.2947	0.0350	-0.1358	-0.0599	0.2935	0.0412	-0.1363	-0.0602
	(0.4895)	(0.7803)	(0.3669)	(0.4851)	(0.4934)	(0.7443)	(0.3478)	(0.4556)
Child's Ethnic Group: Gurage	0.6025	0.4676	-0.1294	-0.2112	0.6014	0.4624	-0.1282	-0.2122
	(0.1607)	(0.1219)	(0.3245)	(0.1959)	(0.1681)	(0.1273)	(0.3287)	(0.1963)
Child's Ethnic Group: Oromo	0.2194	0.2485**	0.0313	-0.0343	0.2200	0.2471**	0.0313	-0.0341
	(0.2520)	(0.0407)	(0.7995)	(0.5617)	(0.2344)	(0.0427)	(0.8019)	(0.5848)
Child's Ethnic Group: Tigrian	0.0013	-0.0304	-0.0213	0.0325	0.0003	-0.0229	-0.0221	0.0324
	(0.9935)	(0.8849)	(0.9285)	(0.7572)	(0.9977)	(0.9113)	(0.9193)	(0.7581)
Child's Ethnic Group: Other	0.0027	0.2490**	0.0480	-0.0519	0.0028	0.2458**	0.0484	-0.0520
	(0.9899)	(0.0376)	(0.5723)	(0.3270)	(0.9899)	(0.0387)	(0.5741)	(0.3319)
Long Term Illness	-0.2479*	-0.1411	0.1099*	0.0697	-0.2506**	-0.1402	0.1108*	0.0681
	(0.0438)	(0.3540)	(0.1038)	(0.2688)	(0.0439)	(0.3501)	(0.0998)	(0.2792)
Cooking Fuel Used: Wood	-0.0114	0.2091	0.0568	-0.1026*	-0.0125	0.2081	0.0574	-0.1033*
	(0.9038)	(0.2085)	(0.3698)	(0.0826)	(0.8991)	(0.2202)	(0.3723)	(0.0765)
Cooking Fuel Used: Kerosene	0.0508	0.3388	0.1663	-0.0761	0.0511	0.3282	0.1678	-0.0766
	(0.9209)	(0.2477)	(0.3355)	(0.5126)	(0.9237)	(0.2739)	(0.3384)	(0.5150)
Cooking Fuel Used: Charcoal	0.1526	0.2708	0.0787	-0.1183	0.1546	0.2658	0.0788	-0.1175
	(0.7467)	(0.3047)	(0.4447)	(0.3105)	(0.7548)	(0.3079)	(0.4564)	(0.2988)
Cooking Fuel Used: Gas/Electricity	0.0190	0.2950	0.1562	-0.1051	0.0258	0.2908	0.1543	-0.1014
	(0.9441)	(0.1861)	(0.2037)	(0.2616)	(0.9295)	(0.1868)	(0.2063)	(0.2683)
Cooking Fuel Used: Other	0.0715	0.1849	0.0627	-0.0532	0.0714	0.1826	0.0631	-0.0534
	(0.6441)	(0.2538)	(0.4979)	(0.3707)	(0.6464)	(0.2550)	(0.4994)	(0.3697)
Heating Fuel Used: Wood	0.2066	-0.1119	-0.0669	0.0179	0.2096	-0.1161	-0.0673	0.0194
	(0.2668)	(0.5779)	(0.3014)	(0.8030)	(0.2592)	(0.5695)	(0.3060)	(0.7859)
Heating Fuel Used: Charcoal	0.1448	0.0357	-0.0812	-0.0131	0.1438	0.0315	-0.0802	-0.0139
	(0.4140)	(0.8738)	(0.4499)	(0.8815)	(0.4170)	(0.8909)	(0.4599)	(0.8810)
Heating Fuel Used: None	0.1977	-0.0732	-0.1142	0.0082	0.1982	-0.0768	-0.1138	0.0083
	(0.2362)	(0.7202)	(0.1928)	(0.9170)	(0.2320)	(0.7111)	(0.1974)	(0.9236)
Heating Fuel Used: Other	0.0651	-0.1786	0.0433	0.0328	0.0620	-0.1796	0.0446	0.0310
	(0.5650)	(0.2885)	(0.7127)	(0.6102)	(0.5907)	(0.2823)	(0.7117)	(0.6296)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.2005	0.1490	0.1400	0.1159	0.2009	0.1493	0.1402	0.1166

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

3.D Using A Cumulative PM2.5 Exposure Measure

Table 3.D.1: IV First Stage: Regression of Hourly PM2.5 on Hourly Wind speed and other Climate Controls (Prenatal Time Period: 2000 - 2002)

	PM2.5
	(1)
Windspeed	-0.3522***
	(0.0010)
Rainfall	0.4593
	(0.9115)
Temperature	0.1507
	(0.3560)
Rainfall*Temperature	0.1901
	(0.3625)
Rainfall_Squared	-0.7995**
	(0.0392)
Temperature_Squared	0.0004
	(0.8744)
F-statistics	15.58
N	526,080
r2	0.2881

Note: Additional controls include hourly fixed effect, monthly fixed effect, yearly fixed effect and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3.D.2: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 0-1

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-0.0083	0.0011	0.0035*	-0.0001				
	(0.2074)	(0.6426)	(0.0785)	(0.9427)				
Prenatal PM2.5 Exposure: Trimester 1					-0.0132*	-0.0030	0.0045*	0.0007
					(0.0907)	(0.3413)	(0.0691)	(0.7668)
Prenatal PM2.5 Exposure: Trimester 2					-0.0083	0.0020	0.0029	-0.0004
					(0.1594)	(0.4681)	(0.1485)	(0.8436)
Prenatal PM2.5 Exposure: Trimester 3					-0.0027	0.0044	0.0034	-0.0007
					(0.6834)	(0.1239)	(0.1301)	(0.7116)
Postnatal PM2.5	-0.0933	-0.0550	0.0425	-0.0020	-0.0984	-0.0518	0.0383	-0.0032
	(0.4938)	(0.5421)	(0.5039)	(0.9635)	(0.4739)	(0.5618)	(0.5593)	(0.9367)
Child's Age (in Months)	-0.8394**	-0.4809	0.0972	0.1163	-0.4381	-0.1998	0.0593	0.0632
	(0.0455)	(0.2305)	(0.5227)	(0.5161)	(0.1585)	(0.5543)	(0.6333)	(0.6768)
Child's Age-squared	0.0247**	0.0136	-0.0017	-0.0042	0.0127	0.0048	-0.0004	-0.0025
	(0.0365)	(0.3046)	(0.6755)	(0.5107)	(0.1753)	(0.6730)	(0.9165)	(0.6636)
Female	0.2884***	0.1326	-0.0902***	-0.0391	0.2778**	0.1247	-0.0889***	-0.0375
	(0.0066)	(0.1116)	(0.0016)	(0.2269)	(0.0097)	(0.1375)	(0.0010)	(0.2401)
Female Head	0.0465	0.0185	-0.0536	-0.0318	0.0512	0.0213	-0.0538	-0.0323
	(0.8849)	(0.9325)	(0.5375)	(0.6972)	(0.8606)	(0.9289)	(0.5298)	(0.6996)
Mother's Age	-0.0248	-0.0068	0.0137	0.0021	-0.0296	-0.0095	0.0137	0.0025
	(0.6089)	(0.8273)	(0.3473)	(0.8700)	(0.5619)	(0.7570)	(0.3535)	(0.8468)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001	0.0008	0.0005	-0.0002	-0.0001
	(0.4062)	(0.4399)	(0.3151)	(0.7651)	(0.3898)	(0.4102)	(0.3115)	(0.7553)
Father's Age	0.0120	0.0049	-0.0093	0.0064	0.0155	0.0070	-0.0094	0.0060
	(0.6122)	(0.8516)	(0.4592)	(0.6055)	(0.5101)	(0.7806)	(0.4340)	(0.6346)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001	-0.0003	-0.0001	0.0001	-0.0001
	(0.3653)	(0.7630)	(0.4315)	(0.6297)	(0.2971)	(0.7095)	(0.4128)	(0.6545)
Mother's Years of Schooling	0.0046	-0.0087	0.0024	0.0059	0.0055	-0.0079	0.0022	0.0057
	(0.8459)	(0.3979)	(0.6995)	(0.3125)	(0.8267)	(0.4419)	(0.7106)	(0.3278)
Father's Years of Schooling	0.0205	0.0168	-0.0109**	-0.0050	0.0202	0.0166	-0.0109**	-0.0050
	(0.2046)	(0.1408)	(0.0194)	(0.3049)	(0.2154)	(0.1390)	(0.0196)	(0.2989)
BCG Vaccine	0.1243	0.0774	0.0179	0.0168	0.1156	0.0734	0.0172	0.0173
	(0.2786)	(0.4565)	(0.6729)	(0.6604)	(0.3211)	(0.4906)	(0.6911)	(0.6583)
Measles Vaccine	0.3865***	0.2103**	-0.0913*	-0.0940*	0.3908***	0.2127**	-0.0913*	-0.0944*
	(0.0009)	(0.0230)	(0.0826)	(0.0611)	(0.0002)	(0.0168)	(0.0900)	(0.0528)
Household Size	0.0669	0.0661***	-0.0251*	-0.0288***	0.0666	0.0662***	-0.0254*	-0.0288***
	(0.1795)	(0.0052)	(0.0908)	(0.0038)	(0.1824)	(0.0047)	(0.0938)	(0.0044)
Number of Children born to Mother	-0.0756	-0.1086**	0.0300*	0.0383***	-0.0741	-0.1077**	0.0299*	0.0382***
	(0.1185)	(0.0131)	(0.0558)	(0.0080)	(0.1202)	(0.0105)	(0.0540)	(0.0069)
Wealth Index	2.0193***	1.8927***	-0.5872**	-0.7300***	2.0184***	1.8876***	-0.5839**	-0.7285***
	(0.0052)	(0.0002)	(0.0251)	(0.0001)	(0.0058)	(0.0000)	(0.0260)	(0.0000)
Child's Religion: Christian	0.1325	0.1023	-0.0071	-0.0064	0.1392	0.1052	-0.0065	-0.0067
	(0.4300)	(0.2611)	(0.9287)	(0.9590)	(0.3901)	(0.2382)	(0.9317)	(0.9578)
Child's Religion: Other	0.4805	0.3461	-0.1783	-0.1305	0.4993	0.3551	-0.1772	-0.1318
	(0.3900)	(0.3080)	(0.3026)	(0.5805)	(0.3716)	(0.2929)	(0.3068)	(0.5669)
Child's Ethnic Group: Gurage	0.4707	0.5192**	-0.0951	-0.0584	0.4462	0.5053**	-0.0951	-0.0561
	(0.3185)	(0.0266)	(0.7344)	(0.6405)	(0.3347)	(0.0298)	(0.7278)	(0.6582)
Child's Ethnic Group: Oromo	-0.5133	-0.0923	0.1403	0.0812	-0.5100	-0.0908	0.1406	0.0810
	(0.1462)	(0.8540)	(0.1336)	(0.3104)	(0.1513)	(0.8594)	(0.1330)	(0.3155)
Child's Ethnic Group: Tigrian	-0.5513*	-0.2707	0.1981*	0.1065	-0.5390*	-0.2582	0.1941*	0.1037
	(0.0574)	(0.4530)	(0.0546)	(0.5075)	(0.0575)	(0.5048)	(0.0654)	(0.5208)
Child's Ethnic Group: Other	-0.6628**	-0.1154	0.1544	0.0577	-0.6549**	-0.1122	0.1552*	0.0574
	(0.0483)	(0.6445)	(0.1002)	(0.5382)	(0.0468)	(0.6527)	(0.0989)	(0.5414)
Long Term Illness	-0.0641	-0.1537	0.0181	0.0735	-0.0744	-0.1575	0.0167	0.0739
	(0.7810)	(0.1242)	(0.8241)	(0.1426)	(0.7492)	(0.1182)	(0.8398)	(0.1481)
Cooking Fuel Used: Wood	0.4015	0.3279**	-0.0716	-0.0803*	0.3985	0.3267**	-0.0720	-0.0802*
	(0.1555)	(0.0109)	(0.2133)	(0.0835)	(0.1576)	(0.0137)	(0.2098)	(0.0803)
Cooking Fuel Used: Kerosene	-0.1307	0.0838	0.0307	-0.0192	-0.1408	0.0752	0.0328	-0.0174
	(0.7185)	(0.7256)	(0.8395)	(0.8507)	(0.7052)	(0.7562)	(0.8316)	(0.8661)
Cooking Fuel Used: Charcoal	0.1712	0.1454	-0.0156	-0.0467	0.1608	0.1359	-0.0131	-0.0447
	(0.3771)	(0.5869)	(0.8433)	(0.6759)	(0.4040)	(0.5945)	(0.8727)	(0.6903)
Cooking Fuel Used: Gas/Electricity	0.1511	-0.4747	-0.1150	0.1109	0.1376	-0.4918	-0.1083	0.1149
	(0.8626)	(0.4113)	(0.7098)	(0.5442)	(0.8704)	(0.4007)	(0.7131)	(0.5294)
Cooking Fuel Used: Other	0.0744	-0.4603	0.1411	0.2339	0.1436	-0.4231	0.1425	0.2280
	(0.8906)	(0.2588)	(0.3700)	(0.1779)	(0.7973)	(0.3224)	(0.3643)	(0.1921)
Heating Fuel Used: Wood	-0.0656	0.0123	-0.0433	-0.0426	-0.0804	0.0077	-0.0460	-0.0424
	(0.6542)	(0.9059)	(0.3000)	(0.6237)	(0.5945)	(0.9441)	(0.2746)	(0.6267)
Heating Fuel Used: Charcoal	-0.4754**	-0.2535	0.0491	0.0040	-0.5092**	-0.2686	0.0462	0.0059
	(0.0322)	(0.2482)	(0.3554)	(0.9694)	(0.0235)	(0.2278)	(0.3988)	(0.9498)
Heating Fuel Used: None	0.0065	-0.0470	-0.1360**	-0.0800	-0.0144	-0.0577	-0.1368**	-0.0784
	(0.9708)	(0.7877)	(0.0126)	(0.3788)	(0.9330)	(0.7458)	(0.0139)	(0.3847)
Heating Fuel Used: Other	-0.7933*	-0.4781**	0.0139	0.1347	-0.8431*	-0.4845**	-0.0015	0.1329
	(0.0584)	(0.0298)	(0.9247)	(0.5951)	(0.0574)	(0.0388)	(0.9926)	(0.5665)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3162	0.3800	0.2393	0.2971	0.3193	0.3822	0.2401	0.2977

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.D.3: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 4-5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	0.0040	0.0010	-0.0001	0.0007				
	(0.3658)	(0.7918)	(0.9409)	(0.7356)				
Prenatal PM2.5 Exposure: Trimester 1					0.0062	0.0004	-0.0004	0.0011
					(0.2905)	(0.9418)	(0.8715)	(0.7009)
Prenatal PM2.5 Exposure: Trimester 2					0.0022	-0.0002	0.0005	0.0002
					(0.6506)	(0.9760)	(0.8171)	(0.9532)
Prenatal PM2.5 Exposure: Trimester 3					0.0038	0.0014	-0.0002	0.0007
					(0.3957)	(0.6918)	(0.9049)	(0.7251)
Postnatal PM2.5	-0.0669	-0.1140	0.1535	0.0125	-0.1118	-0.0511	0.1497	0.0084
	(0.9232)	(0.7698)	(0.4571)	(0.9468)	(0.8970)	(0.9119)	(0.5347)	(0.9730)
Child's Age (in Months)	-0.3440	-0.1786	0.1075	0.0732	-0.4647	-0.0909	0.1134	0.0545
	(0.3938)	(0.6431)	(0.5934)	(0.6801)	(0.3431)	(0.8091)	(0.6471)	(0.7939)
Child's Age-squared	0.0034	0.0018	-0.0012	-0.0006	0.0044	0.0013	-0.0013	-0.0004
	(0.2944)	(0.5160)	(0.4702)	(0.6429)	(0.2552)	(0.6335)	(0.5025)	(0.7670)
Female	0.1128*	-0.0703	-0.0386	0.0386	0.1140*	-0.0706	-0.0388	0.0389
	(0.0822)	(0.3082)	(0.2134)	(0.2394)	(0.0772)	(0.3111)	(0.2015)	(0.2459)
Female Head	-0.2468	-0.2295*	0.0936*	0.0724	-0.2487	-0.2306*	0.0942*	0.0719
	(0.1376)	(0.0533)	(0.0611)	(0.3649)	(0.1383)	(0.0510)	(0.0611)	(0.3713)
Mother's Age	-0.0930*	-0.0345	0.0101	-0.0084	-0.0939*	-0.0348	0.0103	-0.0087
	(0.0637)	(0.3991)	(0.6425)	(0.6863)	(0.0587)	(0.3866)	(0.6370)	(0.6701)
Mother's Age-squared	0.0016**	0.0007	-0.0002	0.0001	0.0016*	0.0007	-0.0002	0.0001
	(0.0437)	(0.2638)	(0.6077)	(0.7918)	(0.0390)	(0.2693)	(0.5912)	(0.7823)
Father's Age	0.0568**	0.0087	-0.0072	0.0045	0.0576**	0.0082	-0.0073	0.0047
	(0.0276)	(0.7730)	(0.5844)	(0.7834)	(0.0232)	(0.7871)	(0.5762)	(0.7793)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0361)	(0.7241)	(0.5096)	(0.8738)	(0.0301)	(0.7142)	(0.4975)	(0.8716)
Mother's Years of Schooling	0.0161	0.0007	-0.0032	-0.0031	0.0155	0.0004	-0.0030	-0.0033
	(0.1866)	(0.9559)	(0.6980)	(0.5387)	(0.1984)	(0.9809)	(0.7137)	(0.5119)
Father's Years of Schooling	0.0165	0.0123	-0.0118*	-0.0062	0.0165	0.0121	-0.0117*	-0.0062
	(0.1274)	(0.2471)	(0.0572)	(0.1097)	(0.1324)	(0.2575)	(0.0550)	(0.1101)
BCG Vaccine	0.1534	0.1083	-0.1156	-0.0003	0.1549	0.1083	-0.1159	0.0001
	(0.4125)	(0.4755)	(0.1408)	(0.9972)	(0.4053)	(0.4859)	(0.1414)	(0.9999)
Measles Vaccine	0.1846	0.2254	0.0052	-0.1178	0.1778	0.2256	0.0065	-0.1193
	(0.3365)	(0.2358)	(0.9593)	(0.2579)	(0.3558)	(0.2317)	(0.9454)	(0.2602)
Household Size	0.0123	-0.0178	0.0028	0.0092	0.0112	-0.0178	0.0030	0.0090
	(0.4157)	(0.4028)	(0.7809)	(0.2942)	(0.4481)	(0.4062)	(0.7683)	(0.3191)
Number of Children born to Mother	-0.0471	-0.0117	-0.0012	0.0006	-0.0468	-0.0117	-0.0013	0.0007
	(0.1498)	(0.6968)	(0.9286)	(0.9601)	(0.1550)	(0.6921)	(0.9291)	(0.9591)
Wealth Index	0.9865*	0.7668*	-0.3949*	-0.3963**	0.9857*	0.7777*	-0.3969*	-0.3955**
	(0.0740)	(0.0969)	(0.0606)	(0.0284)	(0.0764)	(0.0944)	(0.0563)	(0.0332)
Child's Religion: Christian	0.0957	0.1072	0.0256	-0.0222	0.0972	0.1096	0.0249	-0.0217
	(0.6199)	(0.3688)	(0.7620)	(0.6201)	(0.6179)	(0.3580)	(0.7746)	(0.6316)
Child's Religion: Other	0.2928	0.0349	-0.1353	-0.0607	0.2879	0.0418	-0.1358	-0.0611
	(0.4943)	(0.7802)	(0.3623)	(0.4674)	(0.5047)	(0.7386)	(0.3347)	(0.4283)
Child's Ethnic Group: Gurage	0.6035	0.4671	-0.1302	-0.2101	0.6015	0.4615	-0.1287	-0.2111
	(0.1601)	(0.1234)	(0.3209)	(0.1994)	(0.1681)	(0.1294)	(0.3249)	(0.1984)
Child's Ethnic Group: Oromo	0.2157	0.2463**	0.0301	-0.0333	0.2139	0.2448**	0.0307	-0.0338
	(0.2548)	(0.0412)	(0.8062)	(0.5685)	(0.2390)	(0.0404)	(0.8062)	(0.5819)
Child's Ethnic Group: Tigrian	0.0018	-0.0319	-0.0230	0.0347	0.0026	-0.0270	-0.0241	0.0353
	(0.9910)	(0.8778)	(0.9215)	(0.7363)	(0.9851)	(0.8965)	(0.9133)	(0.7337)
Child's Ethnic Group: Other	0.0032	0.2499**	0.0487	-0.0527	0.0022	0.2476**	0.0493	-0.0532
	(0.9879)	(0.0347)	(0.5693)	(0.3109)	(0.9914)	(0.0346)	(0.5674)	(0.3084)
Long Term Illness	-0.2411**	-0.1380	0.1111	0.0690	-0.2457*	-0.1382	0.1120*	0.0680
	(0.0498)	(0.3684)	(0.1026)	(0.2791)	(0.0509)	(0.3671)	(0.0982)	(0.2871)
Cooking Fuel Used: Wood	-0.0115	0.2100	0.0578	-0.1038*	-0.0141	0.2080	0.0587	-0.1046*
	(0.9064)	(0.2112)	(0.3552)	(0.0783)	(0.8892)	(0.2249)	(0.3543)	(0.0727)
Cooking Fuel Used: Kerosene	0.0528	0.3410	0.1678	-0.0778	0.0498	0.3314	0.1703	-0.0794
	(0.9178)	(0.2493)	(0.3320)	(0.5070)	(0.9276)	(0.2748)	(0.3310)	(0.5063)
Cooking Fuel Used: Charcoal	0.1560	0.2727	0.0797	-0.1190	0.1586	0.2669	0.0803	-0.1190
	(0.7440)	(0.3045)	(0.4435)	(0.3081)	(0.7610)	(0.3085)	(0.4509)	(0.2969)
Cooking Fuel Used: Gas/Electricity	0.0214	0.2983	0.1588	-0.1080	0.0312	0.2981	0.1569	-0.1059
	(0.9384)	(0.1819)	(0.1958)	(0.2517)	(0.9130)	(0.1765)	(0.1990)	(0.2535)
Cooking Fuel Used: Other	0.0679	0.1832	0.0619	-0.0527	0.0663	0.1800	0.0628	-0.0533
	(0.6624)	(0.2585)	(0.5035)	(0.3771)	(0.6688)	(0.2632)	(0.4989)	(0.3792)
Heating Fuel Used: Wood	0.2139	-0.1098	-0.0669	0.0189	0.2190	-0.1106	-0.0677	0.0199
	(0.2638)	(0.5887)	(0.3098)	(0.7936)	(0.2493)	(0.5859)	(0.3062)	(0.7730)
Heating Fuel Used: Charcoal	0.1523	0.0375	-0.0816	-0.0116	0.1507	0.0352	-0.0808	-0.0122
	(0.3956)	(0.8704)	(0.4525)	(0.8971)	(0.4067)	(0.8810)	(0.4667)	(0.8971)
Heating Fuel Used: None	0.2043	-0.0714	-0.1143	0.0092	0.2055	-0.0735	-0.1142	0.0093
	(0.2352)	(0.7292)	(0.2011)	(0.9087)	(0.2282)	(0.7248)	(0.2022)	(0.9134)
Heating Fuel Used: Other	0.0703	-0.1774	0.0429	0.0339	0.0666	-0.1786	0.0439	0.0330
	(0.5443)	(0.2981)	(0.7140)	(0.5962)	(0.5694)	(0.2911)	(0.7139)	(0.6095)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.2010	0.1491	0.1398	0.1155	0.2020	0.1493	0.1402	0.1159

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * $p < 0.10$ ** $p<0.05$ *** $p < 0.01$.

3.E Using a 12-Month Gestation Period

Table 3.E.1: IV First Stage: Regression of Hourly PM2.5 on Hourly Wind speed and other Climate Controls (Prenatal Time Period: 2000 - 2002)

	PM2.5
	(1)
Windspeed	-0.3522***
	(0.0010)
Rainfall	0.4593
	(0.9115)
Temperature	0.1507
	(0.3560)
Rainfall*Temperature	0.1901
	(0.3625)
Rainfall_Squared	-0.7995**
	(0.0392)
Temperature_Squared	0.0004
	(0.8744)
F-statistics	15.58
N	526,080
r2	0.2881

Note: Additional controls include hourly fixed effect, monthly fixed effect, yearly fixed effect and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.E.2: IV Second Stage: Results Showing the Effect of In-Utero Air Pollution on Child Health at Ages 0-1

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-0.1336	2.9053	0.9046	-1.7913				
	(0.9660)	(0.1853)	(0.5744)	(0.1649)				
Prenatal PM2.5 Exposure: Quadrimester 1					-0.9430	-0.0963	0.4276	-0.4130
					(0.4142)	(0.9223)	(0.5167)	(0.4190)
Prenatal PM2.5 Exposure: Quadrimester 2					-0.7617	0.8531	0.3310	-0.7436
					(0.5316)	(0.3035)	(0.5742)	(0.1767)
Prenatal PM2.5 Exposure: Quadrimester 3					0.0334	1.0230	0.2943	-0.5980
					(0.9748)	(0.1682)	(0.5925)	(0.1322)
Postnatal PM2.5	-0.1188	-0.0558	0.0521	0.0002	-0.1599	-0.0705	0.0545	-0.0049
	(0.3756)	(0.5560)	(0.3621)	(0.9946)	(0.2451)	(0.4361)	(0.3434)	(0.9113)
Child's Age (in Months)	-0.7918*	-0.4353	0.0922	0.0849	-0.4975	-0.3171	0.0733	0.1167
	(0.0579)	(0.2411)	(0.5028)	(0.5843)	(0.1792)	(0.3685)	(0.5947)	(0.5123)
Child's Age-squared	0.0224**	0.0125	-0.0012	-0.0033	0.0131	0.0080	-0.0005	-0.0041
	(0.0590)	(0.3069)	(0.7584)	(0.5652)	(0.2590)	(0.4960)	(0.8922)	(0.5112)
Female	0.2811***	0.1318	-0.0876***	-0.0381	0.2736**	0.1258	-0.0869***	-0.0377
	(0.0079)	(0.1096)	(0.0018)	(0.2342)	(0.0108)	(0.1342)	(0.0011)	(0.2357)
Female Head	0.0536	0.0089	-0.0592	-0.0263	0.0567	0.0208	-0.0604	-0.0302
	(0.8643)	(0.9663)	(0.5074)	(0.7612)	(0.8483)	(0.9264)	(0.4982)	(0.7139)
Mother's Age	-0.0225	-0.0071	0.0127	0.0021	-0.0252	-0.0059	0.0127	0.0009
	(0.6450)	(0.8217)	(0.3837)	(0.8686)	(0.6235)	(0.8502)	(0.4006)	(0.9384)
Mother's Age-squared	0.0007	0.0004	-0.0002	-0.0001	0.0007	0.0004	-0.0002	-0.0000
	(0.4282)	(0.4324)	(0.3435)	(0.7622)	(0.4341)	(0.4850)	(0.3590)	(0.8310)
Father's Age	0.0107	0.0050	-0.0088	0.0064	0.0132	0.0035	-0.0087	0.0077
	(0.6560)	(0.8503)	(0.4826)	(0.5995)	(0.5833)	(0.8902)	(0.4639)	(0.5298)
Father's Age-squared	-0.0003	-0.0001	0.0001	-0.0001	-0.0003	-0.0001	0.0001	-0.0001
	(0.3938)	(0.7736)	(0.4496)	(0.6109)	(0.3598)	(0.8245)	(0.4481)	(0.5421)
Mother's Years of Schooling	0.0051	-0.0077	0.0025	0.0052	0.0056	-0.0076	0.0025	0.0054
	(0.8375)	(0.4575)	(0.6851)	(0.3487)	(0.8274)	(0.4769)	(0.6788)	(0.3257)
Father's Years of Schooling	0.0203	0.0166	-0.0109**	-0.0049	0.0196	0.0168	-0.0109**	-0.0052
	(0.2107)	(0.1356)	(0.0185)	(0.3012)	(0.2338)	(0.1393)	(0.0198)	(0.2710)
BCG Vaccine	0.1347	0.0801	0.0147	0.0145	0.1293	0.0810	0.0147	0.0126
	(0.2308)	(0.4311)	(0.7406)	(0.6966)	(0.2461)	(0.4432)	(0.7378)	(0.7425)
Measles Vaccine	0.3828***	0.2053**	-0.0914*	-0.0906*	0.3909***	0.2120**	-0.0922*	-0.0911*
	(0.0011)	(0.0213)	(0.0993)	(0.0664)	(0.0004)	(0.0211)	(0.0962)	(0.0663)
Household Size	0.0710	0.0663**	-0.0266*	-0.0291***	0.0696	0.0686***	-0.0268*	-0.0304***
	(0.1407)	(0.0035)	(0.0575)	(0.0035)	(0.1605)	(0.0028)	(0.0621)	(0.0019)
Number of Children born to Mother	-0.0787	-0.1080**	0.0313**	0.0382***	-0.0768	-0.1090**	0.0314**	0.0391***
	(0.1008)	(0.0123)	(0.0383)	(0.0082)	(0.1054)	(0.0100)	(0.0371)	(0.0063)
Wealth Index	1.9971**	1.8942***	-0.5782***	-0.7294***	2.0116***	1.8804***	-0.5772**	-0.7200***
	(0.0047)	(0.0002)	(0.0237)	(0.0001)	(0.0049)	(0.0000)	(0.0236)	(0.0000)
Child's Religion: Christian	0.1428	0.1071	-0.0097	-0.0100	0.1556	0.1102	-0.0103	-0.0078
	(0.3832)	(0.2497)	(0.8974)	(0.9385)	(0.3260)	(0.2240)	(0.8880)	(0.9499)
Child's Religion: Other	0.5079	0.3403	-0.1906	-0.1287	0.5458	0.3499	-0.1925	-0.1224
	(0.3608)	(0.3044)	(0.2831)	(0.5749)	(0.3399)	(0.2960)	(0.2962)	(0.5872)
Child's Ethnic Group: Gurage	0.4825	0.5338**	-0.0954	-0.0682	0.4468	0.5310**	-0.0942	-0.0766
	(0.3057)	(0.0279)	(0.7193)	(0.5868)	(0.3204)	(0.0298)	(0.7228)	(0.5334)
Child's Ethnic Group: Oromo	-0.5093	-0.0825	0.1416	0.0749	-0.5109	-0.0849	0.1419	0.0754
	(0.1390)	(0.8608)	(0.1287)	(0.3269)	(0.1455)	(0.8655)	(0.1333)	(0.3258)
Child's Ethnic Group: Tigrian	-0.5347*	-0.2581	0.1954*	0.0976	-0.5441*	-0.2594	0.1957*	0.0956
	(0.0670)	(0.4877)	(0.0718)	(0.5610)	(0.0506)	(0.4897)	(0.0693)	(0.5578)
Child's Ethnic Group: Other	-0.6505**	-0.1089	0.1515*	0.0529	-0.6510**	-0.1032	0.1510*	0.0505
	(0.0467)	(0.6594)	(0.0951)	(0.5669)	(0.0417)	(0.6830)	(0.0914)	(0.5869)
Long Term Illness	-0.0718	-0.1536	0.0211	0.0740	-0.0882	-0.1686*	0.0230	0.0756
	(0.7614)	(0.1209)	(0.7973)	(0.1327)	(0.7093)	(0.0908)	(0.7786)	(0.1285)
Cooking Fuel Used: Wood	0.3983	0.3255**	-0.0712	-0.0786	0.4008	0.3277**	-0.0714	-0.0789
	(0.1571)	(0.0149)	(0.2068)	(0.1013)	(0.1585)	(0.0145)	(0.2085)	(0.1080)
Cooking Fuel Used: Kerosene	-0.1241	0.0691	0.0239	-0.0105	-0.1216	0.1004	0.0208	-0.0223
	(0.7301)	(0.7728)	(0.8733)	(0.9187)	(0.7395)	(0.6835)	(0.8896)	(0.8287)
Cooking Fuel Used: Charcoal	0.1712	0.1389	-0.0175	-0.0428	0.1682	0.1400	-0.0175	-0.0440
	(0.3760)	(0.6097)	(0.8277)	(0.7035)	(0.3897)	(0.5894)	(0.8226)	(0.6990)
Cooking Fuel Used: Gas/Electricity	0.1466	-0.4941	-0.1189	0.1232	0.1524	-0.4736	-0.1210	0.1166
	(0.8671)	(0.4016)	(0.7008)	(0.5185)	(0.8587)	(0.4147)	(0.6968)	(0.5511)
Cooking Fuel Used: Other	0.0518	-0.4646	0.1485	0.2380	0.1217	-0.4434	0.1447	0.2483
	(0.9308)	(0.2580)	(0.3623)	(0.1752)	(0.8389)	(0.3012)	(0.3885)	(0.1639)
Heating Fuel Used: Wood	-0.0596	0.0096	-0.0464	-0.0414	-0.0688	0.0173	-0.0469	-0.0469
	(0.6890)	(0.9308)	(0.2743)	(0.6332)	(0.6558)	(0.8844)	(0.2836)	(0.5891)
Heating Fuel Used: Charcoal	-0.4802**	-0.2520	0.0514	0.0034	-0.5152**	-0.2679	0.0539	0.0003
	(0.0248)	(0.2466)	(0.3328)	(0.9736)	(0.0180)	(0.2345)	(0.3181)	(0.9977)
Heating Fuel Used: None	-0.0062	-0.0482	-0.1315**	-0.0785	-0.0271	-0.0586	-0.1299**	-0.0799
	(0.9721)	(0.7819)	(0.0142)	(0.3871)	(0.8815)	(0.7526)	(0.0173)	(0.3822)
Heating Fuel Used: Other	-0.8166*	-0.4724**	0.0245	0.1327	-0.8660**	-0.4895**	0.0274	0.1262
	(0.0532)	(0.0335)	(0.8652)	(0.6062)	(0.0472)	(0.0342)	(0.8575)	(0.6355)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.3149	0.3805	0.2371	0.2986	0.3171	0.3826	0.2373	0.3003

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Table 3.E.3: IV Second Stage: Results Showing the Effect of In Utero Air Pollution on Child Health at Ages 4-5

	HFA (1)	WFA (2)	Stunting (3)	Underweight (4)	HFA (5)	WFA (6)	Stunting (7)	Underweight (8)
Prenatal PM2.5 Exposure	-2.8718	1.5003	0.7821	-0.1659				
	(0.3349)	(0.5659)	(0.6116)	(0.8920)				
Prenatal PM2.5 Exposure: Quadrimester 1					-1.6698	0.1457	0.4356	0.0321
					(0.1193)	(0.8756)	(0.4239)	(0.9415)
Prenatal PM2.5 Exposure: Quadrimester 2					-0.6167	0.5112	0.2408	-0.1458
					(0.5368)	(0.6414)	(0.6386)	(0.7725)
Prenatal PM2.5 Exposure: Quadrimester 3					-0.8309	0.5814	0.2223	-0.0651
					(0.3653)	(0.5167)	(0.6646)	(0.8711)
Postnatal PM2.5	0.0258	-0.0947	0.1492	0.0274	-0.0677	-0.1109	0.1599	0.0482
	(0.9664)	(0.7696)	(0.4418)	(0.8655)	(0.9132)	(0.7448)	(0.4135)	(0.7830)
Child's Age (in Months)	-0.3502	-0.1270	0.1241	0.0796	-0.5016	-0.0941	0.1178	0.1314
	(0.3575)	(0.7305)	(0.5653)	(0.6312)	(0.2558)	(0.7688)	(0.6475)	(0.5458)
Child's Age-squared	0.0034	0.0015	-0.0013	-0.0007	0.0043	0.0012	-0.0012	-0.0010
	(0.2518)	(0.5636)	(0.4529)	(0.6009)	(0.2267)	(0.6057)	(0.5387)	(0.5363)
Female	0.1130*	-0.0693	-0.0383	0.0388	0.1116*	-0.0704	-0.0378	0.0388
	(0.0787)	(0.3091)	(0.2158)	(0.2390)	(0.0770)	(0.3051)	(0.2157)	(0.2435)
Female Head	-0.2406	-0.2292*	0.0930*	0.0733	-0.2480	-0.2331**	0.0949*	0.0741
	(0.1415)	(0.0500)	(0.0605)	(0.3570)	(0.1366)	(0.0481)	(0.0591)	(0.3590)
Mother's Age	-0.0937*	-0.0350	0.0100	-0.0086	-0.0916*	-0.0337	0.0094	-0.0088
	(0.0576)	(0.3885)	(0.6427)	(0.6815)	(0.0622)	(0.4015)	(0.6654)	(0.6714)
Mother's Age-squared	0.0016**	0.0007	-0.0002	0.0001	0.0016**	0.0007	-0.0002	0.0001
	(0.0375)	(0.2598)	(0.6081)	(0.7847)	(0.0420)	(0.2813)	(0.6194)	(0.7758)
Father's Age	0.0580**	0.0087	-0.0074	0.0047	0.0560**	0.0072	-0.0067	0.0048
	(0.0243)	(0.7730)	(0.5831)	(0.7775)	(0.0296)	(0.8145)	(0.6104)	(0.7766)
Father's Age-squared	-0.0006**	-0.0001	0.0001	-0.0000	-0.0006**	-0.0001	0.0001	-0.0000
	(0.0306)	(0.7278)	(0.5067)	(0.8653)	(0.0341)	(0.7509)	(0.5210)	(0.8629)
Mother's Years of Schooling	0.0151	0.0011	-0.0029	-0.0032	0.0149	0.0009	-0.0028	-0.0032
	(0.2198)	(0.9213)	(0.7230)	(0.5341)	(0.2158)	(0.9394)	(0.7343)	(0.5309)
Father's Years of Schooling	0.0172	0.0120	-0.0119*	-0.0061	0.0176	0.0121	-0.0120*	-0.0062*
	(0.1110)	(0.2460)	(0.0539)	(0.1007)	(0.1005)	(0.2393)	(0.0510)	(0.0852)
BCG Vaccine	0.1443	0.1087	-0.1145	-0.0014	0.1537	0.1132	-0.1167	-0.0027
	(0.4426)	(0.4559)	(0.1390)	(0.9867)	(0.4161)	(0.4510)	(0.1329)	(0.9766)
Measles Vaccine	0.1836	0.2315	0.0072	-0.1171	0.1677	0.2248	0.0106	-0.1148
	(0.3440)	(0.2109)	(0.9473)	(0.2558)	(0.3660)	(0.2240)	(0.9111)	(0.2787)
Household Size	0.0093	-0.0169	0.0034	0.0089	0.0093	-0.0170	0.0035	0.0089
	(0.5413)	(0.4200)	(0.7295)	(0.2799)	(0.5525)	(0.4124)	(0.7305)	(0.2826)
Number of Children born to Mother	-0.0460	-0.0122	-0.0015	0.0007	-0.0455	-0.0118	-0.0017	0.0006
	(0.1593)	(0.6786)	(0.9108)	(0.9582)	(0.1692)	(0.6866)	(0.9037)	(0.9598)
Wealth Index	1.0042*	0.7710*	-0.3956*	-0.3934**	0.9775*	0.7696*	-0.3938*	-0.3865**
	(0.0685)	(0.0964)	(0.0593)	(0.0279)	(0.0803)	(0.0996)	(0.0598)	(0.0389)
Child's Religion: Christian	0.0811	0.1093	0.0279	-0.0238	0.0826	0.1129	0.0264	-0.0232
	(0.6642)	(0.3816)	(0.7467)	(0.6071)	(0.6606)	(0.3604)	(0.7662)	(0.6119)
Child's Religion: Other	0.2960	0.0341	-0.1359	-0.0603	0.2937	0.0362	-0.1367	-0.0591
	(0.4464)	(0.7812)	(0.3456)	(0.4506)	(0.4598)	(0.7607)	(0.3342)	(0.4095)
Child's Ethnic Group: Gurage	0.5892	0.4750	-0.1261	-0.2109	0.5914	0.4694	-0.1240	-0.2132
	(0.1504)	(0.1157)	(0.3198)	(0.1957)	(0.1606)	(0.1205)	(0.3264)	(0.1912)
Child's Ethnic Group: Oromo	0.2265	0.2456**	0.0287	-0.0320	0.2190	0.2411**	0.0308	-0.0313
	(0.2498)	(0.0418)	(0.8147)	(0.5765)	(0.2570)	(0.0449)	(0.8045)	(0.5930)
Child's Ethnic Group: Tigrian	0.0053	-0.0315	-0.0232	0.0352	-0.0139	-0.0334	-0.0216	0.0399
	(0.9711)	(0.8788)	(0.9179)	(0.7308)	(0.9108)	(0.8654)	(0.9181)	(0.6969)
Child's Ethnic Group: Other	0.0057	0.2470**	0.0475	-0.0528	0.0142	0.2498**	0.0460	-0.0543
	(0.9793)	(0.0369)	(0.5818)	(0.2971)	(0.9505)	(0.0373)	(0.5976)	(0.2660)
Long Term Illness	-0.2505**	-0.1406	0.1113	0.0674	-0.2368*	-0.1332	0.1078	0.0659
	(0.0446)	(0.3498)	(0.1030)	(0.2773)	(0.0533)	(0.3736)	(0.1076)	(0.3006)
Cooking Fuel Used: Wood	-0.0181	0.2119	0.0591	-0.1044*	-0.0127	0.2127	0.0586	-0.1057*
	(0.8471)	(0.2095)	(0.3363)	(0.0821)	(0.9043)	(0.2210)	(0.3670)	(0.0795)
Cooking Fuel Used: Kerosene	0.0601	0.3330	0.1646	-0.0780	0.1076	0.3426	0.1585	-0.0881
	(0.9162)	(0.2746)	(0.3240)	(0.5086)	(0.8383)	(0.2679)	(0.3381)	(0.4543)
Cooking Fuel Used: Charcoal	0.1521	0.2704	0.0794	-0.1199	0.1557	0.2699	0.0795	-0.1210
	(0.7629)	(0.3074)	(0.4384)	(0.3043)	(0.7571)	(0.3057)	(0.4484)	(0.2909)
Cooking Fuel Used: Gas/Electricity	0.0235	0.2911	0.1563	-0.1088	0.0553	0.3012	0.1508	-0.1144
	(0.9337)	(0.1903)	(0.1807)	(0.2446)	(0.8494)	(0.1655)	(0.1929)	(0.2204)
Cooking Fuel Used: Other	0.0754	0.1834	0.0612	-0.0517	0.0759	0.1791	0.0629	-0.0532
	(0.6239)	(0.2506)	(0.5076)	(0.3809)	(0.6069)	(0.2622)	(0.4947)	(0.3856)
Heating Fuel Used: Wood	0.2061	-0.1118	-0.0666	0.0176	0.2144	-0.1116	-0.0671	0.0154
	(0.2751)	(0.5759)	(0.3087)	(0.8065)	(0.2550)	(0.5827)	(0.3112)	(0.8248)
Heating Fuel Used: Charcoal	0.1417	0.0375	-0.0805	-0.0130	0.1462	0.0358	-0.0800	-0.0147
	(0.4340)	(0.8664)	(0.4623)	(0.8851)	(0.4029)	(0.8772)	(0.4623)	(0.8782)
Heating Fuel Used: None	0.1953	-0.0719	-0.1135	0.0080	0.2029	-0.0719	-0.1138	0.0059
	(0.2518)	(0.7212)	(0.2042)	(0.9189)	(0.2228)	(0.7284)	(0.2013)	(0.9432)
Heating Fuel Used: Other	0.0647	-0.1782	0.0433	0.0331	0.0680	-0.1772	0.0427	0.0325
	(0.5729)	(0.2886)	(0.7105)	(0.6077)	(0.5401)	(0.2909)	(0.7132)	(0.6170)
N	1069	1069	1069	1069	1069	1069	1069	1069
r2	0.2013	0.1494	0.1402	0.1154	0.2037	0.1501	0.1409	0.1159

Note: Additional controls include weather controls (average monthly rainfall 9 months prior to birth (prenatal), average monthly temperature 9 months prior to birth (prenatal), the interaction between prenatal rainfall and temperature, prenatal rainfall and temperature squared, average monthly postnatal rainfall, average monthly postnatal temperature, the interaction between postnatal rainfall and temperature, postnatal rainfall and temperature squared), year of birth fixed effect, month of birth fixed effect, survey date fixed effect, and community fixed effect. Wild cluster bootstrap p-values at community level in parentheses. Significance level denoted at * p <0.10 **p<0.05 ***p < 0.01.

Chapter 4

Droughts and its Impacts on Child Marriage Outcomes in Kenya

Abstract

In this paper, we examine the role that exogenous shocks to income (droughts) have in shaping the welfare of children and in determining child marriage outcomes for young girls in Kenya. Using a pooled survey of cross-sectional data together with data on climate, our study, through the use of the Cox proportional hazards model, provides evidence for the adverse effects of droughts on child marriage. We find that young girls exposed to a drought at time period t are significantly more likely to experience the marriage hazard at time t by approximately 9%. With respect to the hazard of child marriage (ages 10-17), our results show a higher effect of droughts, indicating an increase in the child marriage probability of 13%. Our results also show that young girls are likely to experience increases in fertility as a result of a drought, showing increases in the probability of first birth within the same period and also in the following period of approximately 9-17%. An investigation of heterogeneous effects suggests that girls from rural households with lower levels of income are the most vulnerable to the adverse effects of droughts on marriage and fertility.

4.1 Introduction

Child marriage remains a common phenomenon in today's society and an important area of concern for policy makers around the world. Children marrying during their early years (before the age of 18) have little to no choice with regards to whom they marry or when they marry, posing a key violation of fundamental human rights (UNICEF, 2021*b*). Whilst child marriage is not particularly uncommon for boys, it disproportionately affects women and girls, trapping them to a lifetime of violence and economic disadvantage. Early marriage compromises a girl's development by resulting in early pregnancy, which prompts additional concerns because as children themselves, they are not physically or emotionally ready to become mothers (Smaak and Varia, 2015; Singh and Revollo, 2016; Wodon et al., 2017). As young brides, they are at a higher risk of experiencing health insecurities, educational disruptions, and social seclusion, restricting their opportunities for career, professional and personal development. They are more prone to abuse and discrimination and also less likely to have autonomy in making decisions about their own lives (Jensen and Thornton, 2003; Kidman, 2017).

The overwhelming effects of child marriage are well known in the literature, and while efforts to lower child marriage rates have been put in place globally, the figures remain significantly high. According to the United Nations (2021*a*), about 650 million women alive today married before their 18th birthday, and at least 12 million girls marry as children every year. This translates to 28 girls every minute. These figures double in the least developed regions reaching about 40% of women marrying as children (United Nations, 2021*a*). In regions like Africa, child marriage is rampant and seen as the new norm owing to a combination of several factors including low income levels, low levels of educational exposure, culture and religious beliefs. Of the 20 countries topping the child marriage charts, African countries account for 15, despite the fact that 90% of countries in this region have the legislated minimum age for marriage as 18 years (Statista, 2021). Africa is also a continent that is considered the most prone to changing climate conditions which pose further risks and challenge to household economic activities and sources of income, and thus places many young girls at risk, as households in this region resort to child marriage in their stride towards reducing variability in income and consumption (Lowes and Nunn, 2017).

Given this, this paper aims to examine the role of exogenous shocks to income (droughts) in shaping the welfare of children and in determining child marriage outcomes for young girls in a sub-Saharan African country, Kenya. Droughts are recurrent in many communities and as a result, can have long-lasting impacts on household welfare particularly in developing regions that depend heavily on rain-fed agriculture as their major source of livelihood (Pereira, 2017; World Food Programme, 2019). Kenya, as an African country, is a country that is not only characterised with a high prevalence of child marriage given its estimate of 30% of girls marrying before age 18, but also with a high variability in weather conditions, putting many households at risk as agriculture constitutes the backbone of Kenya's economy, accounting for 35% of the country's GDP and employing more than 40% and 70% of their total population and rural population, respectively (Warria, 2019; USAID, 2021). Using a pooled sample of cross-sectional data for Kenya, our study thus examines the extent of vulnerability of young girls with regards to their marital outcomes and consequently their fertility outcomes to droughts in Kenya through exploiting variations in rainfall and temperature over time and space.

Only recently have a handful of studies emerged in trying to investigate the core determinants of child marriage. The large majority of studies in the past have focused mainly on the consequences of child marriage and much less is known about the factors that drive girls into early marriage. Understanding what gives rise to child marriage is crucial, particularly in terms of policy design aimed at protecting vulnerable young girls from barbaric practices, promoting women's socio-economic welfare, and enhancing overall economic development. Studies such as Singh and Vennam (2016), Rumble et al. (2018) and Asna-ashary et al. (2020) all show that among the list of critical factors, poverty is the most common denominator driving child marriage rates.[1] These studies show that poorer households or households living in rural areas with poorer housing conditions have much higher tendencies of pushing their children into child marriages. For example, the study by Singh and Vennam (2016), using data on India to examine the factors shaping trajectories into child marriage find that girls from poorer households are 45% more likely to get married before 19 years when compared to richer households, while girls from rural areas are more than twice as likely to get married (42% probability) than girls living in urban areas (19% probability). The study by Rumble et al. (2018) also on the determinants

[1]The literature review provided in this study is comprehensive and up-to-date. It is conducted using a wide range of databases including Google Scholar, Science Direct, Journal Storage (JSTOR) and EconLit.

of child marriage equally show that wealth index and region of residence are two very important factors for Indonesian households in determining whether their girl child marries before age 18. They find that being from a household in the top wealth quantile reduces a girl's likelihood to marry before she turns 18 (approximately 18% reduction), while being from a rural household increases the probability of child marriage by 11%.

In theory, amongst many communities a bride price is paid by the groom's family to the bride's family as a traditional rite to seal the marital union of both parties (Rusare, 2021). A harsh repercussion of this payment system is that young girls are seen as assets to their families, and thus households' living conditions such as low levels of income or any slight economic inconvenience may incentivise them to force their daughters into early marriage (Lowes and Nunn, 2017). A household hit by a negative shock under this system, for example, will be forced to "sell" their daughters into child marriage as a form of coping mechanism from economic hardship. Girls, particularly those from poorer households serve as a shield against adverse shocks, and marriage, in return, is used as a tool by households to lessen economic burden and protect income and consumption (Dewi and Dartanto, 2019). This phenomenon is especially true for households in developing regions with limited access to credit markets, where daughters are sold even before reaching puberty, thus further exacerbating the prevalence of child marriage (UNICEF, 2001; Lafraniere, 2005).

Previous studies in the literature on household shocks and its impacts on child marriage outcomes, particularly in developing countries, have been relatively scarce in general with a large majority of them focusing on household/self-reported measures of shocks namely, poor health conditions or the death of a household member. For example, a study by Villar (2021) in Senegal examines the impact of paternal death on early marriage using cross-sectional data. Implementing the Ordinary Least Squares (OLS) Regression, Villar (2021) finds that children who have experienced paternal death are significantly more likely to be child brides (38% increase), teenage mothers (12% increase), as well as divorcees than their non-orphan counterparts. The author in his study also shows that younger paternal orphans are more likely to be fostered (as a form of coping strategy), with no significant impact on educational outcomes or child labour activities. Also finding similar results is Beegle and Krutikova (2008). Beegle and Krutikova (2008) in their study on parental mortality and marriage patterns in

Tanzania show that the death of a father before age 15 increases the probability of marriage for girls aged 17–23 by approximately 25%. Their results also show that orphaned girls that were either educated prior to the shock, from relatively richer households, or from households whose head worked in non-farm sectors are shielded from child marriages. In another study on four African countries (Burkina Faso, Ghana, Malawi, Uganda), Chae (2013), examining the impact of paternal orphanhood on transition into early marriage, find significant effects in one country (Uganda) where young girls (ages 12-19) who lost their father before the age of 10 experienced a 74% increased probability of entering into marriage than non-orphan girls.

One of the major challenge that generally arises with the common usage of self-reported measures of shock such as the death of a parent as seen in the above studies is the endogeneity present in the death variable. Issues such as omitted relevant variables relating to household behavioural patterns that could predict both the health or death of a household member and child marriage behaviours can ultimately result in a bias of the marriage estimates. To address this concern, a few studies in the literature (Trinh and Zhang, 2020; Corno et al., 2020; Dewi and Dartanto, 2019) have used more exogenous measures of shocks such as extreme weather events or natural disasters to show a causal link between household shocks and child marriage outcomes. The study by Trinh and Zhang (2020), for example, use rainfall deviations as an instrument for household expenditure reductions to examine the impact of adverse shocks on child marriage in India and Vietnam. The authors in their study show that changes in household expenditure (a 1 % decrease) resulting from adverse rainfall shocks causes a 0.7% increase in the probability of child marriage in Vietnam. In India, however, an opposite result is the case where a fall in expenditure causes a decrease in child marriage patterns. Trinh and Zhang (2020) explain this finding through the existence of the dowry payments made by the bride's family in India.[2] A similar result is also found by Corno et al. (2020) in their study on extreme weather events (droughts) and marriage patterns in sub-Saharan Africa and India. Using cross-sectional data on 31 sub-Saharan African countries and India, the authors employing the OLS regression, show that for sub-Saharan Africa where the bride price system is commonly in place, girls who experience a drought between the ages of 12 and 17 are significantly more likely to experience child marriage (0.27% increase), whereas for India, where the bride price system is not practiced,

[2]In the rare case of India, a dowry which involves a payment from the bride's family to the groom's family as part of the marital tradition is made to seal the union of both parties.

no significant effect of drought is found on child marriage. Finally, in a study by Dewi and Dartanto (2019) on Indonesia, the authors using the number of natural disasters occurring at the village level as a measure of household shocks show that a unit increase in the number of natural disasters increases the probability of child marriage by 0.1%. The study also finds disaster mitigation and management to work effectively in reducing the prevalence of child marriage in Indonesia.

Our study builds on the existing research and makes two important contributions. First, in the literature on household shocks and child marriage, studies such as Beegle and Krutikova (2008), Dewi and Dartanto (2019) and Villar (2021) in their analysis use measures of shocks within a wide range of time interval preceding the child marriage event, not particularly knowing the exact time or age the shock was experienced by the child or household. This could potentially lead to a bias (attenuation bias) in the marriage estimates especially if the time interval in-between the shock occurring and the marriage outcome is wide as a lot of actions or reactions could have happened within that time. Our study differs from these studies through the use of a detailed cross-sectional dataset from Kenya, containing information on the exact timing of marriage for each child. This allows us to build an individual-panel data from the year we assume a child becomes first at risk (age 10) to their age of marriage. In this regard, we contribute to the literature by accurately assigning to each child their weather exposure for each year during their relevant child marriage or risk period, thus allowing for less bias in our estimates. Second, we contribute to the literature by estimating the effect of extreme weather events (droughts) on child marriage outcomes through the use of survival analysis. Though common in the health literature, survival analysis has not been used for studies on household shocks and child marriage. The advantage of this method above other methods such as the OLS or probit model commonly used in previous studies like Villar (2021) and Corno et al. (2020) is that survival analysis effectively deals with rare events in the data, censoring, truncation and time varying covariates that could potentially bias the child marriage estimates. It also allows for a non-parametric modelling of the baseline hazard function, allowing for a more flexible estimation approach. This method would thus prove more useful in estimating the causal effect of droughts on child marriage outcomes.

To briefly summarise our findings, our results provide evidence for the adverse effects of droughts on child marriage outcomes. More specifically, we find that children aged 10-24 exposed to droughts in a given year are more likely to enter into marriage within that same year by approximately 9%. When we focus only on child marriage (ages 10-17), the coefficient slightly increases and remain significant, showing an increase in the probability of experiencing the hazard (child marriage) when hit by a drought of 13%. Our study also finds a corresponding effect on fertility outcomes, with child fertility in period t increasing by approximately 17% when a child is exposed to a drought in the previous period. Furthermore, in our analysis of heterogeneity, our findings suggests that girls from rural households with lower levels of income are the most vulnerable to the adverse effects of droughts on child marriage and fertility outcomes.

The rest of this paper is organised as follows. Section 4.2 presents a description of the marriage situation in Kenya; section 4.3 discusses the data and presents the descriptive statistics; section 4.4 outlines the empirical model; section 4.5 discusses the results and robustness checks; and section 4.6 concludes.

4.2 The Marriage Situation in Kenya

Early marriage in Kenya has been on a slow decline in recent years. Currently, Kenya is ranked 20th in the absolute number of child marriage worldwide, reported at 600,000 girls married before 18 (Emurugat, 2019). 30% of girls are married before their 18th birthday and 6% are married before their 15th birthday (Gitau et al., 2016; Warria, 2019). These figures vary across regions and some regions such as the North Eastern and Coast regions have child marriage rates reaching highs of 56% and 41%, respectively (UNICEF, 2018). Although Kenya, alongside other sub-Saharan African countries have long since introduced laws as far back as the early 2000s (Children's Act of 2001) that aim to protect young girls from all forms of abuse including child marriage, current figures show child marriage to still be rampant among Kenyan societies, effectively highlighting the redundancy of such laws.

The Children's Act of 2001 places age 18 as the minimum age of consent and marriage in Kenya for both girls and boys (Children's Act, 2001). The Act promotes the rights of every Kenyan child, giving them rights to education, health care, parental care, as well as protection from discrimination, child labour, domestic abuse and sexual abuse. The Law also states the intentions of Kenyan legislators to penalize any individual that is seen to wilfully or as an act of negligence, infringe on the rights of any Kenyan child. These laws are further stressed upon in the 2010 Kenyan constitution which gives children the rights to acquire basic education of 12 years and any activities such as child marriage seen to dissuade young girls from participating in compulsory education is criminalised (Laws of Kenya, 2010; Right to Education Project, 2014). Kenya is also a country that is party to several international treaties including the United Nations Convention on Elimination of All forms of Discrimination Against Women and the Convention on the Rights of the Child that seek to protect children's right to life, survival, and development (United Nations, 1979, 1989).

In general, the legal systems and laws prohibiting child marriage in Kenya are widely established, however, a lack of enforcement plays a critical role in explaining the prevalence of child marriage. According to Warria (2019), the lack of awareness by the general public as well as law enforcement agents on marriage laws in Kenya, and the lack of information on how to effectively implement such laws is one of the major reasons why child marriage is still rampant. Furthermore, although legislations prohibit marriage before 18, child marriage is still legal under customary law in Kenya, as customs of several communities, and Islamic law sets no minimum age for marriage (Serrao, 2018; Warria, 2019; Measure Evaluation, 2021). These customary and religious practices impose major contradictions in child marriage laws that often result in the weakening of existing child protection systems in Kenya.

Amongst several cultural practices, the bride pride payment system as well as the lack of equality between boys and girls, widely spread across Kenya, are some of the prime cultural factors influencing child marriage rates. Studies have shown that among some major tribes in Kenya (Kikuyu and Luhya), payments as high as 200,000-500,000 shillings ($1800-$4500) encompassing food items, cattles, goats, and gifts are made to the bride's family as part of the marital traditional rites (Wanjala, 2012; Os, 2021). Pastoralist communities such as the Somali and Luo, for example, where cattle rearing is common, are well known to frequently marry off their daughters at very young ages in return for handsome payments in cows and cattles (Ganira et al., 2015; Lowe et al., 2021). In some communities like the Maasai, the bride price payment system is further aggravated with the common knowledge that girls are to be disregarded and not considered permanent members of their families. Girls among the Maasai are worth the value of 1-2 cows, a herd of sheep and goats (Parsitau, 2017). This means that they have little to no value except as a means of transaction to bring wealth to their families. Furthermore, long-standing cultural practices deeply rooted in the Maasai culture such as the female genital mutilation commonly implemented among girls ages 11-13 as a passage rite into womanhood and early marriage further exacerbates the prevalence of child marriage among this tribe (Jepkemboi, 2007; Parsitau, 2017).

In other tribes like the Luo, beliefs such as girls of puberty age dying before marriage and thus becoming violent ghosts, causing barrenness to all females in her household worsen child marriage rates (Ganira et al., 2015). Among the Samburu tribe, highly extreme and violent beliefs and practices such as the practice of beading exists, where warriors are allowed to have sexual relationships with girls from as young as 9 years from the same clan, in preparation for marriage (Ahlstedt, 2017). If these young girls get pregnant, they are forced to have abortions or kill their newborns as it is considered an abomination to bear children with a man from their clan. Subsequently, young girls among the Samburus are often resigned with little to no zeal for life, allowing them easily succumb into forced marriages (Ahlstedt, 2017).

In general, in spite of the legislations set in place against child marriages in Kenya, the practice is still prevalent due to existing socio-cultural norms and traditions, religious beliefs, and weak systems of enforcement (Ganira et al., 2015; Warria, 2019). These key factors, particularly that of socio-cultural norms and traditions that influence child marriage practices in Kenya, are more pronounced in communities where poverty levels are high and where the traditional preference for boys over girls is predominant (Ganira et al., 2015; Warria, 2019). With over 23 million people living below the poverty line in Kenya, majority of households especially those from rural areas are often influenced to educate their sons over their daughters, leaving young girls idle, weak and vulnerable, and thus putting societal pressure on young girls and their families to participate in barbaric practices that exacerbate child marriage rates in Kenya (Jepkemboi, 2007; Wafula, 2020).

4.3 Data

4.3.1 Household Data

The dataset used in this study is a pooled survey of the 2003, 2008, and 2014/15

Demographic and Health Survey (DHS) for Kenya. The Demographic and Health Survey is a nationally representative survey carried out by the ICF International and sponsored by the United States Agency for International Development (USAID) in over 90 low-income countries. The primary objective of the survey is to provide up-to-date information on health and population for policy makers and health practitioners to enable them design effective policies that encompass improving access to health care, promoting health seeking behaviours, as well as promoting other important growth indicators such as access to education and employment (DHS, 2021). The survey is widely used for monitoring demographic trends across regions, as it contains detailed information on child and maternal mortality, nutritional status, domestic violence, reproductive health, family planning, sexual behaviours, employment, and education.

The DHS for Kenya uses a two-stage sampling procedure based on the 1999 Population and Housing Census, with clusters chosen in the first stage, and households then randomly selected from the respective clusters in the second stage. In total, about 8,500, 9,000 and 36,000 households were randomly selected in 2003, 2008, and 2014 from a total of 2400 clusters in the DHS survey for Kenya.[3] Household questionnaires and women questionnaires were then distributed in all randomly selected households, and men questionnaires were given to every second household. Women aged 15-49 were interviewed in the women's survey (available in the Individual Recode dataset), while men aged 15-59 were interviewed in the men's survey (available in the Men's Recode dataset).

For the purpose of our analysis, we make use of the 3 most recent Individual Recode (Women) files for Kenya, as these are the only years that include information on GPS locations of households in the survey. Each woman in the survey is asked whether she has ever been married or not, and if the answer is yes, details are then provided on her age, year, and month of first marriage or union. Due to data limitations and the nature of our analysis, we focus on women who are aged 15-24 at the time of the survey, leaving us with a sample size of 18,524 exclusive of missing values in outcome and control variables.[4]

Table 4.1 provides the summary statistics for the key variables used in our analysis. The top panel, panel A, presents the summary statistics for individual characteristics, while the

[3]We use adjusted population sample weights in all our regressions in order to account for differences in sample size across years.

[4]The sample size before removing missing values was 21,848.

Table 4.1: Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Panel A: Individual Characteristics					
Current Age	18,524	19.33	2.87	15.00	24.00
Marital Status:					
Currently Married	18,524	0.35	0.47	0.00	1.00
Formerly Married	18,524	0.04	0.19	0.00	1.00
Never Married	18,524	0.61	0.48	0.00	1.00
Age of First Marriage	7,181	17.11	2.58	10.00	24.00
Marriage before the year turning 18	7,181	0.50	0.50	0.00	1.00
Marriage before the year turning 17	7,181	0.35	0.48	0.00	1.00
Age at First Birth	7,475	17.83	2.35	10.00	24.00
Age at First Birth Conditional on Marriage	6,101	17.81	2.36	10.00	24.00
Birth before the year turning 18	7,181	0.45	0.49	0.00	1.00
Birth before the year turning 17	7,181	0.29	0.45	0.00	1.00
Educational Level (in years)	18,524	7.78	3.61	0.00	21.00
Religon:					
Christian	18,524	0.83	0.37	0.00	1.00
Muslim	18,524	0.14	0.35	0.00	1.00
Other	18,524	0.03	0.13	0.00	1.00
Ethnic Group:					
Kalenjin	18,524	0.12	0.33	0.00	1.00
Kamba	18,524	0.09	0.29	0.00	1.00
Kikuyu	18,524	0.15	0.36	0.00	1.00
Kisii	18,524	0.06	0.23	0.00	1.00
Luhya	18,524	0.14	0.35	0.00	1.00
Luo	18,524	0.12	0.33	0.00	1.00
Meru	18,524	0.04	0.21	0.00	1.00
Swahili	18,524	0.07	0.25	0.00	1.00
Somali	18,524	0.07	0.25	0.00	1.00
Other	18,524	0.14	0.35	0.00	1.00
Panel B: Household Characteristics					
Region:					
Rift Valley	18,524	0.24	0.43	0.00	1.00
Eastern	18,524	0.15	0.35	0.00	1.00
Nyanza	18,524	0.15	0.35	0.00	1.00
Coast	18,524	0.13	0.33	0.00	1.00
Western	18,524	0.11	0.32	0.00	1.00
Central	18,524	0.10	0.29	0.00	1.00
Nairobi	18,524	0.07	0.25	0.00	1.00
North Eastern	18,524	0.06	0.23	0.00	1.00
Gender of HH Head (Female)	18,524	0.36	0.48	0.00	1.00
Education of HH Head (In Years)	18,524	7.16	4.86	0.00	25.00
Age of HH Head (Years)	18,524	42.39	15.53	15.00	97.00
HH Size	18,524	5.64	2.79	1.00	24.00
Wealth Quantile : Poorest	18,524	0.21	0.41	0.00	1.00
Wealth Quantile : Poorer	18,524	0.19	0.39	0.00	1.00
Wealth Quantile : Middle	18,524	0.19	0.39	0.00	1.00
Wealth Quantile : Richer	18,524	0.19	0.39	0.00	1.00
Wealth Quantile : Richest	18,524	0.22	0.42	0.00	1.00
Wealth Index Score	18,524	0.02	0.99	-9.00	3.59

bottom panel, panel B, presents the summary statistics for the household characteristics. Beginning with the individual characteristics, panel A shows that on average, girls in our sample are about 19 years of age, with a significant proportion of them (39%) either currently married or formerly married. Our sample shows the average age of first marriage for girls to be 17 years, indicating that the average girl within our sample marries as a child. With regards to our main outcome variable, child marriage, Table 4.1 shows that amongst the young girls who have been married, nearly a half (50%) got married before the year in which they turn 18, and about 35% got married before the year in which they turn 17. Consequently, fertility outcomes are also predominant in our sample, with the mean age at first birth shown to be approximately 17.8 years, and the proportion of girls giving birth before age 18 and 17 seen as 45% and 29%, respectively. Our data also shows the mean years of education for girls in our sample to be 7 years, indicating that the average DHS girl has completed primary education. The majority of young girls are Christians (83%), with the dominant tribes being the Kikuyu (15%), Luhya (14%), Kalenjin (12%), Luo (12%), and Kamba (9%).

In terms of household characteristics, the percentage of households living in the eight regions of Kenya; Rift Valley, Eastern, Nyanza, Coast, Western, Central, Nairobi and North Eastern are 24%, 15%, 15%, 13% and 11%, 10%, 7%, and 6%, respectively. The average Kenyan DHS household is comprised of six members with approximately 64% constituting as male headed households. Household heads are on average 42 years old, with approximately 7.1 years of education, indicating that the average head has attained up to primary level of education. Lastly, with regards to household wealth status, Table 4.1 shows that almost 40% of our sample is classified as poor ("poorer" and "poorest"), as indicated by the DHS, with 19% classified as middle classed, and 19% and 22% classified as the top quantile of the wealth index: "richer" and richest", respectively.[5]

4.3.2 Weather Data

Monthly rainfall data for Kenya is obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a database developed by the U.S. geological survey

[5]The wealth index score is a z-score derived by DHS using all households living conditions, assets and utility services. Given this wealth score, households are then classified by the DHS according to percentiles in the wealth index z-score distribution (Rutstein, 2015)

and the Climate Hazards Group, at the University of California, Santa Barbara. CHIRPS is a 35+ year quasi-global rainfall dataset, spanning 50-degree-South to 50-degree-North (and all longitudes), starting in 1981 to near-present. The database blends 0.05° ($\sim$ 5.3 km) resolution satellite imagery with interpolated weather station data to create gridded rainfall estimates for trend analysis and seasonal drought monitoring.[6] This data is combined with maximum, minimum, and average surface temperature data taken from the University of East Anglia Climate Research Unit (CRU). The CRU, a database created through the interpolation of weather station data from over 4,000 stations throughout the world, provides monthly gridded climate data for the globe from 1900 to present at a 0.5° resolution (Harris et al., 2014).

Our weather data is merged with the household data by overlaying the latitude and longitude data for the clusters (grid cells) provided in the geospatial data files of the DHS, onto the gridded weather dataset, with all households in each community assigned the same level of rainfall and temperature. We present in Appendix 4.A the weather data for our study area for time periods 1981 to 2017. Figures 4.A.1, 4.A.2 and 4.A.3 map the spatial variation in mean annual rainfall, mean annual maximum temperature and mean annual minimum temperature from 1981 to 2017 in Kenya. As the figures show, there is considerable amount of variation in rainfall and temperature across regions of Kenya, with rainfall ranging from as low as 100mm in the northern and eastern arid regions, to over 2000mm in the south western regions of Kenya. Annual minimum and maximum temperature is also seen to range from a low of about 7°C and 19°C, respectively in the less arid regions (south western regions), to highs of 25°C and 36°C, respectively in the northern and eastern arid regions of Kenya. The figures as seen in Appendix 4.A in general show that a substantial proportion of Kenya (predominantly the northern and eastern regions) receive less than 500mm of rainfall a year. We also see from Figure 4.A.4 which graphs the seasonal patterns (monthly means) in rainfall across all DHS clusters, that on average the country experiences a bimodal pattern in rainfall, with two rainy seasons namely; a long rainy season from March to May (MAM), and a short rainy season from October to December. Rainfall in the primary rainy season (March to May) generally accounts for the

[6] The rainfall data is calculated by combining a pentadal precipitation climatology; the Cold Cloud Duration (CCD) information based on thermal infrared data archived from the Climate Prediction Centre (CPC) and the National Climatic Data Centre (NCDC); atmospheric model rainfall fields from the NOAA Climate Forecast System version 2 (CFSv2); and in situ precipitation observations (Toté et al., 2015).

majority of rainfall in Kenya (73%), and crops planted during this season, usually harvested in August-October, accounts for 80% of the country's annual crop production (D'Alessandro et al., 2015; Ayugi et al., 2016). As a result, the amount of rainfall during the long rainy season (March to May) is critical for crop production, and the most severe droughts in Kenya are usually due to the shortage of the MAM rainfall (Ayugi et al., 2016).

4.3.3 Measuring Droughts

Various indices have been used in the literature to quantify drought such as the Standardised Precipitation Index (SPI), the Standardised Precipitation Evapotranspiration Index (SPEI), Palmer Drought Severity Index, Soil Moisture Deficit Index, and the Surface Water Supply Index. Among these indices, rainfall is the common climate variable for drought assessment and monitoring. The widely used SPI, for example, measures precipitation anomalies for a given time and location and has been recognised as a key drought indicator by the World Meteorological Organisation (WMO, 2016), and a universal meteorological drought index by the Lincoln Declaration on Drought (Hayes et al., 2011). The SPI is commonly chosen over several other drought indices such as the Palmer Drought Severity Index because it serves as a better representation of abnormal dryness or wetness, and it is more comparable across regions with different climates.

Despite its widespread acceptance, the SPI has been criticised for solely being based on precipitation. Studies like Ritchie (1998) and Manning et al. (2018) have argued that within the agricultural context, knowing how much water leaves the soil and returns to the atmosphere (evapotranspiration) is of more importance since it is the soil moisture availability (precipitation net of evapotranspiration) that is crucial for the growing of crops, and hence is what determines agricultural droughts (WMO, 2010). To address this concern, the Standardised Precipitation Evapotranspiration Index (SPEI) was developed by Vicente-Serrano et al. (2010). The SPEI, though similar to the SPI, provides a better measure for drought severity by accounting for atmospheric conditions other than precipitation that affect soil evaporative demand, such as temperature, wind speed, and humidity. This is relevant because through accounting for variables like temperature it also considers evapotranspiration, which can consume up to 80% of rainfall (Abramopoulos et al., 1988). Thus, by incorporating evapotranspiration, the SPEI effectively deals with the shortcomings of the SPI to include the importance of soil water availability/water stress on crops.

The SPEI measures drought severity, intensity and duration, and is estimated by first calculating the Potential Evapotranspiration (PET) using the Hargreaves method. The Hargreaves method, proposed by Hargreaves and Allen (2003), is the most commonly used temperature-based method (based on temperature and solar radiation) for calculating PET. It is a method recommended by the FAO as air temperature and solar radiation explain at least 80% of evapotranspiration variability (Hargreaves and Samani, 1982; Priestley and Taylor, 1972; Martí et al., 2015). The Hargreaves method estimate PET as follows:

$$PET = 0.0023 * R_a * (d)^{0.5}(T_{mean} + 17.8) \tag{4.1}$$

where R_a is the mean extra-terrestrial radiation (mm/day) (a function of the location's latitude), d is the temperature difference (mean monthly maximum temperature - mean monthly minimum temperature (°C)), and T_{mean} is the mean monthly temperature (°C).

Following this, the climatic water balance (D) which measures the difference between the precipitation (P) and PET for the month i is calculated:

$$D_i = P_i - PET_i \tag{4.2}$$

This provides a simple measure of the water surplus or deficit for the analyzed month. The calculated D_i values are then aggregated at different time scales (e.g. 1 month, 4 month, 12 month), which is then modelled using a three-parameter log-logistic distribution. The three-parameter log-logistic was chosen to capture deficit values given the likelihood of observing negative climatic water balance values in arid and semi-arid areas. Thus, the Log-logistic distribution was recommended for the SPEI due to its ability to provide a better fit for extreme negative values as well as its ability to adopt different shapes to model the frequencies of the D series at different time scales (Vicente-Serrano et al., 2010).

The probability density function of a three-parameter log-logistic distributed variable is expressed as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left(1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right)^{-2} \tag{4.3}$$

where α, β and γ are scale, shape and origin parameters, respectively, for D values in the range $\gamma > D < \infty$. The Parameters of the log-logistic distribution are obtained using the L-moment procedure.[7] The probability distribution function for the D series, according to the log-logistic distribution, is then given as:

$$F(x) = \left[1 + \left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{4.4}$$

With F(x), the SPEI can easily be obtained as the standardized values of F(x) according to the method of Abramowitz and Stegun (1965). For example, following the classical approximation of Abramowitz and Stegun (1965):

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{4.5}$$

where:

$$W = \sqrt{-2ln(P)} \quad for\ P \leq 0.5$$

and P is the probability of exceeding a determined D value, P=1-F(x). If P>0.5, then P is replaced by 1-P and the sign of the resultant SPEI is reversed. The constants are $C_0 = 2.515517$, $C_1 = 0.802853$, C_2 =0.010328, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

The average value of the SPEI is 0, and the standard deviation is 1. The SPEI is a standardized variable, and it can therefore be compared with other SPEI values over time and space. Like the SPI, it can be calculated for different times scales (e.g. one, three, twelve, forty-eight months), each representing a specific type of drought such as a metrological drought for a 1-month time scale, an agricultural drought for a 3-6-month time-scale, or a hydrological drought for longer time periods.

The SPEI index can be generated using the SPEI package in R (Beguería et al., 2014). In this paper, we utilise the R SPEI package, and calculate a 3-month SPEI linked to the main planting season (March- May) in Kenya. A drought is identified as haven occurred for a given year and community if the SPEI value linked to the year's and community's agricultural season is less than -0.5 standard deviations.[8] Our drought measure is therefore a dummy variable given by:

$$Drought_{d,t} = 1\ if\ (SPEI_{d,t} < -0.5)$$

[7]Please refer to Vicente-Serrano et al. (2010) for a detailed analysis of how the parameters and the SPEI index is calculated.

[8]In the sensitivity analysis we also use other SPEI cut-off values including -0.8, -1, and -2.

and 0, otherwise. This allows for a relatively intuitive interpretation of the results.[9]

It is important to note that in accounting for droughts, we utilise the location of girls at the time of the survey, rather than the location where girls lived and grew up before marriage. It may thus be possible that migration has already occurred due to marriage. Unfortunately, the DHS data does not provide any information on migration status of household members, as information is only provided on where a girl currently resides and not on where she was at the time of her first marriage. This limitation may thus introduce some measurement error to our estimates particularly if the distance between the current location of residence and location before marriage is far. Several studies on marriage migration in sub-Saharan Africa (Mbaye and Wagner, 2017; Corno et al., 2020) have however shown that in general, the majority of women (about 77%) marry within their community and do not migrate at the time of marriage. Moreover, if migration does occur, it only happens within very short distances (Mbaye and Wagner, 2017). Given this, we would expect any measurement error due to marriage migration to be very minimal in our analysis.

In figure 4.A.5 of Appendix 4.A, we plot the percentage of communities in our survey that experience a drought in each given calendar year from 1981 to 2017. The figure generally shows a significant amount of variation in the proportion of communities experiencing droughts across years, with a few years like 1983 and 2011 showing a high prevalence of drought in our sample (approximately 80%), and other years like 1981 and 1982 showing low levels of drought prevalence.

4.4 Empirical Model

The primary objective of this study is to identify the causal impact of droughts on child marriage outcomes. To implement this, we make use of a duration model, analysing the duration between when a girl is first at risk of experiencing the hazard namely child marriage (t_0) and when she experiences the hazard (t_m). Under this approach, our household data is converted into a person-year panel format, using the age at first marriage as the key determining variable. Given this, a person who gets married at age (t_m) contributes (t_m - t_0 + 1) observations to the

[9] The use of dummy variables/cut-offs to classify SPEI drought is done according to the drought literature (McKee et al., 1993; Paulo et al., 2012; Wang et al., 2014; Tirivarombo et al., 2018).

sample: one observation for each year at risk until she experiences the hazard and gets married, after which she exits the sample. In our analysis, we assume t_0 to be 10 years of age, as this is the minimum age for which an individual reports getting married in the dataset (shown in Table 4.1).

Given that our primary outcome of interest is marriage (child marriage), we examine marriage outcomes for girls up until age 17 and 24, depending on the model specification. This implies that girls marrying after age 17 or age 24 (depending on the model), or girls not married as at the time of the survey are right censored.[10] A girl who gets married at age 17 for example, would have an event/marriage vector of $\{M_{0,10}, M_{0,11}, M_{0,12}, M_{0,13}, M_{0,14}, M_{0,15}, M_{0,16}, M_{1,17}\}$, appearing 8 times in the data with values of 0 for the event of marriage from age 10 to 16, and a value of 1 at age 17 when the marriage occurs. A girl who is not married by age 18 would appear 8 times in the data with a marriage vector of all zeros.

Using the above sample, we estimate the probability of experiencing hazard (marriage) in period t and exiting the sample, using the Cox proportional hazards model. The Cox model, developed by Cox (1972), is a model that is widely used to analyse survival data with censoring. It is used to identify differences in survival time due to treatment and control variables. It is chosen over other survival models like the Kaplan-Meier, Exponential and the Weibull survival models due to (i) its non-parametric nature which makes no assumptions or specifications on the shape of the baseline hazard function and (ii) its ability to flexibly control for time-invariant and time-varying covariates (Deo et al., 2021). In the Cox proportional hazards model, the hazard rate, $h_i(t)$, representing the rate or probability of an event occurring and an individual exiting the sample at time interval t and *t+1* conditional on haven survived before time t is modelled by the following equation:

$$h_i(t) = h_0(t)exp(\beta X_i) \tag{4.6}$$

$$h_i(t) = h_0(t)exp(\beta_1 Drought_{idt} + \beta_2 Drought_{idt-1} + \beta_3 X_{idt} + \theta\lambda_k + \delta\mu_d + \sigma\eta_t) \tag{4.7}$$

Where $h_0(t)$ is the baseline hazard (the hazard rate when X_i equals 0), t is the duration of time, X_i is a vector of treatment and control variables, and β is a set of parameters to be estimated. It is worth noting that a key characteristic of the Cox model as seen in Equation

[10] It is worth noting that our model specification treats girls who are not married and are observed in the data before they turn 18 or 24 in a similar way to those observed at age 18 or 24 and are still not married.

(4.6) is that changes in covariates have a multiplicative shift on the hazard rate. This implies that the hazard rates for different values of covariates are proportional to each other through the baseline hazard function, $h_0(t)$. A direct consequence of this is that the hazard ratio is constant over time.[11]

In our more specific model of Equation (4.7), $h_i(t)$ is the hazard of marriage, t is the respective time periods between a girl's age at which she is first at risk of marriage and the age of marriage, and X_i is our vector of covariates that include our SPEI indicators for drought ($Drought_{idt}$ and $Drought_{idt-1}$) for girl i in district d at time period or age t and *t-1*;[12] a vector of individual controls X_{idt} such as religion and ethnicity;[13] birth-year fixed effects, λ_k, controlling for cohort differences in probability of experiencing hazard;[14] time (season) fixed effect, η_t, controlling for common trends in weather; and district fixed effects, μ_d, controlling for any unobserved drivers of marriage outcomes that may correlate with drought over space. Standard errors are clustered at the district level to account for spatial correlation in the error term.

Our main coefficients of interest, β_1 and β_2, measure the effect of droughts occurring in periods t and *t-1* on the probability of experiencing the hazard (child marriage). Identification of unbiased estimates and causal effects of droughts on marriage outcomes (β_1 and β_2) require droughts to be as good as randomly assigned, conditional on observables. The inclusion of control variables including birth-year fixed effects, district fixed effects, and time fixed effects in our model ensures that this assumption is met, such that our drought estimates are based solely on temporal random fluctuations in weather variables within each locale. Given that Kenya is a country heavily reliant on rainfed agriculture with a bride-price system in place, we expect droughts to have adverse effects on child marriage outcomes (increase in the probability of experiencing child marriage) via reductions in agricultural productivity and household income

[11]This can easily be tested using the Schoenfeld residuals (Schoenfeld, 1982), and consequently modified to include interactions between time duration (t) and key variables of interest.

[12]As a robustness check we also include additional lags up to period *t-3* in all regressions.

[13]We do not include other household controls like household size, education of the household head and so on as these variables are likely to change over time and thus could potentially be different when girls were at certain ages at time periods preceding the survey date. As a robustness check, however, we try alternative specifications including additional individual and household controls.

[14]We cannot include direct controls for age in the Cox proportional hazards model as it would be collinear with the hazard function.

especially if access to credit is constrained, i.e., we expect β_1 and β_2 in Equation (4.7) to be positive and significant (> 0; hazards ratios > 1).

4.5 Results

4.5.1 Effect of Droughts on the Timing of Marriage and Child Marriage

We present our first set of results showing the effect of droughts on the hazard of marriage in Table 4.2. Columns (1)-(2) present the results (odd ratios) from using a simple Logit model, while columns (3)-(6) present the results using our survival analysis model (cox model) presented in Equation (4.7). Consistent with the literature, our results, in general, show an adverse effect of extreme weather events (droughts) on marriage outcomes for young girls in Kenya. Starting with our simple Logit model, column (1), showing the results on the timing of marriage for young girls aged 10-24, shows that girls within this age group who experience a drought in period t are more likely to enter into marriage within that same year. Our results show an increased probability of 10% of entering into marriage in a given year for girls (aged 10-24) that experience a period t drought compared to their same aged counterparts who do not experience any drought. Column (1), also showing the results for our lagged drought variable, indicates no significant impact of period *t-1* drought on marriage outcomes for girls in this age-group, thus providing evidence for the lack of persistence of droughts on marriage outcomes for young girls in Kenya.

When we restrict our sample to children (ages 10-17), our results in column (2) show the coefficient on our drought variable to be larger, indicating a slightly bigger effect of droughts on the probability of experiencing marriage for this age range. More specifically, we find that young girls who are exposed to droughts in a given year t are more likely to enter into marriage, specifically child marriage by approximately 15%. This larger effect as seen for this age-group is consistent with the literature on early marriage that show that younger girls are seen to be more of an “asset” both to their families and potential suitors since they can be better controlled by their husbands, more likely to be virgins, and also more likely to be fertile. As a result, they are significantly more likely to be at risk of the hazard of early marriage as more substantial

Table 4.2: Effect of Droughts on the Timing of Marriage and on Child Marriage

	EV = Marriage	EV = Child Marriage	EV = Marriage	EV = Child Marriage	EV = Marriage	EV = Child Marriage
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Logit model)	(Logit Model)	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI Drought (t)	1.1035**	1.1536**	1.0866**	1.1342**	1.2586**	1.2185
	(0.0503)	(0.0676)	(0.0432)	(0.0600)	(0.1399)	(0.2622)
SPEI Drought (t-1)	1.0586	1.0557	1.0498	1.0530	1.3048**	1.3004
	(0.0482)	(0.0719)	(0.0413)	(0.0646)	(0.1547)	(0.2686)
SPEI Drought (t)*Time					0.9823	0.9888
					(0.0123)	(0.0324)
SPEI Drought (t-1)*Time					0.9746**	0.9680
					(0.0125)	(0.0301)
Religion: Muslim	1.3417***	1.3043*	1.2866***	1.2663*	1.2851***	1.2759*
	-0.1527	(0.1818)	(0.1256)	(0.1597)	(0.1251)	(0.1600)
Religion: Other	2.6806***	2.9502***	2.2581***	2.5274***	2.2586***	2.5292***
	(0.3402)	(0.3747)	(0.2313)	(0.2726)	(0.2309)	(0.2727)
Ethnicity: kalenjin	0.5976***	0.5895**	0.6353***	0.6167**	0.6370***	0.6164**
	(0.0964)	(0.1315)	(0.0897)	(0.1252)	(0.0898)	(0.1252)
Ethnicity: kamba	0.7918	0.5161***	0.8107	0.5362***	0.8119	0.5356***
	(0.1156)	(0.1196)	(0.1038)	(0.1158)	(0.1035)	(0.1158)
Ethnicity: kikuyu	0.6316***	0.4988***	0.6619***	0.5226***	0.6624***	0.5221***
	(0.0909)	(0.1082)	(0.0835)	(0.1040)	(0.0833)	(0.1040)
Ethnicity: kisii	0.7743	0.6067**	0.7960	0.6308**	0.7973	0.6299**
	(0.1251)	(0.1453)	(0.1125)	(0.1386)	(0.1123)	(0.1385)
Ethnicity: luhya	0.7674*	0.6899*	0.7882*	0.7082*	0.7887*	0.7084*
	(0.1109)	(0.1379)	(0.0995)	(0.1292)	(0.0993)	(0.1293)
Ethnicity: luo	1.0233	1.0417	1.0154	1.0359	1.0147	1.0366
	(0.1498)	(0.2048)	(0.1292)	(0.1851)	(0.1286)	(0.1853)
Ethnicity: Meru	0.6871**	0.7412	0.7120**	0.7550	0.7108**	0.7533
	(0.1259)	(0.2153)	(0.1161)	(0.2048)	(0.1157)	(0.2046)
Ethnicity: other	0.9922	0.9997	0.9862	0.9922	0.9872	0.9919
	(0.1367)	(0.1913)	(0.1178)	(0.1717)	(0.1176)	(0.1717)
Ethnicity: Somali	1.0130	1.2864	0.9880	1.2256	0.9877	1.2227
	(0.1833)	(0.3192)	(0.1556)	(0.2701)	(0.1553)	(0.2698)
Observations	158,099	131,532	158,099	131,532	158,099	131,532
chi2	90177	78864	90199	91864	85811	123121

Note: "EV" represents Event Variable. All models include additional controls for time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Logit models (1) and (2) also include additional controls for *t*. It is worth mentioning that the control variables; religion and ethnicity are likely to be correlated with each other as religions like Islam/Muslim are particularly dominant among some tribes such as the Somalis. However, the inclusion of the religion and ethnicity variables in the regression are important to control for cultural and religious differences that might affect key variables of interests. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p $<$ 0.10 **p $<$ 0.05 ***p $<$ 0.01.

sums (bride-price) are paid on their behalf (Papps et al., 1983; The Guardian, 2009). With regards to the lagged effect of droughts on child marriage, our results, as indicated in column (2), again provide no evidence for the persistence of droughts on child marriage outcomes.

We next move to our main model (Cox proportional hazards model), which unlike the standard Logit model adjusts for time to event t in the hazard function and accounts for censoring in the dataset. Columns (3)-(4) provide the results for the Cox model including all relevant covariates as explained in section 4.4, while columns (5)-(6) provide the results for an extension of the Cox model introducing interactions between our drought variables and time (a variable measuring the number of years since first being at risk of the hazard of marriage). In general, we find that although the results from our Cox model as indicated in Table 4.2 show similar and significant effects to our Logit model for our drought variables, the coefficients are less inflated. Column (3), showing the effect of droughts on the hazard of marriage, shows that young girls who experience a drought in period t have shorter survival times and are more likely to experience the marriage hazard at time t by approximately 9%. The Column (3) also shows no significant effect on the lagged drought variable, indicating no effect of period t-1 drought on survival times. When we restrict our sample to ages 10-17 (examining the hazard of child marriage), our result, as indicated in column (4), show only a significant effect on period t drought, signifying an increase in the hazard rate of 13% at time t for a period t drought. Again, similar to our Logit model, our Cox model provides evidence for a more pronounced effect for this restricted sample of younger group of girls.

It may be unrealistic to assume that the effect of droughts on the marriage hazard is constant with time. To this effect, we incorporate in models (5) and (6) drought-time interactions. We find the coefficients on the interaction terms to be significant only in the wider time duration model (model 5) and on the lagged drought variable, indicating that within the age range of 10 to 24, the adverse effect of droughts on the hazard of marriage diminishes with time. In other words, as girls become older and their time since first being at risk of marriage increases, they are shielded and are less likely to enter into marriage as a result of a drought. Our results show an additional effect of -3% of droughts on the hazard of marriage.

Overall, our results are similar to the findings of Beegle and Krutikova (2008), Villar (2021), and Corno et al. (2020) who show that young girls exposed to adverse shocks such as droughts or the death of a household member have much higher tendencies (2%-38%) of entering into early marriages. When we compare the magnitude of our drought coefficients to other individual characteristics such as religious background controlled for in our model, we find that although droughts have noticeable and significant impacts, the effects are less substantial to that of religion on marriage outcomes. In fact, our findings show the impacts of religious beliefs to almost double that of droughts on child marriage, with muslim girls seen to be about 26-34% more likely to enter into early marriage than their christian counterparts. Nevertheless, the effect of extreme weather events (droughts) on household and child welfare is critical, and as such girls from households, particularly those living in drought prone regions, must be shielded from any adverse impacts that droughts may have on welfare.

4.5.2 Effect of Droughts on Child Fertility Outcomes

One dramatic consequence of early marriage is early fertility. As young girls are driven into early marriage due to household shocks, they are also highly likely to experience early fertility (Singh and Revollo, 2016; Corno et al., 2020). Moreover, research has shown that children serve as a bolster to household economic activities which when combined with the lowered opportunity costs of having children acts as an incentive for increased fertility outcomes in times of economic distress (Cain, 1981; Davis, 2017). Tables 4.3 and 4.4 provide the results for the effect of droughts on the timing of fertility for our overall sample and for separate samples of married and unmarried young girls.

Beginning with Table 4.3, columns (3)-(6), showing the results from the Cox model, generally provide evidence for an increase in probability of experiencing hazard (fertility) as a result of droughts. We find that for girls ages 10-24, whilst experiencing a drought at time period or age t has no significant impact on the probability of first birth within that same time period, experiencing a drought in the previous period increases the probability of hazard (first birth) in the following period by approximately 13.8%. When we restrict our sample to girls ages 10-17 (child fertility), our findings show a slightly larger effect of droughts. Column (4) of Table 4.3 shows that while the effect of period t drought on child fertility in period t is marginally significant at the 10% significance level (8% increase), the effect of a drought happening in the previous period has a strong and significant impact on fertility at time or age

Table 4.3: Effects of Droughts on the Timing of Fertility and on Child Fertility

	EV = Fertility	EV = Child Fertility	EV = Fertility	EV = Child Fertility	EV = Fertility	EV = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Logit model)	(Logit Model)	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI Drought (t)	1.0670	1.0964	1.0579	1.0854*	1.1850	0.9024
	(0.0486)	(0.0661)	(0.0415)	(0.0590)	(0.1399)	(0.2288)
SPEI Drought (t-1)	1.1629***	1.1940***	1.1381***	1.1748***	1.1303	1.0079
	(0.0503)	(0.0666)	(0.0422)	(0.0593)	(0.1315)	(0.2441)
SPEI Drought (t)*Time					0.9869	1.0278
					(0.0129)	(0.0376)
SPEI Drought (t-1)*Time					1.0008	1.0230
					(0.0127)	(0.0360)
Religion: Muslim	1.0982	0.9955	1.0832	0.9948	1.0832	0.9954
	(0.1110)	(0.1350)	(0.0936)	(0.1223)	(0.0935)	(0.1221)
Religion: Other	2.3063***	2.5791***	1.9792***	2.2471***	1.9789***	2.2462***
	(0.2716)	(0.3558)	(0.1862)	(0.2623)	(0.1863)	(0.2624)
Ethnicity: kalenjin	0.8897	0.6121**	0.9063	0.6412**	0.9061	0.6413**
	(0.1341)	(0.1250)	(0.1180)	(0.1191)	(0.1179)	(0.1191)
Ethnicity: kamba	0.9330	0.4660***	0.9399	0.4928***	0.9395	0.4934***
	(0.1265)	(0.0958)	(0.1104)	(0.0943)	(0.1104)	(0.0944)
Ethnicity: kikuyu	0.7984	0.5042***	0.8189*	0.5337***	0.8185*	0.5342***
	(0.1116)	(0.0970)	(0.0994)	(0.0942)	(0.0994)	(0.0944)
Ethnicity: kisii	0.8639	0.6559*	0.8850	0.6867*	0.8851	0.6874*
	(0.1551)	(0.1539)	(0.1374)	(0.1471)	(0.1374)	(0.1474)
Ethnicity: luhya	1.1475	0.7364	1.1275	0.7587	1.1269	0.7591
	(0.1729)	(0.1453)	(0.1468)	(0.1371)	(0.1468)	(0.1372)
Ethnicity: luo	1.3038*	0.9927	1.2608*	0.9937	1.2599*	0.9930
	(0.1898)	(0.1827)	(0.1584)	(0.1671)	(0.1582)	(0.1672)
Ethnicity: Meru	0.7668	0.4828***	0.7930	0.5114***	0.7924	0.5126***
	(0.1304)	(0.1267)	(0.1181)	(0.1252)	(0.1181)	(0.1254)
Ethnicity: other	1.1852	0.7750	1.1574	0.7951	1.1569	0.7949
	(0.1600)	(0.1336)	(0.1348)	(0.1251)	(0.1348)	(0.1251)
Ethnicity: Somali	0.9169	0.7008	0.9206	0.7276	0.9200	0.7283
	(0.1720)	(0.2070)	(0.1499)	(0.1964)	(0.1498)	(0.1969)
Observations	158,941	132,842	158,941	132,842	158,941	132,842
chi2	162939	753301	155399	2.970e+06	97127	4.033e+06

Note: "EV" represents Event Variable. All models include additional controls for time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Logit models (1) and (2) also include additional controls for *t*. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p $<$ 0.10 **p $<$ 0.05 ***p $<$ 0.01.

Table 4.4: Effects of Droughts on the Timing of Fertility and on Child Fertility for Married and Unmarried Young Girls

	Married						Unmaried	
	EV = Fertility	EV = Child Fertility	EV = Fertility	EV = Child Fertility	EV = Fertility	EV = Child Fertility	EV = Fertility	EV = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI Drought (t)	0.9949	1.0003	0.9742	1.0402	0.9958	1.0100	1.1384*	1.1413
	(0.0464)	(0.0668)	(0.0449)	(0.0681)	(0.0412)	(0.0569)	(0.0740)	(0.0986)
SPEI Drought (t-1)	1.1259***	1.1520**	1.0977**	1.2023**	1.0696**	1.0933**	1.1116	1.1508*
	(0.0468)	(0.0771)	(0.0454)	(0.0862)	(0.0378)	(0.0596)	(0.0755)	(0.0976)
Religion: Muslim	0.9821	0.9212	0.8591	0.8832	0.8750	0.8468	0.9324	0.9205
	(0.0790)	(0.1171)	(0.0939)	(0.1215)	(0.0723)	(0.0881)	(0.1871)	(0.2162)
Religion: Other	1.3546***	1.5100***	0.9011	0.8794	0.9489	0.9350	2.7833***	3.6379***
	(0.1277)	(0.1958)	(0.1689)	(0.1810)	(0.0763)	(0.1034)	(0.6727)	(0.9392)
Ethnicity: kalenjin	0.8613	0.5076***	0.9326	0.6319*	1.0191	0.7223*	1.2496	0.9073
	(0.1268)	(0.1201)	(0.1540)	(0.1519)	(0.1248)	(0.1287)	(0.3330)	(0.2913)
Ethnicity: kamba	0.6911***	0.3718***	0.8490	0.6279**	1.0143	0.9946	1.5310*	0.7252
	(0.0932)	(0.0930)	(0.1257)	(0.1472)	(0.1318)	(0.2253)	(0.3764)	(0.2326)
Ethnicity: kikuyu	0.7928*	0.5133***	0.9323	0.6814*	1.0197	0.7856	0.9881	0.6536
	(0.1107)	(0.1232)	(0.1344)	(0.1495)	(0.1198)	(0.1378)	(0.2604)	(0.2115)
Ethnicity: kisii	0.7055**	0.5186**	0.7627	0.7177	0.8253	0.7868	1.3530	1.0248
	(0.1230)	(0.1468)	(0.1395)	(0.1862)	(0.1208)	(0.1750)	(0.3992)	(0.3628)
Ethnicity: luhya	0.9212	0.5226***	1.0998	0.7530	1.1271	0.8112	1.6846*	1.1612
	(0.1321)	(0.1164)	(0.1629)	(0.1567)	(0.1343)	(0.1364)	(0.4517)	(0.3741)
Ethnicity: luo	0.9508	0.6896	0.9506	0.8249	0.9677	0.8515	2.0023***	1.5886
	(0.1349)	(0.1577)	(0.1435)	(0.1729)	(0.1153)	(0.1441)	(0.5243)	(0.4723)
Ethnicity: Meru	0.7887	0.5312**	0.8991	0.8177	1.0065	0.8622	0.8221	0.5140*
	(0.1428)	(0.1690)	(0.1592)	(0.2760)	(0.1704)	(0.3011)	(0.2444)	(0.1978)
Ethnicity: other	0.9680	0.6839*	0.9330	0.6451**	1.0096	0.7759	1.4231	0.8698
	(0.1231)	(0.1334)	(0.1282)	(0.1215)	(0.1121)	(0.1210)	(0.3705)	(0.2706)
Ethnicity: Somali	0.9142	0.8270	0.7509	0.6992	1.1003	1.0879	0.1862***	0.1244***
	(0.1804)	(0.2457)	(0.1893)	(0.2330)	(0.1685)	(0.2480)	(0.0924)	(0.0641)
Observations	55,779	45,081	55,779	45,081	12,851	6,085	103,162	87,761
chi2	7.692e+06	349021	4.660e+08	5.992e+06	29840	21358	63717	175851

Note: "EV" represents Event Variable. Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Models (3) & (4) for the married sample controls for an additional time since marriage control variable, whilst models (5) & (6) re-adjust the time dimension in our cox model which captures the time since being first at risk of fertility to time since being married. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

t. Our findings show an increase in the probability of experiencing the hazard of fertility at time *t* of 17.4% for droughts occurring in the previous period. In terms of our models with interactions (columns (5) and (6)), we find the coefficients on the interaction terms to be insignificant, suggesting that unlike that of marriage outcomes showing younger girls to be more at risk, the adverse effect of droughts on the hazard of fertility do not significantly vary with age in our sample.

When we split our sample into married and unmarried sub-samples, the results as presented in Table 4.4, indicate strong and significant impacts of droughts on fertility only for the married sample. Columns (1)-(2) of 4.4 presents the default results for the married sample with *t* in the Cox model indicated as the time since first being at risk of fertility, columns (3)-(4) includes additional controls in the married sample for time since marriage, and columns (5)-(6) re-adjusts the time dimension in our Cox model from time since first being at risk of fertility to time since being married. In general, our findings are consistent across models, where we find that young girls ages 10-24 who are married and experience a drought at time period *t-1* have a much higher probability of experiencing the fertility hazard in the following period of approximately 12%, compared to girls who are married but do not experience any drought. With respect to child fertility, slightly bigger effects are found in Table 4.4 for the married sample, with a previous period (*t-1*) drought increasing the probability of child fertility in the following period *t* by approximately 15%.

With regards to our unmarried sample of young girls, our findings as indicated in columns (7)-(8) generally show mild effects of droughts, with marginally significant coefficients on periods *t* and *t-1* drought variables. The results show an increase of 13% in the probability of first birth in a given year *t*, following a drought in the same year for the age group 10-24, whilst for the hazard of child fertility, we find a marginally significant effect (15% increase) in probability of first birth in period *t* for a drought occurring in the previous period. In general, our finding indicates that indeed marriage outcomes and fertility go hand in hand for young girls, particularly during periods of economic distress in Kenya, and while the effect on marriage is almost immediate, the fertility consequences tend to occur after a few months following the shock.

4.5.3 Heterogeneous Effects

We next examine the existence of heterogeneity in the impact of droughts on marriage and fertility. Heterogeneous effects of droughts (if any) are of grave interest and importance as they are often useful in revealing (i) the groups that are most vulnerable to adverse shocks, and (ii) the kinds of ex-ante and ex-post coping strategies that can be employed by households to enhance their resilience and help mitigate negative impacts of adverse shocks. We check for heterogeneity in the impact of droughts on marriage and fertility outcomes by the household characteristic, area of residence.[15] Tables 4.5 provides the results from the Cox model including interaction terms between our drought variables and the area of residence for households. In general, our results provide evidence for heterogeneity in terms of the household's area of residence. Table 4.5, presenting the results, shows that girls living in the rural regions of Kenya are generally more at risk of entering marriage as a result of a drought. We find an additional effect of 16-22% for girls living in rural areas compared to girls in urban areas. This effect, though, is only strongly significant for our model with a wider age interval (column (1)). In terms of fertility (column (3)-(4)), our results show insignificant interaction effects, indicating no disparities by region in the effect of droughts on fertility outcomes.

Overall, our findings show that shocks to households such as droughts acts as an incentive for households to push their daughters into early marriages, and this adverse effect is exacerbated for households living in rural areas with potentially low levels of income. This finding corroborates the results of Singh and Vennam (2016), Rumble et al. (2018) and Asna-ashary et al. (2020) that show that indeed poverty is the most common denominator driving child marriage rates, and poorer households or households living in rural areas with poorer housing conditions have much higher tendencies (19-45% probability) of pushing their children into early marriages.

4.5.4 Robustness Checks

To check the robustness of our findings, we present results from estimating various alternate

[15] We focus only on this household characteristic in our model of heterogeneity given that it is less likely to change over time due to marriage as the literature on marriage migration in sub-Saharan Africa (Mbaye and Wagner, 2017; Corno et al., 2020) show that the majority of women marry within their community and do not migrate at the time of marriage.

Table 4.5: Heterogeneous Effect by Household Area of Residence

	Event Variable = Marriage	Event Variable = Child Marriage	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	0.9753	0.9811	1.1080*	1.1287
	(0.0636)	(0.0938)	(0.0690)	(0.1058)
SPEI Drought (t-1)	0.9968	1.1919	1.1513**	1.0827
	(0.0633)	(0.1313)	(0.0737)	(0.0992)
Rural Area	1.2022	1.3737	0.8172	0.7134
	(0.3596)	(0.5850)	(0.2045)	(0.3111)
SPEI Drought (t)*Rural Area	1.1686**	1.2262*	0.9360	0.9436
	(0.0839)	(0.1303)	(0.0619)	(0.0951)
SPEI Drought (t-1)*Rural Area	1.0754	0.8397	0.9858	1.1188
	(0.0731)	(0.0964)	(0.0659)	(0.1112)
Religion: Muslim	1.2909***	1.2824**	1.0809	0.9913
	(0.1263)	(0.1608)	(0.0936)	(0.1218)
Religion: Other	2.2646***	2.5312***	1.9783***	2.2496***
	(0.2326)	(0.2733)	(0.1863)	(0.2628)
Ethnicity: kalenjin	0.6325***	0.6106**	0.9092	0.6443**
	(0.0890)	(0.1247)	(0.1182)	(0.1188)
Ethnicity: kamba	0.8080*	0.5325***	0.9430	0.4947***
	(0.1032)	(0.1162)	(0.1105)	(0.0941)
Ethnicity: kikuyu	0.6591***	0.5195***	0.8211	0.5353***
	(0.0827)	(0.1039)	(0.0995)	(0.0938)
Ethnicity: kisii	0.7897*	0.6221**	0.8901	0.6927*
	(0.1114)	(0.1384)	(0.1380)	(0.1471)
Ethnicity: luhya	0.7826*	0.6992*	1.1331	0.7649
	(0.0985)	(0.1290)	(0.1473)	(0.1370)
Ethnicity: luo	1.0070	1.0226	1.2667*	0.9993
	(0.1278)	(0.1854)	(0.1587)	(0.1660)
Ethnicity: Meru	0.7037**	0.7475	0.7961	0.5151***
	(0.1147)	(0.2039)	(0.1183)	(0.1255)
Ethnicity: other	0.9797	0.9822	1.1617	0.7987
	(0.1165)	(0.1718)	(0.1351)	(0.1244)
Ethnicity: Somali	0.9788	1.2118	0.9262	0.7334
	(0.1541)	(0.2691)	(0.1505)	(0.1968)
Observations	158,111	131,537	158,941	132,842
chi2	50668***	58253***	150022***	2.167e+06***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

specifications in Appendix 4.B. First, we include additional controls such as additional household characteristics in all our models, as mentioned in section 4.4. Although, these controls are measured at the time of the survey, they are likely to give a fair indication of the general living conditions and household status as at the various times young girls were at risk of the marriage and fertility hazard. We present the results for this specification in Appendix 4.B. Tables 4.B.1, 4.B.2 and 4.B.3 of Appendix 4.B generally show our findings to be robust to the inclusion of these additional controls, with similar results to our main specification that show that young girls have a higher probability of entering into marriage and experiencing fertility when hit by a drought. Tables 4.B.1-4.B.3 show increases of about 7-16% in the probability of experiencing the marriage and fertility hazards as a result of a drought.

Second, we introduce additional drought lag variables (Drought (*t-2*) and Drought (*t-3*)) in all our regressions, to test whether the persistent effects of droughts go beyond one period. The findings presented in Tables 4.C.1, 4.C.2 and 4.C.3 of Appendix 4.C generally show significant coefficients on our Drought (*t*) and Drought (*t-1*) variables, but insignificant coefficients on the other lag variables, thereby suggesting no evidence for an extended duration of drought on marriage or fertility outcomes.

Third, we modify our drought variables and use different cut-offs for our SPEI drought indicator. Our SPEI drought variables are reconstructed to take a value of 1 if the SPEI value linked to the main Kenyan planting season for a given year is less than -0.8, and 0 otherwise. We also use additional SPEI cut-offs of -1 and -2. The results, presented in Appendix 4.D, are all robust to these specifications, where we find similar results to our main specification, with young girls generally more likely to experience the marriage and fertility hazard as a result of a drought.

Finally, we randomise our drought variable across communities and years in our data, implementing a Fisher type randomisation test for our significant drought variables in our model (models (3)-(4) of Tables 4.2 and 4.3). This allows us to compute the probability of observing significant estimates within the randomly assigned drought data. The k-density plots showing the estimated t-statistics for droughts (*t*) and (*t-1*) for our marriage and fertility outcomes are presented in Appendix 4.E. From the diagrams (1)-(4), we see that the majority of test-statistics are close to zero, suggesting that the initial estimated test-statistic of drought indicated by the red vertical line is unlikely to be random. In fact, the p-value computing the proportion of datasets in which the test statistic values are as extreme or more extreme than the value of the test statistic computed on the original sample range from 0.001-0.019 for our marriage and fertility outcomes.

4.6 Conclusion

Extreme weather events plays a significant role in shaping the welfare of children and has therefore become an increasing focus in recent times. In this paper, we examine the impacts that extreme weather events, specifically droughts have on child marriage and fertility outcomes of young girls in a sub-Saharan African country, Kenya, where access to credit is limited and the common cultural practice of the bride pride system is ingrained. Using a pooled survey of cross-sectional data together with weather data, our study employs the Cox proportional hazards model in analysing the role that droughts have in pushing vulnerable young girls into early marriages and fertility.

Our results, in general, provide evidence for the adverse effects of droughts on early marriage and fertility outcomes. More specifically, we find that young girls between the ages of 10-24 from households exposed to a drought at time period t are more likely to enter into marriage within that same year by approximately 9%. For the age-interval of 10-17 (child marriage), we find that a drought occurring at time period t increases the likelihood of experiencing hazard by 13%, indicating a much higher probability of entering into the hazard of marriage. Our results also show that these young girls are also likely to experience increases in fertility outcomes, particularly for the married sub-sample, as a result of a drought, with increases in the probability of first birth within the same period and also the following period of approximately 9-17%. In terms of heterogeneity, we find that girls living in rural households with potentially lower levels of income are more susceptible to the adverse impacts of droughts on marriage and fertility outcomes.

Overall, our findings indicate that shocks to households indeed act as a key barrier to the welfare and development of young girls as they are seen as "assets" to their households and are pushed into early marriages in times of economic distress. This finding has significant policy implications in terms of creating pathways to ensure that households, particularly rural households have the necessary financial support system that would prevent them from resorting to child marriage as the only means of survival. Additionally, given that researchers and climate scientists have predicted a higher frequency and intensity of weather disasters including droughts in the coming years (IPCC, 2021), and given the large consequences of climate disasters on welfare that is projected to be much more significant in the future, our findings call for policy makers particularly in disaster (drought) prone regions to design and implement more pragmatic policies that will assist small-scale farmers in adapting to changing climate conditions. These include employing early risk detectors warning systems, planting more drought-resistant crops, and implementing more efficient agricultural management practices that could help shield these farmers and their households from variability in income and consumption.

Appendix

4.A Weather Data

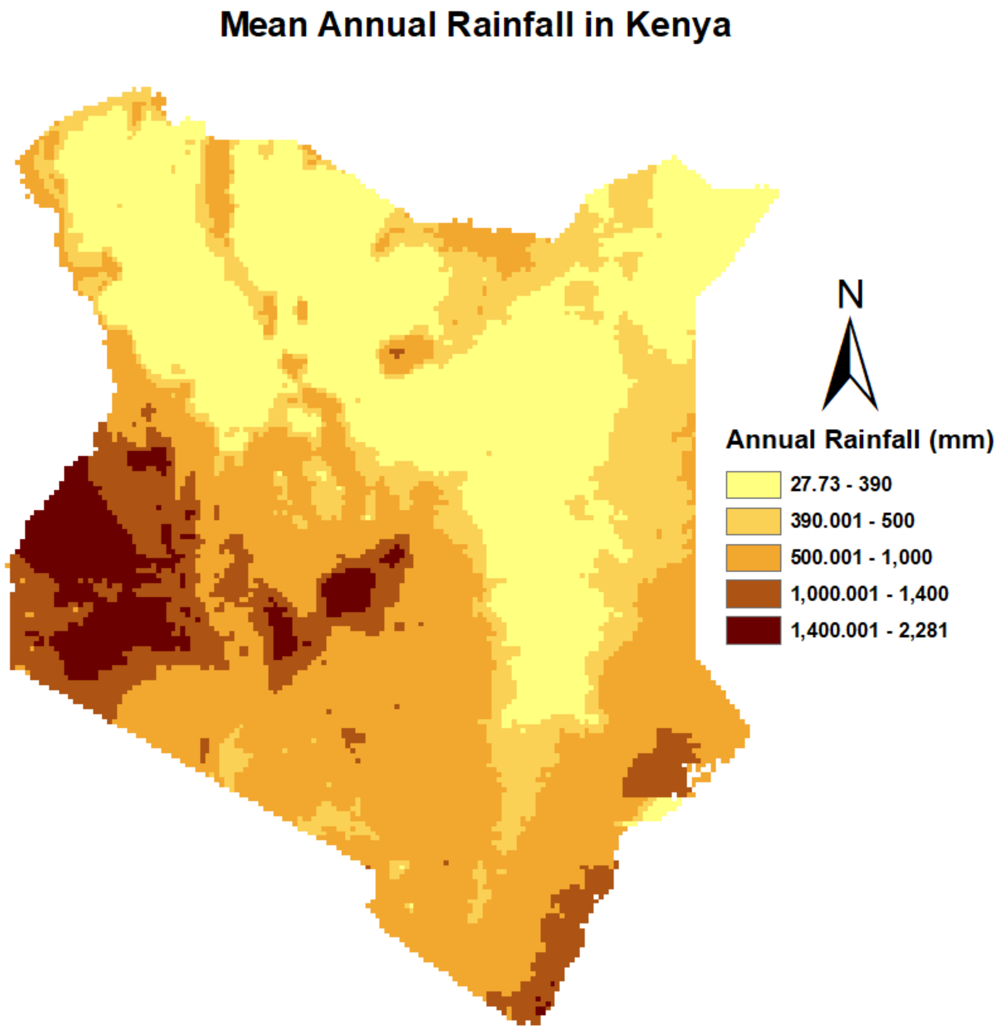

Figure 4.A.1: Spatial Variation in Mean Annual Rainfall for Periods 1981-2017 in Kenya.

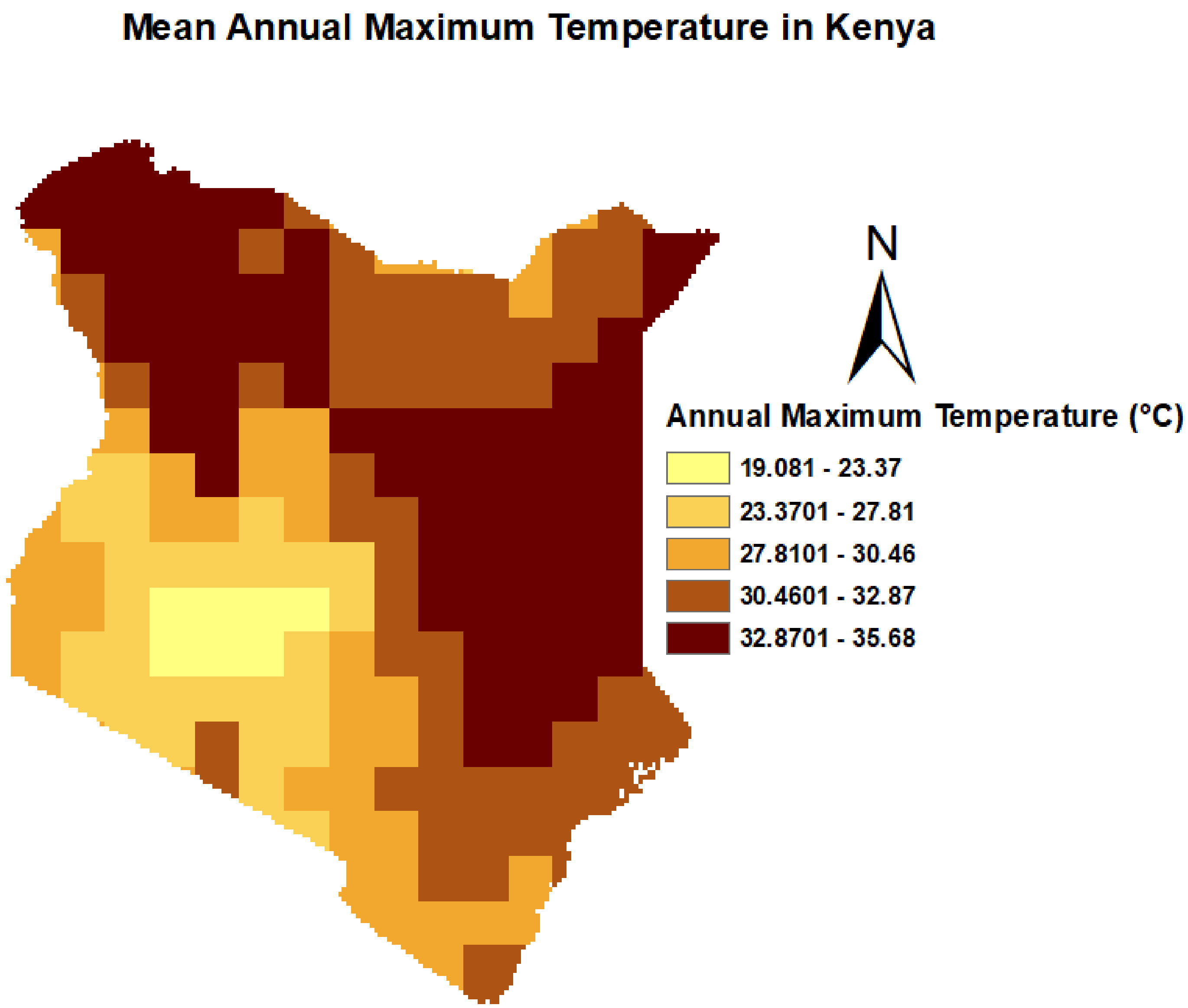

Figure 4.A.2: Spatial Variation in Mean Annual Maximum Temperature for Periods 1981-2017 in Kenya.

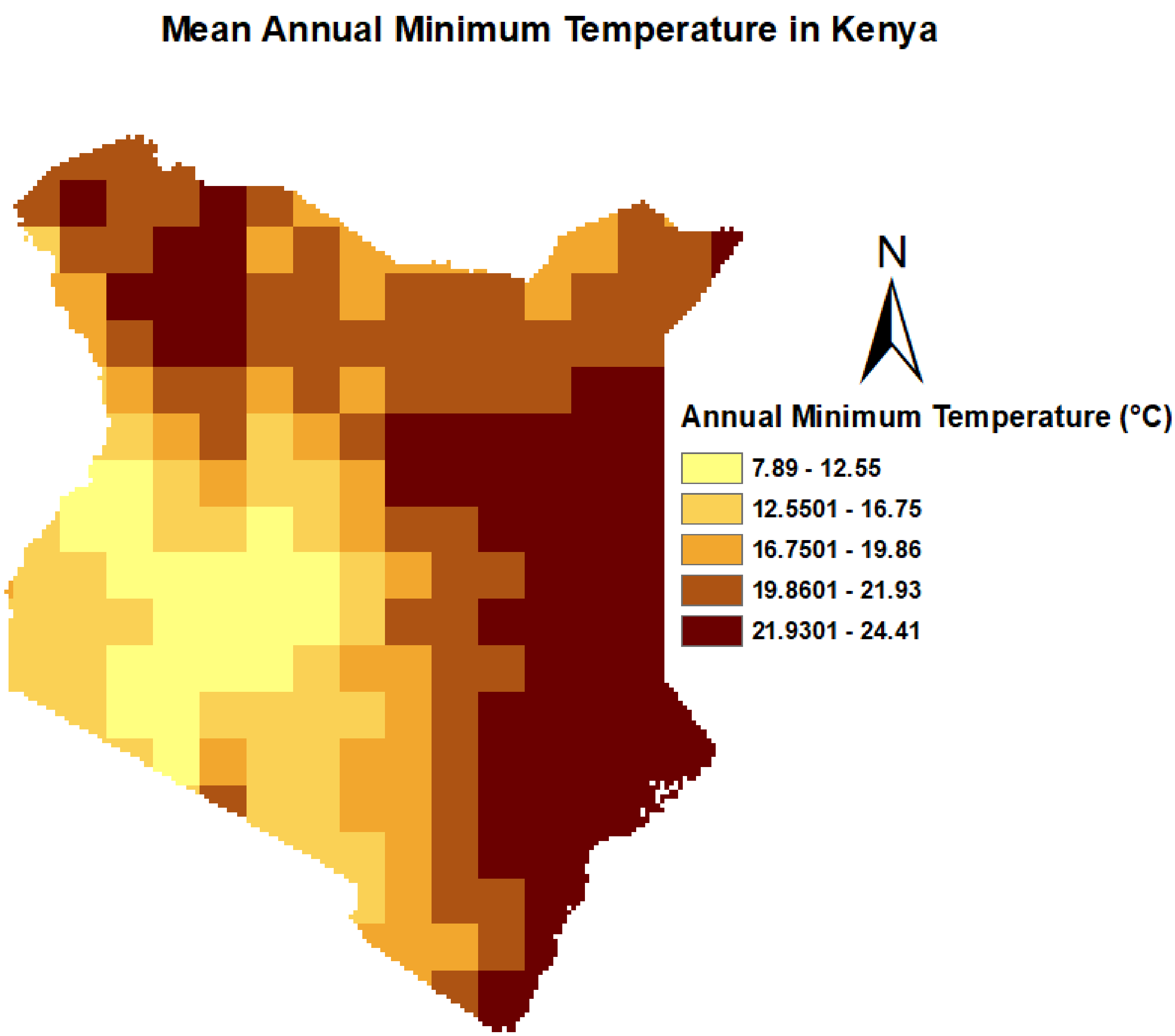

Figure 4.A.3: Spatial Variation in Mean Annual Minimum Temperature for Periods 1981-2017 in Kenya.

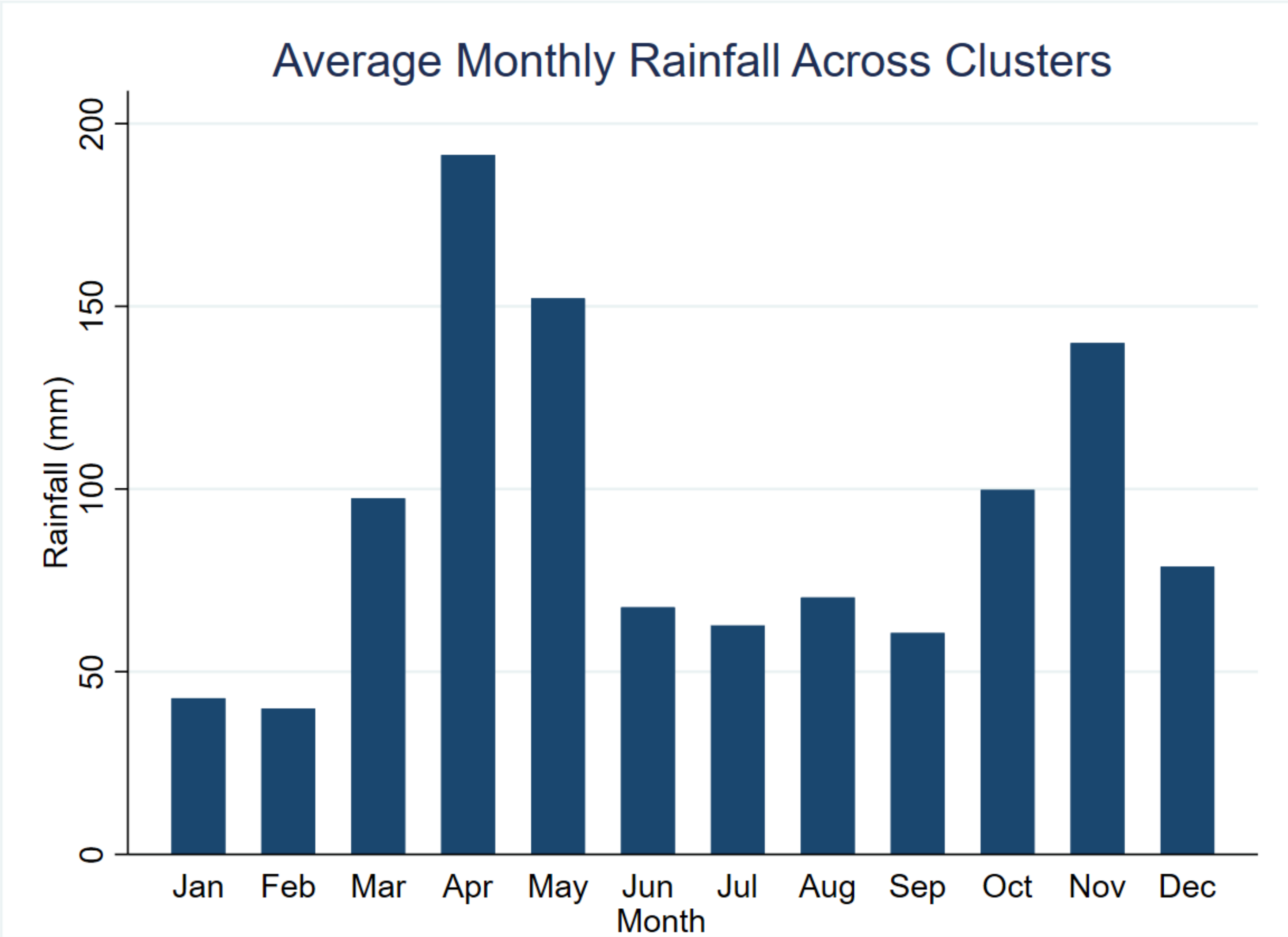

Figure 4.A.4: Graph Showing the Mean Monthly Rainfall across all Kenyan DHS Clusters for Time Periods 1981-2017.

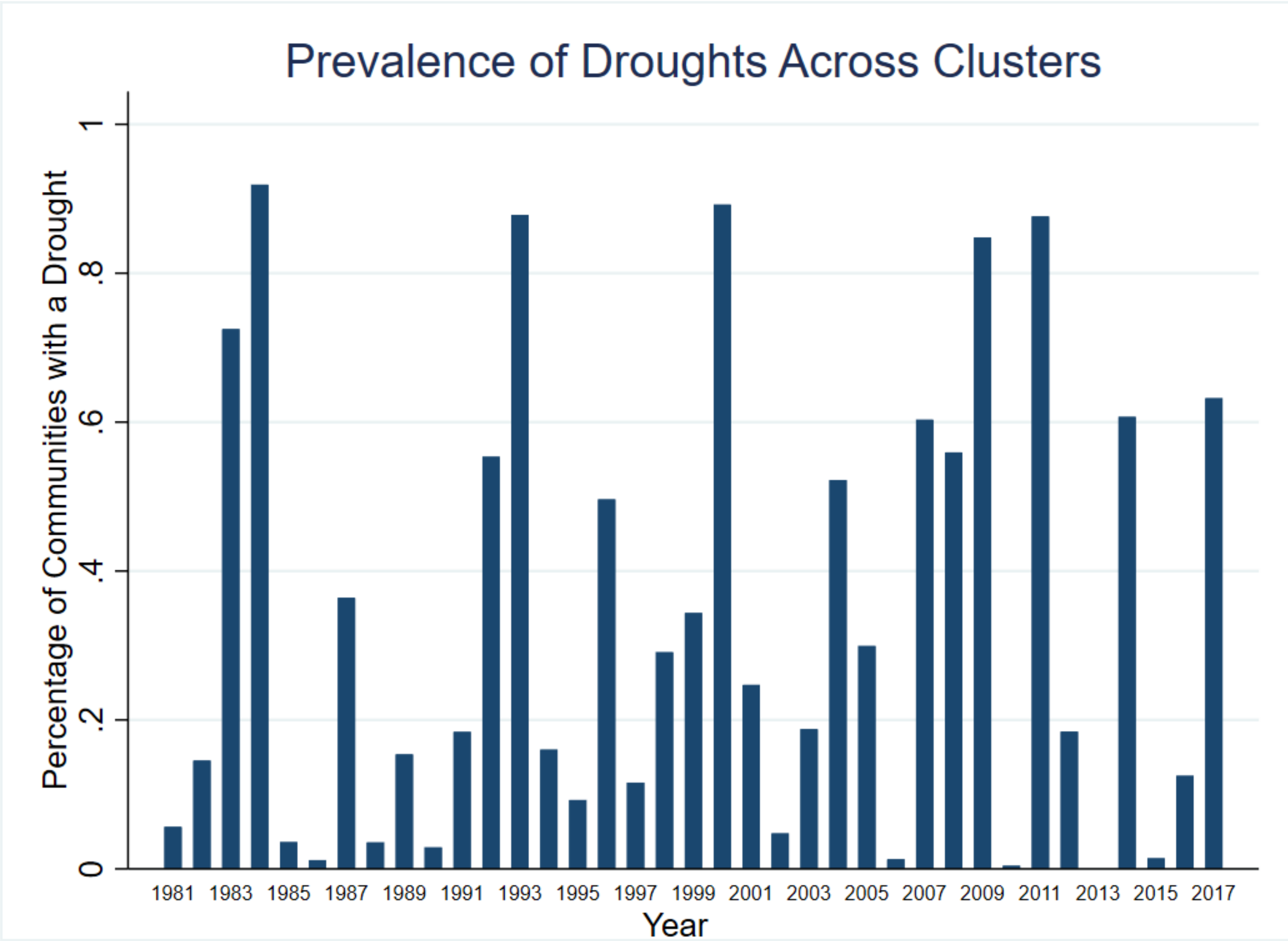

Figure 4.A.5: Graph Showing the Prevalence of Droughts Across DHS Clusters from 1981-2017

4.B Regression Results Showing All Additional Controls

Table 4.B.1: Effects of Droughts on the Timing of Marriage and on Child Marriage

	Event Variable = Marriage	Event Variable = Child Marriage	Event Variable = Marriage	Event Variable = Child Marriage
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0741**	1.1309**	1.2154*	1.2309
	(0.0411)	(0.0598)	(0.1366)	(0.2654)
SPEI Drought (t-1)	1.0384	1.0541	1.3012**	1.3361
	(0.0397)	(0.0646)	(0.1512)	(0.2762)
SPEI Drought (t)*Time			0.9850	0.9868
			(0.0124)	(0.0322)
SPEI Drought (t-1)*Time			0.9737**	0.9642
			(0.0121)	(0.0300)
Gender of HH	0.3643***	0.4442***	0.3644***	0.4443***
	(0.0162)	(0.0244)	(0.0162)	(0.0244)
Educational Level of HH (in Years)	0.9334***	0.9098***	0.9335***	0.9098***
	(0.0049)	(0.0067)	(0.0049)	(0.0067)
Age of HH	0.9162***	0.9107***	0.9163***	0.9107***
	(0.0047)	(0.0058)	(0.0047)	(0.0058)
Age-squared of HH	1.0007***	1.0008***	1.0007***	1.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Wealth Index	0.7343***	0.7537***	0.7337***	0.7539***
	(0.0247)	(0.0376)	(0.0245)	(0.0376)
HH Size	0.9839*	1.0236**	0.9840*	1.0236**
	(0.0090)	(0.0113)	(0.0090)	(0.0113)
Religion: Muslim	1.3256***	1.2454*	1.3236***	1.2466*
	(0.1251)	(0.1625)	(0.1245)	(0.1631)
Religion: Other	1.5484***	1.6494***	1.5487***	1.6508***
	(0.1512)	(0.1916)	(0.1513)	(0.1919)
Ethnicity: kalenjin	0.8483	0.8607	0.8513	0.8593
	(0.1039)	(0.1733)	(0.1041)	(0.1730)
Ethnicity: kamba	0.9331	0.6995	0.9359	0.6979
	(0.1041)	(0.1560)	(0.1039)	(0.1558)
Ethnicity: kikuyu	1.0366	0.8419	1.0386	0.8404
	(0.1192)	(0.1776)	(0.1191)	(0.1773)
Ethnicity: kisii	1.0309	0.9500	1.0331	0.9486
	(0.1265)	(0.2141)	(0.1265)	(0.2137)
Ethnicity: luhya	0.9484	0.8971	0.9504	0.8966
	(0.1025)	(0.1661)	(0.1024)	(0.1661)
Ethnicity: luo	1.3238**	1.4760**	1.3248**	1.4758**
	(0.1482)	(0.2838)	(0.1477)	(0.2836)
Ethnicity: Meru	0.8633	1.0398	0.8633	1.0360
	(0.1213)	(0.2684)	(0.1211)	(0.2675)
Ethnicity: other	1.0298	1.0319	1.0326	1.0304
	(0.1159)	(0.1813)	(0.1157)	(0.1811)
Ethnicity: Somali	1.0429	1.2239	1.0442	1.2163
	(0.1564)	(0.3031)	(0.1560)	(0.3013)
Observations	157,224	130,825	157,224	130,825
chi2	54961***	215785***	46658***	164156***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p $<$ 0.10 **p $<$ 0.05 ***p $<$ 0.01.

Table 4.B.2: Effects of Droughts on the Timing of Fertility and on Child Fertility

	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0471	1.0867	1.1534	0.9045
	(0.0401)	(0.0589)	(0.1367)	(0.2301)
SPEI Drought (t-1)	1.1303***	1.1680***	1.1330	1.0618
	(0.0417)	(0.0583)	(0.1318)	(0.2526)
SPEI Drought (t)*Time			0.9888	1.0275
			(0.0129)	(0.0376)
SPEI Drought (t-1)*Time			0.9997	1.0143
			(0.0126)	(0.0349)
Gender of HH	0.6471***	0.7138***	0.6472***	0.7137***
	(0.0229)	(0.0373)	(0.0230)	(0.0373)
Educational Level of HH (in Years)	0.9450***	0.9338***	0.9450***	0.9338***
	(0.0046)	(0.0066)	(0.0046)	(0.0066)
Age of HH	0.9305***	0.9250***	0.9305***	0.9250***
	(0.0043)	(0.0057)	(0.0043)	(0.0057)
Age-squared of HH	1.0006***	1.0007***	1.0006***	1.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Wealth Index	0.7498***	0.8073***	0.7497***	0.8075***
	(0.0245)	(0.0367)	(0.0244)	(0.0367)
HH Size	1.0597***	1.0560***	1.0598***	1.0560***
	(0.0085)	(0.0114)	(0.0085)	(0.0114)
Religion: Muslim	1.1140	0.9641	1.1140	0.9641
	(0.0927)	(0.1199)	(0.0926)	(0.1198)
Religion: Other	1.4028***	1.6555***	1.4023***	1.6547***
	(0.1540)	(0.2036)	(0.1542)	(0.2035)
Ethnicity: kalenjin	1.1838	0.8236	1.1835	0.8243
	(0.1456)	(0.1542)	(0.1456)	(0.1544)
Ethnicity: kamba	1.1253	0.6002**	1.1251	0.6013**
	(0.1215)	(0.1203)	(0.1215)	(0.1206)
Ethnicity: kikuyu	1.2152*	0.7743	1.2148*	0.7754
	(0.1345)	(0.1383)	(0.1345)	(0.1386)
Ethnicity: kisii	1.2460	0.9810	1.2460	0.9823
	(0.1827)	(0.2063)	(0.1826)	(0.2067)
Ethnicity: luhya	1.3926***	0.9512	1.3919***	0.9525
	(0.1611)	(0.1680)	(0.1611)	(0.1681)
Ethnicity: luo	1.7018***	1.3352*	1.7004***	1.3358*
	(0.1918)	(0.2201)	(0.1916)	(0.2204)
Ethnicity: Meru	1.0090	0.6620*	1.0083	0.6634*
	(0.1424)	(0.1559)	(0.1423)	(0.1562)
Ethnicity: other	1.2380**	0.8097	1.2378**	0.8102
	(0.1344)	(0.1283)	(0.1343)	(0.1284)
Ethnicity: Somali	0.8974	0.7081	0.8971	0.7095
	(0.1393)	(0.2117)	(0.1392)	(0.2124)
Observations	158,073	132,133	158,073	132,133
chi2	335863***	744714***	304485***	893090***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.B.3: Effects of Droughts on the Timing of Fertility and on Child Fertility for Married and Unmarried Young Girls

	Married		Unmmaried	
	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	0.9882	0.9907	1.1199*	1.1320
	(0.0457)	(0.0659)	(0.0713)	(0.0975)
SPEI Drought (t-1)	1.1163***	1.1244**	1.1000	1.1531*
	(0.0458)	(0.0747)	(0.0752)	(0.0947)
Gender of HH	0.9670	0.9328	0.6067***	0.6250***
	(0.0387)	(0.0681)	(0.0359)	(0.0482)
Educational Level of HH (in Years)	0.9603***	0.9516***	0.9386***	0.9263***
	(0.0054)	(0.0093)	(0.0081)	(0.0094)
Age of HH	0.9872**	0.9909	0.9204***	0.9040***
	(0.0062)	(0.0097)	(0.0066)	(0.0082)
Age-squared of HH	0.9998	0.9998	1.0008***	1.0010***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Wealth Index	0.8605***	0.8331***	0.7152***	0.7889***
	(0.0298)	(0.0548)	(0.0358)	(0.0446)
HH Size	1.1078***	1.1112***	1.0288**	0.9993
	(0.0119)	(0.0144)	(0.0128)	(0.0185)
Religion: Muslim	1.0461	0.9534	0.9246	0.9066
	(0.0863)	(0.1216)	(0.1799)	(0.2145)
Religion: Other	1.2091**	1.3553**	2.3612***	2.8040***
	(0.1157)	(0.1808)	(0.5349)	(0.7296)
Ethnicity: kalenjin	1.0649	0.5927**	1.6243*	1.2164
	(0.1549)	(0.1476)	(0.4164)	(0.4280)
Ethnicity: kamba	0.8877	0.4756***	1.7128**	0.8188
	(0.1134)	(0.1260)	(0.4067)	(0.2911)
Ethnicity: kikuyu	1.0825	0.6908	1.4705	0.9194
	(0.1457)	(0.1756)	(0.3697)	(0.3213)
Ethnicity: kisii	1.0058	0.7216	1.8507**	1.4117
	(0.1712)	(0.2099)	(0.5233)	(0.5286)
Ethnicity: luhya	1.1373	0.6323**	2.1691***	1.5936
	(0.1512)	(0.1470)	(0.5461)	(0.5448)
Ethnicity: luo	1.2589*	0.8897	2.7639***	2.2083**
	(0.1723)	(0.2092)	(0.6809)	(0.7281)
Ethnicity: Meru	0.9709	0.6264	1.0865	0.6840
	(0.1781)	(0.2032)	(0.3040)	(0.2721)
Ethnicity: other	1.0948	0.7131	1.6152*	0.9660
	(0.1317)	(0.1467)	(0.4061)	(0.3359)
Ethnicity: Somali	0.9756	0.8836	0.1926***	0.2258***
	(0.1802)	(0.2709)	(0.0945)	(0.1163)
Observations	55,635	44,958	102,438	87,173
chi2	6.313e+06***	4.520e+10***	102145***	120694***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

4.C Regression Results Including Additional Drought Lag Variables

Table 4.C.1: Effects of Droughts on the Timing of Marriage and on Child Marriage

	Event Variable = Marriage	Event Variable = Child Marriage	Event Variable = Marriage	Event Variable = Child Marriage
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0922**	1.1434**	1.2544**	1.2243
	(0.0438)	(0.0610)	(0.1420)	(0.2645)
SPEI Drought (t-1)	1.0561	1.0611	1.2905**	1.3019
	(0.0415)	(0.0653)	(0.1534)	(0.2712)
SPEI Drought (t-2)	1.0752*	1.1024*	1.0322	1.0068
	(0.0437)	(0.0602)	(0.1104)	(0.2048)
SPEI Drought (t-3)	1.0065	1.0802	1.2573*	1.0614
	(0.0407)	(0.0641)	(0.1609)	(0.2334)
SPEI Drought (t)*Time			0.9832	0.9894
			(0.0126)	(0.0326)
SPEI Drought (t-1)*Time			0.9767*	0.9691
			(0.0125)	(0.0305)
SPEI Drought (t-2)*Time			1.0041	1.0139
			(0.0120)	(0.0311)
SPEI Drought (t-3)*Time			0.9746*	1.0028
			(0.0136)	(0.0323)
Religion: Muslim	1.2866**	1.2768*	1.2844**	1.2768*
	(0.1259)	(0.1602)	(0.1253)	(0.1605)
Religion: Other	2.2609***	2.5362***	2.2630***	2.5367***
	(0.2319)	(0.2745)	(0.2318)	(0.2747)
Ethnicity: kalenjin	0.6334***	0.6132**	0.6349***	0.6129**
	(0.0895)	(0.1244)	(0.0897)	(0.1244)
Ethnicity: kamba	0.8110	0.5338***	0.8120	0.5332***
	(0.1039)	(0.1147)	(0.1035)	(0.1147)
Ethnicity: kikuyu	0.6614***	0.5206***	0.6618***	0.5203***
	(0.0835)	(0.1034)	(0.0833)	(0.1034)
Ethnicity: kisii	0.7955	0.6283**	0.7961	0.6277**
	(0.1123)	(0.1374)	(0.1121)	(0.1373)
Ethnicity: luhya	0.7850*	0.7014*	0.7861*	0.7013*
	(0.0992)	(0.1279)	(0.0991)	(0.1280)
Ethnicity: luo	1.0119	1.0254	1.0112	1.0257
	(0.1291)	(0.1829)	(0.1284)	(0.1830)
Ethnicity: Meru	0.7078**	0.7505	0.7064**	0.7489
	(0.1159)	(0.2037)	(0.1155)	(0.2034)
Ethnicity: other	0.9851	0.9889	0.9860	0.9888
	(0.1179)	(0.1709)	(0.1176)	(0.1710)
Ethnicity: Somali	0.9904	1.2314	0.9895	1.2293
	(0.1559)	(0.2710)	(0.1555)	(0.2709)
Observations	158,111	131,537	158,111	131,537
chi2	65112***	32337***	76247***	35044***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.C.2: Effects of Droughts on the Timing of Fertility and on Child Fertility

	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0557	1.0791	1.1683	0.8811
	(0.0417)	(0.0587)	(0.1387)	(0.2257)
SPEI Drought (t-1)	1.1366***	1.1692***	1.0998	0.9912
	(0.0421)	(0.0589)	(0.1275)	(0.2414)
SPEI Drought (t-2)	0.9670	0.9101*	0.8067*	0.7301
	(0.0362)	(0.0489)	(0.0996)	(0.1977)
SPEI Drought (t-3)	1.0354	0.9763	0.9588	0.9263
	(0.0361)	(0.0503)	(0.1196)	(0.2407)
SPEI Drought (t)*Time			0.9886	1.0307
			(0.0130)	(0.0382)
SPEI Drought (t-1)*Time			1.0040	1.0250
			(0.0128)	(0.0364)
SPEI Drought (t-2)*Time			1.0211	1.0327
			(0.0137)	(0.0392)
SPEI Drought (t-3)*Time			1.0090	1.0078
			(0.0140)	(0.0374)
Religion: Muslim	1.0830	0.9946	1.0836	0.9958
	(0.0936)	(0.1218)	(0.0937)	(0.1216)
Religion: Other	1.9779***	2.2412***	1.9785***	2.2398***
	(0.1862)	(0.2615)	(0.1864)	(0.2618)
Ethnicity: kalenjin	0.9057	0.6432**	0.9063	0.6440**
	(0.1180)	(0.1197)	(0.1183)	(0.1198)
Ethnicity: kamba	0.9390	0.4946***	0.9393	0.4955***
	(0.1103)	(0.0950)	(0.1106)	(0.0951)
Ethnicity: kikuyu	0.8182*	0.5354***	0.8187	0.5365***
	(0.0994)	(0.0947)	(0.0997)	(0.0948)
Ethnicity: kisii	0.8846	0.6878*	0.8862	0.6894*
	(0.1374)	(0.1479)	(0.1379)	(0.1483)
Ethnicity: luhya	1.1271	0.7645	1.1267	0.7644
	(0.1469)	(0.1384)	(0.1473)	(0.1384)
Ethnicity: luo	1.2602*	1.0021	1.2606*	1.0006
	(0.1586)	(0.1687)	(0.1591)	(0.1687)
Ethnicity: Meru	0.7922	0.5128***	0.7932	0.5144***
	(0.1180)	(0.1254)	(0.1185)	(0.1257)
Ethnicity: other	1.1568	0.7971	1.1565	0.7971
	(0.1348)	(0.1256)	(0.1352)	(0.1255)
Ethnicity: Somali	0.9202	0.7242	0.9204	0.7259
	(0.1498)	(0.1957)	(0.1500)	(0.1964)
Observations	158,941	132,842	158,941	132,842
chi2	73015***	768234***	177132***	500727***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.C.3: Effects of Droughts on the Timing of Fertility and on Child Fertility for Married and Unmarried Young Girls

	Married		Unmmaried	
	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	0.9956	0.9976	1.1292*	1.1260
	(0.0468)	(0.0667)	(0.0740)	(0.0975)
SPEI Drought (t-1)	1.1270***	1.1488**	1.1040	1.1370
	(0.0466)	(0.0769)	(0.0755)	(0.0973)
SPEI Drought (t-2)	1.0031	0.9703	0.9033	0.8313**
	(0.0462)	(0.0701)	(0.0605)	(0.0697)
SPEI Drought (t-3)	1.0273	0.9596	1.0468	0.9853
	(0.0406)	(0.0602)	(0.0639)	(0.0843)
Religion: Muslim	0.9826	0.9213	0.9327	0.9188
	(0.0791)	(0.1167)	(0.1870)	(0.2151)
Religion: Other	1.3560***	1.5044***	2.7834***	3.6723***
	(0.1279)	(0.1949)	(0.6712)	(0.9447)
Ethnicity: kalenjin	0.8603	0.5084***	1.2497	0.9111
	(0.1267)	(0.1202)	(0.3323)	(0.2929)
Ethnicity: kamba	0.6904***	0.3729***	1.5280*	0.7293
	(0.0930)	(0.0936)	(0.3752)	(0.2339)
Ethnicity: kikuyu	0.7924*	0.5137***	0.9873	0.6559
	(0.1107)	(0.1233)	(0.2597)	(0.2120)
Ethnicity: kisii	0.7054**	0.5188**	1.3501	1.0255
	(0.1230)	(0.1470)	(0.3980)	(0.3635)
Ethnicity: luhya	0.9196	0.5246***	1.6870*	1.1715
	(0.1318)	(0.1167)	(0.4517)	(0.3777)
Ethnicity: luo	0.9489	0.6928	2.0051***	1.6104
	(0.1347)	(0.1583)	(0.5246)	(0.4791)
Ethnicity: Meru	0.7884	0.5334**	0.8203	0.5117*
	(0.1428)	(0.1693)	(0.2439)	(0.1979)
Ethnicity: other	0.9666	0.6854*	1.4208	0.8736
	(0.1229)	(0.1336)	(0.3693)	(0.2720)
Ethnicity: Somali	0.9144	0.8255	0.1861***	0.1249***
	(0.1804)	(0.2458)	(0.0923)	(0.0645)
Observations	55,779	45,081	103,162	87,761
chi2	7.721e+06***	628273***	94247***	219457***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p $<$ 0.10 **p $<$ 0.05 ***p $<$ 0.01.

4.D Regression Results Using Alternate SPEI Cut-off: < -0.8

Table 4.D.1: Effects of Droughts on the Timing of Marriage and on Child Marriage

	Event Variable = Marriage	Event Variable = Child Marriage	Event Variable = Marriage	Event Variable = Child Marriage
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0698**	1.1287**	1.2855**	1.2209
	(0.0418)	(0.0625)	(0.1503)	(0.2684)
SPEI Drought (t-1)	1.0508	1.0404	1.2785**	1.2521
	(0.0419)	(0.0632)	(0.1531)	(0.2698)
SPEI Drought (t)*Time			0.9779*	0.9878
			(0.0130)	(0.0332)
SPEI Drought (t-1)*Time			0.9771*	0.9720
			(0.0128)	(0.0313)
Religion: Muslim	1.2874***	1.2762*	1.2856***	1.2761*
	(0.1257)	(0.1597)	(0.1251)	(0.1600)
Religion: Other	2.2577***	2.5278***	2.2570***	2.5295***
	(0.2308)	(0.2723)	(0.2304)	(0.2725)
Ethnicity: kalenjin	0.6353***	0.6173**	0.6368***	0.6169**
	(0.0896)	(0.1252)	(0.0897)	(0.1252)
Ethnicity: kamba	0.8114	0.5359***	0.8122	0.5352***
	(0.1038)	(0.1157)	(0.1034)	(0.1156)
Ethnicity: kikuyu	0.6615***	0.5224***	0.6617***	0.5218***
	(0.0834)	(0.1040)	(0.0831)	(0.1039)
Ethnicity: kisii	0.7974	0.6309**	0.7972	0.6301**
	(0.1126)	(0.1387)	(0.1122)	(0.1386)
Ethnicity: luhya	0.7885*	0.7090*	0.7885*	0.7092*
	(0.0995)	(0.1294)	(0.0992)	(0.1295)
Ethnicity: luo	1.0148	1.0360	1.0136	1.0368
	(0.1291)	(0.1852)	(0.1285)	(0.1856)
Ethnicity: Meru	0.7071**	0.7555	0.7060**	0.7537
	(0.1156)	(0.2048)	(0.1152)	(0.2045)
Ethnicity: other	0.9855	0.9922	0.9858	0.9917
	(0.1177)	(0.1715)	(0.1173)	(0.1715)
Ethnicity: Somali	0.9845	1.2191	0.9837	1.2166
	(0.1546)	(0.2679)	(0.1542)	(0.2676)
Observations	158,111	131,537	158,111	131,537
chi2	93397***	108014***	78109***	145466***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.D.2: Effects of Droughts on the Timing of Fertility and on Child Fertility

	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0614	1.1117*	1.1851	0.8896
	(0.0422)	(0.0615)	(0.1449)	(0.2261)
SPEI Drought (t-1)	1.1363***	1.1902***	1.1071	0.9100
	(0.0441)	(0.0637)	(0.1350)	(0.2255)
SPEI Drought (t)*Time			0.9873	1.0337
			(0.0134)	(0.0380)
SPEI Drought (t-1)*Time			1.0030	1.0406
			(0.0131)	(0.0373)
Religion: Muslim	1.0892	1.0062	1.0893	1.0064
	(0.0940)	(0.1235)	(0.0940)	(0.1232)
Religion: Other	1.9789***	2.2495***	1.9787***	2.2478***
	(0.1867)	(0.2631)	(0.1867)	(0.2634)
Ethnicity: kalenjin	0.9064	0.6468**	0.9061	0.6466**
	(0.1180)	(0.1197)	(0.1180)	(0.1198)
Ethnicity: kamba	0.9395	0.4968***	0.9392	0.4974***
	(0.1104)	(0.0945)	(0.1104)	(0.0946)
Ethnicity: kikuyu	0.8191	0.5385***	0.8188	0.5390***
	(0.0996)	(0.0948)	(0.0996)	(0.0950)
Ethnicity: kisii	0.8885	0.6937*	0.8881	0.6945*
	(0.1379)	(0.1483)	(0.1379)	(0.1488)
Ethnicity: luhya	1.1285	0.7655	1.1280	0.7653
	(0.1471)	(0.1378)	(0.1471)	(0.1380)
Ethnicity: luo	1.2601*	0.9988	1.2592*	0.9968
	(0.1586)	(0.1675)	(0.1584)	(0.1677)
Ethnicity: Meru	0.7926	0.5164***	0.7919	0.5178***
	(0.1181)	(0.1261)	(0.1181)	(0.1264)
Ethnicity: other	1.1573	0.8007	1.1566	0.8003
	(0.1350)	(0.1252)	(0.1349)	(0.1253)
Ethnicity: Somali	0.9317	0.7477	0.9310	0.7490
	(0.1528)	(0.1980)	(0.1527)	(0.1987)
Observations	158,939	132,840	158,939	132,840
chi2	136064***	3.500e+06***	192058***	1.544e+06***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.D.3: Effects of Droughts on the Timing of Fertility and on Child Fertility for Married and Unmarried Young Girls

	Married		Unmmaried	
	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	0.9834	0.9926	1.1550*	1.1841*
	(0.0477)	(0.0680)	(0.0786)	(0.1040)
SPEI Drought (t-1)	1.1197***	1.1494**	1.0989	1.2330*
	(0.0485)	(0.0799)	(0.0755)	(0.1036)
Religion: Muslim	0.9822	0.9211	0.9517	0.9181
	(0.0793)	(0.1175)	(0.1910)	(0.2343)
Religion: Other	1.3528***	1.5078***	2.7854***	3.5943***
	(0.1278)	(0.1959)	(0.6734)	(0.9247)
Ethnicity: kalenjin	0.8617	0.5094***	1.2568	0.9164
	(0.1269)	(0.1207)	(0.3352)	(0.2905)
Ethnicity: kamba	0.6910***	0.3718***	1.5290*	0.7098
	(0.0932)	(0.0929)	(0.3768)	(0.2274)
Ethnicity: kikuyu	0.7923*	0.5139***	0.9949	0.6634
	(0.1108)	(0.1235)	(0.2627)	(0.2127)
Ethnicity: kisii	0.7060**	0.5189**	1.3692	1.0614
	(0.1230)	(0.1470)	(0.4045)	(0.3712)
Ethnicity: luhya	0.9211	0.5237***	1.6971**	1.1510
	(0.1321)	(0.1167)	(0.4559)	(0.3698)
Ethnicity: luo	0.9507	0.6912	2.0109***	1.5938
	(0.1350)	(0.1585)	(0.5277)	(0.4710)
Ethnicity: Meru	0.7867	0.5319**	0.8239	0.4874*
	(0.1425)	(0.1692)	(0.2454)	(0.1863)
Ethnicity: other	0.9677	0.6843*	1.4333	0.8657
	(0.1231)	(0.1337)	(0.3735)	(0.2657)
Ethnicity: Somali	0.9125	0.8261	0.2718**	0.2112***
	(0.1799)	(0.2455)	(0.1412)	(0.1120)
Observations	55,779	45,081	103,160	87,871
chi2	8.053e+06***	572048***	131644***	162996***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p $<$ 0.10 **p $<$ 0.05 ***p $<$ 0.01.

Regression Results Using Alternate SPEI Cut-off: < -1

Table 4.D.4: Effects of Droughts on the Timing of Marriage and on Child Marriage

	Event Variable = Marriage	Event Variable = Child Marriage	Event Variable = Marriage	Event Variable = Child Marriage
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0808**	1.1433**	1.2703**	1.2220
	(0.0441)	(0.0655)	(0.1543)	(0.2730)
SPEI Drought (t-1)	1.0338	1.0024	1.1677	1.0492
	(0.0423)	(0.0621)	(0.1431)	(0.2343)
SPEI Drought (t)*Time			0.9806	0.9898
			(0.0136)	(0.0337)
SPEI Drought (t-1)*Time			0.9857	0.9930
			(0.0131)	(0.0329)
Religion: Muslim	1.2874***	1.2754*	1.2858***	1.2755*
	(0.1256)	(0.1595)	(0.1252)	(0.1597)
Religion: Other	2.2597***	2.5258***	2.2561***	2.5265***
	(0.2307)	(0.2718)	(0.2305)	(0.2720)
Ethnicity: kalenjin	0.6359***	0.6186**	0.6371***	0.6185**
	(0.0896)	(0.1255)	(0.0898)	(0.1255)
Ethnicity: kamba	0.8122	0.5367***	0.8125	0.5364***
	(0.1039)	(0.1161)	(0.1036)	(0.1161)
Ethnicity: kikuyu	0.6619***	0.5233***	0.6620***	0.5230***
	(0.0834)	(0.1043)	(0.0833)	(0.1042)
Ethnicity: kisii	0.7959	0.6296**	0.7960	0.6294**
	(0.1124)	(0.1385)	(0.1122)	(0.1385)
Ethnicity: luhya	0.7891*	0.7112*	0.7892*	0.7111*
	(0.0995)	(0.1298)	(0.0994)	(0.1298)
Ethnicity: luo	1.0165	1.0404	1.0156	1.0406
	(0.1292)	(0.1862)	(0.1288)	(0.1863)
Ethnicity: Meru	0.7066**	0.7558	0.7063**	0.7553
	(0.1155)	(0.2049)	(0.1153)	(0.2048)
Ethnicity: other	0.9863	0.9946	0.9869	0.9944
	(0.1178)	(0.1721)	(0.1176)	(0.1721)
Ethnicity: Somali	0.9860	1.2220	0.9854	1.2209
	(0.1549)	(0.2688)	(0.1547)	(0.2686)
Observations	158,111	131,537	158,111	131,537
chi2	93002***	133270***	77199***	165186***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.D.5: Effects of Droughts on the Timing of Fertility and on Child Fertility

	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0584	1.1026*	1.1699	0.9651
	(0.0433)	(0.0619)	(0.1474)	(0.2503)
SPEI Drought (t-1)	1.1397***	1.1809***	1.0666	0.9580
	(0.0444)	(0.0634)	(0.1317)	(0.2470)
SPEI Drought (t)*Time			0.9885	1.0201
			(0.0138)	(0.0380)
SPEI Drought (t-1)*Time			1.0077	1.0314
			(0.0134)	(0.0385)
Religion: Muslim	1.0886	1.0061	1.0888	1.0060
	(0.0939)	(0.1232)	(0.0939)	(0.1230)
Religion: Other	1.9790***	2.2453***	1.9793***	2.2434***
	(0.1866)	(0.2625)	(0.1867)	(0.2626)
Ethnicity: kalenjin	0.9072	0.6492**	0.9074	0.6493**
	(0.1178)	(0.1200)	(0.1178)	(0.1201)
Ethnicity: kamba	0.9415	0.4985***	0.9415	0.4991***
	(0.1104)	(0.0950)	(0.1104)	(0.0950)
Ethnicity: kikuyu	0.8203	0.5400***	0.8204	0.5406***
	(0.0995)	(0.0950)	(0.0995)	(0.0951)
Ethnicity: kisii	0.8862	0.6905*	0.8864	0.6910*
	(0.1376)	(0.1476)	(0.1376)	(0.1478)
Ethnicity: luhya	1.1301	0.7687	1.1304	0.7689
	(0.1468)	(0.1382)	(0.1469)	(0.1383)
Ethnicity: luo	1.2643*	1.0058	1.2643*	1.0054
	(0.1585)	(0.1682)	(0.1584)	(0.1684)
Ethnicity: Meru	0.7919	0.5169***	0.7917	0.5181***
	(0.1177)	(0.1261)	(0.1177)	(0.1264)
Ethnicity: other	1.1599	0.8046	1.1597	0.8048
	(0.1347)	(0.1257)	(0.1348)	(0.1258)
Ethnicity: Somali	0.9347	0.7512	0.9345	0.7522
	(0.1532)	(0.1991)	(0.1531)	(0.1995)
Observations	158,939	132,840	158,939	132,840
chi2	138631***	1.477e+06***	140245***	1.657e+06***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.D.6: Effects of Droughts on the Timing of Fertility and on Child Fertility for Married and Unmarried Young Girls

	Married		Unmmaried	
	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	0.9850	0.9858	1.1377*	1.1798*
	(0.0485)	(0.0689)	(0.0793)	(0.1063)
SPEI Drought (t-1)	1.1114**	1.1286*	1.1202	1.2008**
	(0.0486)	(0.0786)	(0.0783)	(0.1024)
Religion: Muslim	0.9816	0.9207	0.9511	0.9572
	(0.0792)	(0.1173)	(0.1908)	(0.2234)
Religion: Other	1.3533***	1.5069***	2.7874***	3.6494***
	(0.1277)	(0.1957)	(0.6737)	(0.9388)
Ethnicity: kalenjin	0.8634	0.5100***	1.2605	0.9262
	(0.1272)	(0.1206)	(0.3356)	(0.2954)
Ethnicity: kamba	0.6928***	0.3730***	1.5352*	0.7311
	(0.0935)	(0.0937)	(0.3774)	(0.2334)
Ethnicity: kikuyu	0.7938*	0.5143***	0.9975	0.6679
	(0.1110)	(0.1235)	(0.2629)	(0.2150)
Ethnicity: kisii	0.7069**	0.5176**	1.3639	1.0418
	(0.1233)	(0.1465)	(0.4026)	(0.3675)
Ethnicity: luhya	0.9234	0.5254***	1.7014**	1.1860
	(0.1324)	(0.1169)	(0.4562)	(0.3801)
Ethnicity: luo	0.9542	0.6929	2.0210***	1.6204
	(0.1354)	(0.1583)	(0.5291)	(0.4789)
Ethnicity: Meru	0.7875	0.5320**	0.8244	0.5173*
	(0.1427)	(0.1692)	(0.2450)	(0.1984)
Ethnicity: other	0.9708	0.6857*	1.4382	0.8907
	(0.1235)	(0.1337)	(0.3738)	(0.2742)
Ethnicity: Somali	0.9162	0.8270	0.2727**	0.2116***
	(0.1805)	(0.2457)	(0.1415)	(0.1124)
Observations	55,779	45,081	103,160	87,759
chi2	4.434e+06***	347936***	119824***	199562***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Regression Results Using Alternate SPEI Cut-off: < -2

Table 4.D.7: Effects of Droughts on the Timing of Marriage and on Child Marriage

	Event Variable = Marriage	Event Variable = Child Marriage	Event Variable = Marriage	Event Variable = Child Marriage
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.1314***	1.1994***	1.2718*	1.3120
	(0.0489)	(0.0711)	(0.1707)	(0.3198)
SPEI Drought (t-1)	1.0654	1.0535	1.2776*	1.0694
	(0.0469)	(0.0705)	(0.1653)	(0.2604)
SPEI Drought (t)*Time			0.9857	0.9864
			(0.0155)	(0.0366)
SPEI Drought (t-1)*Time			0.9788	0.9977
			(0.0137)	(0.0358)
Religion: Muslim	1.2883***	1.2774*	1.2872***	1.2777*
	(0.1257)	(0.1601)	(0.1255)	(0.1602)
Religion: Other	2.2604***	2.5282***	2.2591***	2.5286***
	(0.2312)	(0.2719)	(0.2309)	(0.2721)
Ethnicity: kalenjin	0.6366***	0.6218**	0.6377***	0.6217**
	(0.0899)	(0.1262)	(0.0900)	(0.1262)
Ethnicity: kamba	0.8132	0.5399***	0.8140	0.5395***
	(0.1043)	(0.1171)	(0.1040)	(0.1170)
Ethnicity: kikuyu	0.6627***	0.5254***	0.6629***	0.5251***
	(0.0837)	(0.1049)	(0.0835)	(0.1048)
Ethnicity: kisii	0.7959	0.6299**	0.7958	0.6297**
	(0.1126)	(0.1387)	(0.1123)	(0.1387)
Ethnicity: luhya	0.7894*	0.7134*	0.7898*	0.7132*
	(0.0997)	(0.1305)	(0.0995)	(0.1305)
Ethnicity: luo	1.0163	1.0434	1.0162	1.0432
	(0.1295)	(0.1874)	(0.1291)	(0.1873)
Ethnicity: Meru	0.7061**	0.7593	0.7067**	0.7588
	(0.1155)	(0.2060)	(0.1155)	(0.2060)
Ethnicity: other	0.9869	0.9996	0.9881	0.9993
	(0.1181)	(0.1733)	(0.1179)	(0.1733)
Ethnicity: Somali	0.9901	1.2342	0.9895	1.2327
	(0.1563)	(0.2729)	(0.1559)	(0.2726)
Observations	158,111	131,537	158,111	131,537
chi2	73192***	56679***	81690***	65886***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.D.8: Effects of Droughts on the Timing of Fertility and on Child Fertility

	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.1690*	1.2268*	1.2904*	1.2111
	(0.0490)	(0.0743)	(0.1781)	(0.3514)
SPEI Drought (t-1)	1.1869***	1.2551***	1.1071	1.0495
	(0.0489)	(0.0721)	(0.1511)	(0.2958)
SPEI Drought (t)*Time			0.9885	1.0020
			(0.0154)	(0.0410)
SPEI Drought (t-1)*Time			1.0080	1.0264
			(0.0149)	(0.0413)
Religion: Muslim	1.0905	1.0088	1.0906	1.0088
	(0.0941)	(0.1236)	(0.0941)	(0.1235)
Religion: Other	1.9803***	2.2536***	1.9808***	2.2538***
	(0.1871)	(0.2631)	(0.1872)	(0.2631)
Ethnicity: kalenjin	0.9091	0.6548**	0.9094	0.6554**
	(0.1180)	(0.1205)	(0.1180)	(0.1206)
Ethnicity: kamba	0.9445	0.5041***	0.9447	0.5046***
	(0.1111)	(0.0964)	(0.1111)	(0.0964)
Ethnicity: kikuyu	0.8222	0.5434***	0.8223	0.5439***
	(0.0997)	(0.0956)	(0.0998)	(0.0957)
Ethnicity: kisii	0.8864	0.6920*	0.8867	0.6923*
	(0.1377)	(0.1478)	(0.1377)	(0.1479)
Ethnicity: luhya	1.1313	0.7733	1.1315	0.7735
	(0.1470)	(0.1387)	(0.1471)	(0.1387)
Ethnicity: luo	1.2651*	1.0110	1.2654*	1.0114
	(0.1588)	(0.1689)	(0.1588)	(0.1690)
Ethnicity: Meru	0.7908	0.5193***	0.7908	0.5203***
	(0.1178)	(0.1266)	(0.1178)	(0.1268)
Ethnicity: other	1.1614	0.8099	1.1615	0.8103
	(0.1351)	(0.1265)	(0.1352)	(0.1266)
Ethnicity: Somali	0.9390	0.7597	0.9391	0.7607
	(0.1549)	(0.2026)	(0.1549)	(0.2029)
Observations	158,939	132,840	158,939	132,840
chi2	123568***	412476***	202836***	389175***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p < 0.10 **p < 0.05 ***p < 0.01.

Table 4.D.9: Effects of Droughts on the Timing of Fertility and on Child Fertility for Married and Unmarried Young Girls

	Married		Unmmaried	
	Event Variable = Fertility	Event Variable = Child Fertility	Event Variable = Fertility	Event Variable = Child Fertility
	Age Group: 10-24	Age Group: 10-17	Age Group: 10-24	Age Group: 10-17
	(Cox Model)	(Cox Model)	(Cox Model)	(Cox Model)
	(1)	(2)	(3)	(4)
SPEI Drought (t)	1.0638	1.0719	1.2278	1.2623*
	(0.0536)	(0.0788)	(0.0917)	(0.1233)
SPEI Drought (t-1)	1.1439***	1.1978**	1.1397*	1.2677*
	(0.0542)	(0.0916)	(0.0854)	(0.1145)
Religion: Muslim	0.9828	0.9219	0.9499	0.9180
	(0.0791)	(0.1172)	(0.1904)	(0.2339)
Religion: Other	1.3548***	1.5105***	2.7851***	3.5977***
	(0.1282)	(0.1961)	(0.6740)	(0.9233)
Ethnicity: kalenjin	0.8635	0.5138***	1.2677	0.9300
	(0.1273)	(0.1214)	(0.3377)	(0.2956)
Ethnicity: kamba	0.6936***	0.3755***	1.5449*	0.7216
	(0.0939)	(0.0945)	(0.3808)	(0.2318)
Ethnicity: kikuyu	0.7951	0.5188***	1.0011	0.6684
	(0.1115)	(0.1247)	(0.2641)	(0.2149)
Ethnicity: kisii	0.7059**	0.5176**	1.3698	1.0572
	(0.1233)	(0.1467)	(0.4047)	(0.3710)
Ethnicity: luhya	0.9226	0.5265***	1.7100**	1.1673
	(0.1325)	(0.1172)	(0.4589)	(0.3762)
Ethnicity: luo	0.9538	0.6935	2.0306***	1.6201
	(0.1357)	(0.1585)	(0.5324)	(0.4802)
Ethnicity: Meru	0.7863	0.5342**	0.8238	0.4880*
	(0.1429)	(0.1692)	(0.2453)	(0.1877)
Ethnicity: other	0.9713	0.6891*	1.4440	0.8761
	(0.1239)	(0.1345)	(0.3759)	(0.2703)
Ethnicity: Somali	0.9194	0.8376	0.2739**	0.2128***
	(0.1824)	(0.2493)	(0.1421)	(0.1128)
Observations	55,779	45,081	103,160	87,871
chi2	3.490e+07***	1.060e+07***	86335***	181700***

Note: Additional controls include time (season) fixed effect, birth year (cohort) fixed effect, and community fixed effect. Clustered robust standard errors at community level in parentheses. Significance level denoted as *p $<$ 0.10 **p $<$ 0.05 ***p $<$ 0.01.

4.E Fisher Randomisation Test

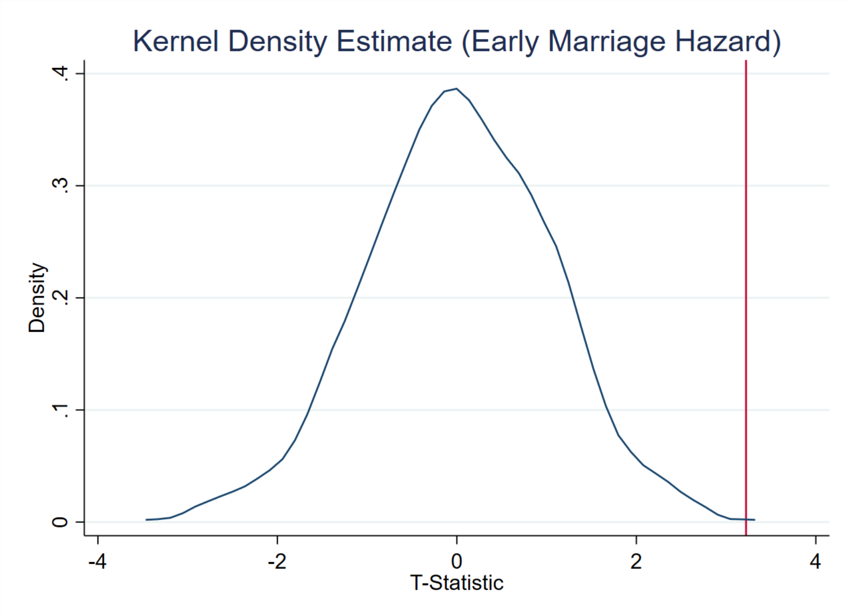

Figure 4.E.1: Fisher Randomisation Test: K-Density Plot Showing the Estimated T-statistics for the Early Marriage Hazard.

Note: The p-value which shows the proportion of test statistic more extreme than the original test statistic on the Drought (t) variable in Column 3 of Table (4.2), indicated by the red vertical line is 0.001.

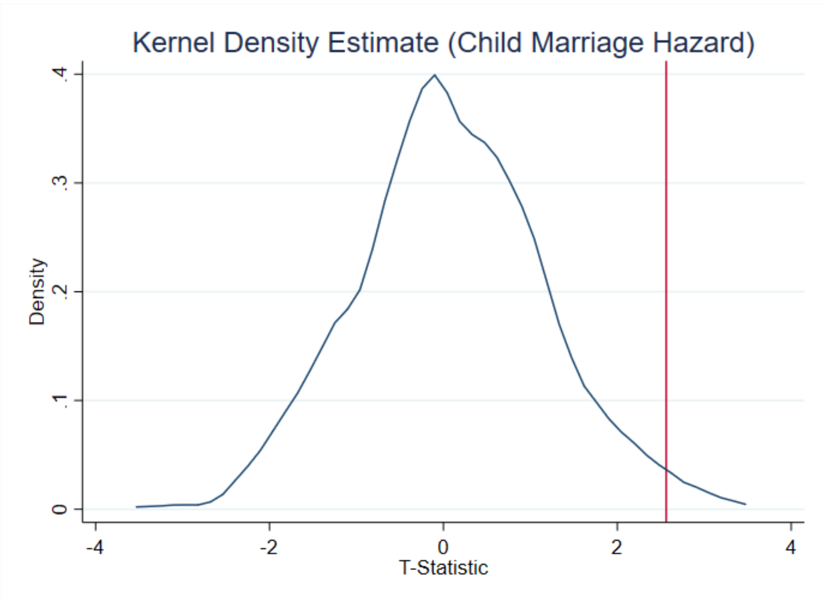

Figure 4.E.2: Fisher Randomisation Test: K-Density Plot Showing the Estimated T-statistics for the Child Marriage Hazard.

Note: The p-value which shows the proportion of test statistic more extreme than the original test statistic on the Drought (t) variable in Column 4 of Table (4.2), indicated by the red vertical line is 0.019.

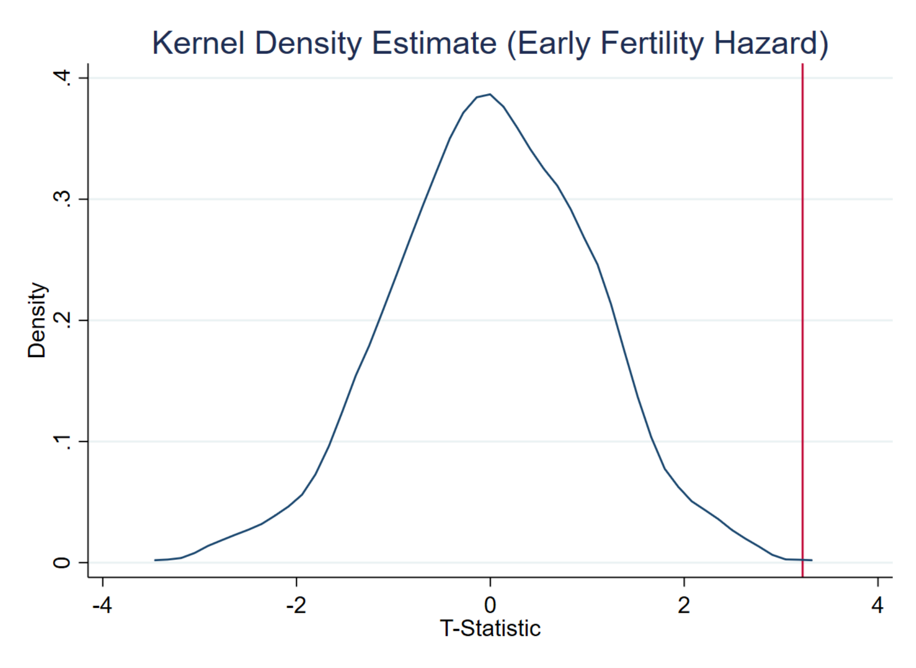

Figure 4.E.3: Fisher Randomisation Test: K-Density Plot Showing the Estimated T-statistics for the Early Fertility Hazard.

Note: The p-value which shows the proportion of test statistic more extreme than the original test statistic on the Drought (*t-1*) variable in Column 3 of Table (4.3), indicated by the red vertical line is 0.0012.

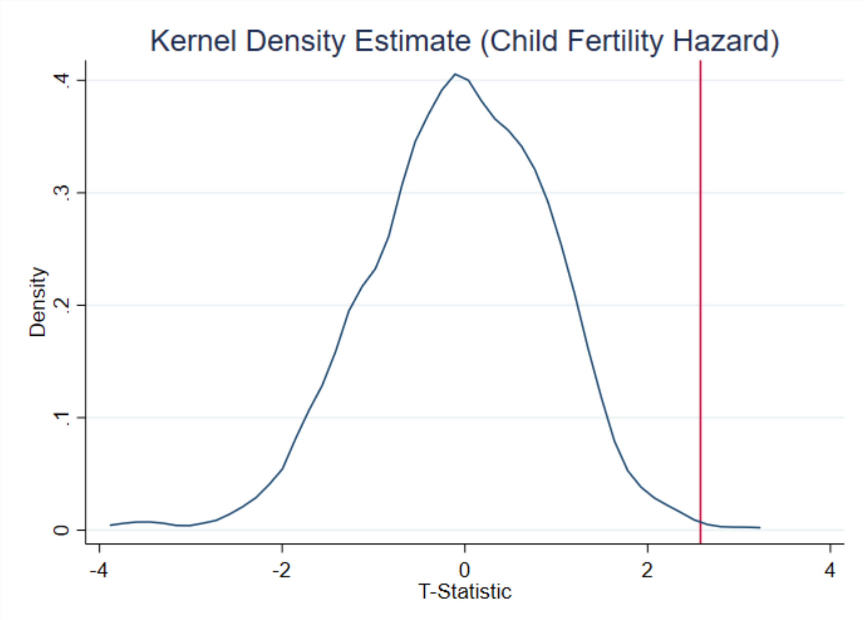

Figure 4.E.4: Fisher Randomisation Test: K-Density Plot Showing the Estimated T-statistics for the Child Fertility Hazard.

Note: The p-value which shows the proportion of test statistic more extreme than the original test statistic on the Drought (*t-1*) variable in Column 4 of Table (4.3), indicated by the red vertical line is 0.0021.

Chapter 5

Concluding Remarks

5.1 Summary

Early childhood is critical as it offers the opportunity in shaping the trajectories of young minds and paves a way for holistic growth and development. For children to reach their full potential, investment in health, education, protection from abuse, and a sense of security is required. Yet, this opportunity is often missed for millions of children in disadvantaged regions. This thesis, comprised of three independent but related empirical essays, examines important aspects of child development and investigates the role of climate change in putting millions at risk in disadvantaged regions and in thus determining the welfare and development of children.

In the first essay, we draw on a unique and detailed panel data tracking child development outcomes over 15 years in rural Ethiopia to investigate the impact of droughts on child education. Overall, our analysis from our child fixed-effect model points to the fact that children suffer greatly in terms of their educational outcomes when exposed to droughts. In other words, ensuring that households from disadvantaged regions are protected from environmental hazards like droughts is likely to protect the wellbeing of children and lessen impediments to their education. Our results also suggests that boys (in terms of their cognitive ability), younger children, and children from less educated households are the most vulnerable to the adverse impacts of droughts on educational outcomes. Finally, we find no evidence for the Ethiopian Productive Safety Net Programme in alleviating any negative impacts of droughts on child educational outcomes.

In the second essay, we combine satellite PM2.5 data and individual-level data to analyse the impact of ambient air pollution on child health outcomes in Ethiopia. Employing the instrumental variable regression and using wind speed as an instrument, we find weak evidence for the harmful effects of air pollution on child health. We show that within our preferred model specification which incorporates monthly adjustments for seasonality in our pollution variable, exposure to ambient air pollution has little to no effect on child health. The only effect of in-utero PM2.5 on child health outcomes found in our study is the marginally significant outcome on the weight-for-age variable at ages 0-1 for Trimester 1 level exposure. We find that increases in in-utero PM2.5 of 1 $\mu g/m^3$ during trimester 1 of pregnancy causes a reduction in the weight-for-age z-score of approximately 0.66 standard deviations. Our findings in this paper also provide weak evidence for heterogeneous effects of air pollution by child's gender, mother's level of education, and household area of residence, where we find significant effects only for household area of residence, indicating that children from rural households, with less access to healthcare are more adversely impacted by negative effects of in-utero air pollution on health. Overall, our findings highlight the importance of controlling for endogeneity and seasonal pollution patterns in examining the relationship between PM2.5 and child health outcomes.

The final paper of this thesis focuses on the impact of extreme weather events (droughts) on child marriage and fertility outcomes for young girls in Kenya. Child marriage is a common phenomenon in sub-Saharan Africa and often times used as a coping mechanism for poor households in times of economic distress (Dewi and Dartanto, 2019). The findings from this paper supports this notion by providing evidence for the adverse effects of exogenous shocks to income (droughts) on child marriage. The findings also show child fertility outcomes to be negatively impacted by droughts, particularly for the married sample, indicating that conditional on marriage, fertility rates are higher during periods of economic distress. Finally, findings from this paper also indicate that girls living in rural households with potentially lower levels of income are more susceptible to the adverse effects of droughts on marriage and fertility.

5.2 Policy Implications

Overall, this thesis, on the welfare impacts of climate change on children, has significant policy implications in terms of ensuring that policies to address welfare and development in response to climate change need to be targeted towards the most vulnerable group of individuals, children living in poor households. The first essay of this thesis which provides evidence for the negative impacts of extreme weather events (droughts) on the educational outcomes of children suggests that droughts may act as a key barrier to the schooling outcomes of children among rural households in sub-Saharan Africa. Thus, policies addressing child welfare in this region should first focus on protecting vulnerable young children from extreme weather events such as droughts. This is especially important given the large consequences of weather disasters on welfare, projected to be much more significant in the future due to a higher frequency and intensity of weather disasters arising from climate change (IPCC, 2021). Therefore, governments and societies, particularly within the sub-Saharan African region, need to design and implement more pragmatic policies that will assist rural agricultural households in adapting to changing climate conditions. These could include employing early weather-risk detector warning systems, planting more drought-resistant crops, promoting diversification of livelihood sources, enhancing livestock diversity, improving access to credit facilities, and implementing more efficient agricultural management practices such as increasing water storage facilities, that could help shield farmers and their households from variability in income and consumption arising from adverse events such as droughts.

Secondly, given the vulnerability of investments in education to changes in income, particularly in rural regions, policies aimed at enhancing child welfare in sub-Saharan Africa need to focus on improving the educational outcomes of young vulnerable children. These educational policies should not only consider investment in children in their critical stages (pre-school period), but also continued investment in children in their pre-school years and beyond. Although, Ethiopia, alongside other African countries, have excelled tremendously in getting enrolment rates up, dropout rates and learning quality in this region remain low. As such, policies addressing child education in Africa must focus on retention rate and improving access to quality education, especially for the rural poor.

Policies targeting school retention may include connecting students with financial support pathways: Many students, particularly in rural communities do not have the adequate financial support system to remain in school. Therefore, it is imperative for governments, schools and communities to identify these students and connect them with the appropriate avenues through which they could receive the financial support required. This could be through local NGOS, the private sector or social welfare networks that assist in providing students with educational financial support such as payment of school fees (providing scholarships) and purchasing of school materials (books and school uniforms). The provision of educational support scholarship programs for students also need to made easily available in rural areas. In terms of improving the quality of education, policies aimed at providing opportunities for teachers and schools to continuously up-skill need to be put in place to promote good quality learning. These could include offering primary and secondary schools a range of training workshops or partnering with education training institutions designed to support the professional development of educators.

Finally, given that this thesis (first essay) shows no significant impact of the Ethiopian cash transfer programme in alleviating any negative impacts associated with droughts, it calls for safety net policy programmes to be designed in a more accurate and effective manner. This includes giving out more handsome payments to poor rural households, ensuring that benefiting from the cash transfer programme is strictly conditional on enrolling children in school and providing evidence of consistent educational progress, and ensuring that recipient children are prevented from taking up additional labour roles that could potentially disrupt schooling outcomes in times of financial distress. Such policy design is of grave importance particularly in developing regions like sub-Saharan Africa highly prone to the risks associated with climate change and where investments in education is low.

In terms of the second essay, which shows little to no evidence for the adverse effects of air pollution on child health outcomes, the results call for further research using better quality data, particularly air pollution data due to the limitations present in the analysis. As such, policy makers in Ethiopia and in other sub-Saharan African countries need to ensure that air pollution control is made a top priority by investing in more robust air pollution monitoring systems. The implementation of a more robust air pollution system in this region would allow for the effective tracking of ground level pollution across geographical locations. This would thus play a significant role in combating high pollution levels and allow for a more robust research analysis aimed at examining any negative impact of air pollution on health.

Finally, in terms of the final essay of this thesis, which provides evidence for the adverse impacts of droughts on child marriage and fertility outcomes, our findings call for policy makers to create pathways in ensuring that households, particularly rural households, have the necessary financial support system that prevent them from resorting to child marriage during periods of financial distress. These could include; providing well-designed cash transfer schemes, improving access to credit facilities, promoting income diversification, and ensuring that households practice more efficient drought management practices such as planting more drought-resistant crops and investing in water storage facilities. Furthermore, our findings call for policy makers within the sub-Saharan African region to fortify targeting the eradication of child marriage practices. This could include; creating more awareness on the dangers of child marriage, particularly within rural communities, abolishing barbaric cultural practices that promote child marriage practices such as the bride price payment system and female genital mutilation, and ensuring that existing laws prohibiting child marriage practices are upheld and enforced. In general, creating an environment where young girls are aware of their fundamental human rights and are protected, and where customary and religious laws do not impose major contradictions in existing child marriage laws is of utmost importance and is paramount in strengthening existing child protection systems in Kenya and in other sub-Saharan African countries.

5.3 Limitations and Suggestions for Future Research

Although this thesis uses high quality data with results robust to various specifications and in line with previous research, it has a number of limitations. Firstly, in the first and second paper, the sample used is relatively small after excluding missing values. This might thus reduce variation in our analysis and possibly lead to some bias in our estimates. This limitation is particularly important in the second paper on in-utero air pollution and child health outcomes where having a relatively smaller sample (compared to previous studies) with children who are born during the same time period (2001-2002) comes at a much higher cost of limited variation in our data, particularly in our in-utero air pollution variable. Secondly, in the second chapter, the fact that we focus on a single country (Ethiopia) which has very similar patterns in PM2.5 across regions, and very low pollution levels on average relative to commonly used study countries like China or India is a limitation in our analysis and could be a driving factor as to why we find little to no effect of in-utero air pollution on child health. Thus, future research on the welfare impacts of climate change, particularly with regard to air pollution in sub-Saharan Africa may need to use a larger study sample as well as better pollution data with a much higher spatial resolution in order to be able to accurately individualise air pollution estimates, consequently allowing for wider variation within the estimation sample. Finally, in terms of limitations, in the third chapter on extreme weather events (droughts) and child marriage, due to the unavailability of precise locations in our dataset, we utilise the location of girls at the time of the survey in accounting for droughts rather than the location where girls lived and grew up before marriage. It may thus be possible that migration has already occurred due to marriage. Although, research on marriage migration in sub-Saharan Africa (Mbaye and Wagner, 2017; Corno et al., 2020) have shown that the majority of women (about 77%) marry within their community and do not migrate at the time of marriage, this limitation may introduce some measurement error to our estimates. An avenue for future research should thus be to use better quality data with detailed information on the living history of respondents in order to limit measurement error and potential bias of estimates.

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