Essays on development economics

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Essays on Development Economics:

Climate Change, Education and Development

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DISSERTATION

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SUMMARY

This dissertation consists of four empirical studies and examines how environmental and developmental changes affect decisions about food consumption, agricultural production, and investments in human development. More specifically, it investigates: (1) if and how smallholder farmers respond to weather variations during the early planting season by adjusting their land allocation decisions; (2) if and how access to irrigation affects the diet quality of farming households; (3) whether living close to higher education institutions improves school performance at lower educational levels; and (4) whether rural roads support education and/or employment for children.

Chapter 2 presents the first causal estimates of the impact of early planting season weather patterns on smallholder farmers' decisions on the allocation of agricultural land. The study is motivated by recent economics and psychology literature that suggests that recent realizations of an event have a disproportionately large influence on human expectations about the likelihood of that event occurring again. Using panel data obtained over seven years and high-resolution weather data, we show that smallholder farmers adjust their land allocation decisions in response to short-term weather variability.

Chapter three contributes to the literature by examining the nutritional effects of small-scale irrigation. Despite the recognized nutritional benefits of agricultural developments, there is a dearth of research on the nutritional effects of agricultural asset ownership, particularly regarding the link between irrigation use and rural welfare. Nevertheless, since the degree of substitutability between water and other crop inputs is very low, a separate analysis is required to examine the impact of irrigation on the welfare status of farm households. We use the Endogenous Switching Regression model to account for endogeneity concerns. Our results indicate that access to irrigation has a positive effect on diet quality, with an increased likelihood of producing nutritious foods and adopting productivity-enhancing innovations as the main mechanisms.

The fourth chapter looks into how universities affect host communities. In contrast to earlier studies that mainly concentrated on the spillover effects in the form of creating jobs, stimulating innovation, and producing graduates, we add to the body of knowledge by shedding light on the impact on lower-level schooling of female adolescence in host communities. We use Ethiopia's recent rapid expansion of public universities as a case and implement the event study framework to exploit variations in the timing of the establishment of universities between 2007 and 2014. We demonstrate the positive spillover effects of public universities by showing how they promote ed-

ucational attainment among girls. We also document other behavioral changes, such as changes in fertility and reproduction decisions and information-seeking behavior of female adolescents.

The fifth chapter investigates the impacts of rural roads on children's schooling and labor allocation decisions. Existing studies that investigate the contributions of rural roads mainly focused on short-term gains disregarding the long-term benefits such as human capital development. Our study contributes to the literature by examining whether Ethiopia's Universal Rural Road Access Program, which commenced in 2011, reshaped children's labor allocation and educational outcomes. We combine national level panel data with novel road network data. The endogeneity concern arising from the non-random road placement decision is addressed by combining the Difference in Difference techniques with a matching approach. We use multiple schooling and labor outcome indicators, and our results consistently suggest that road access does not encourage school absenteeism or early dropouts to enter the labor force.

In the sixth chapter of the dissertation, we provide a conclusion and policy recommendations based on the results presented in each chapter.

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INTRODUCTION

1.1 MOTIVATION

Understanding the characteristics of poor economies and exploring strategies for economic development are among the fundamental themes that inspired early economists and continue to inspire the current generation of economists (Schultz, 1980; Banerjee & Duflo, 2007; Balboni et al., 2022). Among them, in his Nobel Lecture, Theodore Schultz emphasized the significance of understanding the agricultural sector in combating global poverty, noting that the vast majority of the poor heavily rely on this sector for their survival. Others identified the lack of competent human capital as one of the fundamental roadblocks developing economies encounter to attaining economic growth and social progress. In this regard, prominent economists, including Schultz (1980), stress the importance of a skilled workforce for economic advancement (the list includes, among others, Schultz (1961); Todaro (1975); Barro (1991)). This makes building human capital and enhancing the performance of the agricultural sector among the top policy concerns for developing countries.

Climate change is the most significant challenge to the agriculture sector, and its effects on agriculture affect human well-being in a variety of ways. These effects span the macroeconomic spectrum, affecting export, economic growth, and political stability, to the microeconomic ones, affecting food insecurity, health, academic achievement, domestic violence, and migration (Dell et al., 2012; Jones & Olken, 2010; Maccini & Yang, 2009; Miguel et al., 2004; Deschênes et al., 2009). The consequences of such effects could be felt for a long time and passed on to the following generation (Hyland & Russ, 2019).

While the effects of climate change have been extensively documented on a global scale (e.g., Burke et al. (2015); Diffenbaugh & Burke (2019)), they are expected to be more severe in developing countries, especially in Sub-Saharan Africa (SSA) due to its dependence on rain-fed agriculture and lack of institutions to adapt and mitigate climate shocks (Antle, 1995). Making the already difficult matter worse, forecasts from climatological models strongly suggest that developing countries would likely see a disproportionally increased temperature and rainfall variability (Bathiany et al., 2018). As a result, improving farmers' adaptive capacity and understanding their current adaptation strategies is essential. To this end, various studies have investigated existing adaptation options. These studies demonstrate how past weather patterns affect farmers' decisions by shaping their expectations for upcoming weather conditions. Recent research has also demonstrated that farmers swiftly modify their production decisions based on the current weather circumstances in addition to reacting based on historical weather experiences. For instance, farmers may change the planting date or reallocate production inputs based on the current weather conditions (Cui & Xie, 2022; Jagnani et al., 2021).

Providing irrigation access is one way to ensure water access in the face of climate change. Given that the size and frequency of weather variability are growing and becoming more difficult for smallholder farmers to manage on their own, governments are paying more attention to the development of the agricultural sector through irrigation (You et al., 2011). Particularly, small-scale irrigation systems, which rely on technologies that do not require a significant initial investment, operation costs, or maintenance costs, are viewed as catalysts for enhancing the rural livelihoods of smallholders of SSA who are usually dispersed throughout the community (de Bont et al., 2019).

Irrigation has the potential to foster economic growth and tackle poverty in a variety of micro and macroeconomic channels. From a macro perspective, it increases overall agricultural production, creates jobs, and stabilizes food prices. From a micro perspective, it facilitates the adoption of agricultural innovations, minimizes yield losses, and expands cropping patterns and commercialization (Hussain & Hanjra, 2004). Securing water access via irrigation also enables farmers to make choices that will maximize their gains, such as engaging in the production of risky crops rather than choosing sub-optimal options out of concern for potential losses. This includes growing nutrient-rich crops like vegetables and fruits or less nutrient-rich cash crops. Such adjustments could lead to changes in the types and amounts of food that smallholders have at home since separate decisions between production and consumption are not expected to occur in smallholder settings that deal with imperfect input, financial, and output markets (Janvry et al., 1991).

Improving nutrition status through producing nutritious food items at own plots has attracted attention in recent years. Particularly, as the world's attention shifts from the problem of food insecurity to tackling the problems of malnutrition, there is a paradigm shift from boosting the production of low-cost, high-calorie staple crops to the cultivation of micronutrient-rich food items (Sanchez et al., 2020). It has been demonstrated that improving access to nutritious foods from own production is positively related to better health outcomes, such as the availability of essential nutrients, vitamins, minerals, and childbirth weight, which are crucial factors for human capital formulation.

Along with good health, access to education is another essential instrument for promoting human capital development. Although empirical findings at the macroeconomic level are equivocal, microeconomic studies have shown that education helps to improve economic performance by fostering innovation and productivity, reducing crime rates, fertility, mortality, and income inequality, and enhancing health and citizenship, among other things (Bell et al., 2022; Milligan et al., 2004; Cutler et al., 2006). Relatedly, Easterly & Levine (1997) claim that the low economic growth of SSA is partly expanded by the low rates of education, and Lange et al. (2018) contend that Africa needs to have an educated and resilient population to eradicate poverty and inequality, accelerate structural change.

While there is a consensus on the importance of providing universal access to primary and secondary education, this goal remains out of reach for many SSA countries and it may not be achieved in the near future (Bennell, 2021). SSA has the greatest rates of educational exclusion of any region of the world. For example, more than 20% of children between the ages of 6 and 11 do not attend school, as do more than 33% and 60% of youths between the ages of 12 and 14 and 15 and 17, respectively (Lewin, 2020). The issue is also clearly seen from the perspective of higher education. The current gross tertiary education enrollment ratio in SSA is less than 10%, which is again well below the global average of 38%.

A few reasons that contribute to the low enrollment rate are poverty, child labor, health, social norms, school accessibility, and lack of aspiration (Glewwe & Muralidharan, 2016; Kremer et al., 2013). Another important aspect that contributes to children leaving school may be the opportunity cost of schooling. For instance, exposure to the job market due to new roads may inspire children to work and earn money now rather than forego this benefit and invest their time in schooling in the hopes that their investment would pay off in the future. In rural areas where households believe children need to complete a certain level of education to find employment, the ability of parents to pay for their children's higher education as well as the accessibility of higher education institutions may both have an impact on enrollment rates (Banerjee et al., 2011).

Investing in lower-level education over higher education is preferred in developing countries for a variety of reasons. Low rates of social benefit and concerns about rising inequality are some of the reasons for such low investment levels. The other factor that discourages investment in higher education is its investment cost. The World Bank (2020), for example, shows that even though only three percent of students in the region are enrolled in higher education, it makes up 21% of the government's education budget.[1] The other arguments against higher education expansion stem from the concern that inequality may increase if wealthy families make up the majority of

1 Relatedly, Pradhan (1996) also shows that public spending on higher education in Africa is 44 times higher per student than it is for an elementary school student.

those who directly benefit from public investments in higher education. This claim is supported by Bennell (2021), which shows that while the share of the richest groups enrolling in higher education in SSA has increased significantly over the past few decades, few youngsters of low-income parents attend these institutions. Due to this, the likes of Psacharopoulos et al. (1986), have pushed developing countries to design new educational policy frameworks that either liberalize higher education or enact a specific higher education tax to subsidize lower education.

This dissertation covers four diverse topics, with a focus on building human capital and enhancing the performance of the agricultural sector by building climate change resilience. Each chapter is thoroughly and independently researched, has its own literature review, and uses different data and methodologies. By doing so, each chapter makes a unique contribution to the literature in addition to its contribution to policy discourses since it focuses on topics that have not been thoroughly explored or have received less attention in earlier works. Even though the study is solely focused on Ethiopia, the findings from this study could apply to countries that have similar characteristics.

1.2 OBJECTIVES AND RESEARCH QUESTIONS

The dissertation consists of four independent chapters. Its main objective is to provide a broader understanding of how environmental and developmental changes affect agricultural production, food consumption, and investment in human development decisions in the context of developing countries. The research questions addressed in each chapter are:

1. Do farmers adjust their land-allocation decisions in response to the early planting season weather variation? (Chapter 2)
2. How does access to small-scale irrigation affect farm households' diet quality? What are the potential impact pathways? (Chapter 3)
3. Do universities have spillover effects on lower-level school outcomes of female adolescence? (Chapter 4)
4. How does access to rural roads affect children's schooling and labor outcomes? (Chapter 5)

1.3 THE CONTEXT

Economies worldwide saw remarkable growth, albeit at varying speeds, and poverty levels significantly decreased over the past decades (Chen & Ravallion, 2010; Sala-i Martin, 2006). Contrary to this, SSA is experiencing an increase in extreme poverty, with a current poverty rate of over 41% (WHO et al., 2020). Weather variability is a major driver of poverty in the region and Ethiopia is one of the countries that face the challenge.

Drought extremes and rainfall variability are a recurring phenomenon in Ethiopia, and the recurring periods are becoming shorter (Degefie et al., 2019). Numerous studies have demonstrated how seriously exposed the rural lives in the country are to these variations. The effects include its effects on poverty rates (Dercon & Christiaensen, 2011), health (Dimitrova, 2021), education (Randell & Gray, 2016), migration, and population mobility (Ezra & Kiros, 2001; Gray & Mueller, 2012), and decisions on agricultural technology adoption (Alem et al., 2010).

Over the last few decades, Ethiopia's government has made massive investments in the agriculture sector. The government's development plans gave the expansion of irrigated areas a key priority, and irrigation received the largest allocation of the total budget for the Agricultural Growth Program (Passarelli et al., 2018). The country had 2.528 million ha of land irrigated by a small-scale irrigation system at the end of 2019, up from 853,000 ha in 2009/10 (Gebul, 2021).

Along with giving the agricultural sector priority, the government also made significant investments in road and educational infrastructure. The number of elementary schools tripled between 1996 and 2014, while the number of students increased from less than 3 million to more than 18 million during that same period (MoE & UNICEF, 2012). Similarly, the government hugely invested in expanding road access. For instance, the government built more than 62,000 km of new all-weather rural roads between 2012 and 2015 (Kebede, 2022).

Despite the aforementioned achievements, the country still faces several socioeconomic problems. Millions in the country still face severe hardships due to weather changes. According to figures from OCHA (2022), the drought, which started in October 2020 and was followed by three consecutive disastrous dry seasons, had impacted more than 24 million people in the country. Out of them, 9.9 million face severe food insecurity. Unacceptably high rates of food insecurity and malnutrition among vulnerable groups also continue to be major public health problems in the country. As shown in the Global Nutrition Report (2018), the country is off-track to achieve most of the SDGs' nutritional targets. Regarding its performance in developing human capital, MoE & UNICEF (2012) show that 2.6 million primary school-age children—of whom 57% are girls—are not enrolled, and only 25% of students who are old enough to attend secondary school do so.

1.4 STRUCTURE OF THE DISSERTATION

The dissertation presents four distinct chapters, each of which focuses on a different subject that are key policy challenges developing countries face in designing development strategies. All chapters are empirical in nature, although theories have played a significant role in providing direction for the analysis.

The second chapter causally estimates the impact of weather variation realized before the actual planting season on agricultural land allocation decisions. Existing studies in the region mainly focused on adaptations based on past rainfall experiences. However, the temperature has been rising in Africa by up to two times the global rate (Engelbrecht et al., 2015), and recent studies are showing that rising temperatures in the region are associated with multiple socioeconomic problems, including an increased risk of mortality, malnutrition, as well as a decrease in birthweight (Baker & Anttila-Hughes, 2020; Blom et al., 2022). As a result, it is critical to ascertain whether farmers modify their farm management decisions in response to temperature variation. Particularly, understanding the pace at which farmers react to fluctuations in weather patterns is essential to formulate effective measures that minimize long-lasting welfare losses (Jagnani et al., 2021). Hence, the second chapter of this dissertation will take adaptation beyond the usual options and investigates the impacts of early planting season temperature variation on land allocation decisions by focusing on maize producers in Ethiopia.

We use village-level panel data from Ethiopia's Annual Agricultural Sample Survey and high-resolution temperature and rainfall data from the ERA-Interim Reanalysis archive and CHIRPS to construct weather variables for early planting and planting stages based on a crop-specific calendar. By focusing on smallholder maize producers, we show that farmers adjust land allocation decisions in response to higher temperatures during early planting. In addition to measuring a hitherto unidentified adaptation margin, we show how crop substitution effects contribute to the increase in the land used for maize production because of warming temperatures.

The third chapter examines how access to irrigation affects the variety of farm households' diet quality and explores pathways through which irrigation affects this diversity. Irrigation can improve nutritional status by allowing farmers to grow and consume nutrient-rich crops or by enabling them to purchase such foods due to their income increment through increased output and diversion to high-value crops. Conversely, having access to irrigation would also change cropping patterns and hurt diet quality by causing farmers to focus on less-nutritious cash crops. Despite these theoretical claims, the effects of irrigation on nutritional outcomes received little attention. Our study is possibly one of the few studies that rigorously examined the connections between irrigation and nutrition as well as potential impact pathways.

The data utilized for this chapter is derived from the Ethiopian Socioeconomic Survey. To address endogeneity concerns, we utilize the endogenous switching regression model, and we combine the propensity score-matching model with an approach that solves systems of equations to investigate possible mechanisms. We show that irrigation can be effectively utilized to enhance the nutritional quality of smallholder diets.

In addition, we identify two key pathways: improving access to nutritious food items through own production and increasing the adoption of productivity-enhancing inputs.

In the fourth chapter, we investigate if the presence of public universities in the neighborhood affects educational attainment at lower educational levels. Investments made by developing countries to expand higher education are challenged for some reasons, including their high cost, poor rates of social value, and concern over escalating inequality. This claim, however, ignores the expected "trickle-down" effects in the form of socioeconomic positive externalities. Existing research has shown that universities act as a catalyst for socioeconomic development in the areas in which they are located by boosting regional economies through job creation, increased entrepreneurship, and strengthening human capital, among others. Because university expansion is a relatively recent phenomenon in SSA, there are not as many studies looking at their spillover effects. By taking advantage of the recent expansion of public universities in Ethiopia, we contribute to the body of knowledge by shedding light on the influence of universities on lower-level schooling of female adolescence, a topic that has been overlooked by previous studies. Focusing on female educational outcomes is valuable from a policy perspective since educating females can close the gender gap by increasing employment prospects (Erten & Keskin, 2018), boosting health (Brunello et al., 2013), and giving them more autonomy (Hahn et al., 2018), among other benefits.

We use Demographics and Health Surveys to construct our outcome and control variables. We compile the list of universities in the country and their foundation years from the World Higher Education Database and the Ministry of Education publications. We employ an event study framework to exploit variation in the timing of university establishment between 2007 and 2014 and conduct several tests to rule out any endogeneity problems. Our findings demonstrate public institutions encourage educational attainment among girls.

In addition to the money spent by the government on building new educational institutions, the direct and indirect costs paid by households related to education also determine school outcomes. As households rely on time-discounted returns to schooling to make this decision, they weigh the future benefits of investing in education against the current costs (Jensen, 2010). The cost includes the opportunity costs of keeping children in school rather than working, and a variety of factors might affect these costs. For example, having access to roads increases children's employment prospects, and parents may encourage their children to work and support the family financially. As a result, road access might encourage early school dropout and absenteeism. Contrarily, improved road access can improve educational outcomes by improving school access. Additionally, it raises parental spending power on education by making it simpler to find non-farm jobs and boosting the profitability of their agricultural business (Asher & Novosad, 2020). In the fifth chapter, we investigate if there is a trade-off or complementarity between road access and educational outcomes by focusing on the recent road expansion program in Ethiopia. We also investigate whether the impacts of road access differ based on gender, age, and exposure to drought shocks.

We combine panel data from LSMS with novel road network data obtained from the Ethiopian Roads Authority. We mitigate the endogeneity concern arising from the non-random road placement decision by combining the Difference in Difference techniques with a matching strategy. We demonstrate that, contrary to findings from other parts of the world, rural road access does not promote early dropout or absenteeism.

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2

EARLY GROWING SEASON WEATHER VARIATION, EXPECTATION FORMATION, AND AGRICULTURAL LAND ALLOCATION DECISIONS IN ETHIOPIA

ABSTRACT

Using unique crop-specific data gathered over seven years, we study if and how maize-producing farmers in Ethiopia adjust their land allocation decisions in response to pre-planting-season weather variations. We show that farmers adjust their land allocation decisions in response to increased temperatures early in the growing season. In addition to quantifying a substantial adaptation margin that has not been documented before, our study also reveals the presence of a weather variation-induced expansion of maize production into areas that are less suitable for maize cultivation.

JEL Classification: O13, Q15, Q54, C33
Keywords: Weather variation; Adaptation; Land allocation; Crop substitution

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2.1 INTRODUCTION

There are pertinent reasons to be concerned about the effects of climate change on the agriculture sector. As climate predictions show warmer and more variable futures, an increasing number of studies explore the socioeconomic implications of a warmer climate, including the effects on agriculture under different scenarios (Hsiang et al., 2017; Costinot et al., 2016; Schlenker & Roberts, 2009). Schlenker & Roberts (2009) showed, for example, that even the slowest warming scenario could reduce crop yield by up to 46 percent. Studies also show that climate change disproportionately hits the poorest segments of the population of developing countries, mainly due to their poor adaptive capacity, high dependence on rain-fed agriculture, and economic fragility (Müller et al., 2011; Cooper et al., 2008). This calls for improvements in farmers' adaptive capacity and a better understanding of their adaptation techniques. Besides, it is also critical to examine the potential adaptation margins because such information is vital for a more accurate assessment of the expected economic losses due to climate change and weather variation. Particularly, understanding how promptly farmers respond to weather shocks close to the planting season provides valuable information to formulate policies that help to enhance adaptive capacity and avoid long-lasting welfare losses (Jagnani et al., 2021; Ramsey et al., 2021).

Literature shows that farmers in the region use different strategies to manage climate risks (e. g., Maddison (2007); Shikuku et al. (2017); Deressa et al. (2009); Call et al. (2019). However, the bulk of existing studies concentrates on how farmers adjust their decisions based on climate knowledge acquired over the long term. Since the majority of farm management decisions are made based on weather expectations before the actual events are realized, and because such subjective predictions are heavily influenced by prior weather experience, investigating the role of climate knowledge gained over time is valuable for policy development. However, both economics and psychology literature (e.g., Ji & Cobourn (2021); Camerer & Loewenstein (2004)) argue that recent realizations of an event have a disproportionately large influence on human expectations about the likelihood of that event occurring again. For example, Ji & Cobourn (2021) argue that, because farmers over-weight recent weather events in their expectation formation, such events heavily influence their farm management decisions. As a result, understanding how farmers react to short-term weather variations is essential to understand the nexus between weather variations and farmers' adaptation strategies.

A few recent empirical studies have looked at farmers' responses to short-term weather variations. Jagnani et al. (2021) show that Kenyan farmers adjust their input use decisions in response to temperature variations that happened during the initial cropping cycle. Relatedly, Cui & Xie (2022) show that farmers in China adjust their planting dates based on weather conditions realized eight weeks before the actual planting period.[1] We contribute to this growing area of research by providing a causal estimate of the impacts of initial planting season weather patterns on land allocation decisions using data from a low-income context. Specifically, by disaggregating the climate variables into pre-planting and planting stages of the crop growing cycle, we investigate the extent to which smallholder farmers in Ethiopia adjust land allocation decisions in response to plausibly exogenous weather variations experienced before the actual planting time. Ethiopia provides an appealing setting for this research, where weather variation is high and rain-fed agricultural activities constitute the single most important source of income for virtually all rural households. As a result, rural livelihoods in the country are highly vulnerable to weather fluctuations. The availability of one of the world's largest yearly detailed agricultural surveys also provides a unique database.

Several studies have investigated the role of weather conditions on land allocation decisions. Among them, He & Chen (2022); Morton et al. (2006); Zaveri et al. (2020); Li et al. (2013) explain how the share of cropland, forest, and grazing land change with variations in weather. Though these studies provide pertinent information about the role of weather patterns on land allocation decisions, they defined land-use decisions broadly by aggregating land covered by all crop types as a single variable. However, since each crop has its own specific heat and moisture requirements, weather variation is expected to have disproportionately stronger effects on some crops than others. Such productivity differentials are expected to encourage farmers to reallocate their fields to crops that are better suited to the current weather conditions (Arora et al., 2020). As a result, the probability that a farmer allocates land to a given crop depends on the comparative advantage of that crop (Cui, 2020*b*; Seo & Mendelsohn, 2008). Hence, if farmers notice warmer temperatures weeks before the planting season, they may prefer to produce crops that withstand such conditions or adopt drought-resistant varieties. For instance, warmer temperatures are expected to boost the productivity of staple crops, such as maize, by hastening photosynthesis (Jagnani et al., 2021). Relatedly, Sesmero et al. (2018) showed that farmers allocate more resources to the production of maize if their expectations about weather conditions become more pessimistic.

Among crop-specific studies, Cui (2020*b*) demonstrates that growing season climate change, measured by historical data over the past 30 years, significantly affects the land allocation decisions of maize farmers in the United States. However, Cui (2020*b*) relates farmers' reactions to long-term climate change rather than weather variations that occur around the planting seasons. Miao et al. (2016) show how excessive rainfall during the planting season discourages farmers in the United States from growing maize, whereas Cui (2020*a*) illustrates how farmers alter harvest decisions by for-

1 Somehow related to this, recent research by Letta et al. (2022) has demonstrated how food prices respond quickly to drought conditions during the growing season due to anticipated supply shortages before any harvest failure occurs.

going crops when faced with weather shocks using county-level data from the US. According to Aragón et al. (2021), Peruvian farmers respond to higher temperatures by increasing the production of tubers. Lesk et al. (2016) show how extreme weather events affect the worldwide area allotted for cereal production. Other studies like Seo & Mendelsohn (2008); Kurukulasuriya & Mendelsohn (2008) explore the relationship between crop choice and climatic variables by relying on cross-sectional data. However, results from cross-sectional analyses are vulnerable to omitted variable bias and do not permit establishing a causal link between weather variation and agricultural outcomes (Blanc & Schlenker, 2017).[2]

We contribute to the literature in several ways. First, we provide an estimate of the causal impact of weather variation realized before actual planting on land allocation decisions by focusing on maize-producing farmers in Ethiopia. We combine village-level panel data gathered over seven years with high-resolution weather data to obtain accurate weather variation indicators that are comparable across time and space. Second, we investigate the role of the natural endowment on farmers' adaptation decisions. Geographical factors like environmental suitability for a given crop could have a differential impact on farmers' adaptation strategies. For example, if maize is the best crop for a specific region, producers may choose to use modern technology such as drought-resistant varieties rather than abandoning the crop during unfavorable weather conditions. Drier conditions during the planting seasons might also lead to the expansion of drought-tolerant crops such as maize into less suitable areas. We examine if farmers' response to pre-planting season weather variation depends on the suitability of the fields for maize production using the FAO-GAEZ suitability database that reports the productivity potential of a given area for different crops.

To identify the impacts of the pre-planting season weather variation on farmers' land allocation decisions, our identification strategy makes use of an exogenous within-season year-to-year weather variation within rural villages. Our identification is plausible because farm households are unlikely to accurately predict the upcoming season's weather conditions across time and place (Deschênes & Greenstone, 2007; Burke & Emerick, 2016).

The remaining sections of the paper are organized as follows. Section two discusses the socioeconomic importance of maize in Ethiopia and the mechanisms through which weather variability affects maize production and farmers' resource allocation decisions. A detailed description of the sources and types of data used in the analysis is presented in section three. The fourth section discusses the methodological strategy employed in the study. The fifth section presents and discusses the findings of the study, and the final section concludes.

2 In addition to studies that investigate the role of weather variability on land allocation decisions, some studies have also looked at the role of price (e.g.: Haile et al. (2016); Hendricks et al. (2014), access to insurance (e.g.: Wu (1999); Yu et al. (2018)), competition with other enterprises (e.g.: Li et al. (2019); Motamed et al. (2016)) and access to irrigation water (e.g.: Taraz (2017); Manning et al. (2017)).

2.2 PROFILE OF MAIZE IN ETHIOPIA

Maize is one of the dominant crops in Ethiopia. The crop accounts for one-third of the overall grain production in the country (Central Statistical Agency of Ethiopia, 2018, 2019). Estimates also show that smallholder farmers in the country allocate at least half of their farmland to maize production in major growing areas (Ertiro et al., 2019). Its adaptability, the growing demand for maize stover, and its yield of food calories per ha. are some of the reasons that have contributed to its popularity (Abate et al., 2015).[3]

FAOSTAT (2020) shows that maize production in the country increased five-fold between 1993 and 2018. The country has a relatively good productivity record compared with the averages of Africa in general and Eastern Africa in particular (Figure A.1). However, the productivity gap between Ethiopia and the global average or other country groups remains high. Low levels of technology adoption, poor access to input and financial markets, and frequent weather variability are among the main reasons for such low productivity levels (Croppenstedt et al., 2003; Kassie et al., 2018).

Though maize is considered a suitable crop for warmer conditions, several studies show that the crop is also sensitive to water shortage and heat stress (Schlenker & Roberts, 2009; Lobell et al., 2011). The effects of weather variability on maize production depend on timing and intensity. For instance, Seyoum et al. (2017) show that drought in the early growth stages reduces yield by up to 80%, whereas the yield reduction associated with droughts after the flowering period is only 10%. This is partly associated with the fact that high temperatures during the early stages affect kernel development by limiting the number and size of endosperm cells. Likewise, adverse weather conditions during the seedling and vegetative stages can also affect maize growth by limiting growth rate, delaying canopy closure, and reducing soil shading (Engelen-Eigles et al., 2000; Commuri & Jones, 2001).

2.3 DATA

Our study is based on data generated from three main sources: the Annual Agricultural Sample Survey of the Central Statistics Agency of Ethiopia (CSA), the Land Suitability Index from the FAO-GAEZ database, and weather data from various sources.

We use Ethiopia's Annual Agricultural Sample Survey (AgSS) as the main source for the outcome and control variables. CSA annually collects the agricultural sample survey that covers over 36,000 private farm holders, focusing on the main cropping season that corresponds to any temporary crop harvested between September and February (locally known as Meher season). Ninety percent of the total cereal output

3 The daily per capita fat, calories, and Protein contribution of maize in the Ethiopian diet have already reached 1.31g, 398 kcal, and 9.2g, respectively (FAOSTAT, 2020).

in the country is produced during this season (Asfaw et al., 2018). CSA collects AgSS annually at the end of the Meher cropping season's harvesting period.

The AgSS data collection process involves a stratified two-stage sampling technique. In the first stage, around 2000 enumeration areas (EAs) are selected using sampling probability proportional to the number of farm households obtained from the most recent Population and Housing Census Frame for the country. This stage is followed by the selection of about 20 agricultural households from each sample EA using random sampling, making AgSS one of the world's largest annual agricultural surveys (Mann et al., 2019).

Starting from 2010, CSA has adjusted its sample selection process. Accordingly, the same EAs are used in each consecutive survey year, but households are re-sampled every year. Using this base, we construct a panel dataset by aggregating values at the EA level. This creates a balanced panel sample comprising 1,815 EAs over the period 2010-16. Figure A.4, shows the location of the study villages (EAs). Throughout the paper, we use enumeration area and village interchangeably.[4]

Table A.1 provides the descriptive statistics for the working variables aggregated at the village level. Eighty percent of households are headed by men. A typical village has household heads that are on average 43 years old with a family size slightly higher than five individuals per household. The average number of oxen owned is 0.87. In terms of access to institutions, 18% of them used credit, and 59 percent of them had access to agricultural extension programs. Regarding their land allocation decisions, maize takes up 6.7 hectares of land, whereas barley, sorghum, teff, wheat, pulses, and oilseed take up 3.2, 6.5, 9.3, 5.0, 6.3, and 2.6 hectares, respectively.

Daily data on rainfall and temperature are sourced from the Climate Hazards Group InfraRed Precipitation Station (Funk et al., 2015) and the ERA-Interim Reanalysis archive, respectively.[5] Both datasets have a 0.25x0.25 degree resolution.[6] From the daily observations, aggregate weather variables are constructed for two stages of the crop growth cycle for each survey period. We construct the crop growth cycle following Jagnani et al. (2021). The two stages are (1) the pre-planting period (or initial planting stages), which accounts for the land preparation period, and (2) the planting period, which accounts for the planting and fertilizer application period. Both periods cover 60 days before and after the beginning of the planting date, respectively. The stages are constructed based on a time-invariant crop-planting calendar accessed from the Nelson Institute for Environmental Studies of the University of Wisconsin-Madison (Sacks et al., 2010). Sacks et al. (2010) provide 0.5-degree resolution grid-

4 Detailed sampling procedure can be found on the agency's website at `http://www.statsethiopia.gov.et/`

5 Meteorological data can also be accessed from the Ethiopian Meteorological Service. However, the number of missing observations or values reported as zero on days when no records are made creates a significant empirical problem (Colmer, 2021). In particular, since the construction of our weather variables requires daily records, a complete list of observations is essential.

6 We collected data from 15,851 grid cells in total.

ded maps for the cropping calendar of 19 major crops, including maize.[7] As a result, since we are measuring the weather variables by holding the crop calendar fixed from season to season, our weather variables are unlikely to be affected by endogenous weather-induced changes.

To investigate the role of land suitability for maize production on farmers' responses to weather variation, we utilize the FAO-GAEZ dataset.[8] FAO-GAEZ calculates the suitability of a given field for a particular crop by predicting the maximum attainable yields using agronomic models and three main inputs: (1) crop attributes (mainly estimated through field experiments); (2) physical attributes (including soil characteristics, elevation, and land gradient); (3) assumptions about the level of modern inputs utilization.[9] We use the maize suitability index constructed for rain-fed farming with the assumption of low input utilization. By taking the national average production potential as a threshold, we categorize EAs into two groups: suitable and less suitable EAs. Table A.1, provides the descriptive statistics for the potential yields along with other working variables.

2.4 ESTIMATION STRATEGY

We estimate the following panel fixed effects model of the effect of weather variation prior to planting on land allocations:[10]

$$\begin{aligned} Y_{rdvt} = {} & \beta_i[Temp]^{pp}_{rdvt} + \omega_i[Rain]^{pp}_{rdvt} + \gamma_i[Temp]^{pt}_{rdvt} + \delta_i[Rain]^{pt}_{rdvt} + \\ & \theta X_{rdvt} + \alpha_v + \varphi_{rt} + \varepsilon_{rdvt} \end{aligned} \tag{2.1}$$

Y_{rdvt} is the dependent variable that represents the area of cultivated land planted to maize (in hectares) in a given region r, district d, village v, and time t. $Temp$ stands for our indicators of temperature. We use the average daily temperature in a given season measured in degrees Celsius as our main indicator, following Cui & Xie (2022). We also check alternative definitions as a robustness exercise. $Rain$ is our indicator of rainfall conditions. Although rainfall is uncommon in the months leading up to the planting season, rainfall conditions around the planting period are undoubtedly among the most crucial factors expected to influence farmers' resource allocation decisions in countries like Ethiopia, where the vast majority of farmers do not have access to irrigation. We follow the recommendations of related studies (e.g., Kassie et al.

7 Estimation details of the calendar alongside the description of sources and types of data used to construct the calendar can be found in Sacks et al. (2010).
8 The FAO-GAEZ is also used by Costinot et al. (2016); Nunn & Qian (2011).
9 Detailed information on data sources and types used to calculate the indices, along with assumptions, and an overview of estimation approaches can be accessed at: `http://webarchive.iiasa.ac.at/Research/LUC/GAEZv3.0/docs/GAEZ_Model_Documentation.pdf`
10 A simplified theoretical framework that models farmers' land allocation decisions is presented in the appendix.

(2014); Lobell & Asseng (2017)) and used Wet Days Frequency to control both the amount and distribution of rainfall. The superscript *pp* and *pt* represent pre-planting (initial) and planting seasons, respectively. β and ω are our parameters of interest. α_v controls for village fixed effects and φ_{rt} accounts for unobservables that vary across regions over time and are expected to absorb the effects of any shock that is explicit to a given region in any given year. X stands for EA-level time-varying controls (e.g., EA-level averages of the ages of the household heads, family size, access to credit, level of irrigation utilization, and oxen size).

Our identification strategy exploits the random within-season year-to-year variations in local weather conditions. The assumption is that changes in weather conditions experienced by a village are exogenous to unobservable household or village-level characteristics that vary over time (Deschênes & Greenstone, 2007; Burke & Emerick, 2016). Our identification is credible since farmers are unlikely to accurately predict upcoming weather conditions across time and location except for specific geographical features like seasonal climatic conditions, which we have controlled by EA, and region-by-year fixed effects. Hence, our identification strategy allows us to construct causal inferences based on the assumption that within-season weather variations are exogenous and conditional on village-level attributes and region-specific time trends.

We also investigate whether the effect of weather variations on land allocated for maize is realized through substitution with other crops. This is done by examining the effects of weather variations on land allocated to maize relative to another crop. This helps to identify how weather variation affects the comparative advantage of maize compared with other crops (Cui, 2020*b*). The regression equation used to address this objective is given as:

$$\begin{aligned}(\frac{L_M}{L_M+L_O})_{rdvt} = \beta_i[Temp]^{pp}_{rdvt} + \omega_i[Rain]^{pp}_{rdvt} + \gamma_i[Temp]^{pt}_{rdvt} + \delta_i[Rain]^{pt}_{rdvt} + \\ \theta X_{rdvt} + \alpha_v + \varphi_{rt} + \varepsilon_{rdvt}\end{aligned} \quad (2.2)$$

where L_M and L_O stand for the size of land allocated for maize and a specific alternative crop, respectively. We focus on major crops (e.g., barley, teff, wheat, etc. as shown in Table A.1 and 2.6). All remaining variables and other terms follow equation 2.1.

In estimating the above equations, there could be spatial interactions across neighboring locations of the study area, and failing to account for such interactions may lead to biased and inconsistent estimates (LeSage, 1997; Fisher et al., 2012).[11] For instance, the land allocation decisions of neighboring EAs (our dependent variable) could be spatially correlated since they might share similar geographic attributes (like

11 The possible sources of interactions are interactions in one or a combination of the dependent variables, regressors, or error terms across locations (Anselin, 2022).

soil fertility status) and input and output markets.[12] Similarly, the extrapolation techniques used to generate gridded and reanalyzed climate data can create spatial correlations between the climate variables (our independent variables) (Auffhammer et al., 2013). Studies also show that rainfall at a given location could be correlated with rainfall received in neighboring areas (Maccini & Yang, 2009). Spatial correlation might also arise due to spatial correlation of the error terms due to confounding variables in omitted climatic measures (Auffhammer & Schlenker, 2014). In principle, the empirical model has to control for spatial interactions from all three sources (dependent and independent variables and error terms) to produce unbiased and consistent estimates. However, the problem of over-fitting makes it difficult to use models that can effectively control the interactions from the three sources in applied research (Elhorst, 2014). Studies such as Mamo et al. (2019) argue that the parameters of the spatial model can be identified without facing the problem of over-fitting by controlling for spatial correlation in the independent and dependent variable using the Spatial Durbin Model (SDM) and by accounting for spatial dependence in the error term through clustering the standard errors. Hence, as a robustness check, we estimate the impacts of weather variation on land allocation decisions using the Spatial Durbin Model.[13]

2.5 RESULTS AND DISCUSSION

2.5.1 *The effects of pre-planting season weather variation on the size of land allocated for maize production*

Table 2.1 presents the estimated effects of weather variation realized during the pre-planting seasons. As shown in column 1, temperature variation in the pre-planting season has a significant impact on farmers' land allocation decisions. More specifically, it shows that after controlling for EA fixed effects as well as time-varying region level characteristics along with other factors, a 1°C in the pre-planting season increases the size of land allocated to maize production by 14.8 percent. The results are in line with those of Aragón et al. (2021) and He & Chen (2022), who demonstrated how smallholder farms adapt to high temperatures by changing their land allocation decision. Given the rarity of rainfall during the pre-planting season, the insignificance of rainfall coefficients is unsurprising.

Related studies (e.g., Aragón et al. (2021)) show that farmers modify their land allocation decisions based on the planting season temperature conditions. As a result, we re-estimate the impacts by controlling for the planting season weather con-

12 This fact is empirically verified by Miao et al. (2016).
13 We used *xsmle*, a user-written Stata command designed by Belotti et al. (2017) to fit spatial panel data models.

ditions (both temperature and rainfall variation) to see if the estimated effect of the pre-planting weather condition is absorbing the effects of growing season weather conditions. As shown in column 2 of Table 2.1, the effects of pre-planting season temperature remain statistically significant after controlling for the growing season weather conditions.

Table 2.1: Estimated impacts of average temperature on maize land allocation

	(1)	(2)
Variables	Maize land (log)	Maize land (log)
Temperature pre-planting	0.148***	0.140***
	(0.037)	(0.041)
Rainfall pre-planting	-0.003	-0.002
	(0.010)	(0.010)
Planting season weather	No	Yes
Other controls	Yes	Yes
Region year fixed effects	Yes	Yes
EA fixed effect	Yes	Yes
Observations	12,705	12,705
R-squared	0.864	0.865

Note: The table presents the effects of pre-planting season weather conditions on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop; Controls included in the analysis are the age of the household head, family size, number of oxen owned, and access to credit, extension service, and irrigation. Planting season weather accounts for temperature and rainfall variations in the planting season. Standard errors clustered at the district level in parentheses; *** p<0.01.

The magnitude of the effects of pre-planting season temperature on the size of land allocated for maize production is economically sizable. To put this in context, we use our predicted coefficient to compute the extent of the change in total land covered by maize. The 14 percent increase in the size of land allocated to maize production (column 2 of Table 2.1) translates to an additional 0.94 hectares of maize production at the EA level, based on the sample mean of 6.7 ha. The results should be viewed in light of the fact that the average year-to-year temperature variations within EA during the pre-planting and planting seasons are 0.50 and 0.72 degrees Celsius, respectively, representing 2.7 and 3.4 percent differences from their averages.

The positive and significant relationship between higher temperature levels during the pre-planting season and the area of land allocated for maize production could be because of the nature of the crop. Warmer temperatures are expected to increase the productivity of staples, including maize, by speeding up photosynthesis (Jagnani et al., 2021). As shown in Figures A.2 and A.3, the average daily temperatures in the study area throughout the study period were mostly within the range over which maize yields generally increase as temperatures rise (Lobell et al., 2011). Studies such as Seo & Mendelsohn (2008) and Wang et al. (2010) show that farmers tend to grow maize as temperatures rise. The other reason for this relationship might be linked to the recent progress made in improving the accessibility of drought-tolerant maize varieties in the country. For instance, as of 2016, about 9000 tons of certified drought-resistant maize variety, known as BH661 was distributed in the country and the seed covered 18 percent of maize land in the country (Ertiro et al., 2019).[14]

2.5.2 *Robustness checks*

We run a variety of tests to examine the robustness of our main results.

2.5.2.A *Incorporating additional controls: Past weather variation and own prices*

Because most farm management decisions are made based on expectations about future weather conditions, past weather conditions substantially influence farmers' decisions. In line with this, Ji & Cobourn (2021) showed how lagged weather conditions influence land allocation decisions of farm households. Hence, we run a robustness test to see if our results are influenced by the previous year's growing season weather conditions (both temperature and rainfall variation). Column (1) of Table 2.2 provides the result estimated by including one-year lagged planting season weather patterns.

In the main results presented in Table 2.1, the region-by-year fixed effect is used to control price effects at the regional level. Here, the strength of the results is tested by incorporating maize prices measured from the nearest market. Among existing studies that estimated the effects of price on land allocation decisions, Chavas & Holt (1990) and Lee & Helmberger (1985) used one-year lagged prices, whereas Lin & Dismukes (2007) relied on future prices. The consistency of the result is tested by incorporating both one-year lagged and future prices. Columns (2) and (3) of Table 2.2 present the results.[15] As shown in the Table, the results of the main regression equation remain qualitatively identical in these robustness checks.

2.5.2.B *Alternative temperature measures*

Different temperature metrics may indicate different elements of climate impacts and relying just on average temperatures may overlook other factors (Cui & Xie, 2022). For example, degree-days, which is a measure of cumulative heat, have been used

14 The cultivation of the BH661 variety for commercial farming is officially approved by the National Variety Release Standing Committee in 2011.

15 The average lagged and future prices are calculated at the closest market using monthly food price data obtained from the market monitory survey of the WFP. The price data is accessed from `//dataviz.vam.wfp.org/economic_explorer/prices`.

Table 2.2: Estimated impacts of average temperature on maize land allocation: Incorporating additional controls

	(1)	(2)	(3)
Variables	Maize land (log)	Maize land (log)	Maize land (log)
Temperature pre-planting	0.192***	0.126***	0.141***
	(0.042)	(0.041)	(0.041)
Rainfall pre-planting	0.01	-0.002	-0.001
	(0.01)	(0.01)	(0.01)
Planting season weather	Yes	Yes	Yes
Lagged planting season weather	Yes	No	No
Lagged average price	No	Yes	No
Future price	No	No	Yes
Other controls	Yes	Yes	Yes
Region by year fixed effect	Yes	Yes	Yes
Observations	12,705	12,705	12,705
R-squared	0.872	0.865	0.865

Note: The dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; See notes under Table 2.1 for additional information such as the list of control variables. *** $p<0.01$.

by both agronomic and economic literature to illustrate the link between temperature and agricultural productivity. Even though we are not directly analyzing the impacts on agricultural productivity, we use degree-days as an alternative indicator for a robustness test.

A degree-day is calculated as the intensity of daily exposure to defined upper and lower temperature ranges at which heat and cold stresses are expected to begin and impede plant growth (Roberts et al., 2013). Related works (e.g., Worku et al. (2012) and Jagnani et al. (2021)) consider 8°C and 30°C as the lower and upper thresholds in calculating degree-days. Table 2.3 shows the estimated effects of degree-days on farmers' land allocation decisions. We show qualitatively identical results with the results of the main regression equation, though it is notable that pre-planting rainfall now becomes significant at the 10% level.

2.5.2.c *Accounting for spatial interactions*

As we discussed in the methodology section of this paper, failing to account for spatial interactions properly can lead to biased estimates. As a result, we use the spatial panel regression model to evaluate the effects of pre-planting season weather conditions on

Table 2.3: Estimated impacts of average temperature on maize land allocation: Alternative weather definition

Variables	Maize land (log)
Pre-planting season degree-days	0.141***
	(0.04)
Rainfall pre-planting	-0.005*
	(0.003)
Planting season weather	Yes
Other controls	Yes
Region by year fixed effect	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Note: The dependent variable is the log value of land under maize crop. GDD: Degree days computed by considering 8°C and 30°C as the lower and upper thresholds. For comparison, we used daily averages of Degree days; Standard errors clustered at district level in parentheses; See notes under Table 2.1 for additional information such as the list of control variables. *** $p<0.01$.

land allocation decisions in our next robustness check. As can be seen from Table 2.4, the findings of the main regression equation remain qualitatively unaffected.

2.5.2.D *Falsification test*

We used a falsification test to see if the reported impacts of pre-planting temperature variation on land allocation decisions are absorbing the effects of other time-varying unobservables. We follow Sesmero et al. (2018) and re-estimate our main model by changing the timing of weather data. Accordingly, we re-estimate Table-2.1 by replacing our pre-planting season temperature with future planting season temperatures (by one wave). The future weather condition is unlikely to influence the current year's land allocation decision since farmers do not have access to such information during the decision-making process. If the variable significantly explains the allocation decisions, it suggests that the reported impacts in the main result are due to the effects of other time-varying unobservables. As shown in Table 2.5, the coefficient of the mismatched weather variable is not statistically significant, implying that unobserved factors are unlikely to confound the effect of pre-planting weather conditions reported in our main result. We also present a consistent result in Table A.6, using weather conditions during the post-harvesting season as an alternative variable.

Table 2.4: Estimated impacts of average temperature on maize land allocation: Accounting for spatial interactions

Variables	Maize land (log)
Temp pre-planting	0.190***
	(0.046)
Rainfall pre-planting	-0.020
	(0.013)
Planting season weather	Yes
Other controls	Yes
Region by year fixed effect	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Note: The dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; See notes under Table 2.1 for additional information such as the list of control variables. *** p<0.01.

2.5.2.e *Additional tests*

In our main analysis, we consider 60 days before the commencement of the planting season to be an appropriate time to remain in the spirit of Jagnani et al. (2021). We looked at the impacts using 45 and 30 days to see if the result is sensitive to the length of the time spam. As shown in Tables A.2, the finding remains consistent despite the difference in date.[16] We also rerun our main model with a finer set of district-by-year fixed effects to account for any district-specific time-varying features, which might not be controlled by our control variables. Table A.3, shows the result, which is consistent with our main finding. We also used a simple machine learning technique to calculate the percentage of variation in the dependent variable explained by each independent variable. As indicated in Table A.5, the most important variable is pre-planting temperature, which accounts for over a quarter of the variation in land allocated for maize production. Lastly, we present additional robustness test results in the (Tables A.4-A.8) that include changing the definitions of our main working variables.

16 We also looked at the effects over a shorter period and discovered that as the time span gets shorter, the magnitude and statistical significance of the effect decrease, eventually becoming insignificant. This is in line with Sesmero et al. (2018), who highlighted how difficult it is to adjust agricultural input allocation decisions within a very short period of time.

Table 2.5: Placebo regression

Variables	Maize land (log)
Future temperature	-0.043
	(0.030)
Rainfall control	Yes
Planting season weather	Yes
Other controls	Yes
Region by year fixed effect	Yes
EA fixed effect	Yes

Note: The table presents the effects of future average temperature (Future temperature) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; See notes under Table 2.1 for additional information such as the list of control variables.

2.5.3 *Weather variation and crop substitutions*

After examining the effects of pre-planting weather conditions on maize growers' land allocation decisions, we fit equation (2.2) to see if crop substitution effects partially explain the change in the areas of maize. The findings indicate the presence of crop substitution effects caused by the pre-planting season temperature variation. It shows that higher temperatures during the pre-planting period increase the share of land covered by maize relative to alternative crops such as barley, sorghum, teff, and oilseed (Table 2.6). It is worth emphasizing that if the pre-planting season temperature variations affect both maize and the alternative crops to a similar extent, no effect would have been observed. Among existing studies, Cui (2020*b*) shows that a 0.1°C increase in past temperature increases land allocated to maize and soybean by up to three percent relative to wheat, while Wang et al. (2010) showed that warm temperature encourages maize production but discourages the production of soybeans and vegetables.

2.5.4 *Impact heterogeneity*

2.5.4.A *Based on soil suitability*

The result of the heterogeneous effects of land suitability on farmers' responsiveness to pre-planting season weather conditions is presented in Table A.9. We find no differences in the effects of pre-planting season temperature variation based on the suitability of the villages for maize production. This means that, regardless of the suitability

Table 2.6: Effect of weather variability on crop substitution

Variables	Barley	Sorghum	Teff	Wheat	Pulse	Oilseed
Temperature pre-planting	0.0145**	0.0156*	0.0172***	0.008	-0.006	0.0193**
	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Rainfall pre-planting	0.001	-0.000	-0.002	0.000	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Planting season weather	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes	Yes	Yes
EA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,705	12,705	12,705	12,705	12,705	12,705
R-squared	0.823	0.744	0.81	0.848	0.838	0.703

Note: The dependent variables are the share of land covered by maize relative to the alternative crops. Standard errors clustered at district level in parentheses; See notes under Table 2.1 for the list of other control variables. *** p<0.01, ** p<0.05, * p<0.1.

of villages for maize production, farmers adjust the size of land allocated to maize production due to pre-planting season weather variation. The result demonstrates the feasibility of expanding maize production into new areas to adapt to changing weather patterns. A recent study by Sloat et al. (2020) shows how rain-fed maize production migrated to areas that were not previously major producers due to climate change. Similarly, Skarbø & VanderMolen (2016) document the expansion of maize production practices towards higher altitudes due to climate change.

2.5.4.b *Based on the temperature level*

To see if farmers' responsiveness to pre-planting season weather conditions varies based on the temperature level, we also run our model by including an interaction term of the pre-planting season temperature and a binary variable showing whether the temperature of the EA is above the total average (or median). However, as we present in Table A.10, we could not find statistically significant effects of the interaction terms. This might be because the average temperature in the studied area during the research period was within the range where maize yield increases as the temperature rises (Figures A.2 and A.3). As noted by Lobell et al. (2011), and others, heat stress reduces maize yield only when temperatures exceed 30°C .

2.6 CONCLUSION

The recent literature on the impacts of climate change and weather variation on agriculture predominately focuses on estimating the impacts on crop yields, and many of them have documented adverse effects. Another popular research theme within climate economics literature is the study of farmers' adaptation to climate change. This paper contributes to this strand of the literature by examining the effects of pre-planting season weather variation on the land allocation decisions of farmers, focusing on Ethiopian maize producers.

We document that, controlling for village-level fixed effects as well as time-varying region-level characteristics along with other factors, a 1°C temperature increase in the pre-planting season increases the area of land allocated to maize production by 14.8 percent. We show that part of the increase in land allocated to maize is achieved by replacing other crops. We also provide some evidence that weather variation encourages the expansion of maize into less suitable areas. We confirm that these results are not confounded by the previous year's growing season weather conditions or maize price. We also employed a spatial panel data model to account for geographical and temporal effects, which also confirm our main results.

The findings in this paper have the following implications. The results on land allocation adjustments due to the pre-planting season warming contribute to a limited but growing body of work that includes evidence of farmers' response to weather variation by adjusting their input allocation decisions (Jagnani et al., 2021) and planting dates (Cui & Xie, 2022). The findings highlight that focusing only on annual temperatures (ignoring the effects of pre-planting season temperature variation) leaves a significant short-term behavioral response that is important for policy formulation. Similarly, unlike previous studies that looked at how weather variation impacts total cropland (e.g., He & Chen (2022); Morton et al. (2006)), or land covered by certain food groups (such as Aragón et al. (2021) that focused on land allotted to tuber production), this study focuses on crop level analysis and contributes to the literature by showing how weather variation alters the comparative advantages of crops.

The findings of the study have several policy implications. By estimating the effects of pre-planting season weather variation on farm households' land allocation decisions, we have documented a notable adaptation margin that has been overlooked in previous studies. For instance, the vast majority of studies looking at the impact of rising temperatures on agriculture use field experiments or simulations, overlooking the potential for adaptation Miao et al. (2016). However, as we have shown above, farmers adjust land allocation decisions in response to weather variations, and ignoring this crucial adaptation margin may lead to an overestimation of actual climate-related losses (Aragón et al., 2021). To put this in perspective, Zhao et al. (2017) and Lesk et al. (2016) showed that each degree Celsius temperature increase reduces worldwide maize yields by 7.4% and 10%, respectively, whereas research conducted in various parts of Ethiopia revealed up to 43% maize yield reduction by the end of the century (Abera et al., 2018; Degife et al., 2021). As a result, accounting for the 14 percent adaptation margin due to a one-degree Celsius temperature increase during the preplanting season that we have documented might significantly reduce the expected losses.

It is also important to underscore the fact that farm households' decision to expand maize production to cope with increased temperatures might be at the cost of crop rotation. Studies show that crop rotations improve farm profit by reducing crop losses due to disease and pests and maintaining soil fertility (Cai et al., 2013). In addition, the expansion of maize into less suitable areas might have implications for farm productivity. As a result, future research may look at the effects of such adaptation strategies on farm productivity and profitability.

Improving the accessibility of micronutrient-rich foods by diversifying farm production has recently drawn attention to achieving food and nutrition security (Poole et al., 2021; Sanchez et al., 2020). Hence, as land allocation changes the amount of land devoted to a particular crop, it can have implications for the type and amount of food produced and supplied to the market. Notably, for developing countries like Ethiopia, where a significant share of food comes from domestic production, weather variation-induced reallocation of land can affect the types and amount of food that is available and accessible to the population. As a result, the substitution of cash crops for staple crops like maize to withstand weather variation might have implications for farm households' market participation and diet quality. This might underscore the importance of investing in the production and distribution of drought-resistant seeds for high-value crops.

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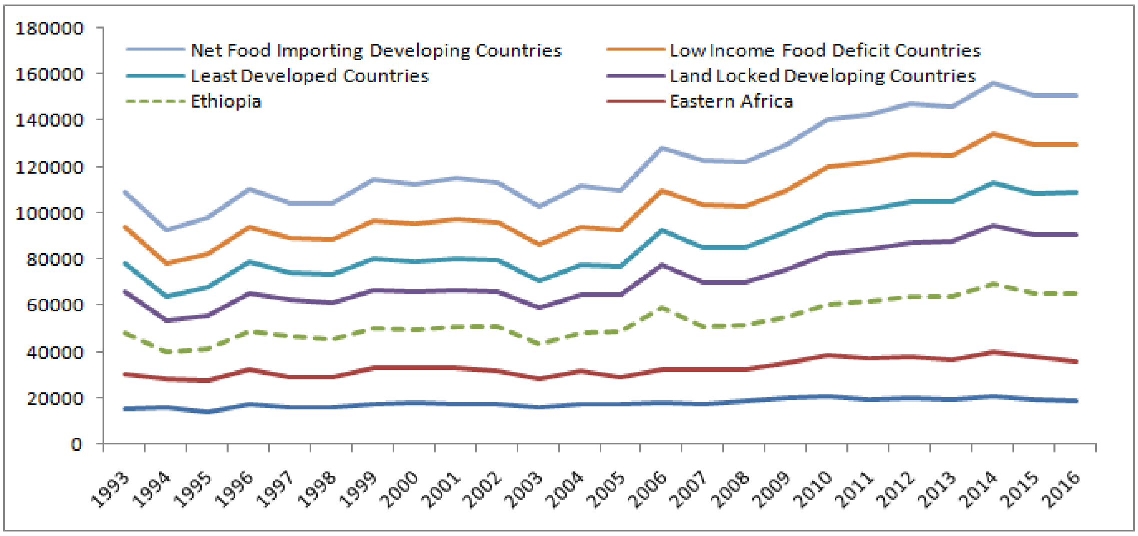
A

APPENDIX

TABLES AND FIGURES



Note: Harvested maize production per unit of harvested land measured in hectograms per hectare (hg/ha) on the y-axis.

Figure A.1: Maize production in Ethiopia.

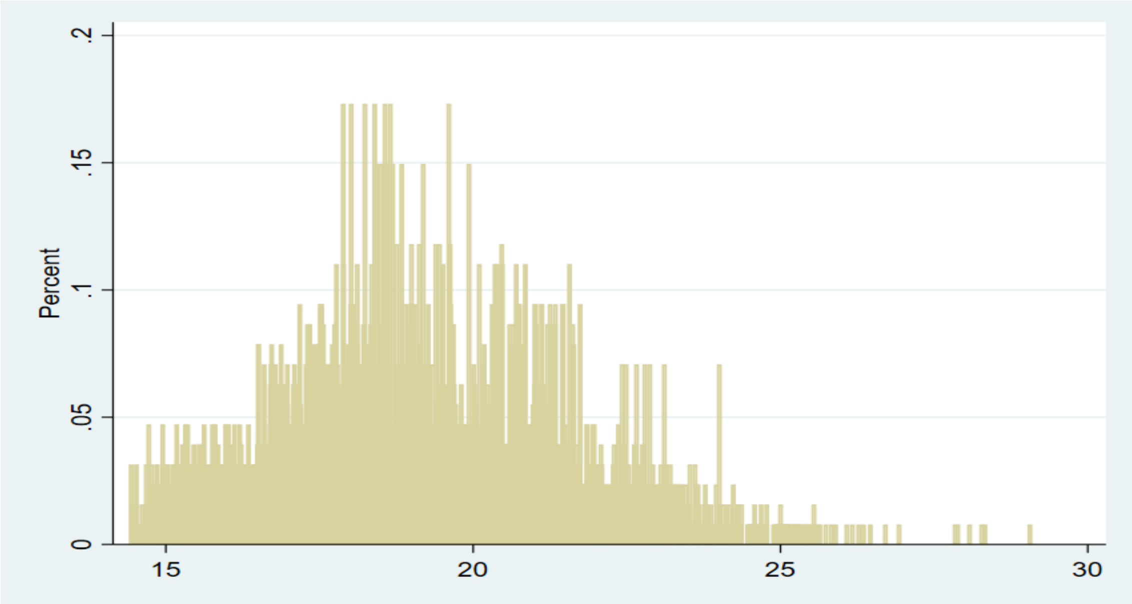


Figure A.2: Average daily temperature during pre-planting season

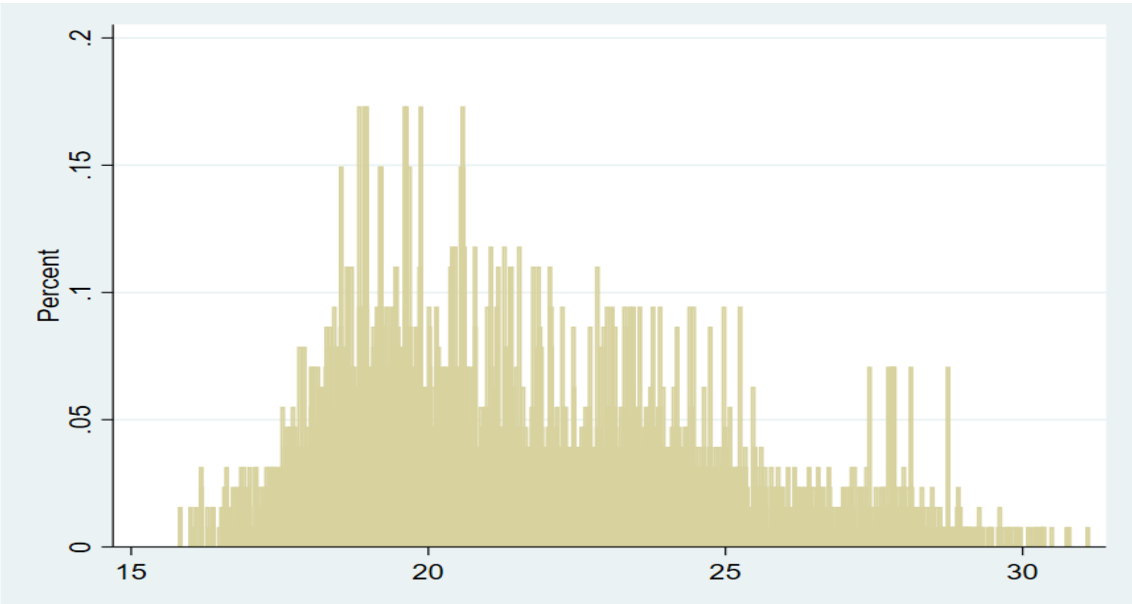
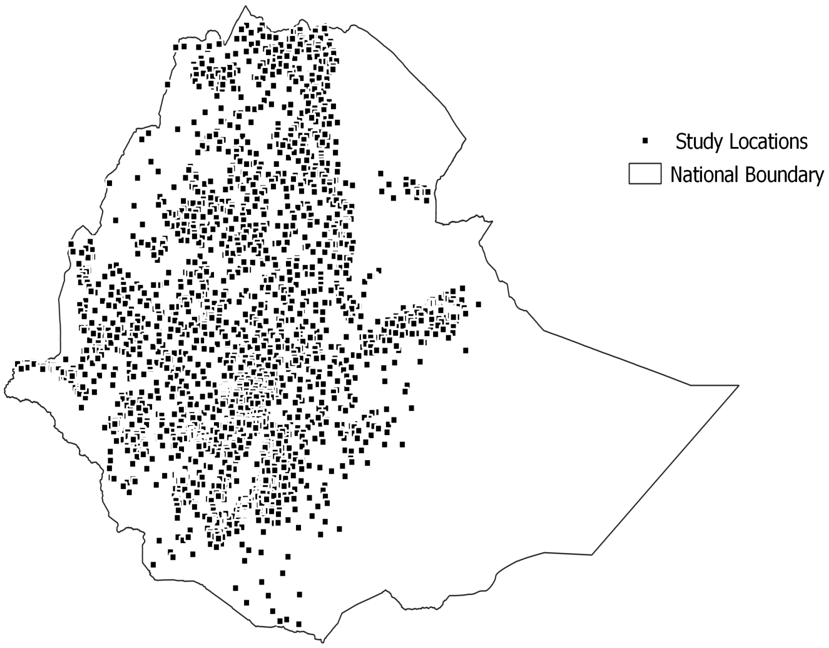


Figure A.3: Average daily temperature during planting season



Note: The survey covers all parts of the country except some parts of Afar and Somali regional states, which are located in the northeast and southeast of the country. Households in the excluded area are pastoralists and they do not have a sedentary way of life.

Figure A.4: Location of the sampled areas

Table A.1: Summary statistics of working variables

Variables	Mean	Std. Dev.
Sex of the household head (male=1; female=0)	0.805	0.114
Age of the household head	43.392	5.319
Family size	5.192	0.837
Number of oxen owned	0.87	0.688
Access to credit (Yes=1; No=0)	0.181	0.237
Access to agricultural extension (Yes=1;No=0)	0.586	0.493
Size of cropped land with access to irrigation (ha)	1.225	7.992
Average temperature during pre-planting season	18.747	2.071
Wet day frequency during pre-planting season	1.589	2.207
Average temperature during planting season	21.062	2.506
Wet day frequency during planting season	12.198	9.43
Commutative heat degree days during pre-planting season	637.036	122.706
Commutative heat degree days during planting season	786.27	134.753
Size of cultivated land covered by maize (ha)	6.689	12.984
Size of cultivated land covered barley	3.204	10.364
Size of cultivated land covered sorghum	6.512	15.573
Size of cultivated land covered teff	9.292	20.229
Size of cultivated land covered wheat	4.996	14.058
Size of cultivated land covered pulse	6.265	12.247
Size of cultivated land covered Oilseeds	2.583	9.52
Average potential maize yield (t/ha)	0.783	0.702

Source: AgSS, 2010-16 and FAO/IIASA. Values are aggregated at EA level

Table A.2: Estimated impacts of weather variability on maize land allocation: Changing the length of the pre-planting season

Variables	Maize land(log)	
	(1)	(2)
Average temperature during pre-planting season	0.107***	0.179***
	(0.038)	(0.037)
Average rainfall during pre-planting season	0.017	0.011
	(0.014)	(0.012)
Planting season weather	Yes	Yes
Other controls	Yes	Yes
Region year fixed effects	Yes	Yes
EA fixed effect	Yes	Yes
Observations	12,705	12,705
R-squared	0.865	0.865

Note: Column (1) is computed using the prior 30 days before the start of the planting season while Column (2) uses 45 days. The dependent variable is the log value of land under maize crop. See notes under Table 2.1 for the list of other control variables. Standard errors clustered at the district level in parentheses; *** $p<0.01$.

Table A.3: Estimated impacts of weather variability on maize land allocation: District by year fixed effect

Variables	Maize land (log)
Average temperature during pre-planting season	0.169***
	(0.039)
Average rainfall during pre-planting season	-0.018*
	(0.010)
Planting season weather	Yes
Other controls	Yes
District by year fixed effect	Yes
EA fixed effect	Yes
Observations	12,705

Note: The table presents the effects of weather variation during the pre-planting season on agricultural land allocation decisions. The model accounts from District by year fixed effect. See notes under Table 2.1 for the list of other control variables. Standard errors clustered at district level in parentheses; *** $p<0.01$.

Table A.4: Estimated impacts based on alternative weather definition: Number of degree days

VARIABLES	Maize land (log)
Number of days in pre-planting within 8°C and 30°C	0.179***
	(0.043)
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Note: The table presents the effects of temperature using alternative definitions (captured via the number of days above 8°C and below 30°C temperature thresholds) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; *** $p<0.01$.

Table A.5: Machine-learning results on the influence of each variable on the size of land allocated for maize production

Variables	Influence (%)
Average temperature during pre-planting season	27.57
Rainfall during pre-planting season	2.99
Average temperature during planting season	13.87
Rainfall during planting season	7.75
Sex of the household head (male=1; female=0)	5.07
Age of the household head	8.86
Family size	5.07
Number of oxen owned	8.35
Access to credit (Yes=1; No=0)	2.90
Access to agricultural extension (Yes=1; No=0)	7.61
Size of cropped land with access to irrigation (ha)	2.51
Year	7.07

Note: The table presents the percentage effect of each variable on the amount of land allocated for the cultivation of maize calculated using a simple machine-learning algorithm.

Table A.6: Placebo regression: Post-harvest weather

Variables	Maize land (log)
Temperature: post-harvest	-0.065
	(0.138)
Other controls	Yes
Region by year fixed effect	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.074

Note: The table presents the effects of post-harvest period average temperature on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors clustered at the district level in parentheses; *** $p<0.01$, ** $p<0.05$.

Table A.7: Estimated impacts based on alternative weather definition: Change in degree day threshold

Variables	Maize land (log)
Growing Degree Days during the pre-planting season	0.141***
	(0.040)
Growing Degree Days during the planting season	Yes
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Note: The table presents the effects of temperature using alternative definitions (captured via degree days computed using 10 and 30 as the lower and upper thresholds in calculating GDD) on agricultural land allocation decisions. The dependent variable is the log value of land under maize crop. Standard errors clustered at district level in parentheses; *** p<0.01.

Table A.8: Estimated impacts of weather variability on maize land allocation: Inverse hyperbolic sine

Variables	Maize land (log)
Average temperature during pre-planting season	0.085***
	(0.023)
Average temperature during planting season	Yes
Rainfall control	Yes
Other control	Yes
Region year fixed effects	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.882

Note: The table presents the effects of within growing season weather conditions on agricultural land allocation decisions. An inverse hyperbolic sine transformed the dependent variable (the size of land covered by maize) is used. Standard errors clustered at district level in parentheses; *** p<0.01, ** p<0.05.

Table A.9: Heterogonous effect of early planting season weather variation based on land suitability

Variables	Maize land (log)
Temperature pre-planting	0.145***
	(0.043)
Suitable # Temperature pre-planting	-0.013
	(0.041)
Rainfall pre-planting	-0.008
	(0.014)
Suitable # Rainfall pre-planting	0.010
	(0.015)
Planting season weather	Yes
Other controls	Yes
Region by year FE	Yes
EA fixed effect	Yes
Observations	12,705
R-squared	0.865

Note: The dependent variable is the log value of land under maize crop. Standard errors clustered at the district level are in parentheses; *** $p<0.01$.

Table A.10: Heterogonous effect of early planting season weather variation based on temperature levels

Variables	(1) Maize land (log)	(2) Maize land (log)
Temperature pre-planting	0.159***	0.125**
	(0.054)	(0.052)
Above mean# Temperature pre-planting	-0.024	
	(0.060)	
Rainfall pre-planting	-0.000	-0.016
	(0.018)	(0.018)
Above mean#Rainfall pre-planting	-0.003	
	(0.021)	
Above median # Temperature pre-planting		0.038
		(0.056)
Above median # Rainfall pre-planting		0.021
		(0.022)
Planting season weather	Yes	Yes
Other controls	Yes	Yes
Region by year fixed effect	Yes	Yes
EA fixed effect	Yes	Yes
Observations	12,705	12,705
R-squared	0.862	0.862

Note: The dependent variable is the log value of land under maize crop. Column 1 presents heterogeneous effect results by categorizing the sample observations based on mean value while column 2 uses the median. Standard errors clustered at the district level are in parentheses; *** $p<0.01$.

THEORETICAL MODEL FOR FARMERS LAND ALLOCATION DECISION AND ESTIMATION STRATEGY

Following the work of Cui (2020b), farmers' land allocation decisions can be modeled as a profit maximization problem in which a farmer allocates a fixed amount of land between two crops—crops 1 and 2. Assuming the production function (y_k) to be a concave function of the weather conditions (C), farm size (A_k), and other inputs (x), the maximization problem can be expressed as follows:

$$\max_{A_1 A_2}(p_1 y_1(A_1, C, x) + p_2 y_2(A_2, C, x) - M) \qquad s.t \qquad A_1 + A_2 = 1 \tag{A.1}$$

M represents a constant marginal cost of land. The farmer is considered to be a price taker (p_1 and p_2), and the total amount of land is scaled to be 1. The marginal effect of weather variability on the optimal size of land allocated to crop 1 can be calculated by optimizing equation (1), as expressed in equations (2):

$$\frac{\partial A_1^*}{\partial C} = \frac{P_1 \frac{\partial^2 y_1}{\partial A_1 \partial C} - P_2 \frac{\partial^2 y_2}{\partial A_2 \partial C}}{P_1 \frac{\partial^2 y_1}{\partial A_1^2} + P_2 \frac{\partial^2 y_2}{\partial A_1^2}} \tag{A.2}$$

Since the production function is assumed to be concave, the denominator of the above expression is expected to be negative. Thus, the impact of weather variability on farmers' land allocation decisions will mainly depend on the relative changes in the marginal values of the land affected by weather variability. If the effect is more severe for crop 1 than crop 2, i.e., $P_1 \frac{\partial^2 y_1}{\partial A_1 \partial C} < P_2 \frac{\partial^2 y_2}{\partial A_2 \partial C} < 0$, then the farmer will increase the size of land allocated to crop 2 by shrinking the size of land allocated to crop 1 compared with the optimal size before the weather change and vice versa.

3

IMPACT OF IRRIGATION ON FARM HOUSEHOLD DIET QUALITY: EVIDENCE FROM ETHIOPIA

ABSTRACT

In theory, irrigation could affect farm households' nutritional status in either direction. On the one hand, irrigation may improve nutritional status by boosting farm productivity and household income. On the other hand, it may deter diet quality by shifting farmers' attention from nutrition-rich food to cash crops. This study examines the impact of irrigation schemes on farm households' nutritional status using nationally representative data from Ethiopia. Using the endogenous switching regression model, the study shows that irrigation improves diet quality. In addition, the study also identifies the production of micronutrient-rich crops such as vegetables and fruit and the adoption of productivity-enhancing inputs as the main pathways through which irrigation affects dietary quality. Hence, irrigation can be considered a viable instrument to enhance the diet quality of smallholders, and efforts should be made to tackle constraints that impede the adoption of irrigation technologies.

JEL Classification: D6, D13, I3, Q12, Q18
Keywords: irrigation, nutrition, selection model, impact evaluation, Ethiopia

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3.1 INTRODUCTION

According to the latest report on the state of food security and nutrition, approximately 10% of the global population is undernourished (WHO et al., 2021). The problem appears to be escalating in Africa, where approximately 21% of the population is undernourished (Global Nutrition Report, 2018). For instance, in Ethiopia, approximately a quarter of the population is estimated to be food insecure. More than half of the population consumes four or fewer food groups out of seven, and starchy staples account for more than 70 percent of the total calorie consumption (WFP & CSA, 2019). Relatedly, per capita, vegetable and fruit consumption in the country are 50.2 and 3.5 kg per year, respectively, which are far below the 146 kg recommendation of the WHO. Strikingly, the problem of malnutrition in the country is not sensitive to wealth status, as a quarter of children from the highest wealth quintile also struggle with stunting, and only 16% of children from the wealthiest families are receiving a minimum acceptable diet (WFP & CSA, 2019; USAID, 2019).

The country has been working with its partners to establish nutrition-related interventions. For example, the second National Nutrition Program, which was developed in 2015, aims to integrate nutritional needs with the agricultural sectors to end hunger by 2030.[1] In fact, since the vast majority of poor and undernourished people depend on small-scale agriculture to support their livelihoods, improving the performance of the sector can play a vital role in eradicating poverty and malnutrition.

As argued by Haddad et al. (2016), examining the performance of the agricultural sector from the perspective of supporting healthier diets is urgently needed to inform nutrition-sensitive agriculture strategies. Accordingly, numerous studies have explored the linkages between agriculture and nutrition in recent years, mostly in developing countries.[2] Among them, the vast majority (including Tesfaye & Tirivayi (2020); Hirvonen & Hoddinott (2017); Sibhatu & Qaim (2018)) studied the link between farm production diversity and the quality of household diet.[3] Others such as Carletto et al. (2017) and Ogutu & Qaim (2019) examined the role of commercialization on diet quality and nutritional security.

However, as rigorously reviewed by Shankar et al. (2019), the research base on the nutrition implications of agricultural asset ownership is thin and incomplete. In particular, as observed by Balasubramanya & Stifel (2020), studies that explore the link between irrigation use and rural welfare remain unexpectedly undeveloped. They argued that the great majority of existing studies treat water as a given input or focus on the management aspects of the resource. Nevertheless, since the degree of

1 The document can be accessed at `http://extwprlegs1.fao.org/docs/pdf/eth190946.pdf`
2 See Ruel et al. (2018) for a comprehensive review of the relationship between agriculture and nutrition.
3 See Sibhatu & Qaim (2018) for a review of studies that examined the linkage between agricultural production diversity and diet quality.

substitutability between water and other crop inputs is very low, a separate analysis is required to examine the impact of irrigation on the welfare status of farm households.

This being the case, studies that establish an empirical link between irrigation use and nutritional security are scarce. In addition, the few available studies are inconclusive and provide two different lines of argument. Passarelli et al. (2018) and Alaofè et al. (2016) argue that irrigation can improve nutritional status either by allowing farmers to produce (and consume) nutritious foods, including micronutrient-rich vegetables and fruits, or it enables them to purchase nutritious foods due to their income increment through increased output and diversion to high-value crops. Contrary to these arguments, others such as Shively et al. (2012) argue that there could be a potential trade-off, as irrigation would cause a shift in the cropping pattern by moving farmers' attention away from nutrition-rich food to not-so-nutritious cash crops. In line with this, Kafle et al. (2022) and Hagos et al. (2009) showed that cereals and pulses are the most important crops in Ethiopia's rain-fed system, whereas horticultural crops are widely grown in the irrigation system.[4]

Nonetheless, most of the existing studies either argue without empirical support or fail to account for selectivity bias. For instance, Hagos et al. (2017) did not address the issue of selectivity bias. However, irrigation use decisions may not be random. Hence, if, for instance, resource-rich farmers are more likely to use irrigation, as shown by Passarelli et al. (2018) and Kafle et al. (2022), they may have better nutritional status even in the absence of irrigation. Others such as Alaofè et al. (2016) relied on a few sample sizes taken from four villages, which limits the generalizability of their findings to other areas.

This study adds to the existing literature by providing information on the impact of irrigation on diet quality using nationally representative data from Ethiopia. The government of Ethiopia (GoE) has given due attention to developing the agriculture sector by investing in irrigation infrastructures. In the country, the area of land covered by irrigation exceeded 2.34 million hectares in 2015, and the GoE allocated a substantial amount of the national budget to increase this coverage to 4.14 million hectares by the end of 2020 (NPC, 2016).[5] Studying the impacts of irrigation schemes on the welfare status of farming households may contribute to charting sound policies for future ir-

4 Hussain & Hanjra (2004) also highlight the role of irrigation in shifting farmers' attention toward a market-oriented production system. Similarly,Hagos et al. (2008) argued that small-scale irrigation is a viable option for promoting a market-oriented production system in Ethiopia, as environmental risks, such as rainfall variability, are among the main reasons that trap farmers in the production of low-risk/low-return food grains. High-value crops, such as horticultural crops, are expected to have the highest long-term economic potential (Hagos et al., 2016). Carletto et al. (2011); Euler et al. (2017), and Meng et al. (2020) show cash crops raise household income and living standards.

5 During the period, the total government budget was estimated to be 2.3 trillion Ethiopian Birr (ETB), with ETB 1.3 trillion allocated for capital investment. The infrastructure sector accounted for approximately 48.4 percent of the total capital investment, with 21.6 percent going to irrigation and energy (NPC, 2016). According to the most recent estimates, the country's irrigated agricultural area covers 3.07 million hectares.

rigation development and to justifying whether irrigation can be considered a viable instrument to enhance nutrition security for Ethiopia and beyond.

The remaining sections of the paper are organized as follows. Section two presents a conceptual framework that indicates the possible pathways through which irrigation can affect nutrition. Section three provides information about the data used in this research and the techniques applied to address the objective of the study. Section four presents and discusses the results obtained from different models, and the last section presents conclusions and recommendations.

3.2 CONCEPTUAL FRAMEWORK

Several studies have been carried out to comprehend the impact of improved agricultural practices and new technologies on nutrition security. Out of them, this section reviews those studies that enable us to construct a conceptual framework that explores the possible pathways by which irrigation can affect nutritional outcomes.

3.2.1 *Impact of irrigation on nutritional security through own production*

Irrigation is known to have a positive impact on farm productivity and agricultural innovation adoption, leading to an increase in food availability and accessibility. For instance, the meta-analyses carried out by Du et al. (2018) and Zheng et al. (2019) documented that irrigation can increase crop yield by 19.3% and 30.5%, respectively. Irrigation can also increase food production by boosting farmers' confidence in adopting productivity-enhancing agricultural technologies. Agricultural technologies are usually adopted jointly as complements or supplements. As a result, irrigation can encourage farmers to adopt productivity-enhancing technologies, such as improved varieties and agrochemicals (Launio et al., 2018; Gebrehaweria & Stein, 2011; Abdoulaye & Sanders, 2005). Irrigation can also empower farmers to produce crops multiple times per year and enables crop diversification by increasing cropping intensity (Buisson & Balasubramanya, 2019). This production diversification helps to improve diet diversity (Thomas et al., 2015; Tesfaye & Tirivayi, 2020). It can also enable farmers to diversify their portfolios even by incorporating livestock production since the accessibility of water supports fodder production and supplies drinking water for livestock. This will in turn increase the availability of animal-source foods, which significantly improves diet quality (Rawlins et al., 2014). Irrigation also gives confidence to farmers to switch from low-risk/low-return subsistence farming to cash crops, including high-value and water-intensive crops (Hussain & Hanjra, 2004; Hagos et al., 2009).

3.2.2 *Impact of irrigation on nutritional security through market participation*

Improved agricultural productivity, a move to high-value crops, and the potential to produce more than once a year are all expected to boost irrigation users' earnings. Li et al. (2020); Gebregziabher et al. (2009) support this argument. Among them, Gebregziabher et al. (2009) from Ethiopia show that nonirritating households have less than half the income of irrigating households. This improvement in farm income is expected to boost the ability to access food. For instance, Ogutu et al. (2020) showed that the market participation of smallholder farmers significantly increases the consumption of food purchased without reducing the amount of nutrients consumed from their own production.

3.2.3 *Impact of irrigation on nutritional security through gender empowerment*

In many rural areas, the responsibility of fetching water falls primarily on women and children. Reliable access to water through irrigation can significantly reduce their workload, freeing up more time for them to engage in food preparation and sanitation activities. This, in turn, can improve diet quality, as demonstrated by the inverse relationship between time spent fetching water and diet quality shown by Ahmadi et al. (2017). If women have control over income and food generated through irrigation, their chances of enhancing diet quality increase, as highlighted by Upadhyay et al. (2005). However, irrigation can also lead to a shift in household members' time allocation towards farming or other income-generating activities, which may affect their diet quality.

3.2.4 *Impact of irrigation on nutritional security through health aspects*

Better accessibility of water within the household due to irrigation can also result in better hygiene and sanitation practices. As argued by van der Hoek et al. (2002), the accessibility of water might be much more important in rural areas than the quality of water for health. Figure B.2 outlines the pathway and intermediates through which irrigation can affect nutrition security.

3.3 RESEARCH METHODOLOGY

3.3.1 *Data*

This research uses the comprehensive and nationally representative Ethiopian Socioeconomic Survey administered in 2013/2014. The survey produced rich data at the household, plot, and village levels by covering 433 enumeration areas (EAs) across all regional states of the country. The sample respondents were selected using a two-stage probability sample. In the first stage, EAs were selected using simple random sampling. The location of EAs in the country is indicated in Figure B.1. This stage was followed by the selection of households to be interviewed from each EA.[6] This study uses data collected from rural EAs.

3.3.2 *Indicator of household nutrition*

In this study, household nutrition status is measured using Diet Diversity Scores (DDS), which is an indicator of the variety of foods consumed within and across food groups. Increasing food variety is believed to promote good health by ensuring adequate intake of essential nutrients. Research has consistently shown that a diversified diet is positively associated with nutrient adequacy, dietary quality, and improved health outcomes, such as birth weight and child anthropometric status (Moursi et al., 2008; Rao et al., 2001; Arimond & Ruel, 2004). We calculated DDS based on a 7-day food consumption recall of 12 food groups by following the FAO guideline.

3.4 ESTIMATION STRATEGY

3.4.1 *Estimating the impact of irrigation on DDS*

The relationship between irrigation use and its impact on nutritional status can be modeled, along with a vector of other explanatory variables X and their coefficients ψ, as follows:

$$N_i = X_i\psi + \vartheta I_i + \varepsilon_i \tag{3.1}$$

where N_i stands for the outcome variables, I_i denotes a binary variable indicating whether the farmer uses irrigation or not and ε_i represents the random error term. Hence, the impact of irrigation on the outcome variable would be equal to ϑ if users and nonusers were randomly assigned. However, users and nonusers may not be randomly distributed between the two groups. For example, irrigation users and nonusers may differ based on their wealth status (Passarelli et al., 2018; Kafle et al., 2022), physical and human capital endowments (Koundouri et al., 2006), or risk-taking behavior (Torkamani & Shajari, 2008). In this case, the mean value of the outcome indicators of the two groups differed even in the absence of the treatment

6 Detailed information on sampling procedure, data collection instrument, the types of data collected and related information can be accessed at `http://microdata.worldbank.org/index.php/catalog/2783`

(i.e., irrigation). Hence, this initial bias has to be solved. As selection bias may arise due to systematic differences in terms of both observable and unobservable characteristics, this study adopted the endogenous switching regression model (ESR) to control for these heterogeneities.

The ESR framework's execution requires two stages. Firstly, the selection equation, which shows the decision to use irrigation, is modeled. This stage can be formulated as:

$$I_i^* = X_i\beta + \varepsilon_i \quad with \quad I_i = \begin{cases} 1 & if \quad I_i^* > 0 \\ 0 & otherwise \end{cases} \tag{3.2}$$

where I_i^* is the latent variable for the decision to use irrigation, I_i is its observable counterpart,[7] and X_i are vectors of observed characteristics determining farmers' decision to use irrigation. X_i includes household, community, and environmental factors. As environmental factors, drought index and soil fertility indicators are included. The drought index is measured using the standardized precipitation evapotranspiration index (SPEI), and soil fertility is proxied by the availability of soil nutrients.[8] Controlling for soil fertility helps to account for whether farmers residing in areas that are more suitable for irrigation are cultivating higher value crops given better land quality.

In the second stage of the ESR framework, two outcome regression equations faced by the farmers—to use irrigation (regimes 1) and not to use (regimes 2)—conditional on adoption are estimated. The equations can be expressed as:

$$Regime \quad 1 \quad (users) : D_{1i} = \alpha_1 J_{1i} + e_{1i} \quad if \quad I_i = 1 \tag{3.3a}$$

$$Regime \quad 2 \quad (nonusers) : D_{2i} = \alpha_2 J_{2i} + e_{1i} \quad if \quad I_i = 0 \tag{3.3b}$$

The outcome variable, denoted as D_i, measures the diet diversity score for each regime. The vector J_i represents control variables that are expected to have an impact on the outcome variable. e_i represents the random errors. The errors are assumed to follow a trivariate normal distribution with a mean of zero and a non-singular covariance matrix.

The average treatment effect on the treated (ATT) and of the untreated (ATU) can be estimated from the above framework by comparing the expected values of the outcomes of users and nonusers in actual and counterfactual scenarios. To calculate ATT, the expected outcome of irrigation users is subtracted from the counterfactual

7 In this study, a household is considered as an irrigation user if irrigation is used for agricultural activities in one of the plots operated by the farmer.

8 SPEI is accessed from https://spei.csic.es/ and availability of soil nutrients is obtained from https://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/

scenario where they did not use irrigation. On the other hand, to calculate ATU, the expected outcome of nonusers is subtracted from the counterfactual scenario where they did use irrigation.

For the endogenous switching models to be identified, it is important to include a selection instrument. Accordingly, 'the slope of the plot' is chosen as a selection instrument by conducting a falsification test following Di Falco et al. (2011). The test result, which is presented in Table B.3, indicates that the selected instrument is a viable instrument as it is strongly correlated with the decision to use irrigation and it is found not to be correlated with the outcome variable for the nonusers. Since the Ethiopian land tenure system forbids landholders from selling agricultural land and agricultural land is accessed mainly through inheritance, the presence of selection bias is negligible.

Farmers' decision to use irrigation is significantly influenced by the slope of the plot (Pokhrel et al., 2018). Walker et al. (1989) also listed the slope of the field and its uniformity as the most important determinant to use irrigation. As the slope of the plot affects the water distribution, steeper fields require additional energy (and cost) to move water across areas in the plot. Depending on the direction of the water source, irrigation can also induce erosion and affect water use efficiency. Hence, the slope of the plot can affect farmers' decisions to use irrigation. However, the instrumental variable is not irrefutable. It is possible, for example, that slope would affect agricultural production through other avenues, so the findings of the study should be interpreted with this caveat in mind.

3.4.2 *Exploring the mechanisms*

After evaluating the impacts of irrigation on diet quality, the study explores the impact pathways outlined in the preceding section, depending on data availability. The most common technique for examining impact mechanisms in existing studies is to examine the relationship between the proposed mechanisms and the independent variable. In this strategy, a variable is considered to have some mediation effects if the independent variable substantially predicts the expected mediator. However, Acharya et al. (2016) illustrate that this technique might lead to biased estimates and propose a strategy that treats the problem as a system of equations. In line with this, recent studies, including Pace et al. (2022); Cockx et al. (2018), explored impact pathways by solving structural equations. As both techniques have their own strengths, this study combines the two approaches.

The first technique we used is propensity score matching (PSM). PSM helps to adjust for initial differences between the two groups by matching each irrigation user to a nonuser with similar observable characteristics. To implement PSM, the first step is to calculate the propensity scores for each observation using variables that are not influenced by the treatment variable. After that, a common support region is imposed, a matching estimator is identified, and the matching quality is checked. Finally, the ATT can be estimated as the mean difference in the outcome variable of the irrigation users matched with nonusers who have similar propensity scores and fall within the common support region. This can be expressed as:

$$E[Y(1)I = 1] - E[Y(0)I = 0] = \tau_{ATT} + E[Y(0)I = 1] - E[Y(0)I = 0] \tag{3.4}$$

where τ_{ATT} is the treatment effect on the treated, Y is the outcome indicator (DDS), and I is a dummy variable that indicates whether the household has used irrigation or not. Both terms on the left-hand side are observable, and ATT can be identified if and only if $E[Y(0)I = 1] - E[Y(0)I = 0] = 0$.

The other technique used to identify the mediators is solving the system equations using Stata's 'medsem' package. Under this approach, a variable must fulfill certain preconditions to be considered a mediator (Mehmetoglu, 2018; Zhao et al., 2010). Specifically, after solving the system equation, the independent variable has to have a significant effect on the mediating variable $(X- > M)$ (for our case, irrigation use has to have a statistically significant effect on the production of non-cereals, for example). In the second step, the mediating variable has to have a statistically significant effect on the outcome variable $(M- > Y)$. There will be no mediation effect if either of the above two conditions is not fulfilled, and there could be 'some' mediation if both are fulfilled. Specifically, to have a 'complete' mediation effect, in addition to the above two conditions, Sobel's z-test[9] must be statistically significant, and the coefficient of the independent variable on the dependent variable must be statistically insignificant $(X- > Y)$; otherwise, there will be partial mediation. Detailed theoretical and empirical descriptions of the model can be found in Mehmetoglu (2018) and Zhao et al. (2010).

3.5 RESULTS AND DISCUSSIONS

3.5.1 *Descriptive statistical results of the variables used in the models*

The description and summary statistics of the variables used for this study are presented in Table B.1 and Table B.2. As indicated in Table B.2, 75% of the households are headed by a male. The average age of the household head is approximately 46 years, and 38% of them can read and write at least. On average, households own 1.24

9 The Sobel z-test is a statistical method used to investigate whether an independent variable has an indirect effect on a dependent variable through a mediator. It tests the null hypothesis that there is no significant difference between the total effect of the independent variable and its direct effects on the dependent variable, after controlling for the impact of a potential mediator (Allen, 2017).

hectares of land and 4.7 units of livestock measured in tropical livestock units (TLU). The average family size, measured in terms of adult equivalent, is four. Regarding their access to institutions, 20% of them have accessed credit, and 47% of them live in the village where there is a weekly market. On average, they travel approximately 17 km to reach the nearest major road. The result from a simple ttest implies the difference in terms of some of the characteristics considered in the study as statistically significant. These variables include location dummy, demographic characteristics (sex and family size), wealth status (livestock and land size), and access to the market.

Regarding the outcome variable, the mean DDS is 5.697, which is above the minimum acceptable diet (four or more food groups). However, 26% of the households reported consumption below the minimum acceptable dies. As shown in Table B.4, there is also visible heterogeneity between irrigation users and nonusers in terms of the consumption of different food groups. Cereal is widely consumed by both groups. The consumption of beans, beef, and fish is common in nonuser households, whereas vegetables, fruits, and dairy products are common in user households. This is in line with Alaofè et al. (2016), who showed that irrigation increases the consumption of vegetables and fruits, and Hagos et al. (2009), who highlighted the prevalence of cereals and pulses in Ethiopia's rain-fed system.

Regarding the share of irrigation users, 12% of households are irrigation users. Rivers and ponds are the main sources of irrigation water, as 68 and 7% of irrigation users cited them as their main source of irrigation water. Tables B.5 and B.6 summarize irrigation water sources and crops grown using irrigation, respectively.

3.5.2 *Econometric results*

3.5.2.A *Estimating the impact using the Endogenous Switching Regression*

The full result of the endogenous switching model is presented in Table B.7. The first column displays the coefficient of the selection equation, while DDS_1 and DDS_0 represent the DDS equations for irrigation users and nonusers, respectively. Although this study does not aim to identify the coefficients of the DDS equations for the two groups, the table's results demonstrate that there is heterogeneity in the determinants of the diet diversity score equation between the two groups. This shows that estimating the DDS equation using simple regression analysis by incorporating a dummy variable to indicate irrigation use cannot account for the heterogeneities between the two groups. Moreover, the significance of the correlation term's estimated coefficients (*rho*) in the table indicates that the assumption of no selectivity bias is rejected. The endogenous switching regression model is used to control for such sample selection bias and to account for the heterogeneity that exists between the two groups.

Table 3.1: Estimating the impacts of irrigation on DDS using endogenous switching regression model

Outcome variables	ATT		ATU	
	coef	se	coef	se
DDS	2.149***	0.067	0.339***	0.025

Note: The dependent variable is the diet diversity score that indicates the number of food groups consumed. They are constructed based on the 7-day food consumption recall methods; *** p<0.01

After fitting the ES models, the predicted values of the outcome indicators are used to estimate the average treatment effect of using irrigation on the treated (ATT) and untreated (ATU) groups. The results are presented in Table 3.1. As presented in the table, irrigation increases DDS by an average of 2.15 units for users. Furthermore, the results also show that if nonusers had adopted irrigation technology, their DDS would have increased by an average of 0.34. This result is consistent with the existing knowledge. For example, Baye et al. (2019) and Mekonnen et al. (2019) show a positive association between households' nutritional status and irrigation in Ghana and Ethiopia.

3.5.2.b *Mechanisms*

Tables 3.2 and 3.3 present the results from the analysis of the mechanisms obtained from the PSM and system equation-based models, respectively. The study examines farmers' land allocation decisions, spending on nutritious food items, adoption of commercial inputs, portfolio diversification, and time spent by female household members fetching water as plausible mechanisms.

Table 3.2: Impact pathways: Propensity score matching

Algorithms	Produce Non-cereal		Produce fruit or vegetable		Spending on nutritious food		Adoption of fertilizer		Livestock size		Time for fetching water by female	
	ATT	S.E.	ATT	S.E.	ATT	S.E.	ATT	S.E.	ATT	S.E.	ATT	S.E.
Nearest Neighbor (2)	0.189***	0.026	0.266***	0.039	0.591	6.697	0.09**	0.040	0.545	0.363	0.454	1.368
Nearest Neighbor (3)	0.199***	0.024	0.292***	0.037	1.144	6.602	0.08**	0.038	0.528	0.376	1.298	0.200
Caliper matching												
Radius of 0.01	0.198***	0.018	0.295***	0.035	-2.267	6.637	0.067*	0.035	0.277	0.354	1.272	-0.120
Radius of 0.05	0.19***	0.018	0.289**	0.033	-3.214	6.493	0.067**	0.034	0.206	0.342	1.229	0.040
kernel matching												
Bandwidth of 0.01	0.199***	0.018	0.294***	0.035	-2.771	6.621	0.06*	0.035	0.275	0.353	1.267	-0.080
Bandwidth of 0.05	0.194***	0.017	0.291***	0.033	-1.372	6.429	0.07**	0.034	0.195	0.336	1.208	0.120

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3.3: Impact pathways: System equations

Mediators	P value			Decision	Share
	STEP 1 (X -> M)	STEP 2 (M -> Y)	Sobel-test		
Produce Noncereal	0.00	0.00	0.03	Complete mediation	9.8
Produce fruit or vegetable	0.00	0.00	0.00	Complete mediation	44.4
Spending on nutritious items	0.35	0.00	0.35	No mediation	-
Adoption of fertilizer	0.01	0.00	0.02	Complete mediation	13
Livestock size (TLU)	0.07	0.00	0.09	No mediation	-
Time for fetching water by female	0.53	0.01	0.54	No mediation	-

The result from the PSM technique shows that irrigation increases the probability of the production of non-cereals and the adoption of commercial inputs. However, the effects on spending on nutritious food items, livestock size, and time spent by female household members fetching water are not statistically significant. As presented in the table, irrigation increases, on average, the probabilities of producing noncereal crops by approximately 19% compared with their nonusers counterparts. Similarly, it increases the likelihood of production of either vegetables or fruits by 25 to 29% compared with their nonusers counterparts. Related works by Alaofè et al. (2016) and Naylor et al. (2011) also show that irrigation increases the production and consumption of fruits and vegetables in SSA. In addition, the adoption of irrigation increases the probability of using fertilizers by up to nine percent, compared to non-users. This finding is consistent with previous research, which has documented the complementary relationship between irrigation use and the adoption of commercial inputs such as inorganic fertilizers (Gebrehaweria & Stein, 2011; Abdoulaye & Sanders, 2005). The use of such inputs is expected to improve nutritional status by improving farm productivity. Furthermore, we conducted a sensitivity analysis for all significant outcome variables, and the results are reported in Tables B.9 to B.10.

Consistent with the PSM model findings, the result obtained by solving the system equations also identified the production of noncereal crops and the adoption of new technologies as possible mechanisms (Table 3.3). This technique also provides information on the contributions of the mediators to the total effects by computing the ratio between the indirect and total effects. For example, our results show that the production of fruits and vegetables mediates approximately 44% of the effects of irrigation on diet diversity score, while the adoption of fertilizer mediates around 13% of the effects.

Hence, the results from the two models indicate that the main pathway through which irrigation affects diet quality is through improving access to nutritious food items from own production. The importance of own production for household nutrition status is highlighted by Jones et al. (2014); Sibhatu et al. (2015); Tesfaye & Tirivayi (2020). Even though the income generated from irrigation can serve to improve diet quality by helping farmers purchase essential food items that are not produced at home, income growth alone may not be sufficient to boost diet quality, as the translation from income to diet quality depends heavily upon a series of factors, including women's education and decision-making power (Ogutu & Qaim, 2019; Holland & Rammohan, 2019).

3.6 CONCLUSION

In this research, nationally representative data from Ethiopia was analyzed to investigate the impact of irrigation use on the diet quality of farming households. The study employed the ESR model to control for both observable and unobservable heterogeneities. The findings indicate that irrigation has a significant and positive effect on the diet diversity of farming households. As a result, developing the agriculture sector by investing in small-scale irrigation infrastructure can be considered a viable option to enhance the nutritional status of smallholder farmers. Therefore, efforts should be made to tackle constraints that are impeding the adoption of irrigation technologies. Furthermore, the study also shows that irrigation encourages farmers to produce vegetables and fruits and adopt inorganic fertilizer.

The study has the following limitations. First, since DDS is constructed based on the food consumption data collected at the household level using a 7-day recall method, the study could not account for seasonal fluctuations in food supply and intrahousehold food allocation. The consumption data of the LSLM survey were collected between February and April 2014 along with household characteristics and postharvest agriculture questionnaires. The two months fall between harvesting and the start of the next planting season. As a result, the data collection period represents an average between the food surplus season and the period when stocks are depleted. Second, DDS does not require information on quantities of foods consumed, as it relies on the list of items consumed.

It is important to underline the need for additional research to learn more about how irrigation affects dietary quality and nutritional security. For instance, examining the spillover effects of irrigation on diet quality at the market/community level could be of interest. Other indicators such as the production and consumption of essential macro and micronutrients could be used to measure the impacts of irrigation on nutritional status.

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B

APPENDIX

TABLES AND FIGURES

Figure B.1: Locations of the enumeration areas in the country

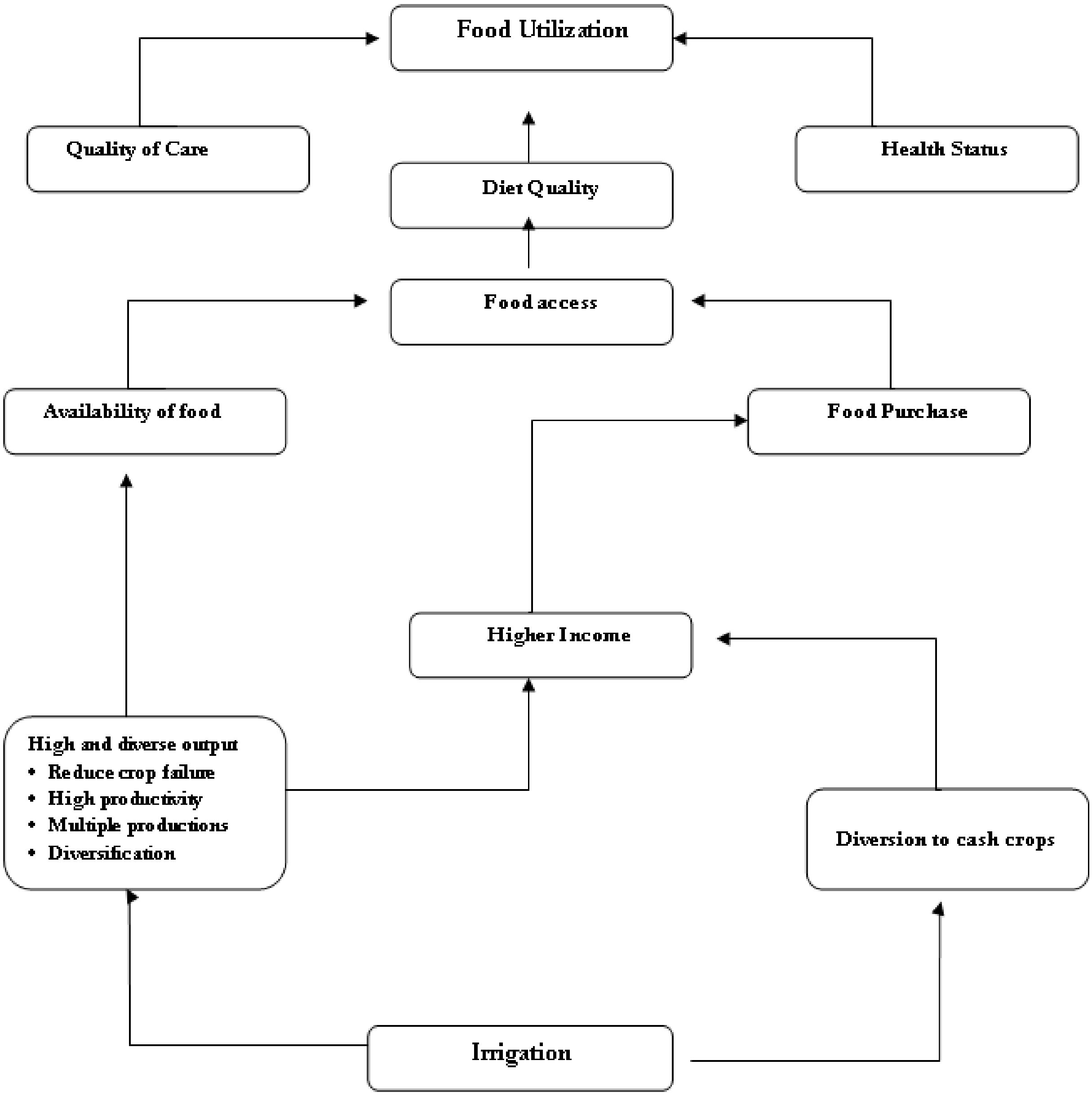


Figure B.2: Conceptual framework of the linkages between irrigation and nutrition outcomes

Table B.1: Definition of variables used for this Study

Variable	Definition
Sex of the head	1 if the household head is male; 0 otherwise.
Age of the head	Number of years the household head lived
Education HH	1 if the household head can read and write; 0 otherwise.
Access to credit	1 if the household accessed credit; 0 otherwise
Livestock ownership	size of livestock owned in tropical livestock unit
Drought index	1 if village level SPEI index is less than -1; 0 otherwise
Distance to road	Distance to the nearest major road in km
Access to market	1 if the household leaves in the community where there is a weekly market; 0 otherwise
Land	size of cultivated land in hectare
Access to Agri extension	1 if the household leaves in the community where there is an extension worker; 0 otherwise
Family size	Number of household members in the adult equivalent
Wealth index	An index computed as the score along the first principal component of a principal component analysis applied to households' assets
Chemical fertilizer	1 if the household uses chemical fertilizer; 0 otherwise
Poor nutrient	1 if the agricultural soil nutrients availability is a severe constraint
Slop of plots	1 if at least one of the plots is flat; 0 otherwise

Table B.2: Summary statistics of variables used for this study

Variables	Pooled (n=2,879)		Nonuser (n=2,564)	Users(n=315)	Mean Diff
	Mean	Std. Dev.	Mean	Mean	
Sex of the head	0.752	0.432	0.784	0.836	-0.052**
Age of the head	46.242	15.324	46.354	46.587	-0.233
Education HH	0.376	0.484	0.375	0.376	-0.001
Access to credit	0.198	0.401	0.216	0.241	-0.025
Livestock ownership	4.764	5.854	4.428	4.997	-0.570*
Drought index	0.027	0.163	0.031	0.006	0.024**
Distance to road	17.067	22.746	15.731	14.141	1.590
Access to market	0.470	0.499	0.492	0.333	0.159***
Land	1.245	1.386	1.226	1.400	-0.174**
Access to agri extension	0.940	0.237	0.940	0.951	-0.011
Family size	4.034	1.924	4.189	4.570	-0.381***
Wealth index	-0.925	0.964	-1.001	-0.889	-0.112**
Chemical fertilizer	0.472	0.499	0.385	0.457	-0.073**
Poor nutrient	0.036	0.187	0.021	0.025	-0.004
Slop of plots	0.784	0.412	0.791	0.841	-0.050**

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.3: Falsification test for the instrument

Variables	Irrigation	DDS
The slope of the plots	0.239**	-0.051
	-0.102	-0.086
Other controls	Yes	Yes
Other controls	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$.

Table B.4: Proportion of households that consumed each food group

Food Group	Nonusers	Users	Mean Diff
Cereals	0.972	0.994	-0.022**
Beans	0.676	0.505	0.171***
Vegetables	0.473	0.502	-0.028
Fruits	0.203	0.257	-0.054**
Meat/poultry	0.206	0.162	0.044*
Egg	0.129	0.121	0.008
Fish	0.018	0.003	0.015*
Oil	0.802	0.838	-0.036
Dairy products	0.386	0.54	-0.154***
condiments	0.96	0.971	-0.012
Roots	0.427	0.39	0.037
Sweet/sugar	0.436	0.616	-0.180***

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.5: Source of water used for irrigation

The source of water used for irrigation	Percent
River	68.58
Lake	1.91
Pond	7.22
Harvested water	1.69
Borehole	7.11
Piped water	0.96
Protected borehole	0.21
Spring	1.06
Stand piped water	0.53

Table B.6: List of crop items produced using irrigation

Crop	Percent	Crop	Percent	Crop	Percent	Crop	Percent
Barley	0.59	Cabbage	0.37	Ground Nuts	0.37	Coffee	6.83
Maize	12.34	Carrot	0.07	Rape Seed	0.07	Cotton	0.07
Millet	0.07	Garlic	0.81	Sesame	0.15	*Enset*	1.91
Oats	0.07	Kale	1.69	Sunflower	0.07	*Gesho*	2.28
Rice	0.07	Lettuce	0.15	Black Pepper	0.07	Sugar Cane	2.87
Sorghum	14.03	Onion	1.1	Red Pepper	0.37	Rue	0.15
Teff	3.31	Green Pepper	0.88	Apples	0.07	*Gishita*	0.07
Wheat	1.4	Potatoes	0.88	Bananas	4.92	Avocados	1.47
Cassava	1.1	Pumpkins	0.51	Lemons	2.87	*Amboshika*	0.29
Chick Peas	0.07	Sweet Potato	2.2	Mandarins	0.44	*Comtatie*	0.22
Haricot Beans	1.47	Tomatoes	1.76	Mangos	4.7	Other Fruits	2.57
Horse Beans	0.29	*Godere*	0.51	Beer Root	0.15	Other Spices	0.07
Oranges	2.87	Lentils	0.07	Guava	1.69	Other Pulses	0.15
Papaya	1.54	Field Peas	0.15	Spinach	0.22	Other Cereal	0.07
Citron	0.15	Cactus	0.29	Chat	13.96		

Table B.7: Maximum likelihood estimates of the Endogenous Switching Regression model

Variables	DDS_1	DDS_0	Irrigation
Sex of the head	-0.053	0.092	0.064
	(0.247)	(0.098)	(0.102)
Age of the head	-0.006	-0.032*	0.011
	(0.046)	(0.017)	(0.016)
Education HH	0.670***	0.428***	-0.03
	(0.211)	(0.08)	(0.078)
Access to credit	0.01	-0.025	-0.016
	(0.245)	(0.095)	(0.09)
Livestock ownership	0.029	0.029***	0.00
	(0.02)	(0.007)	(0.005)
Distance to road	-0.006	-0.004	0.001
	(0.004)	(0.002)	(0.002)
Access to market	0.537**	0.047	-0.200***
	(0.234)	(0.075)	(0.073)
Land	0.109	0.034	0.046*
	(0.084)	(0.031)	(0.026)
Access to Agri extension	-0.061	0.167	0.309*
	(0.468)	(0.16)	(0.182)
Family size	0.102*	0.060***	0.018
	(0.061)	(0.023)	(0.022)
Wealth index	0.396***	0.508***	0.026
	(0.113)	(0.043)	(0.042)
Chemical fertilizer	0.353	0.244***	0.191**
	(0.226)	(0.082)	(0.082)
Poor nutrient	1.461**	0.029	-0.068
	(0.618)	(0.222)	(0.249)
Drought index	-0.143	1.013***	-1.166***
	(0.667)	(0.298)	(0.445)
Slop of plots			0.213**
			(0.102)
Region dummies	Yes	Yes	Yes
sigma	0.361***	0.522***	
	(0.03)	(0.036)	
rho	-0.064	-0.720**	
	(0.322)	(0.344)	
Constant	4.420***	4.494***	-0.521
	(1.184)	(0.602)	(0.494)
Wald test of indep. eqns.: χ^2 = 4.46	Prob > χ^2 = 0.0348		

Table B.8: Sensitivity analysis for production of non-cereals

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1.0	0.0	0.0	1.0	1.0	1.0	1.0
1.3	0.0	0.0	1.0	1.0	1.0	1.0
1.5	0.0	0.0	1.0	1.0	1.0	1.0
1.8	0.0	0.0	1.0	1.0	1.0	1.0
2.0	0.0	0.0	1.0	1.0	1.0	1.0

Note: "gamma= log odds of differential assignment due to unobserved factors;sig+ = upper bound significance level; sig- = lower bound significance level; t-hat+ = upper bound Hodges–Lehmann point estimate;t-hat- = lower bound Hodges–Lehmann point estimate; CI+ = upper bound confidence interval (a=.95); CI- = lower bound confidence interval (a=.95).

Table B.9: Sensitivity analysis for production of fruits and vegetables

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.5	0.5	0.5	0.5
1.25	0	0	0.5	0.5	0.5	0.5
1.5	0	0	0.5	0.5	0.5	0.5
1.75	0	0	0.5	0.5	0.5	0.5
2	0	0	-4.00E-07	0.5	-4.00E-07	0.5

See the note under Table B.8.

Table B.10: Sensitivity analysis for the adoption of inorganic fertilizer

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.5	0.5	0.5	0.5
1.25	0	0	0.5	0.5	0.5	0.5
1.5	0	0	0.5	0.5	0.5	0.5
1.75	0	0	0.5	0.5	0.5	0.5
2	0	0	0.5	0.5	0.5	0.5

See the note under Table B.8.

4

UNIVERSITY EXPANSION AND FEMALE ADOLESCENTS' EDUCATIONAL ATTAINMENT AT LOWER LEVELS: EVIDENCE FROM ETHIOPIA

ABSTRACT

Although it is widely recognized that accounting for spillovers from higher education institutions is essential when formulating educational policy, research on these effects in developing countries is scarce. This study examines the spillover effects of Ethiopia's recent public university expansion program on the educational attainment of female adolescents in the surrounding areas. The study uses econometrics techniques that account for selection biases and causally demonstrates the positive effects of university expansion on female academic achievement. The study also documents other behavioral changes, such as changes in their fertility and reproduction decisions and information-seeking behavior.
JEL Classification: H52, I23, I24, I25, I26, J24
Keywords: Higher Education, Return to Education, Spillovers, Gender

4.1 INTRODUCTION

Despite the widespread acceptance of the need for universal access to primary education, public investment in higher education is sometimes questioned due to its high cost, low rates of social benefit, and worries about rising inequality (Birdsall, 1996; Psacharopoulos & Patrinos, 2004; Ilie & Rose, 2018). As a result, putting the expansion of higher education ahead of other public investments needs to be justified (Viaene & Zilcha, 2013; Schendel & McCowan, 2016). Especially in developing countries where primary and secondary school completion rates are low, expanding universities that require state support from the beginning to day-to-day operations requires a convincing basis.[1]

One of the most frequently cited justifications for public investment in expanding higher education institutions is the expected 'trickle-down' effects on the local economy in the form of spillover effects. It is argued that such externalities should be taken into account when developing educational policies and assessing the effectiveness of government spending. Among the existing studies, Valero & Van Reenen (2019) point out that developing human capital and encouraging innovation are the two key ways universities affect regional economies. Others, like Pastor et al. (2013), claim that universities affect the local economy by raising the demand for human capital, directly either by creating employment opportunities or indirectly by attracting new firms, or by motivating already established ones to grow. Through these channels, universities affect the wage and productivity of the local economy, including those of less-educated groups such as high school drop-outs and high school graduates (Polat, 2017; Moretti, 2004; Bentsen et al., 2019).

However, as Jagnani & Khanna (2020) point out, other important mechanisms need to be investigated from the perspectives of developing economies as they face unique socioeconomic challenges such as lower completion rates at primary and secondary school levels. This being the case, there is limited research on the impacts of higher education institutions on the local economy in developing countries, notably in Sub-Saharan Africa (SSA). Existing studies in this region have either focused on the contributions of universities to macroeconomic performance (e.g., Seetanah & Teeroovengadum (2019); Bloom et al. (2014)), or they have examined the structure of university-industry partnerships mostly through qualitative data analysis tools (e.g., Mensah & Gordon (2020); Zavale & Langa (2018)).

We use Ethiopia's recent public university expansion program as a case study and investigate the impacts of universities on the local economy by focusing on female educational attainment in host communities. More precisely, we investigate whether the presence of universities in the neighborhood improves educational attainment for

1 As an example, Ethiopia has enacted a graduation tax that mandates graduates to cover 15% of the total costs. However, as MoE (2015) points out, the revenue collected through this procedure is quite little.

female adolescents. We use the completion of primary and secondary school levels by female adolescents as our main indicators of school attainment and supplement them with other indicators. From a policy viewpoint, examining the effects on adolescent females' education is fascinatingly important because it has multiplier effects in addition to helping to close the gender gap.[2] Studies have shown that educated women have better employment opportunities (Erten & Keskin, 2018; Eble & Hu, 2019), better health (Brunello et al., 2013), more autonomy (Hahn et al., 2018), and better marriage quality (McCrary & Royer, 2011; Kırdar et al., 2018). Others have found that educating females has intergenerational benefits, such as reduced child physical abuse (Erten & Keskin, 2020), greater child health investments (Keats, 2018; Oreopoulos et al., 2006).

Our study is closely linked with Jagnani & Khanna (2020) that demonstrated how public colleges in India appear to improve educational attainment among school-age children.[3] The structure of Ethiopian public universities differs from that of universities in other countries. In Ethiopia, the Ministry of Education owns the universities, and students from different regions are assigned to universities by the Ministry based on their performance on a national exam and their preferences. As a result, local communities that host universities do not have any special enrollment opportunities. All university activities, including tuition, dorms, meals, and health care, are funded by the state, with students expected to pay roughly 15% of the entire cost after graduation and upon securing employment.

We utilize Ethiopia's recently initiated rapid expansion of its public universities as a case to assess the impacts of universities on the host community. As discussed by Akalu (2016), both the speed and level of university expansion are unparalleled in the country's higher education history. Enrolment has increased dramatically because of the expansion. Prior to the turn of the millennium, the country could only offer access to a relatively small percentage of the eligible population, just roughly 11,000 students and this number increased to 778,766 during the 2015–16 school year, of whom 265,851 were females (Akalu, 2016; MoE, 2016).

For the analysis, we use an event study framework to exploit variations in the timing of university establishment between 2007 and 2014. By simulating the features of a difference-in-differences design, the event study framework aids in evaluating treatment outcomes by comparing outcome trajectories across units treated at various times as well as before and after the start of treatment. Our findings demonstrate the positive spillover effects of public universities by showing how they promote ed-

2 Data availability was another factor in limiting the study to female adolescents.

3 The study is also linked to the broader literature that has examined the socioeconomic spillover effects of higher education institutions on the regional economy, including studies by Kantor & Whalley (2014, 2019); Moretti (2004) and Hout (2012). Additionally, the study is related to the large body of literature that explores the determinants of human capital development, such as studies by Muralidharan & Prakash (2017); Ravallion & Wodon (2000) and to studies that investigate the responsiveness of human capital to public investment, including studies by Adukia et al. (2020); Aggarwal (2018) and Duflo (2001).

ucational attainment among female adolescents. We employ several tests to verify the robustness of the results. The test includes conducting a falsification test, changing the age groups, using alternative outcome indicators, and evaluating the impact using the conventional difference-in-difference approach. We also demonstrated that districts that received new universities were not selected based on their pre-existing educational landscape or economic potential. Besides, the study also presents some additional findings, such as impacts on changing reproduction and fertility decisions, information-seeking behavior, and gender empowerment.

The paper is structured as follows. In the next section, we discuss the different mechanisms through which universities affect lower-level education. Section three explains the data types and sources used for the study. In section four, we present the empirical model used to achieve the study's objectives. We present the findings of the study in the fifth section and then discuss the results and draw a conclusion.

4.2 UNIVERSITY EXPANSION AND LOWER-LEVEL EDUCATION

Universities might influence schooling at lower levels in a variety of ways. Universities have been demonstrated to raise wages for both skilled and unskilled workers in multiple ways, including creating jobs, and enhancing productivity through learning spillovers and knowledge diffusion (Rosenthal & Strange, 2008; Moretti, 2004). By attracting new businesses that create a wider variety of job opportunities, universities may also help raise residents' incomes. In this regard, Somani (2021) found that living close to higher educational institutes in Ethiopia increases employment opportunities and earnings. Such benefits of universities in the form of job opportunities and earnings are expected to boost demand for schooling by easing household income constraints for investing in schooling. The role of household financial status in human capital investment in Ethiopia is shown by Mani et al. (2013); Cockburn & Dostie (2007), among others.

Universities would also influence the demand for education by creating a new market for products that may not have existed before. For instance, Ethiopia's newly constructed universities are expected to accommodate around 10,000 students (FDRE, 2005). Every university in the country has to provide students with three meals per day and other essentials, which is expected to boost the income of nearby farming households. Similarly, spending by the university, visitors, students, and academia is expected to increase the income of the local communities and stimulate the local economy (Pastor et al., 2013). Particularly, the influence of universities on the local economy will be considerably greater if the universities are funded by the national (federal) government, as is the case in Ethiopia (Schündeln & Playforth, 2014).

Universities can also increase the demand for lower-level education by boosting educational quality through training programs, resource sharing, and collaborations.

Ethiopia's Higher Education Proclamation mandates that public universities provide professional services to the surrounding communities, including the provision of skill-based training, disseminating knowledge and technologies, and providing technical and material support for primary and secondary schools (FDRE, 2009). Nearly every university in the country now regularly offers 'secondary school students Science, Technology, Engineering, and Mathematics' (STEM) training to high school students in the surrounding community. They also help the local schools by donating books and constructing libraries for primary and secondary schools. For example, Jigjiga University, one of the county's newest universities, donated over 70,000 reference books, and established three full-fledged libraries for nearby schools, in addition to providing STEM training to some secondary and preparatory school students.[4] Resource and knowledge spillovers from such activities of the universities are expected to increase the demand for education by increasing the expected returns on education because of improving education quality. As noted by Jensen (2010), schooling decisions are substantially influenced by perceptions about the return of education.

Universities can also act as a catalyst for opening up the region to other development practitioners to undertake collaborative activities that can improve the well-being of the surrounding community, such as improving family health and gender empowerment. Werabe University, for example, a new university in the country, listed delivering multiple women empowerment training and conducting joint research with local authorities to promote community livelihoods, as well as the distribution of improved agricultural varieties, as some of the activities they provided to their surrounding community.[5] Relatedly, public higher education institutions also stimulate investments in essential infrastructures in the neighboring areas such as electricity, roads, and water (Jagnani & Khanna, 2020). Likewise, three drinking water projects were built by Worabe University for the university's surrounding villages.[6] The provision of such infrastructures encourages enrolment by freeing up time that would otherwise be spent by children fetching water or doing other domestic tasks, which is one of the primary reasons why children in Ethiopia miss school (Haile & Haile, 2012; Mussa et al., 2019). In line with this, Masuda & Cook (2013) showed that improved water access significantly enhances schooling in Ethiopia.

The other mechanism through which the presence of universities raises demand for education could be by boosting children's aspirations for further education and influencing parents' perceptions of their children's return to school (Jagnani & Khanna, 2020; Nguyen, 2008). The experiences of Turkey, South Korea, China, and India show that the expansion of higher education improves enrollment opportunities for females (Polat, 2017; Choi, 2015; Yue, 2015; Sekhri et al., 2022). Similarly, Ethiopia's universities are seeing an increase in the number of female faculty members and students

4 https://www.jju.edu.et/CSD.php
5 https://www.wru.edu.et/training
6 https://www.wru.edu.et/outreach-project

because of the expansion of public universities (Semela, 2011). Increasing women's visibility in universities can have a role-model effect on the community surrounding the university. In line with this, a large body of studies has demonstrated the impact of same-gender role models on females' educational aspirations (e.g., Bettinger & Long (2005); Dee (2004, 2005). Hence, by exposing children and parents to the practical benefits of education from individuals they know, universities may help them grasp the wider picture of education.

Based on the above arguments, our study investigates the impact of universities on female adolescent educational achievement in host communities. To that end, we examine the effects of Ethiopia's recent rapid development of public universities on a variety of school outcomes five and ten years after they first enroll students. The time frame used in our analysis is slightly longer than the period used in earlier studies that looked at spillover effects from higher educational institutions, such as Jagnani & Khanna (2020) and Somani (2021). For example, Jagnani & Khanna (2020) demonstrated that colleges raised lower-level school attainment by up to 30% in just four years, while Somani (2021) showed how universities in Ethiopia improved employment opportunities for nearby residents within one and seven years after their inception. Given that some of the highlighted mechanisms, such as creating job opportunities (Somani, 2021), increasing the visibility of females as students and teachers (Semela, 2011), and providing professional and material support to nearby communities (discussed in section 4.2), have already been observed, the time frame is reasonably adequate to determine whether universities affect the educational outcomes of nearby communities.

4.3 DATA AND WORKING VARIABLES

This study draws on data from three rounds of the repeated cross-sectional survey of the Demographics and Health Surveys (DHS) conducted in 2005, 2011, and 2016. The Ethiopian DHS uses a two-stage stratified sampling technique to choose sample respondents. Enumeration areas (EAs) were selected from a comprehensive list of EAs obtained from the Ethiopian Central Statistics Agency, with probability proportionate to the size of each regional state's EA. In the second stage, sample households are selected for the identified enumeration areas with an equal chance. The DHS targets women aged 15 to 49, and a total of 15,683, 16,515 14,070 were included in the survey in 2016, 2011, and 2005.

The main variable of interest is females' educational status measured by completion of primary and secondary educational levels. According to recent studies and publications from the Ministry of education, the most important problem in the country is not enrolment, but rather a failure to complete education. For example, while the gross enrollment rate in primary education is 102%, the completion rate is between

54% and 68%. Likewise, around 55% of female secondary school-age youths are out of school (EPDC, 2018; World Bank, n.d.). As discussed by Duflo et al. (2021) and Musaddiq & Said (2023) the need to focus on the completion of educational levels is becoming more policy-relevant as the primary school enrollment rate in developing countries approaches 100%. As a result, we focus on the completion of primary and secondary school as the main educational attainment indicators and support our indicators with additional indicators as a robustness check.

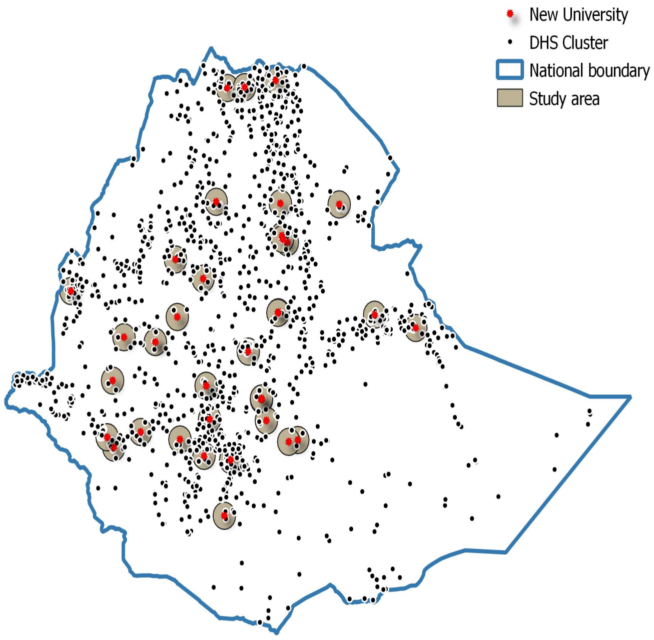
Primary education in Ethiopia lasts from Grade 1 to Grade 8, followed by secondary education until Grade 12. The official primary school entry age is seven years old. As a result, 15 is considered the lower age limit for this study because children younger than that are unlikely to complete primary school. Even though seven is the minimum age required to start primary education, late enrollment, and grade repetition are major issues across the country. For instance, using a large-scale household survey, Woldehanna et al. (2017) show that only 54% of the children joined Grade 1 when they were between the ages of 7-8. The grade repetition in primary education in the country is about 7%. Since we also aim to examine the effects of the expansion of universities on the completion of secondary school, the upper age limit is raised to 25. This helps us account for the widespread problem of late enrollment and grade repetition in the country. In the most conservative scenario that assumes children enter school at age 7 and complete grade 12 without repetition, they finish secondary school at the age of 19. Hence, we test the robustness of the results by limiting the maximum age to 20.

The list of universities in the country and their establishment years[7] are compiled mainly from the World Higher Education Database (WHED) and complemented with additional information gathered from the publications of the Ministry of Education and university websites. The locations of newly established universities are then matched with the DHS survey EAs using the geographic coordinates of the dataset. Following this, we restrict the research area to those who reside within 30 km of the newly established public universities, while EAs, where universities have not yet been established, are excluded from the analysis to prevent comparisons between places that are dissimilar. This is done following related works by Jagnani & Khanna (2020) and Erbabian (2020), which measured the spillover effects of higher education institutions on lower-level school outcomes. Besides, we also excluded from the analysis people who moved to the treatment region after universities were founded to address the issue of newcomers who could value education more than the host community. The next section provides a detailed discussion of our estimating strategy, along with multiple robustness tests.

Figure 4.1 presents the location of the universities and the Enumeration Areas. While 55% of them were established in 2007, 35% of them were established by 2011.

7 The year of establishment refers to the year the university started enrolling students.

The remaining, 10% was set in 2012 and 2014. Hence, relatively most of the universities are established around or before the 2011 DHS survey. Universities established during the research period are shown in Table C.5.



Note: Only universities established between 2007 and 2014 are included. The majority of universities have branches at different sites. By compiling a list from each university's website, we take into account all campuses of the universities.

Figure 4.1: Map of the study area.

4.4 EMPIRICAL STRATEGY

We use an event study framework to investigate the impacts of the expansion of universities in Ethiopia between 2007 and 2014. The event study framework is becoming increasingly popular in policy analysis and applied economics, including labor and education economics literature (e.g., Miller & Park (2022); Jagnani & Khanna (2020); Cengiz et al. (2019); Larsen (2020)). The framework enables the evaluation of treatment effects when the treatment is administered non-randomly in a staggered rollout manner and the researcher has data collected before and after the start of the treatment. More precisely, it assists in evaluating treatment outcomes by comparing outcome trajectories across units treated at various points in time as well as before and after the start of treatment by emulating the characteristics of a difference-in-differences design (Borusyak et al., 2021). The framework also allows examining the impacts without worrying about coincidental changes in a single year since the 'treatment' are not expected to be introduced in one specific year like the classical difference-in-difference designs (Jagnani & Khanna, 2020). Additionally, it makes it possible to examine the dynamics of treatment effects and check for the validity of the assumption of parallel pre-treatment outcome trajectories. The empirical model employed in our study to make use of the temporal and spatial variance in the expansion of universities in Ethiopia is presented in Equation 4.1:

$$Y_{ivt} = \sum_{\tau=-\rho}^{-2} \beta_\tau 1(t - T_j^* = \tau) + \sum_{\tau=0}^{m} \beta_\tau 1(t - T_j^* = \tau) + \eta_v + X_{ivt} + \phi + \varepsilon_{ivt} \tag{4.1}$$

Y_{ivt} is the outcome of interest for a young female i in enumeration area v in year t. η_v and ϕ stand for EA fixed effects and the interaction of survey-round indicators and regional state dummies.[8] X stands for additional control factors that may affect the outcome such as age, marital status, religion, and an indicator that shows whether the female lives in a rural area. ε is an idiosyncratic error term. τ represents event dummies that indicate the time since universities are constructed, calculated as the difference between survey years t and university establishment years (the year when universities started enrolling students)T_j^*. As a result, the coefficients on the event dummies are estimates that represent the average treatment effects of the universities. Because both the expansion of universities and the DHS data collection period are roughly five years apart, the impacts of university expansion are estimated in two-time horizons: short-run, which is within five years, and long-run, which is between five and ten years.

Estimating the impacts of interventions using the event study approach fundamentally relies on the concept of parallel trends, which claims that if no treatment was given, the treated and control groups must maintain the same differences as in the baseline period. As a result, estimating the impacts of universities on local communities is challenging, at least for the following reasons. The location and timing of university construction may be linked to unobserved factors that influence educational outcomes. For example, governments might choose to establish universities in places with high economic potential or in areas where the education market is expected to improve. Besides, universities may also attract professionals, entrepreneurs, and others who are more aware of the advantages of education.

8 Ethiopia is a federation made up of 11 semi-autonomous regional states. Each regional state has its own constitution, executive committee, and sector bureau.

The ministry of education owns public universities in Ethiopia, and students from all across the country are assigned to them based on national wide entrance exams and their preferences. The Higher Education Proclamation of the country explicitly stated that ensuring a fair distribution of public universities throughout the regional states of the country is among the key criterion for determining where to build universities (FDRE, 2009). Similarly, Molla (2018) and Semela (2011) discussed ensuring a fair distribution of public universities as one of the fundamental goals of the country's recent university growth policy. Semela (2011) linked the establishment of universities in historically disadvantaged regions, such as the regional states of Afar, Somali, and Gambella to the government's objective of achieving an equal distribution of universities. Likewise, Molla (2018) discusses creating a more balanced geographic distribution of universities across the country and redressing inequity in all of its forms, including gender inequity, as the core objective of the university expansion program. Molla (2018) used a statement by the State Minister for Higher Education to back up his claim, saying, "Students from these disadvantaged regions have historically been denied access to education and other socio-economic development infrastructures." Similar to this, the National Education Sector Development Program (FDRE, 2005) detailed how political and equity-related factors—rather than economic ones—were used to choose where the new universities would be situated. As a result, the idea that universities were founded in response to future changes in local education markets is less plausible.

Besides, we implement the following steps to find unbiased estimates of the impacts of universities. Firstly, unlike traditional impact evaluation techniques such as the classical difference-in-differences, which necessitate a control group that appears comparable but did not receive the treatment, the event study provides an alternative approach that does not necessitate the same identifying assumptions (Jagnani & Khanna, 2020; Sandler & Sandler, 2014). Hence, following the related works of Jagnani & Khanna (2020) and Erbabian (2020), we restrict the study area to those who live within 30 km of the new public university and EAs that have never received university are not included in the analysis.[9] As treated and untreated areas may greatly differ in terms of unobserved characteristics, excluding untreated areas helps reduce endogeneity issues that could arise from comparing observations from two distinct populations (Jagnani & Khanna, 2020). In addition, because the ever-treated units exhibit latent similarities based on unobserved factors, this technique also makes it possible to more accurately model the real data generation process of the pre-intervention outcomes.

Hence, due to the "staggered rollout" feature of the university expansion program, any unit that obtains university has an event date in which τ_i goes from zero to one

9 The 30km distance was chosen based on related studies and consistent results were found using 25 and 35 km.

and stays there forever. As a result, those who have not yet received treatment ("to be treated") make up the control group. That means if the university was established in 2007, the 2005 survey captures the pre-treatment period, while the 2011 and 2016 rounds represent the post-treatment period. Similarly, for areas that received university in 2012, the pre-treatment phase is captured in the 2005 and 2011 rounds, while the post-treatment period is captured in the 2016 round. As a result, the coefficients on the event dummies are estimates that represent the average treatment effects of impacts of universities in comparison to rounds before the establishment of the university i. e., $\tau = -1$. As a robustness check, we also estimate the treatment effects using EAs who never received a public university during the survey period as a control group. Additionally, we also estimate the impacts using the conventional difference-in-difference model to further validate the results from the event study framework.

Secondly, to address the problem of newcomers who may value education more than the host community and send their children to school, individuals who arrived in the treatment region after universities have been established are excluded from the analysis. The survey explicitly asks respondents how long they have been living in the community, and we use this information to exclude the newcomers from the analysis. [10]

Thirdly, we include EA fixed effects and the interaction of survey-round indicators and regional dummies in our model to account for any community-level time-invariant factors and state-specific changes that might be linked to the outcome variables and/or the presence of a public university. This enables us to account for any changes in economic conditions, norms, and family law, as well as differences in average educational attainment across time. The interaction also takes into consideration any state-level policy changes that might affect schooling such as policies that affect school construction, school quality, and the number of teachers as well as other state-level policy changes that affect demand for education such as laws that can affect the marriage market. This is because regional states are the ones in charge of drafting and implementing policies at local levels. Similarly, individual-level controls that could affect academic performance, like the age and religion of the adolescence are also included. The age of adolescence, for instance, controls for historical events that may have distinct effects on girls of different ages and be related to academic success, such as childhood exposure to adverse shocks or policy changes that might affect girls of the same age such as Universal Primary Education (Erbabian, 2020).

Our fourth approach involves testing the parallel trend assumption indirectly by utilizing the event study framework. In equation 4.1, a negative τ represents the pre-treatment period, while a positive τ symbolizes the post-treatment period. The framework allows exploring if there are selection biases depending on the pre-treatment

10 We also excluded people who moved just before enrollment, but our results stayed the same.

condition by indirectly testing whether the coefficients of τ before the establishment of universities are statistically similar to zero.

Fifthly, to determine whether economic potential has an impact on the choice of which location should receive the university before the rest of the eligible areas, we examine the relationship between the founding years of the university in a particular EA and the EA's potential for food and commercial farming. The government's major objectives during the research period were to ensure food security and transform the economy toward agricultural-led industrialization. As a result, if economic reasons are the main consideration, the government should give priority to regions with the greatest potential. Using the same approach, we examine the relationship between baseline educational outcomes and the year a university is established in a particular EA to examine whether EAs that obtain universities are those with higher educational outcomes. Lastly, we examine the effects of universities on the education of older women over the age of 30 who are not expected to change their schooling decision as a falsification test.

4.5 RESULTS AND DISCUSSION

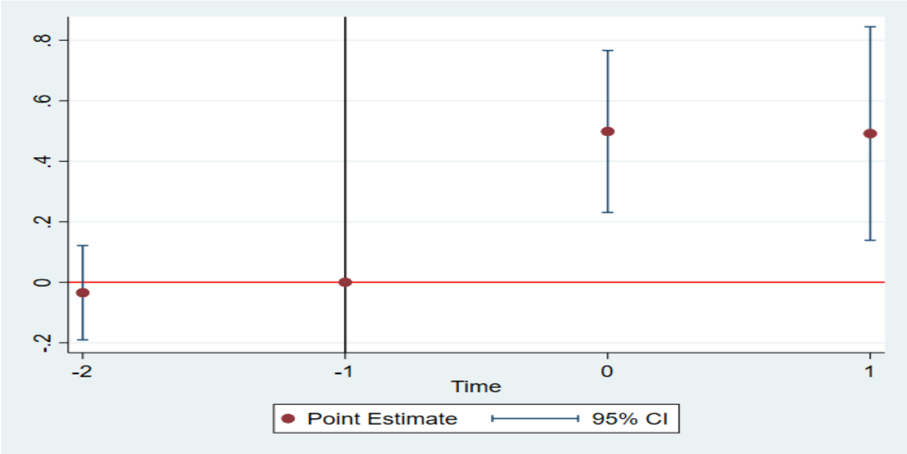
4.5.1 *Main result*

We present in Table C.1 the distribution of working variables in each study group by comparing short and long-run values with the baseline values. Overall, there are significant differences in the outcome variables among the study groups.

Figures 4.2 and 4.3 show the impacts of university exposure on females' likelihood of completing primary and secondary school by solving equation 4.1.[11] As illustrated in the figures, the treatment round coefficients (both short and long-term impacts) are positive and statistically significant. The results indicate that new universities enhance the likelihood of finishing primary school by about 0.49, and the effects are statistically significant at less than 1% (Figure 4.2).

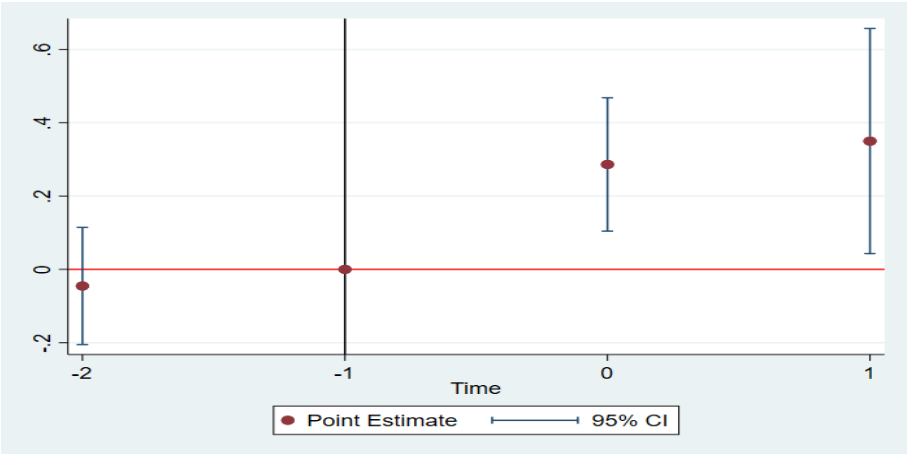
The effects of university exposure on the probability of girls completing secondary school are shown in Figure 4.3. The figure illustrates that the presence of a university in the vicinity increases the likelihood of completing secondary school by 0.28 in the short term and 0.34 in the long term. The estimated coefficients are statistically significant at less than 5%. The attenuation of the relationship is reasonable, as the sample encompasses all girls aged 15 to 25, including those who are not expected to finish secondary school.

11 Stata's 'eventdd' package recently produced by Clarke & Tapia-Schythe (2021) is used to solve the equation.



Note: The figure depicts the effects of universities on the primary school completion rate among adolescent females in the host community. The pre-treatment time is represented by a $\tau < 0$, whereas the short-term and long-term post-treatment periods are represented by $\tau = 0$ and $= 1$, respectively. These values are compared to a value at τ = -1, which represents the immediate pre-treatment period, to find the average treatment effects.

Figure 4.2: Impact of public universities on educational attainment: Primary education.



The figure depicts the effects of universities on the secondary school completion rate among young females in the host community. The pre-treatment time is represented by a τ <0, whereas the short-term and long-term post-treatment periods are represented by $\tau = 0$ and $\tau = 1$, respectively. These values are compared to a value at τ = -1, which represents the immediate pre-treatment period, to find the average treatment effects.

Figure 4.3: Impact of public universities on educational attainment: Secondary education.

Estimates of the treatment effects calculated using the 'never-treated' observation as a control are shown in Figures C.1 and C.2 in the appendix. The results are qualitatively identical to the main results indicated above. Differences in magnitude are likely because the specification that uses 'never-treated' observation as a control group has a disproportionately larger proportion of control units compared to treatment units, or controls in the main study.

Furthermore, we also estimate the impacts of the universities on female adolescents using the conventional difference-in-difference approach to corroborate the findings of the event study framework. For this, female adolescents who received new universities are considered as a treated group and the 'never-treated' observation as a control. The results are presented in Table C.4 in the appendix. As shown in the Table, the results from the conventional difference-in-difference approach support the results of the event study framework. We provide additional results that demonstrate the robustness of the results by using alternative definitions of the outcome indicators such as the highest education level attained by the adolescent female in Figures C.3 to C.5 in the appendix. As indicated in the Tables, universities have increased the highest education level attained and decreased illiteracy or the likelihood that young girls in the host community will not have received a formal education.

In all estimations, a statistically significant impact is found in the outcome indicators that coincide with the post-treatment period but no indication of prior trends. If universities were built in areas where girls are staying in school longer, or if other factors like changes in the local education market influenced the timing of public universities' entry, evidence of a positive pre-trend would have been detected. However, it is important to stress that the absence of a statistically significant difference between the control and treated groups before treatment only serves to support, not to establish, the similar pre-treatment outcome trajectories.

Aside from the absence of a statistically significant difference before the treatment, we also investigated if the development prospects of the areas receiving universities play a role in determining which area should receive a university first. 'Agricultural Development Led Industrialization' was the development strategy of Ethiopia during the 2000s. The strategy aims to achieve initial industrialization while also assuring food security through significant agricultural growth. As a result, if the government wishes to build universities in places with high economic potential, they should start with areas that have abundant agricultural potential over those with lower potential. To put it another way, if location 'A' has a higher agricultural potential than location 'B' and the government must establish institutions in stages, starting with the best option, it should begin with location 'A'. To scrutinize if this is the case, the relationship between the timing of university establishment and the suitability of the areas for cash and food crops is estimated using the FAO-GAEZ suitability database. The FAO-GAEZ suitability database provides estimates of a field's productive potential for various crops with a 0.5x0.5 resolution. Agronomic models are used to calculate the estimates, which take into consideration crop characteristics, physical variables (such as soil quality, height, and land gradient), and assumptions on the level of input utilization.[12]

12 More information can be accessed at `https://www.gaez.iiasa.ac.at/`

We explore if the return potential of locations that receive universities for cotton and sugarcane has an impact on the timing of university establishment. The two commodities are included since the expansion of the textile and sugar industries was among the government's development goals. The government launched ten new sugar factory projects and expanded existing ones considerably during that time. Similarly, becoming one of the leading textile-producing countries by 2025 was part of the county's strategic plan (Khurana, 2018; MoF, 2017). We also investigate the association between the university's founding years and the suitability of the location for the most important food security crops in the country.

Table C.2 in the appendix summarizes the results. As shown in the Table, the results reveal that the suitability of the locations for either cash or food crops does not predict the timing of university establishment, which backs up the points made in the previous section about university allocation across regions. In a similar vein, the relationship between the founding years of the university and the baseline educational outcomes was also looked into to determine whether universities were built in regions with greater educational performance. As shown in Table C.3, there is no statistically significant link between the two variables.

To conduct a falsification test, we estimate the impact of universities on women over the age of 30, who are less likely to change their educational decisions. The results, as depicted in Figures C.8 to C.9, reveal that universities do not have a significant effect on their educational status. If the estimated impacts are absorbing the effects of plausible omitted variables, a significant relationship would have been observed. We also estimate the impacts by changing the maximum age limits as additional robustness tests. The findings of the test results, which considers age 20 as the maximum age limit, are shown in Figures C.6 and C.7. The results support the primary findings and refute the claim that older individuals had an impact on the estimated impacts.

4.5.2 *Impact heterogeneity: Rural vs Urban*

We also investigated if universities have differential impacts on the educational attainment of females residing in rural and urban areas. In developing countries, achieving educational attainment can be particularly challenging for females, with rural areas facing additional obstacles such as insufficient schools, infrastructure, and limited job opportunities that require higher education. Cultural factors such as the marriage market and gender-related issues may also vary in the two settings. As a result, we separately analyzed the impact of universities in rural and urban areas. Our findings, as presented in Figures C.10 to C.13, reveal that universities have a greater impact on girls in rural areas than in urban areas. This disparity may be due to various factors, such as urban areas already having relatively better access to education even before universities were established, while rural areas may have limited resources and opportunities, making universities' impact more significant. Moreover, the anticipated benefits of universities, such as income boost resulting from increased demand for agricultural and other products, improved access to water, and school assistance and training provided by universities, as discussed in section 4.2, are expected to have a more significant impact on rural areas since urban areas may already have access to them even before the establishment of universities.

4.5.3 *Additional outcomes*

Universities can also bring change in living styles in nearby communities through social learning from a high-quality life of the academic community. In this section, the impacts of the new universities on additional outcome factors are presented. Figure C.14 depicts the impact on marital status. As shown in the figure, females who are exposed to universities are more likely to postpone marriage and remain single for longer periods. This is in line with the findings of Black et al. (2008) and Hahn et al. (2018), who claim that a policy change that improves young girls' schooling is linked to fertility and marriage delays. It is important to note that only females aged 15 to 25 are being studied and the findings do not imply that they have abandoned the marriage.

The study also investigated whether or not universities affect the reproductive decisions of adolescents by examining how long they would prefer to wait before having (the next) child. As seen in Figure C.15, the treatment increased the share of females who prefer to wait three or more years in the short run. This is in line with the findings of Hahn et al. (2018) and Chicoine (2021), who found that policies promoting female education reduce fertility, both in terms of actual and desired children. As far as information-seeking habits, universities have boosted newspaper reading, but the effects on radio and television are statistically insignificant (Figures C.16 to C.18). Relatedly, Chicoine (2021) demonstrated how a program that increased female educational attainment also increased awareness of family planning through newspapers and magazine reading.

We also investigated whether the treatment had an impact on reducing domestic violence and improving female participation in household decision-making (Figures C.19 to C.22). To measure domestic violence, we used a binary variable to indicate whether the respondent believed that beating wives was justified in situations such as going out without telling the husband, neglecting the children, arguing with the husband, refusing to have sex, or burning the food. Female participation in decision-making was measured by assessing whether she had a role in decisions related to large household purchases, healthcare, and spending their earnings. We find a significant increase in female participation in decision-making, particularly in large household purchases and healthcare decisions. However, the impact on domestic violence reduction is not statistically significant.

4.6 CONCLUSION

Using Ethiopia's recent public university expansion as an example, we looked at the effects of higher education investments on females' educational attainment using an event study framework that helps to take advantage of variation in the timing of the university's establishment. Our findings show how a government program designed to increase coverage of higher education had unintended effects that enhanced educational outcomes for young females at lower educational levels. Specifically, we show that universities improve the schooling of females who reside nearby, at both the primary and secondary levels. The study also documented a range of behavioral changes beyond the scope of its primary focus, including changes in fertility and reproduction decisions, increased involvement in household decision-making, and a tendency towards information-seeking behavior. Such spillovers are crucial for developing countries like Ethiopia to justify public spending on higher education, where low literacy and school completion rates, and higher dropout rates, are prevalent, with one of the highest numbers of girls out of school.

The finding is also interesting for countries like Ethiopia where gender inequality and discrimination are quite visible (Kumar & Quisumbing, 2015). Well-established bodies of literature have revealed that educated women have, among others, greater autonomy, better work possibilities, and significantly invest in their children's health and education. Schultz (2002), for example, claims that increases in the mother's education are linked to bigger societal benefits in terms of children's health, height, and educational achievement than increases in the father's education.

It is also important to highlight that the event study model used to estimate the treatment effects assumes that university establishment years do not coincide with other unobserved events that could have an impact on future educational outcomes. However, the research period overlaps with the end of the Millennium Development Goals, in which Ethiopia's government, together with other partners, invested extensively to enhance access to education. The country has made incredible improvements during this period that improved access to education, such as school construction, and the hiring of teachers. This has increased school net enrolment rates and reduced the number of children out of school. The gender enrollment gap was also reduced throughout the country (O'Keeffe, 2017). Although we cautioned readers to take this into account when interpreting the estimated impacts, there are no compelling reasons for the government to favor the treated groups given that the government's objective was to attain universal coverage of lower-level schooling. Besides, since most lower-level educational policies in the country are designed at the regional state level, the interaction of regional state dummies with time-fixed effects in our models helps to capture any time-varying regional state-level policy changes that might affect the education sector, such as the construction of schools and the hiring of teachers. The interaction can also help to account for other legislative changes, including raising the legal age of marriage which was approved at the beginning of 2000. In addition, the law was approved and implemented regionally at the beginning of 2000, before the research period (McGavock, 2021).

We were unable to investigate the mechanisms through which university expansion may affect educational outcomes at lower levels due to data limitations. Hence, future research is needed to effectively understand the mechanisms. Lastly, we were also unable to examine the impact on educational quality due to a lack of data. Despite those limitations, our results are significant contributions to the literature and policy discussion on educational policies and evaluating the effectiveness of public spending.

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C

APPENDIX

TABLES AND FIGURES

Table C.1: Description of working variables

Variables	Baseline figures (n=1203)	Mean difference from the baseline: Short-run (n=2603)	Mean difference from the baseline: Long run (n=1203)
Illiteracy (1= cannot read; 0= otherwise)	0.492	-0.189***	-0.250***
Primary education Completion	0.569	0.240***	0.310***
Secondary education Completion	0.249	0.047***	0.171***
Rural (1= yes; 0=no)	1.608	-0.212***	-0.175***
Age of the respondent	19.86	-0.044	-0.094
Status in the household (1= head; 0=otherwise)	0.052	0.028***	0.005
Religion			
Orthodox	0.433	0.080***	0.031*
Catholic	0.011	-0.007**	-0.002
Protestant	0.198	-0.032**	-0.043***
Muslim	0.354	-0.041**	0.014

Note: The Table presents the mean values of the working variables by comparing the baseline values to the mean values in the short and long run. The numbers in column B, for instance, are calculated by subtracting the baseline mean values from short-run mean values (values measured within five years from the establishment of universities in the area). Thus, the short-run period for locations that received universities in 2012 is documented in the 2016 DHS survey round, whereas the short-run for universities founded in 2007 is captured in the 2011 survey;*** p<0.01, ** p<0.05, * p<0.1.

Table C.2: The Relationship between university establishment year And suitability for agricultural development

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wheat	0.035						
	(0.022)						
Sorghum		0.024					
		(0.024)					
Maize			0.041				
			(0.028)				
Sugarcane				-0.026			
				(0.034)			
Cotton					-0.033		
					(0.025)		
Sunflower						0.003	
						(0.024)	
Soybean							-0.026
							(0.02)

Note: The table presents the relationship between the year in which a given university is established and the suitability of the fields for the indicated agricultural commodities measured as an index between 0 and 100. The coefficients are estimated using simple the OLS technique. Standard errors in parentheses *** $p < 0.01$.

Table C.3: The Relationship between university establishment year and baseline educational outcomes

Variables	(A)	(B)	(C)
University established year	-0.01	0.008	-0.003
	(0.01)	(0.01)	(0.01)

Note: The Table shows the relationship between a university's founding year and the EAs' baseline educational outcomes. The coefficients are estimated using simple the OLS technique. The dependent variables are the share of the adolescent who can read within the EA that received university (A), who finished primary education (B), and who finished secondary education (C) during the baseline. The analysis is computed using the 2005 survey. Robust standard errors are in parentheses.

Table C.4: Impact of public universities on educational attainment: Estimated using Difference in Difference

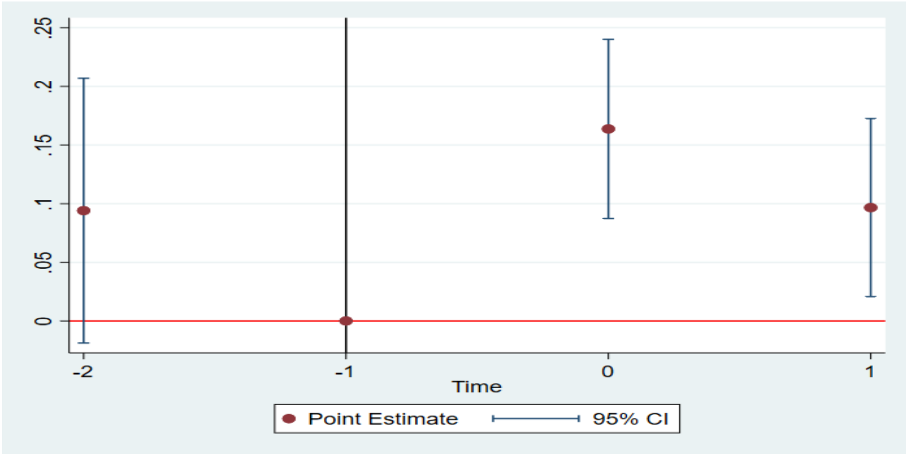
Variables	Illiteracy	No formal	Primary	Secondary
ATET	-0.073**	-0.068***	0.064***	0.068***
	(0.029)	(0.025)	(0.025)	(0.025)
Controls	Yes	Yes	Yes	Yes
EA fixed effects	Yes	Yes	Yes	Yes
Region# survey year	Yes	Yes	Yes	Yes
Observations	25013	25013	25013	25013

Note: The average treatment effect on the treated (ATET) estimates are adjusted for covariates, group effects, and time effects. The dependent variables are Illiteracy (binary outcome that measures ability to read in their native language), no formal education, completion of Primary education, and completion of secondary education, respectively. The list and summary of control variables are discussed in Table C.1. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.5: University establishment year

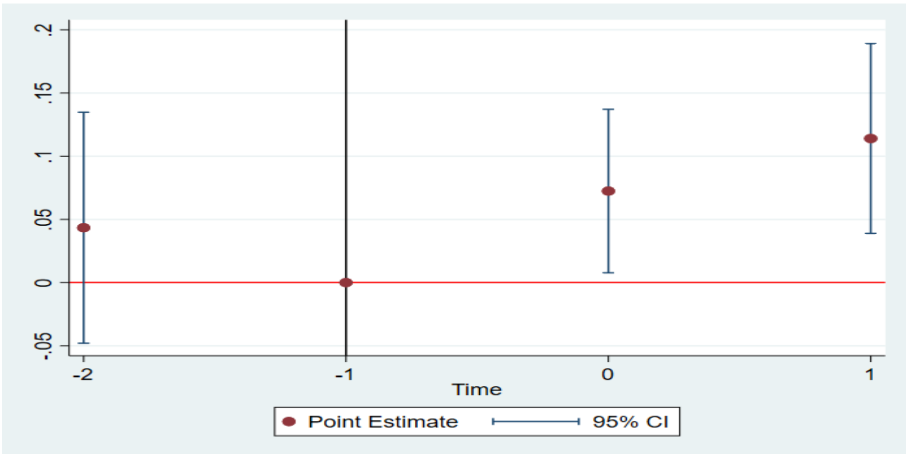
Name	Established year
Wello University	2007
Debre Markos University	2007
Jijiga University	2007
Wollega University	2007
Semera University	2007
Debre Birhan University	2007
Wolaita Sodo University	2007
Mizan–Tepi University	2007
Madda Walabu University	2007
Axum University	2007
Dire Dawa University	2007
Asosa University	2011
Bule Hora University	2011
Addis Ababa Science and Technology University	2011
Adigrat University	2011
Wachamo University	2011
Metu University	2011
Debretabor University	2011
Wolkite University	2012
Arsi University	2014

Notes: Only universities established between 2007 and 2014 are included. The majority of universities have branches at different sites. Wello University, for instance, has two campuses in Dessie and Kombolcha town. Similarly, Mizan-Tepi University has campuses in the towns of Mizan and Tepi. By compiling a list from each university's website, the research takes into account all campuses at every university.



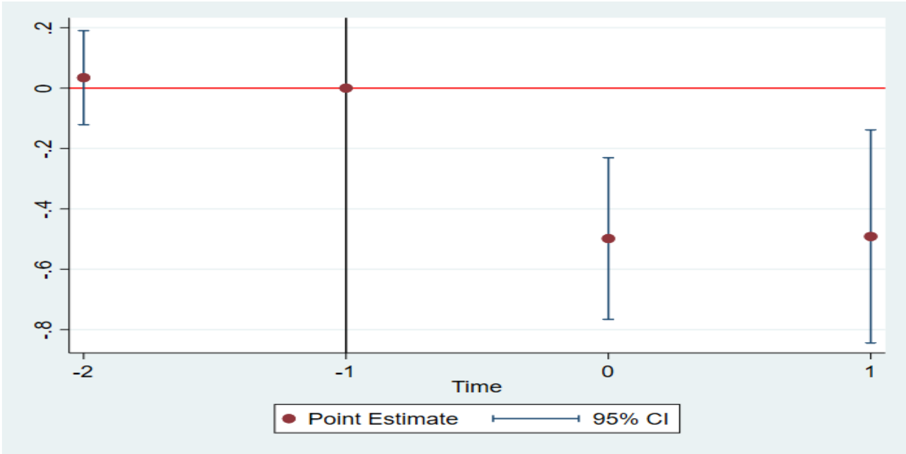
Note: The figure depicts the effects of universities on the completion of primary education among young females in the host community. Observations from the "Never-treated" EAs included in the control group.

Figure C.1: Estimated impact of public universities on completion of primary education using 'Never Treated' as a control.



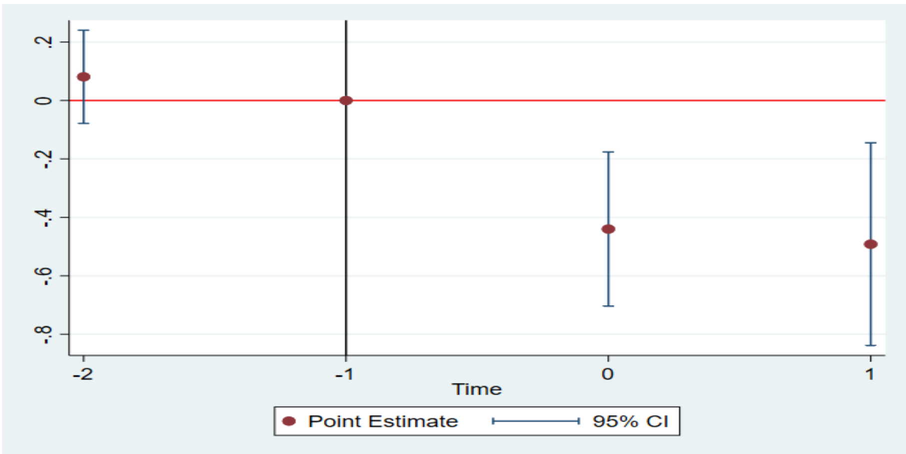
Note: The figure depicts the effects of universities on the completion of secondary education among young females in the host community. Observations from the "Never-treated" EAs included in the control group.

Figure C.2: Estimated impact of public universities on completion of secondary education using 'Never Treated' as a control.



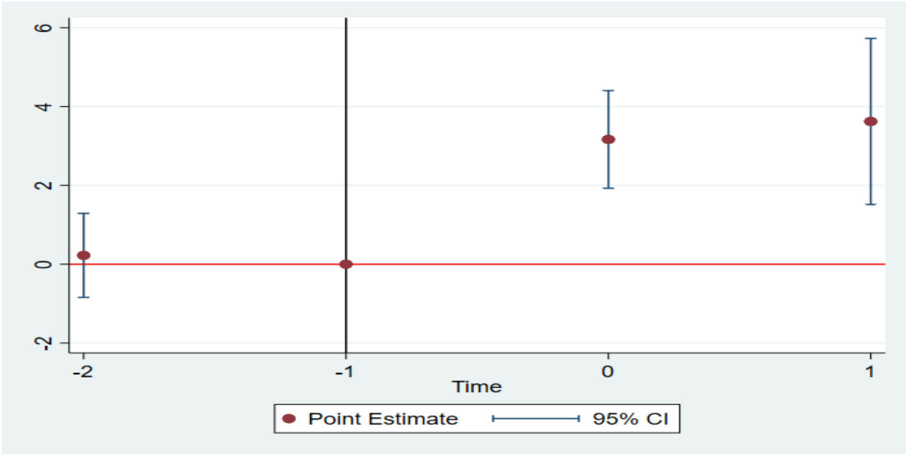
Note: The figure depicts the effects of universities on the share of young females with no formal education in the host community.

Figure C.3: Estimated impact of public universities using alternative educational indicator: No formal education.



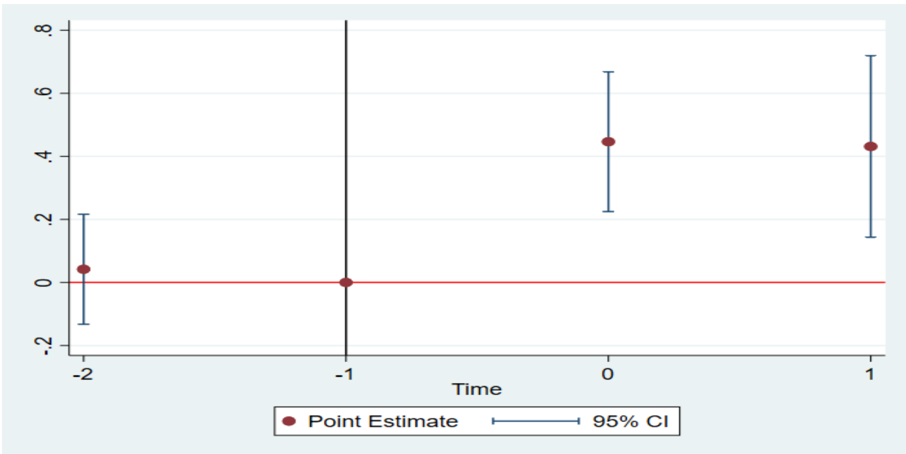
Note: One of the approaches used by the DHS to measure the literacy status of respondents was asking them to read a short phrase written on a card in their native language. The figure shows estimates of the effects of university exposure on female literacy status–measured by a binary variable that takes the value of 1 if they fail to read the phrase written on a card.

Figure C.4: Estimated impact of public universities using alternative educational indicator: Reducing illiteracy.



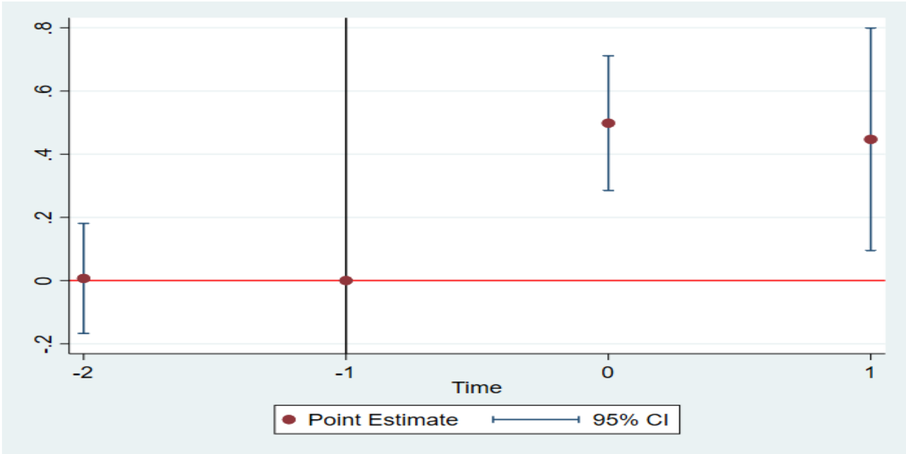
Note: The figure depicts the effects of universities on the highest grade reached by typical young females in the host community.

Figure C.5: Estimated impact of public universities using alternative educational indicator: Highest grade level



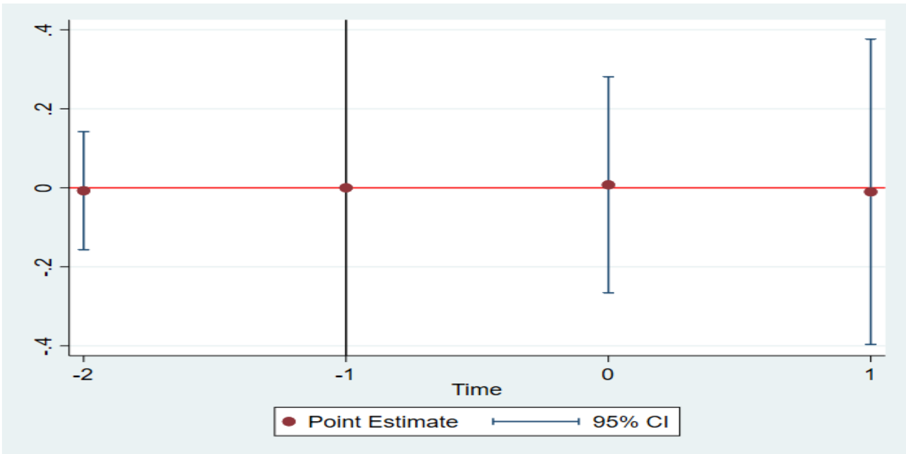
Note: The figure depicts the effects of universities on the completion of primary education among young females in the host community. Only young females between the ages of 15 and 20 during the study period are included in the analysis.

Figure C.6: Estimated impact of public Universities on completion of primary education: Different age intervals (15 to 20)



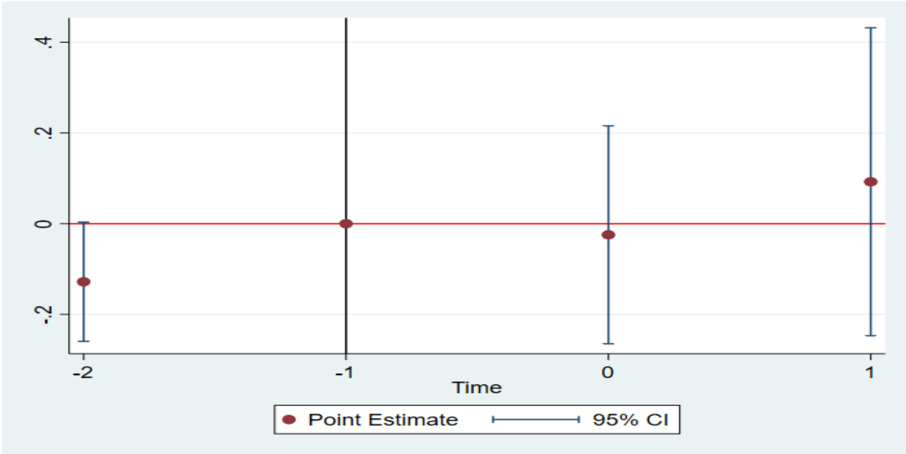
Note: The figure depicts the effects of universities on the completion of secondary education among young females in the host community. Only young females between the ages of 15 and 20 during the study period are included in the analysis.

Figure C.7: Estimated impact of public universities on completion of secondary education: Different age intervals (15 to 20)



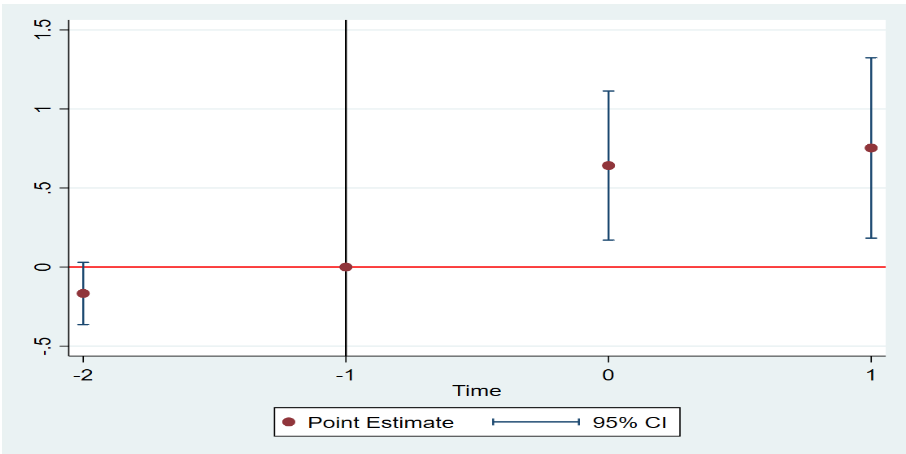
Note: The figure depicts the effects of universities on the primary school completion rate among females aged between 30 and 49 in the host community.

Figure C.8: Falsification test: Completion of primary education.



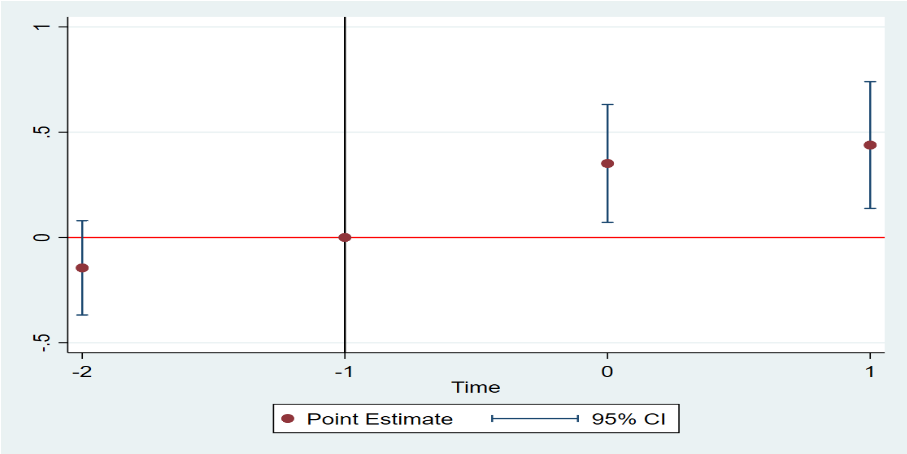
Note: The figure depicts the effects of universities on the secondary school completion rate among females aged between 30 and 49 in the host community.

Figure C.9: Falsification test: Completion of secondary education.



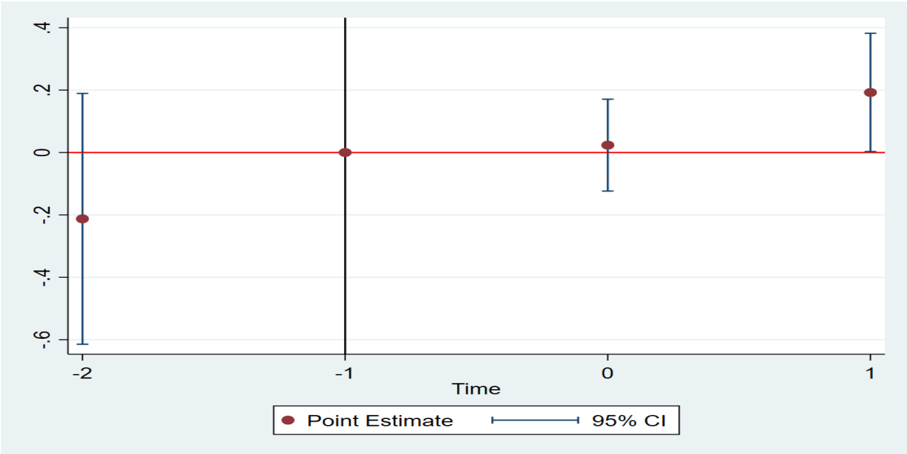
Note: The figure illustrates the impact of universities on the primary school completion rate of adolescent females in rural areas within the host community.

Figure C.10: Completion of primary education: Rural area.



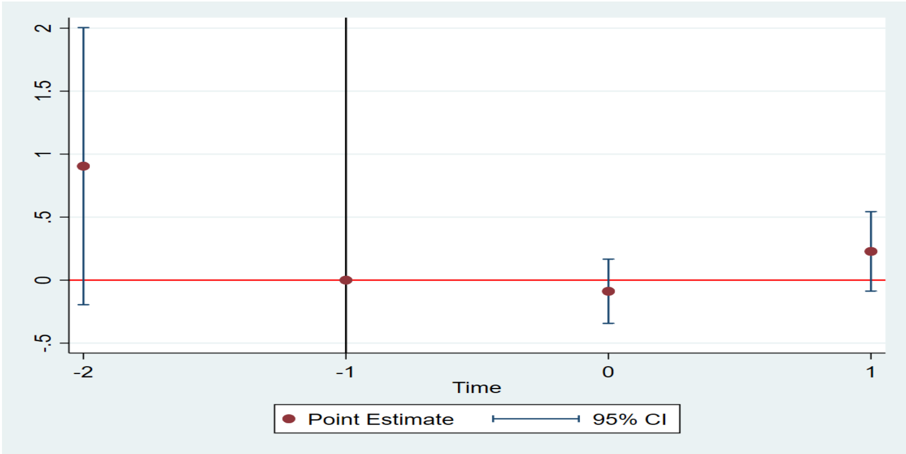
Note: The figure illustrates the impact of universities on the secondary school completion rate of adolescent females in rural areas within the host community.

Figure C.11: Completion of secondary education: Rural area.



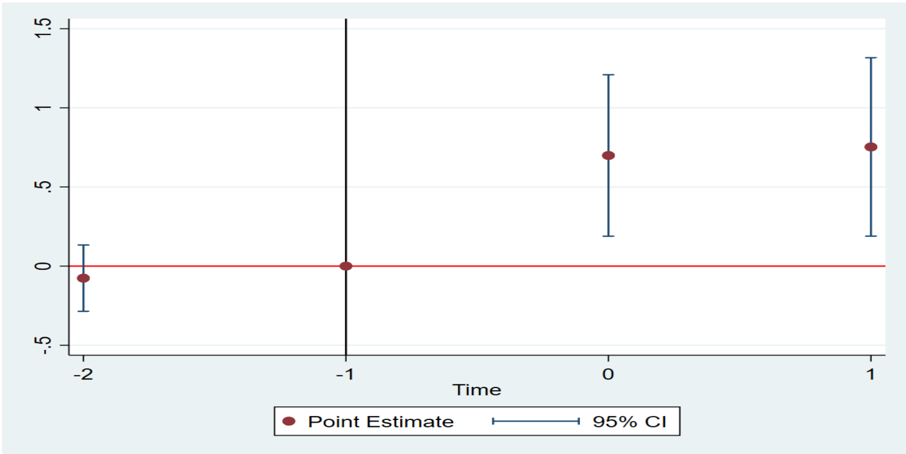
Note: The figure illustrates the impact of universities on the primary school completion rate of adolescent females in urban areas within the host community.

Figure C.12: Completion of primary education: Urban area.



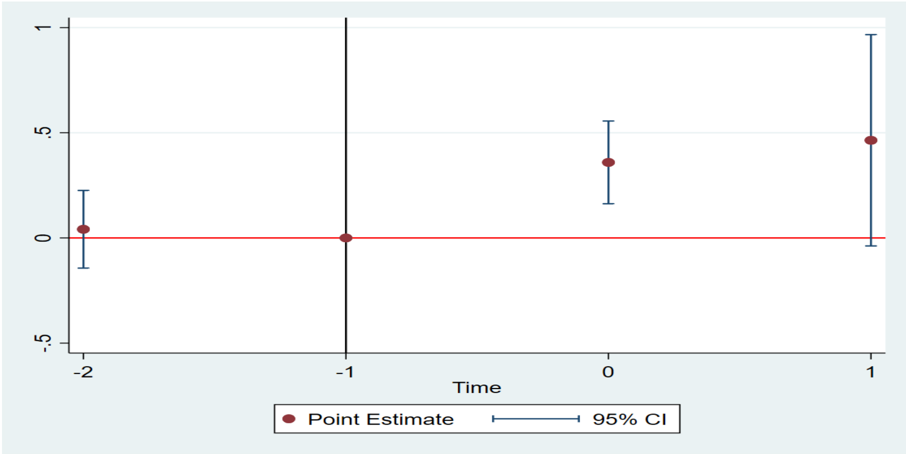
Note: The figure illustrates the impact of universities on the secondary school completion rate of adolescent females in urban areas within the host community.

Figure C.13: Completion of secondary education: Urban area.



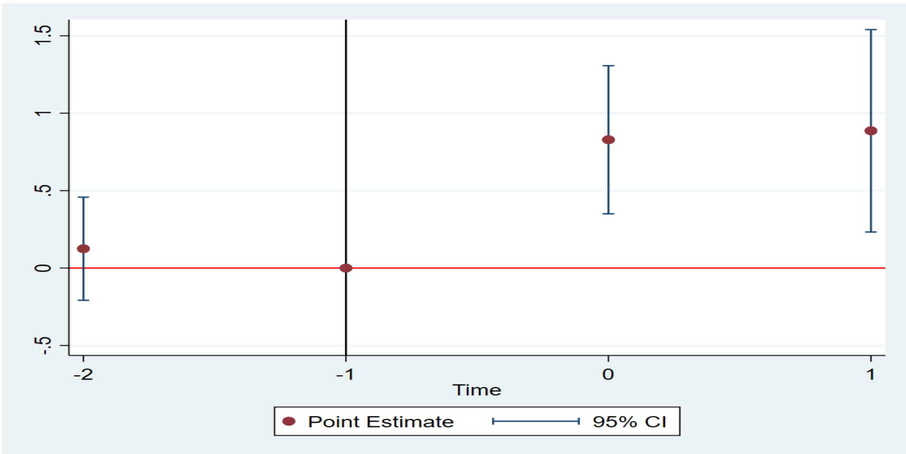
Note: The figure illustrates the impact of universities on marital status captured by whether the person is single or not.

Figure C.14: Impact of public universities on marital status.



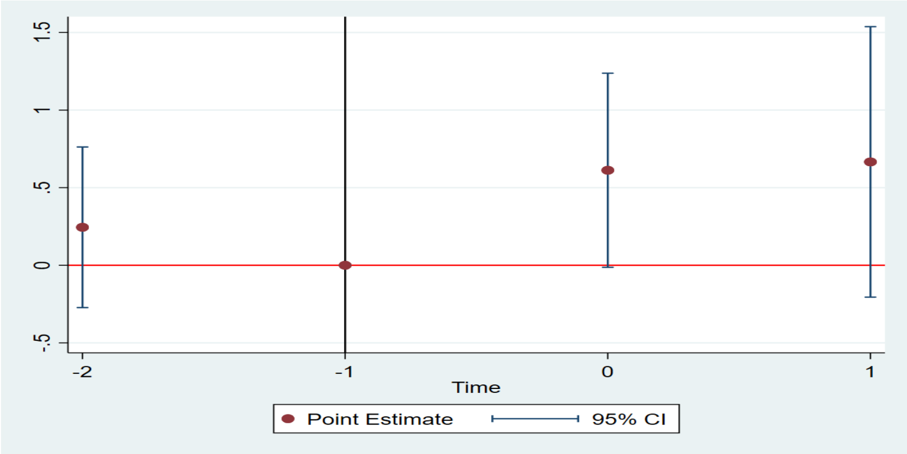
Note: The figure illustrates fertility preferences as captured by the preferred waiting time for the birth of another child

Figure C.15: Impact of public universities on fertility preferences.



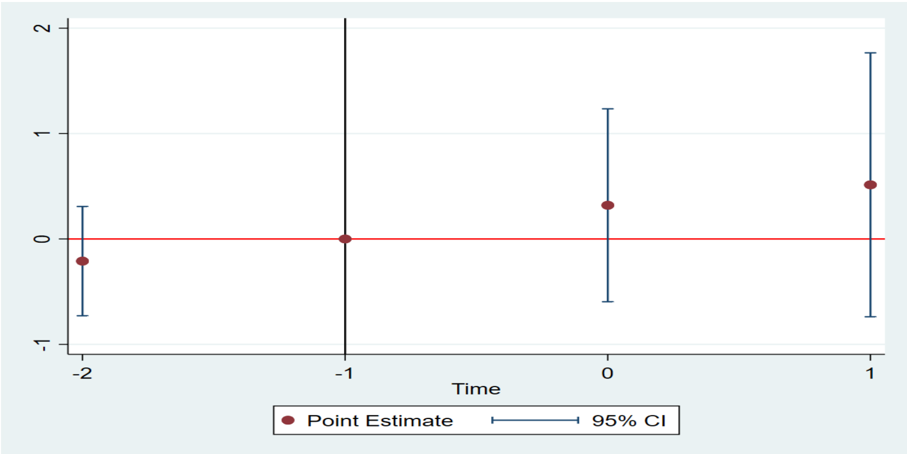
Note: The figure depict the effects of universities on media exposure captured by newspaper reading.

Figure C.16: Impact of public universities on media exposure captured by newspaper reading.



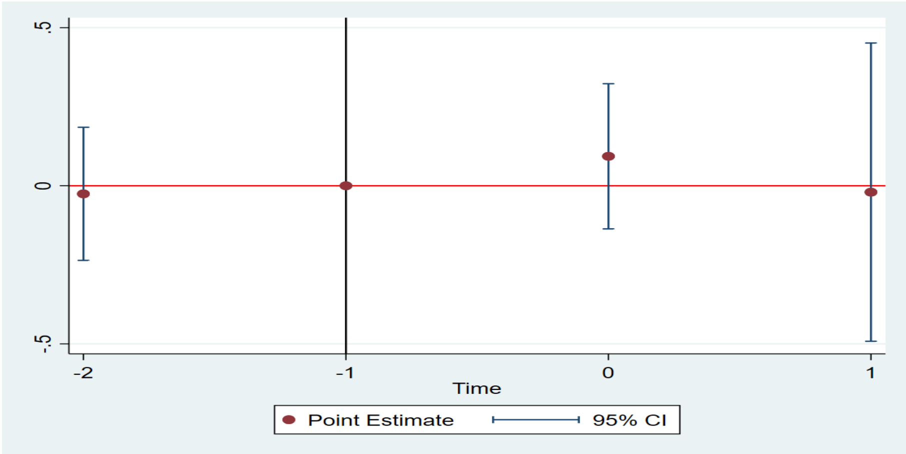
Note: The figure depict the effects of universities on media exposure captured by radio listening.

Figure C.17: Impact of public universities on media exposure captured by radio listening.



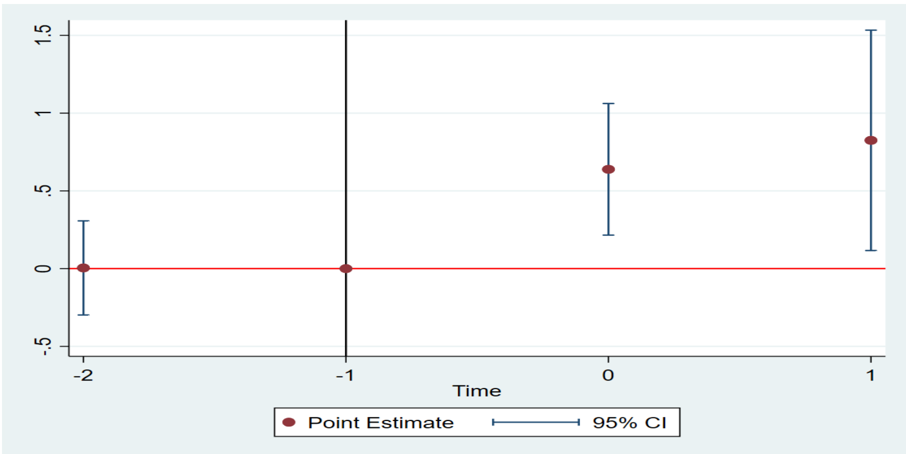
Note: The figure depict the effects of universities on media exposure captured by watching television.

Figure C.18: Impact of public universities on media exposure captured by watching television.



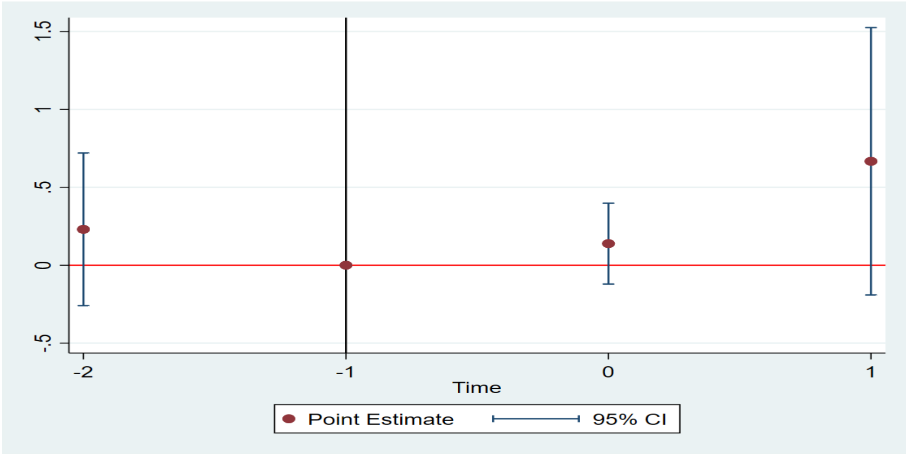
Note: The figure depict the effects of universities on on reducing domestic violence captured by a binary variable to indicate whether the respondent believed that beating wives was justified in situations such as going out without telling the husband, neglecting the children, arguing with the husband, refusing to have sex, or burning the food.

Figure C.19: Impact of public universities on domestic violence.



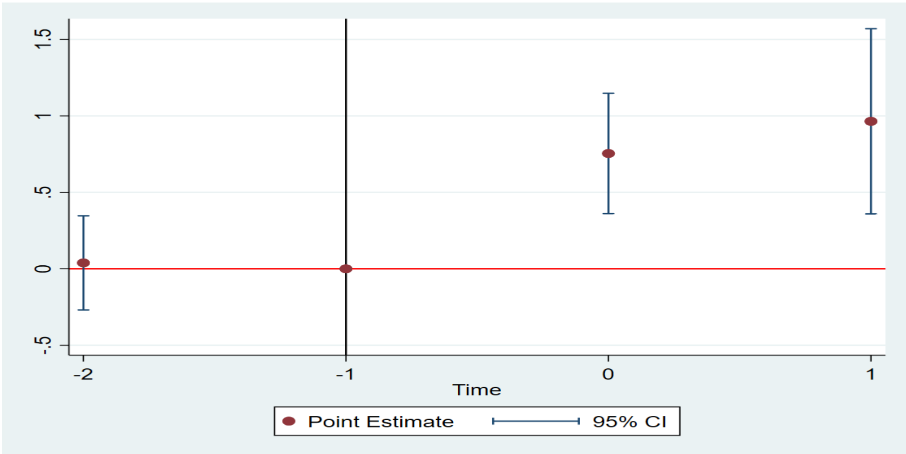
Note: The figure depict the effects of universities on improving female empowerment captured by whether she had a role in decisions related to large household purchases.

Figure C.20: Impact of public universities on decision making: Large household purchases.



Note: The figure depict the effects of universities on improving female empowerment captured by whether she had a role in decisions related to spending their earnings.

Figure C.21: Impact of public universities on decision making: Spending.



Note: The figure depict the effects of universities on improving female empowerment captured by whether she had a role in decisions related to healthcare.

Figure C.22: Impact of public universities on decision making: Health care.

5

RURAL ROADS, CHILD LABOR, AND SCHOOLING IN RURAL ETHIOPIA

ABSTRACT

New roads bring new opportunities including access to employment. However, new employment opportunities might encourage early school dropout and school absenteeism. We investigate the link between rural roads, children's labor allocation, and educational outcomes by focusing on the recent Ethiopian road construction program. In the analysis, we combine household panel data with novel road network data. To address endogeneity concerns, we combine a difference-in-difference estimation model with a matching technique. Our findings consistently show that road access does not encourage school absenteeism or school dropouts to join the labor force. The findings remain consistent across gender and age groups, as well as in the face of a drought shock
JEL Classification: H52, I2, I25, R4
Keywords: human capital, child labor, rural roads, drought, quasi-experiment

5.1 INTRODUCTION

The role of transportation infrastructure in economic development has long been duly acknowledged by both academics and policymakers (Aschauer, 1989; Easterly & Levine, 1997; Kessides, 1993; Queiroz & Gautam, 1992; Riverson et al., 1991). Likewise, the absence or inadequacies of infrastructure are considered to be a major impediment to economic development (Calderón & Servén, 2010; Limao & Venables, 2001). As a result, considerable investments have been made to improve transport infrastructure in developing countries over the last few decades. Despite these investments, little is known about the causal impacts since the decisions about where to construct roads are influenced by endogenous factors such as natural endowments, environmental conditions, political considerations, and economic factors (Burgess et al., 2015; Asher & Novosad, 2020). In this paper, we investigate if improvements in road connectivity have an impact on investments in human capital development and decisions on the child labor allocation in rural economies.

Several studies have recently investigated the effects of transportation infrastructure in various settings. Among the studies that focus on rural and agricultural settings, Khandker et al. (2009); Qin & Zhang (2016); Shrestha (2020); Aggarwal (2018) demonstrate the contribution of road access in improving rural livelihoods by enhancing the accessibility of non-local inputs/products, regulating the prices of food and non-food items, and facilitating market participation.[1] A well-established body of literature also directly measured the effects of road access on the welfare status of rural households (Dercon et al., 2009; Aggarwal, 2018; Nakamura et al., 2020). Others including Asher & Novosad (2020); Gibson & Olivia (2010) investigate the linkage between road access and rural household labor allocation decisions, livelihood diversification, and migration. For instance, Asher & Novosad (2020) argue that rural road accelerates structural transformation by enabling rural workers to access nonfarm employment outside of their villages. However, to date, we are lacking a clear understanding of the impacts of roads on educational outcomes.

Road access can affect educational outcomes by influencing factors that determine the supply and demand for schooling. From a supply standpoint, road access improves the accessibility of schools, which are few in rural areas. Road access removes a substantial barrier to schooling by reducing travel time to school (Petrosino et al., 2012; Sharma & Levinson, 2019). Road access can also boost the local economy (Jacoby & Minten (2009); Berg et al. (2018)), hence, benefits education by improving the financial capacity of the villages to invest in school infrastructure.[2]

1 Relatedly, Kuss et al. (2022) discuss that limited transportation availability in rural areas severely restricts residents from engaging in marketing activities and enhancing their agricultural productivity while increasing the income of individuals who provide transportation services in those areas.

2 Connelly & Zheng (2003) and Dostie & Jayaraman (2006) highlight the role of the local economy for children's education.

On the demand side, new roads in rural areas can influence schooling by improving parents' ability to spend on education, such as school fees and learning materials. This is because roads increase household income by expanding market access, which enhances agriculture profitability and makes nonfarm jobs more accessible (Asher & Novosad, 2020). Improvements in the financial position of a household are expected to have a positive effect on children's schooling (Chowa et al., 2013; Lincove, 2009). Conversely, road access may also alter the opportunity cost of schooling by opening up greater labor market opportunities for children, and parents may encourage children to work and generate money for the family or help with household chores. Particularly in rural areas where occupations demanding skilled labor are often limited, road access is expected to reduce the expected educational returns and the opportunity cost of children's labor significantly (Burde and Linden, 2009). For example, Atkin (2016) and Menon (2010) demonstrate how having more job opportunities in the neighborhood or having credit access to establish own business adversely affects school achievements. However, as argued by Francisco & Tanaka (2019) and Aggarwal (2018), studies that directly explore the link between road access and human capital development are scarce. Through our study, we seek to enrich the literature by investigating whether Ethiopia's Universal Rural Road Access Program (URRAP), launched in 2011, has altered children's labor allocation and educational achievements.

To the best of our knowledge, our study is the first to analyze the effects of rural road access on children's labor allocation and educational outcomes in Sub-Saharan Africa (SSA). Existing studies are mainly from other parts of the world including, India (Aggarwal, 2018; Adukia et al., 2020), the Philippines (Francisco & Tanaka, 2019), Bangladesh (Khandker et al., 2009) and Cambodia (Idei et al., 2020).[3] Our research will focus on SSA, where there is a substantial prevalence of child labor and educational exclusion among school-age children. Compared to other continents, Africa has the highest rate of child labor—more than twice the global average—and child labor is increasing in SSA in contrast to ongoing worldwide improvements (International Labour Organization, 2017). According to UNESCO's most recent statistics, a third of children in SSA between the ages of 12 and 14 are not enrolled in school (UNESCO, 2022). Besides, the findings from the existing literature also remain mixed. On the one hand, studies like Aggarwal (2018) and Li et al. (2019) argue that new roads create a tradeoff between current economic opportunities and long-term investment in human capital in India and China, respectively. They showed that road access negatively affects teenagers' school enrolment and promotes early dropout to join the labor market. Contrary to this, others like Adukia et al. (2020); Francisco & Tanaka (2019)

3 We are also aware of related studies that examined the impact of school proximity and transportation service on human capital development (Muralidharan & Prakash, 2017; Burde & Linden, 2013; Duflo, 2001) and those studies that investigate the responsiveness of investment in human capital development to employment and income opportunities (Fafchamps & Wahba, 2006; Churchill et al., 2021; Edmonds, 2006).

documented the positive contribution of rural roads on school outcomes. Meanwhile, Idei et al. (2020) argue that improved road access alone did not necessarily improve school outcomes. These mixed findings from the existing studies suggest that the effects of rural roads on human capital development may be context-dependent. Our study will increase our understanding of the link between road access and human capital development in Ethiopia, a region of the world that faces contextual differences in terms of institutional and socioeconomic conditions.

The second contribution of the study comes from exploring the heterogeneous effects of road access based on children's gender and age groups, as well as exposure to drought shocks. The relationship between rural roads and the opportunity cost of children's schooling may alter depending on whether or not they have been exposed to drought shocks. Studies have shown that drought shocks can cause school dropout because either the child has to work to fill the gap in the household income or drought-induced income losses might limit parents' ability to spend on education (Gollin & Rogerson, 2014; Groppo & Kraehnert, 2017). As a result, road connectivity may encourage dropout in the event of drought shock by making jobs more accessible. Road access, on the other hand, fosters resilience (Nakamura et al., 2020; Hirvonen et al., 2020) therefore the impact on children's schooling could be minimal. Particularly, in rural Ethiopia, where rain-fed agriculture is the dominant livelihood strategy and children are expected to attend school for a half-day, the interaction between rural roads, child labor, educational outcomes, and drought shock deserves thorough investigation. We also study the impact heterogeneity based on the gender and age of the child. Several studies show that child labor engagement in Ethiopia varies noticeably by gender and age group of the child (e.g., Tafere & Pankhurst (2015); Admassie (2003), and these differences may affect their school outcomes differently. MoE (2020) shows that boys in the country have a higher gross enrollment rate than girls, with a Gender Parity Index of 0.91 and 0.87 for primary and secondary education, respectively.[4] Likewise, girls drop out from primary school at a rate of 13 percent and boys at 14 percent, while their primary school completion rates are 52.2 and 56 percent, respectively (MoE 2020, Michael, 2018). As a result, we explore if road access affects children differently based on their gender and age category.

Lastly, our research contributes to the emerging literature that has started investigating the effects of URRAP, a program that has increased the proportion of villages in Ethiopia with all-weather roads to over 76% (Gebresilasse, 2023; Nakamura et al., 2020; Kebede, 2022). Gebresilasse (2023) investigated the effects of the program on agricultural productivity and illustrated that expansion of rural roads on its own is insufficient to raise agricultural output, but it can do so by up to 6% if combined with agricultural extension services. Kebede (2022) demonstrates how household prefer-

4 The Gender Parity Index is calculated as the ratio of an indicator's values for girls to its corresponding values for boys.

ences greatly affect farm households' agricultural land allocation decisions and how this effect diminishes because of improved access to rural roads. According to Nakamura et al. (2020), the road expansion program was significantly linked to an improvement in household welfare and resistance to drought stress. We contribute to them by investigating the effects on child labor and schooling.

For the analysis, we combine a national-level panel dataset from 2011 and 2016 with newly acquired road network data and gridded climate data. The endogeneity concern arising from the non-random road placement decision is addressed by combining the Difference in Difference techniques with a matching approach. We use current school enrolment, school absenteeism, and completion of a primary school as our main outcome indicators of human capital development. Combining these indicators enables us to better understand the link between rural roads and education. For instance, rural road access-induced employment opportunities might encourage absenteeism without affecting school enrolment or dropout. Similarly, we use multiple indicators to assess if there are changes in child labor use due to road access at both the intensive and extensive margins.

Contrary to what has been discovered in other parts of the world, our results consistently suggest that road access does not improve schooling, measured by current school enrolment, school absenteeism, and completion of primary school. It also does not encourage school absenteeism or early dropouts to enter the labor force. The result is consistent regardless of the gender and age group of the child, or whether the child is exposed to drought shock.

The remaining sections of the papers are organized as follows. The next section gives an overview of the educational structure, school enrollment status, and prevalence of child labor in Ethiopia, along with a description of URRAP. The third section gives a comprehensive summary of the data sources and types utilized. Section four discusses the main working variables while the methods used to address the objectives of the study are explained in section five. In section six, the findings of the study are presented and discussed. The final section presents the conclusions.

5.2 COUNTRY CONTEXT

Over the last few decades, Ethiopia's government has made massive investments in education, and its efforts have yielded significant results. Between 1996 and 2015, the number of primary schools in Ethiopia increased threefold, with the total number of enrolled students rising from 3 million to over 18 million during the same period (Šiška et al., 2020). This being the case, UNICEF (2022) shows that about 2.6 million primary school-aged children, of whom 57 percent are girls, are not enrolled. Likewise, only 25% of children old enough to attend secondary school are attending. Child labor, along with poor health, poverty, and a lack of gender-sensitive education systems and infrastructure facilities, is cited as a barrier to schooling in the country (Tafere & Pankhurst, 2015).

Child labor is a common phenomenon in Ethiopia (Heissler & Porter, 2013). The national child labor survey conducted in 2015 estimates that 42.7 percent of children in the country engage in child labor (CSA & ILO , 2018). Even though studies such as (Admassie, 2003) claim that children in rural areas of the country can simultaneously participate in child labor and attend school without a significant trade-off, CSA & ILO (2018) unveil that the school enrollment rate is meaningfully higher for those who are not participating in child labor compared to those who are involved.

Along with work burdens, distance to school is listed as one of the main barriers to schooling in the country (MoE & UNICEF, 2012; Woldehanna et al., 2021). As the vast majority of the Ethiopian population lives in rural areas with fluctuating weather conditions and rocky topography, access to rural roads plays a vital role in spreading education and securing equitable access for all in such circumstances. However, according to Vandycke et al. (2019), the share of villages with all-season and dry-season roads in 2009 was just 37 and 20 percent, respectively.

In 2011, the Ethiopian government introduced URRAP intending to connect every rural community in the country with all-weather roads. The program was designed in a way that the federal government covers all the required funding, and regional and zonal authorities provide technical support. The responsibility of hiring engineering consultants that are mandated to conduct feasibility studies for each road is also given to the regional government. The lower administration offices (woreda) are responsible for ranking and selecting projects, and implementing the projects. Communities also participate in the URRAP by performing preliminary earthwork such as site clearing (Gebresilasse, 2023; ERA, 2010). As discussed by Kebede (2022), although the URRAP started in 2011, the first year was designated as a capacity-building year and almost all of the roads were started and completed between 2013 and 2015. Figures D.1 show how road access in each regional state has changed before and after the implementation of the program.

5.3 DATA

To conduct our research, we combine panel data from the World Bank's Living Standard Measurement Study (LSMS) collected in 2011 and 2016 with Road Network data sourced from the Ethiopian Roads Authority and gridded climate data.[5] The survey encompasses all areas of the country, except for the non-sedentary population. Our

5 LSMS provides modified location identifiers at the EA level to protect the respondents' privacy. By comparing these modified locations to the actual residence locations, Michler et al. (2022) showed that such adjustment has limited to no impact on estimates.

analysis is based on the panel data that covers the rural sample of enumeration areas (EAs).

We combine the LSMS survey data with geospatial data on the road network that comprises the entire road network of the country. As shown in Figure D.1, the road network has significantly expanded in the study period. We combine the LSMS data with the road network data using community-level location identifiers that are available in both datasets. Our analysis focuses on communities that received rural roads between 2011 and 2016 and those that did not, among the EAs covered by LSMS. We identify households as treated if they are located in communities that were connected by a new road in the primary analysis, and we conduct additional robustness tests that consider local multiplier effects. Specifically, we control for households that reside close to communities that benefited from URRAP.

To investigate how the impacts of road access are influenced by exposure to drought, we use the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010; Beguería et al., 2014). SPEI provides an index that shows water balance by calculating the deviations in total precipitation and evapotranspiration from historical means with a 0.5 degrees spatial resolution. We use the SPEI constructed based on a time scale that corresponds to the main cropping seasons in the country. We merged the SPEI with the child-level observations of the LSMS using the enumeration location identifiers.

5.4 SAMPLE CONSTRUCTION AND MAIN VARIABLES OF INTEREST

We start by trimming the data from the LSMS to exclude individuals who are older than the children's age category at baseline. To do so, we rely on related works as well as Ethiopia's official age requirement for primary school enrollment.

Among the related studies, Haile et al. (2019) examined the effects of drought shock on the health and educational outcomes of children aged 7 to 18 years in Ethiopia. Meanwhile, Colmer (2021) investigated the relationship between rainfall variability, child labor, and schooling among children aged 7 to 19 years during the baseline period. In other related studies, Aggarwal (2018); Francisco & Tanaka (2019), and Idei et al. (2020) focused on the effects of rural roads on children's education in India, the Philippines, and Cambodia, respectively, using data from children aged 5 to 20, 5 to 21, and 7 to 14 years. Our main analysis employs balanced individual-level panel data from children aged 7 to 18 years at the baseline, and we perform robustness checks by limiting the age range to 12, 14, and 16 years.

Raising the age limit to 18 helps us account for the widespread problem of late enrollment and grade repetition in the country. Using our dataset, we illustrate the age distribution of Grade 1 students during the baseline in Table 5.1. As shown in the table, late enrollment is common in the country, and its distribution varies substantially by gender. It shows that only 14 percent of girls and 25 percent of boys in grade one are seven years old, while 5.5% of girls and 3.1% of boys are beyond 15. Nega (2012) and Borbely et al. (2021) also documented the same problem, and they listed child labor, parents' inability to pay direct and indirect school costs, children's health, and school accessibility as some of the reasons for delayed enrolment.

Table 5.1: Age of Grade 1 students at the baseline

Age of Grade 1 students	Pooled (%)	Girls (%)	Boys (%)
7	20.11	14.29	25.51
8	14.29	18.68	10.2
9	13.23	13.19	13.27
10	12.7	14.29	11.22
11	10.58	7.69	13.27
12	10.05	10.99	9.18
13	7.94	8.79	7.14
14	3.17	3.3	3.06
15	3.7	3.3	4.08
Above 15	4.24	5.5	3.06

Source: LSLM (2011)

Once we establish our sample, we proceed with the construction of our working variables. Our main variables of interest consist of child labor and educational outcomes. Since we are measuring the short-term effects of road access (i.e. less than four years after the commencement of the project), we focus on indicators that suit our intention. Accordingly, we use children's current enrollment status and school absenteeism as our main educational outcome indicators and completion of primary school—which relatively shows a long-term school outcome, as an additional indicator. Our definition of current enrollment is represented by a binary variable that takes the value of 1 if the child was enrolled in school at the time of the survey and 0 if the child was not enrolled. Although enrollment has been steadily increasing in the country over the last few decades, around 14 percent of primary school-aged children and, 55 percent of female and 46 percent of male secondary school-aged youths are out of school (EPDC, 2018; World Bank, 2018; UNICEF, 2019). In addition, we consider school absenteeism and measured it as a binary outcome where a child who is continuously absent from school for a week or more during the survey period is assigned a value of 1, and 0 otherwise.

The other major problem in the country is that many students do not complete their education, with 85 percent completing Grade 5, and only 54 percent completing Grade 8.[6] As shown in MoE (2020), the country has a high rate of grade repetition and

6 `https://www.unicef.org/ethiopia/learning-and-development`

dropouts, even in primary school. As a result, we consider the completion of primary school as an additional indicator.

As child labor indicators, we rely on the information on labor use obtained from the LSLM dataset. The survey asks how much time each child spends on household chores, household business, and paid work such as casual, part-time, or temporary labor. Using this information, we construct our outcome variables on a weekly basis. In addition, we created binary variables that show whether the child is engaged in those activities or not. As the majority of related works focus on the extensive margin, combining the two aids in fully capturing the effects. Table D.2 presents the baseline summary of the outcome indicators along with other variables used in the analysis.

5.5 estimation strategy

The relationship between access to roads and children's schooling and labor allocation outcomes can be modeled, along with a vector of other explanatory variables X and their coefficients ψ, as:

$$Y_{ict} = X_{ict}\psi + \Omega R_{ct} + \varepsilon_{it} \tag{5.1}$$

Where Y_{ict} is the outcome variable for child i living in community c at time t, ε_{it} stands for the error term. R_c is a treatment indicator that shows whether an EA obtained an all-weather road during the study period.[7] Following Nakamura et al. (2020) and others who studied the effects of URRAP, we define road access as a binary variable that takes the value of one if a village is traversed by a URRAP road during the study period and zero otherwise.[8] The impact of access to road on the outcome variables is represented by Ω, if road placement decisions were random. However, in most cases, villages get road based on predefined characteristics, and these factors might also correlate with the outcome indicators. For instance, conditions such as agricultural potential and the landscape of EAs could affect road placement decisions. Specific to the URRAP, the availability of labor force/population size is another factor that might influence road placement decisions since residents are the primary contributors of labor input to preliminary site cleaning activities (Kebede, 2022). Furthermore, villages close to roads at the baseline might have a relatively higher probability of getting a road since the distance from the pre-existing road is essential to move inputs and machinery required for road construction (Gebresilasse, 2023). Hence, the endogeneity concern arising from nonrandom road placement decisions needs to be addressed to estimate unbiased estimates of the effects of access to rural roads.

7 The indicator does not take into account the length of the road.

8 As a robustness test, we also employ buffer zones to prevent "contamination" of the control EAs.

A randomized control trial of road provision is unlikely due to the high cost of road construction investments.[9] Ethiopia Road Authority does not have clearly defined and publicly available program rules (such as population size cutoff points) for deciding where to execute URRAP. This precludes us from using a regression discontinuity design. As a result, we address the endogeneity issue by combining the Differences-in-Differences (DID) approach with the matching technique. Combining the two approaches produces robust estimators (Smith & Todd, 2005).

PSM helps to estimate the impact by creating a credible counterfactual group using observable features. To do so, it relies on the Conditional Independence Assumption (CIA). The assumption posits that there are observable factors that determine selection decisions and, if these factors are controlled, the potential outcomes are independent of treatment status. However, the CIA could be too strong as selection might also depend on unobservable characteristics. In this case, DID allows relaxing the CIA assumption if the unobservable factors influencing the selection decision are time-invariant. More precisely, DID helps to cancel out the effect of time-invariant unobservable factors between those who gained road access versus those who did not by taking the difference in outcomes across time. Hence, by joining the two methods, PSM controls for the bias resulting from observables at the baseline, and DID accounts for the bias linked with time-invariant observable and unobservable factors.

For the matching exercise, we use community-level characteristics that are expected to influence road placement. These variables include population size, distance to pre-existing roads, access to the weekly market, agroecology, land use types, and landscape. We also considered the development potential of the EAs for food and commercial farming using the FAO-GAEZ suitability database, as EA's development prospects might affect the chance of receiving roads. We accounted for the suitability of the EAs for multiple cash and food crops in our matching model (Tables D.2 in the Appendix). To ensure the matching quality, we examine covariate balancing, and the result, which displays the average comparison of covariates after matching, is presented in Table D.3. As observed in the Table, the matching approach successfully eliminated the mean difference across all variables that were anticipated to impact road placement decisions.[10]

We evaluate the impacts of rural roads for boys and girls separately to see if they differ based on the gender of the child. However, we are unable to divide our data into two groups based on the drought exposure since the same communities would have experienced different degrees of water balance between the two survey waves. To put it another way, communities that experienced drought shock at baseline may have had an excess water balance at the end line. To this end, we introduce an interaction term to the standard DID model to look at the heterogeneity of the impact of road access

9 The URRAP program took five years to implement and cost over one billion US dollars (Nakamura et al., 2020).

10 Figure D.2 illustrates the common support region for propensity score.

depending on exposure to drought. The mathematical representation of our model is presented in equation 5.2. D_{ct} represents for drought shock. It is defined as a binary variable and takes a value of one if the village had experienced negative SPEI at time t, zero otherwise. Hence, β_6 shows the effects of access to the road on the outcome variables for children not exposed to drought shock (D_{ct}=0), whereas $\beta_6 + \beta_6$ captures the effects when D_{ct}=1.

$$\begin{aligned} Y_{ict} = \beta_o + \beta_1 D_{ct} + \beta_2 R_c + \beta_3 R_c * D_{ct} + \beta_4 post + \beta_5 post * D_{ct} + \beta_6 post * R_c + \\ \beta_7 post * R_c * D_{ct} + \varepsilon_{ict} \end{aligned} \tag{5.2}$$

Before concluding this section, it should be noted that we were unable to perform trend analysis since we only had one round of survey data collected prior to the beginning of the road expansion program. Nevertheless, we contend that by implementing matching techniques at the baseline to consider the disparities in resource endowment, access to institutions, and other socioeconomic characteristics between the treatment and control groups, we have increased the plausibility of the parallel trend assumption. Additionally, we assume no spatial spillover while identifying the impacts of rural roads in our primary model, and we conducted a spatial panel data model as a robustness test to account for spatial effects.

5.6 RESULTS AND DISCUSSION

We start by checking whether there has been a change in the proximity to schools and urban centers in these villages that gained roads during the study period, since the impacts of road access on child schooling and employment manifest through those channels. Table D.1 displays that road access considerably decreases the distance to the nearest asphalt road and primary school, measured in kilometers. This indicates that the construction of new roads has enhanced school accessibility and facilitated the connection of rural areas with the urban center. We examine if this improvement has influenced children's education and labor use.

In the following section, we present results obtained from our econometrics models. For each outcome indicator, we present results from three alternative specifications. In the following Tables, columns (A) display the results from the naïve DID model estimated without additional covariates. Columns (B) show the robustness of our results presented in columns (a) for the inclusion of child, household, and community-level controls. Our main result from the DID model estimated on a matched sample is presented in columns (C).

5.6.1 *Access to rural road, schooling, and child labor*

As shown in Table 5.2, we do not find evidence that road access affects school outcomes. The findings suggest that improving road connectivity alone is not sufficient to improve educational outcomes in rural areas. We re-estimate the relation separately for boys and girls to see if the effects of road access on human capital development vary based on gender. Our results presented in the bottom panels of Table 5.2 also fail to show significant effects of road access on the school outcome indicators for both boys and girls. The significant impacts of road access on school absenteeism for boys in columns A and B vanish in our preferred specification C. We also assess the impacts of road access by splitting our sample into two groups depending on the age of the children at the baseline: children aged 7 to 12 and those aged 12 and above. The results are presented in Tables D.4 and D.5 in the Appendix.[11] For both groups, the estimated impacts of access to the road on the school outcome are consistently statistically insignificant.

11 We follow related studies such as Aggarwal (2018) to establish the age categories.

Table 5.2: Estimated impacts of rural road access on education outcomes

	Current attendance			School absenteeism			Primary education		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.009	0.000	0.005	-0.055	-0.041	-0.053	-0.097**	-0.080*	-0.043
	(0.026)	(0.025)	(0.034)	(0.049)	(0.043)	(0.044)	(0.043)	(0.041)	(0.039)
Period# Road	0.034	0.030	0.044	0.032	0.026	0.046	0.060	0.057	0.034
	(0.031)	(0.032)	(0.042)	(0.057)	(0.056)	(0.068)	(0.049)	(0.049)	(0.051)
Observations	2,045	2,035	1,749	1,682	1,673	1,382	2,730	2,715	2,696
Boys									
Road	0.009	0.013	0.003	-0.038	-0.035	-0.065	-0.101**	-0.084*	-0.064
	(0.035)	(0.035)	(0.039)	(0.056)	(0.047)	(0.056)	(0.049)	(0.044)	(0.045)
Period# Road	0.051	0.043	0.086	0.048	0.037	0.091	0.109**	0.105*	0.045
	(0.043)	(0.044)	(0.057)	(0.070)	(0.069)	(0.084)	(0.055)	(0.055)	(0.058)
Observations	1,104	1,100	933	897	894	714	1,464	1,458	1,397
Girls									
Road	0.005	-0.013	-0.003	-0.075	-0.049	-0.022	-0.095	-0.079	-0.018
	(0.037)	(0.036)	(0.046)	(0.057)	(0.050)	(0.050)	(0.060)	(0.062)	(0.055)
Period# Road	0.019	0.014	0.010	0.018	0.018	-0.010	0.009	0.005	-0.010
	(0.043)	(0.046)	(0.062)	(0.063)	(0.062)	(0.080)	(0.063)	(0.064)	(0.068)
Observations	941	935	755	785	779	611	1,266	1,257	1,198

Notes: The table presents the effects of road access on educational outcomes measured by current attendance, school absenteeism, and completion of primary education. The control variables included in the regression are, time trend, administrative regions, distance to the pre-existing road and the nearest school, population size, landscape, agro-ecology, access to the market, suitability for agricultural production, household size, sex, age, and education of the household head, sex, and age of the child. Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Our findings are consistent with those of Idei et al. (2020), who argue that road access alone is not sufficient to influence school outcomes. However, our findings contrast those of Adukia et al. (2020) and Aggarwal (2018), who reported positive and negative impacts of road access on school outcomes of rural Indian teens, respectively. Among the research that looked at the impact of URRAP, Gebresilasse (2023) argues that the impact of the program on rural households may not be pronounced if it is not complemented with other essential institutions. Somehow related to this, Asher & Novosad (2020) argue that access to the road alone may not enhance rural livelihoods as multiple factors constrain the rural economy in addition to poor road access.

To get a better understanding of the absence of effects, we present self-reported reasons for the child's non-enrollment in Table 5.3. As shown in the table, domestic duties and a lack of interest are cited by 22.2 and 25.3 percent of the children, respectively, while a lack of schools or teachers in the village is cited by only one percent. This suggests that children who have not enrolled face obstacles beyond the distance to school and that simply having access to a road may not be sufficient to raise school enrollment. As Idei et al. (2020) points out, road conditions may be a crucial predictor of child schooling, but they are inadequate on their own since several obstacles in rural areas compel children to attend school. For instance, the nature of rural livelihoods could also be the other factor that determines parental investment in their children's education and the desire of children to learn. As Desalegn (2018) points out, low-paying jobs, like self-employment and unpaid family labor that do not require formal education predominate in rural areas of the country. Furthermore, Roschanski (2007) discusses that improving educational attainment requires more than just boosting school accessibility. Affordability of education (both direct and opportunity costs), the availability and quality of essential facilities, teacher quality and the relevance of the curriculum for local needs, and its ability to improve aspirations and prepare students for employment, are all factors influencing schooling. Relatedly, the UNICEF & MoE (2012) list socioeconomic barriers, such as traditional practices and lack of awareness, poverty, orphanhood, and lack of separate latrines for boys and girls, as some of the reasons that influence schooling in Ethiopia. As a result, enhancing road access alone may not be enough to encourage enrolment, as multiple factors influence children's schooling.

In the next step, we investigate if road access affected the opportunity cost of schooling through increased child labor both at the extensive and intensive margins. Table 5.4 presents the effects on the probability of children's employment (extensive margin) using the pooled sample and sub-samples that split the dataset based on the sex of the child. The first three columns of the table show the results for the effects on child labor as a whole, and then break down the categories of jobs into domestic duties, house-

Table 5.3: Main reasons for not being enrolled

Variable	Percent			Mean Diff
	pooled	control	treated	
Had enough schooling	3.3	3.5	3.1	0.5
Awaiting admission	0.55	0.4	0.8	-0.3
No school / lack of teachers	1.1	0	1.5	-1.50*
No interest	25.27	30.3	16.8	13.50***
Lack of money	14.01	12.3	17.6	-5.3
Marital obligation	6.87	6.1	8.4	-2.3
Sickness	8.52	7.9	9.9	-2
Disability	0.82	0.4	1.5	-1.1
Separation of parents	1.37	1.3	1.5	-0.2
Death of parents	2.2	2.6	1.5	1.1
Too old to attend	0.55	0.4	0.8	-0.3
Domestic obligation	22.25	21.1	24.4	-3.4
Other	13.19	13.6	12.2	1.4
Observations	359	228	131	

Source: LSLM (2011 and 2015)

hold business,[12] and paid jobs. Similarly, the estimated effects on the intensive margin (hours worked per week) are presented in Table 5.5.[13] Our results demonstrate that there is no significant relationship between road access and child labor under both extensive and intense margins, confirming the previous findings. The results are robust for the inclusion of additional covariates (Column B) and implementation of the matching technique (Columns C). A consistent result across different age categories of the children is also presented in Appendix Tables from D.6 to D.15. Among the related works, Nakamura et al. (2020) claim that URRAP roads have increased employment for people living in remote areas of the country during drought stress.

12 We reported results that disaggregated child labor usage for households' own businesses into agricultural and non-agricultural activities in the appendix in Table D.28 and D.29.

13 To deal with the zeros, numbers close to zero are added while computing logarithmic values.

Table 5.4: Impact of rural road access on child labor: Binary outcome indicators

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.024	0.029	0.020	0.033	0.018	0.018	0.061	0.079	0.056	-0.002	0.003	0.003
	(0.039)	(0.037)	(0.042)	(0.047)	(0.044)	(0.054)	(0.055)	(0.054)	(0.064)	(0.011)	(0.012)	(0.015)
Period# Road	-0.008	-0.017	0.009	0.051	0.044	0.022	-0.012	-0.022	0.012	0.006	0.002	0.007
	(0.047)	(0.047)	(0.057)	(0.053)	(0.053)	(0.058)	(0.067)	(0.068)	(0.088)	(0.030)	(0.028)	(0.038)
Observations	2,730	2,715	1,978	2,730	2,715	1,978	2,730	2,715	1,978	2,730	2,715	1,978
Boys												
Road	0.050	0.046	-0.005	0.042	0.033	0.016	0.061	0.056	0.024	-0.006	-0.005	-0.005
	(0.048)	(0.047)	(0.053)	(0.054)	(0.051)	(0.061)	(0.055)	(0.056)	(0.068)	(0.016)	(0.016)	(0.022)
Period# Road	-0.041	-0.048	0.034	0.043	0.035	0.057	-0.026	-0.033	0.004	0.017	0.015	0.045
	(0.060)	(0.060)	(0.072)	(0.066)	(0.066)	(0.077)	(0.074)	(0.075)	(0.090)	(0.033)	(0.032)	(0.039)
Observations	1,464	1,458	1,066	1,464	1,458	1,066	1,464	1,458	1,066	1,464	1,458	1,066
Girls												
Road	-0.004	0.013	0.015	-0.002	0.017	0.062	0.083	0.106	0.078	0.005	0.010	0.006
	(0.048)	(0.045)	(0.063)	(0.054)	(0.052)	(0.070)	(0.071)	(0.070)	(0.094)	(0.011)	(0.012)	(0.013)
Period# Road	0.025	0.009	0.007	0.060	0.040	-0.002	-0.003	-0.011	-0.011	-0.006	-0.011	-0.014
	(0.059)	(0.059)	(0.086)	(0.066)	(0.064)	(0.080)	(0.085)	(0.087)	(0.113)	(0.033)	(0.032)	(0.049)
Observations	1,266	1,257	924	1,266	1,257	924	1,266	1,257	924	1,266	1,257	924

Notes. The table shows how road access affects child labor utilization as assessed by a child's participation in domestic chores, household enterprise, wage jobs, or any combination of these activities (child labor). Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Control variables included in the analysis are listed in Table 5.2.

Table 5.5: Impact of rural road access on child labor: Continuous outcome indicators

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.212	0.282	0.237	0.308	0.152	0.169	0.541	0.760	0.560	-0.070	-0.070	-0.050
	(0.434)	(0.405)	(0.466)	(0.522)	(0.497)	(0.600)	(0.556)	(0.535)	(0.642)	(0.073)	(0.074)	(0.096)
Period# Road	-0.153	-0.241	-0.067	0.438	0.362	0.120	-0.053	-0.148	0.255	-0.031	-0.040	-0.014
	(0.539)	(0.533)	(0.641)	(0.603)	(0.598)	(0.667)	(0.681)	(0.692)	(0.897)	(0.102)	(0.101)	(0.109)
Observations	2,730	2,715	1,978	2,730	2,715	1,978	2,730	2,715	1,978	2,730	2,715	1,978
Boys												
Road	0.473	0.450	-0.047	0.358	0.255	0.077	0.610	0.594	0.360	-0.105	-0.104	-0.107
	(0.522)	(0.510)	(0.576)	(0.599)	(0.573)	(0.692)	(0.571)	(0.562)	(0.683)	(0.112)	(0.107)	(0.158)
Period# Road	-0.389	-0.454	0.287	0.432	0.357	0.599	-0.237	-0.299	0.035	0.042	0.040	0.142
	(0.650)	(0.651)	(0.765)	(0.741)	(0.740)	(0.901)	(0.757)	(0.760)	(0.912)	(0.138)	(0.136)	(0.160)
Observations	1,464	1,458	1,066	1,464	1,458	1,066	1,464	1,458	1,066	1,464	1,458	1,066
Girls												
Road	-0.101	0.168	0.440	-0.040	0.215	0.684	0.692	0.955	0.851	-0.020	-0.039	0.010
	(0.532)	(0.498)	(0.612)	(0.608)	(0.584)	(0.800)	(0.694)	(0.686)	(0.870)	(0.042)	(0.049)	(0.038)
Period# Road	0.073	-0.099	-0.457	0.454	0.223	-0.217	0.078	-0.011	-0.118	-0.118	-0.125	-0.181
	(0.679)	(0.674)	(0.884)	(0.740)	(0.720)	(0.906)	(0.845)	(0.861)	(1.090)	(0.092)	(0.095)	(0.124)
Observations	1,266	1,257	924	1,266	1,257	924	1,266	1,257	924	1,266	1,257	924

Notes. The table shows how road access affects child labor utilization as assessed by hours spent by children for domestic chores, household enterprise, wage jobs, or any combination of these activities (child labor). Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.Control variables included in the analysis are listed in Table 5.2.

5.6.2 *Robustness test*

In section 5.6.1, we reported consistent findings across multiple estimations and outcome indicators, indicating the insignificant effect of rural roads on children's schooling and child labor use. We present several robustness tests in this section.

We begin by limiting the upper age limit to children aged 12, 14, and 16. This will enable us to see if the over-aged children influenced the result. Tables D.4- D.15 in the appendix summarize the findings for various upper age boundaries. As shown in the Tables, the results reported in the main analysis remain unaffected by the change in the upper age limit.

Secondly, because our estimation technique depends on tracing school-age children starting from the baseline, children who reached school age during the study period are not included in the main analysis. We use pooled regression technique to assess the impact by pooling together all children of the two waves aged 7 to 18.[14] Tables from D.22 to D.24 summarize the results of this method. The findings are comparable in general, but the coefficients of the domestic chore in the pooled regression are found to be positive and statistically significant at the 10% significant level. The increase in domestic work might imply that children help with household chores while their parents engage in the labor market. The consistency of school outcomes despite having a significant impact on household chores is consistent with Admassie (2003), who found that children in rural areas of the country could engage in child labor and attend school without making a significant trade-off. Similarly, Colmer (2021) Colmer also refutes the argument that working time reduces learning time, noting that children in the country are required to attend school for a half-day.

Several studies (including Lv et al. (2017); Blair & Staley (1995); Fowles & Tandberg (2017)) have documented that educational outcomes could also be affected by different neighborhood effects, such as the size and status of the labor force and academic achievements, the quality of educational institutions, and job opportunities in the neighborhoods. We conducted a third robustness test where we incorporated a spatial econometrics model to control potential neighborhood effects.[15] We implemented the Spatial Durbin Model following Elhorst (2014) and Mamo et al. (2019) to account for spatial dependence in the independent and dependent variables, and we clustered the error terms to account for spatial dependency in the error term. Because we have geographic coordinate information at the EA level, we aggregate our values at the EA level to construct the spatial weight matrix. Tables D.16 to D.18 summarize the results after accounting for the spatial interaction. As shown in the Tables, the main results

14 As an alternative approach, we examine the impacts of road access using EAs as our unit of analysis. We consider the shares of the outcome variables at the EA level as an outcome variable. The findings are summarized in Tables D.25- D.27.

15 Using the LSMS survey, Tirkaso & Hailu (2022) documented a strong spatial dependency between farms in neighboring EAs.

remain consistent after accounting for the neighborhood effects. Lastly, we re-estimate our model by excluding children who reside less than 10 kilometers from the villages that received new roads to prevent "contamination" of the control EAs.[16] Tables D.19-D.21 present the results from this model and as shown in the tables the main results remain unaffected.

5.6.3 *Heterogeneous effects based on exposure to drought*

Marchetta et al. (2019) and Garg et al. (2020) and others uncovered the effects of adverse weather conditions on children attending school. The mechanisms are mostly related to its effects on agricultural productivity, hence, income. Adverse weather conditions restrict parents' ability to pay direct and indirect school fees and encourage their children to join the labor market. Contrary to this, others like Deuster et al. (2019) argue adverse weather conditions may have the unintended consequence of increasing education investment. The identified mechanisms include internal migration used to cope with adverse weather conditions could locate them in urban areas with greater educational opportunities. Similarly, children may spend most of their time in school if other alternatives, such as working as hired agricultural laborers, are unavailable during droughts. Access to roads could significantly affect those identified mechanics, such as migration, and access to jobs, including jobs in nearby villages or cities. As a result, drought shock may have a heterogeneous effect on the effects of rural roads on children's schooling and labor utilization.

Table 5.6 presents the impacts of road access on the educational outcome and child labor indicators for both drought-affected and non-affected children by estimating equation 5.2. We use school absenteeism and current enrollment status as educational outcome indicators since primary education completion is a commutative outcome that takes at least 8 years of schooling, making the impact of a single-year weather event less compelling. Our results show that the effects of road access on both educational outcomes and child labor uses are statistically insignificant for both children exposed to drought shock and those not.

To back up our findings, we also investigated households' self-reported drought coping strategies and found that strategies that influence children's educational outcomes and labor use are not often used among households affected by the drought shock. Reportedly, only one percent of households reduced their spending on healthcare and education, while 0.1 percent of those affected households sent their children to live elsewhere. The vast majority of the affected households reported relying on unconditional assistance or utilizing their savings or loans as their main coping strategy.

16 We chose 10 kilometers since students are not supposed to go more than that to get to school.

Table 5.6: Heterogeneity of the estimated impacts based on drought shock

Variables	Education Outcomes		Child Labor							
			Binary Outcomes				Continuous Outcomes			
	(I)	(II)	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)
Drought =0	-0.02	0.06	0.003	0.11	-0.031	-0.01	0.16	1.22	-0.36	0.1
	(0.05)	(0.06)	(0.08)	(0.09)	(0.12)	(0.03)	(0.91)	(0.97)	(1.21)	(0.22)
Drought =1	-0.004	-0.14	0.08	0.06	0.11	-0.01	0.77	0.63	1.1	-0.18
	(0.06)	(0.14)	(0.11)	(0.11)	(0.14)	(0.05)	(1.26)	(1.18)	(1.4)	(0.2)

Notes. Columns I and II under educational outcome represent Current attendance and School absenteeism, respectively. Columns (A), (B), (C), and (D), under child labor outcomes represent Labor engagement, Domestic Chores, Household Enterprises, and Wage Jobs, respectively. Standard errors clustered at EA level in parentheses. Control variables included in the analysis are listed in Table 5.2.

5.7 conclusion

In recent decades, substantial investments have been dedicated to enhancing transport infrastructure in developing nations and numerous studies explored its causal impacts ranging from urban to rural settings and from micro to macroeconomic problems. The findings, in general, show that transport infrastructure supports economic development and improves welfare and living standards. Particularly, road access to remote villages improves living standards by facilitating the accessibility of new inputs/products, regulating food and other product prices, and creating new employment opportunities. However, road access could also discourage schooling and promote early dropout to participate in the labor market. Hence, it might affect investment in human capital development.

To explain this puzzle, we examined if rural roads reshape children's labor allocation and educational outcomes using data from Ethiopia. We considered Ethiopia's URRAP commenced in 2011 as a case study and combined Difference in Difference techniques with a matching approach.

Unlike cases reported in Asian countries, our results consistently show that there is no fundamental tradeoff between current school attendance or enrollment and immediate economic opportunities created by road access. We test the robustness of our results using multiple outcome indicators, changing the age boundaries, and including child, household, and community-level controls.

The lack of a tradeoff between road access and children's education is an intriguing finding for a country aiming for universal primary and secondary school access by 2030. On the other hand, the absence of a significant impact of road access on schooling implies that road access by itself is inadequate in promoting investment in human capital. Our descriptive results suggest that domestic child labor is among the leading factor that keeps children out of school. In this context, Akoyi et al. (2018) argue that prohibiting child labor alone will not suffice to enhance educational outcomes; instead, it needs to be supplemented with other efforts. For example, several studies have found that increasing households' income-generating potential, whether through the provision of productive assets or the implementation of effective social safety net programs for vulnerable households, can improve academic outcomes and reduce child labor (Assefa, 2006; Prifti et al., 2021; Porter & Goyal, 2016; Woldehanna, 2010). Improving access to water and animal feeds could also reduce child labor while increasing school attendance. Furthermore, as Admassie (2003) argues, creating a flexible school system that accounts for high labor demand seasons can help to increase enrolment and attendance. Lack of interest is the other main factor identified in our descriptive result that keeps children out of school. Children's aspirations to study further are driven by their desire to be qualified for the occupations they want. Therefore, the lack of attractive professional opportunities in the villages is one of the critical problems restricting aspiration for higher education (Tafere, 2010).

Our data do not allow us to study the impact on educational quality in addition to access. Future studies might focus on the link between access to roads and education quality by using reliable indicators such as standardized exams. We picked indicators that can respond in the short term since we evaluated the short-term effects of road access in less than four years, which is a little shorter than the period employed by previous studies (e.g., Aggarwal (2018); Francisco & Tanaka (2019). As a result, further research is needed in the future to determine the effects of road access over the long and medium-term. Lack of data also prevented the analysis on child labor from distinguishing hazardous works from those that help them by providing them with competencies and skills.

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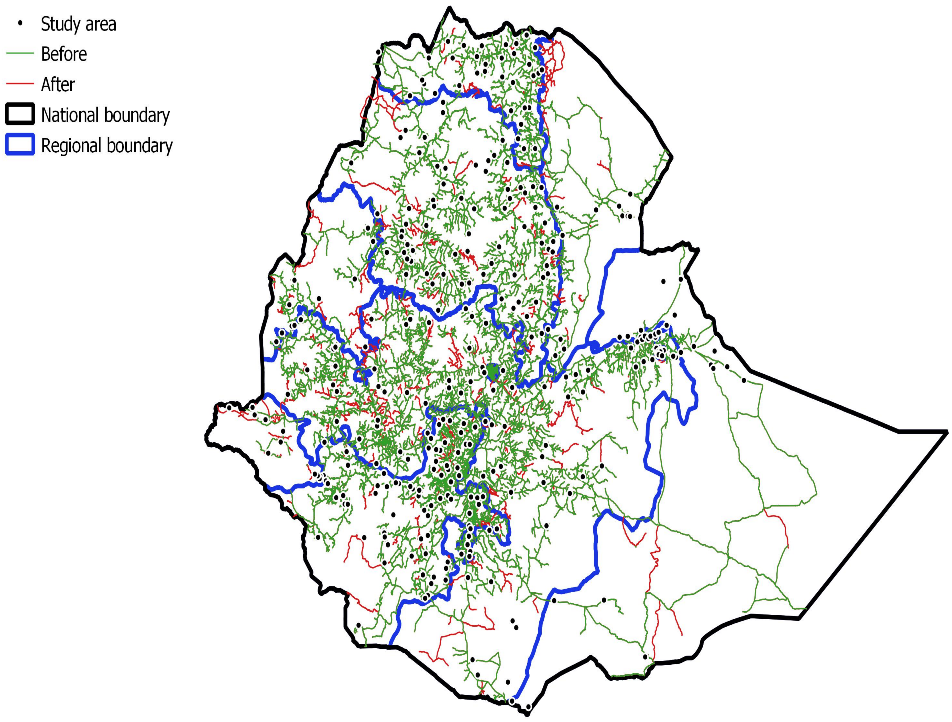
APPENDIX

TABLES AND FIGURES



Source: Authors using LSMS and the road network shapefile obtained from Ethiopian road Authorities.

Figure D.1: Road network in each regional state of the country between 2011 and 2016

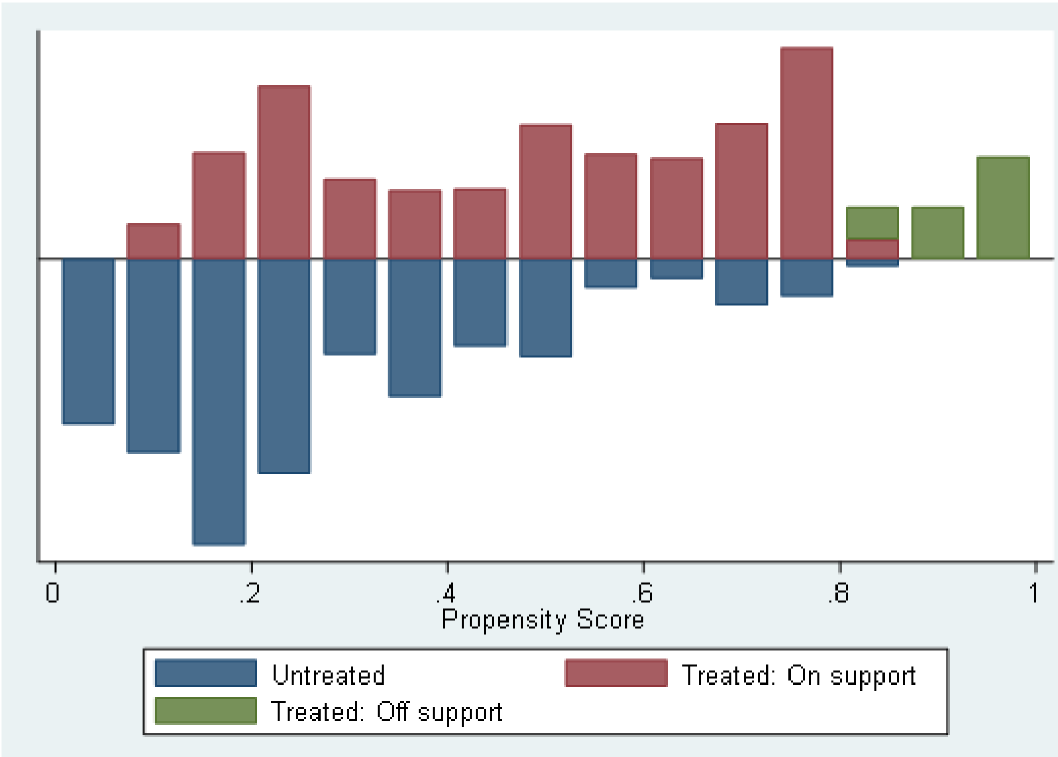


Figure D.2: Propensity score distribution and common support for propensity score estimates

Table D.1: Road access and distance from the nearest schools and asphalt road

VARIABLES	Distance to the nearest		
	Asphalt road	Primary school	Secondary school
Road	11.000***	0.576	-4.229***
	(3.635)	(0.395)	(0.893)
Period# Road	-28.056***	-2.807***	-0.3
	(5.135)	(0.558)	(1.261)

Notes. The table presents the relationship between road access and distance to the nearest schools and asphalt roads, measured in km. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Baseline description of working variables.

Variables	Control (Mean)	Treated (Mean)	Mean Diff)
Labour engagement (1 if the child engaged in any of the activities; 0 otherwise)	0.71	0.734	-0.024
Participation in Domestic chore (1 yes; 0 no)	0.393	0.427	-0.033
Participation in the household enterprise (1 yes; 0 no)	0.549	0.611	-0.061**
Participation in wage job (1 yes; 0 no)	0.021	0.02	0.002
Hours spent for all activities (per week)	67.299	56.9	10.400*
Hours spent for domestic chores (per week)	52.324	42.39	9.934*
Hours spent for household enterprise (per week)	14.827	14.488	0.339
Hours spent for wage job (per week)	0.148	0.022	0.126*
Current attendance (1 yes; 0 no)	0.878	0.887	-0.009
School absenteeism (1 yes; 0 no)	0.192	0.137	0.055**
Completion of primary schooling (1 yes; 0 no)	0.371	0.274	0.097***
Sex of the child (1= boy; 0 girl)	0.561	0.499	0.062**
Age of the child	11.126	11.217	-0.092
Sex of the household head (1= male; 0 female)	0.827	0.859	-0.031
Age of the household head	46.749	46.352	0.397
Literacy status of the household head (1= literate; 0 illiterate)	0.363	0.397	-0.034
Family size in adult equivalent	5.555	5.446	0.109
Tigrai(1= if the child leaves in Tigray region; 0 otherwise)	0.113	0.018	0.095***
Amhara(1= if the child leaves in the Amhara region; 0 otherwise)	0.163	0.297	-0.134***
Oromia (1= if the child leaves in the Oromia region; 0 otherwise)	0.308	0.225	0.082***
SNNP (1= if the child leaves in SNNP region; 0 otherwise)	0.194	0.309	-0.116***
Other regions (1= if the child leaves in other regions; 0 otherwise)	0.223	0.151	0.072***
SPEI	0.07	0.235	-0.165***
Agro-ecology is tropic warm (1= yes; 0 no)	0.189	0.053	0.136***
Agro-ecology is tropic cool (1= yes; 0 no)	0.272	0.262	0.01

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Table D.2 – continued from previous page

Variables	Control (Mean)	Treated (Mean)	Mean Diff)
Distance to nearest primary school (km)	0.979	1.555	-0.576*
Distance to nearest secondary school (km)	21.641	17.364	4.277***
distance to the baseline road(km)	20.689	18.83	1.859
Population size in EA	5397.311	4864.596	532.715***
Share of land covered by bush in EA	25.773	11.939	13.834***
Share of large scale farm in EA	9.979	10.787	-0.808
the landscape is flat (1= yes; 0 no)	0.297	0.186	0.111***
the landscape is slightly sloppy (1= yes; 0 no)	0.146	0.139	0.007
the landscape is moderately sloppy (1= yes; 0 no)	0.228	0.166	0.061***
Access to weekly market (1= yes; 0 no)	0.41	0.342	0.067**
Agricultural production potential of the EA (t/ha)			
Banana	2.146	2.847	-0.701**
Citrus	20.339	21.021	-0.683
Cabbage	12.853	21.424	-8.571***
Onion	21.685	19.934	1.751**
Tomato	20.229	14.128	6.101***
Carrot	21.971	21.342	0.629
Chickpea	5.881	4.399	1.482***
Cowpea	18.103	10.043	8.060***
Groundnut	12.428	7.546	4.882***
Soybean	18.608	11.789	6.819***
Sunflower	23.415	21.938	1.477
Wheat	17.887	24.964	-7.077***
Barley	17.072	24.945	-7.873***
Maize	26.172	23.076	3.095***
Sorghum	28.199	25.057	3.142***

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Table D.2 – continued from previous page

Variables	Control (Mean)	Treated (Mean)	Mean Diff)
Cotton	14.859	9.145	5.714***
Sugarcane	4.804	4.298	0.507

Table D.3: Covariates balance after matching

Weighted Variable(s)	Mean		Diff.	t
	Control	Treated		
Log(distance to the baseline road)	3.19	2.792	-0.399	0.54
Log(Population size)	8.263	8.329	0.066	0.38
Share of land covered by bush in EA	11.819	13.025	1.206	0.34
Share of large scale farm in EA	15.175	12.137	-3.038	0.39
the landscape is flat (1= yes; 0 no)	0.237	0.219	-0.018	0.16
the landscape is slightly sloppy (1= yes; 0 no)	0.148	0.177	0.029	0.29
the landscape is moderately sloppy (1= yes; 0 no)	0.299	0.212	-0.087	0.62
Access to weekly market (1= yes; 0 no)	0.32	0.349	0.029	0.23
Agro-ecology is tropic warm (1= yes; 0 no)	0.072	0.067	-0.005	0.09
Agro-ecology is tropic cool (1= yes; 0 no)	0.254	0.307	0.053	0.45
Agricultural production potential (t/ha) :				
banana	3.764	2.591	-1.172	0.59
Citrus	19.004	19.914	0.91	0.22
Cabbage	15.449	16.134	0.685	0.19
Onion	17.697	19.195	1.498	0.41
Tomato	15.027	16.892	1.865	0.56
Carrot	17.743	18.983	1.24	0.34
Chickpea	5.393	5.605	0.212	0.08
Cowpea	10.234	11.722	1.488	0.41
Groundnut	7.571	8.54	0.969	0.34
Soybean	11.537	13.306	1.769	0.41
Sunflower	19.774	21.74	1.965	0.47
Wheat	19.306	19.643	0.336	0.08
Barley	18.858	19.713	0.855	0.19
Maize	21.358	22.015	0.658	0.16
Sorghum	22.818	24.239	1.421	0.32
Cotton	8.861	10.618	1.757	0.48
Sugarcane	4.813	4.016	-0.797	0.34

Table D.4: Estimated impacts of rural road access on education outcomes: Children aged between 7 and 12 at the baseline

	Current attendance			School absenteeism			Primary education		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.025	0.012	0.013	-0.029	-0.014	-0.029	-0.073	-0.051	-0.092
	(0.025)	(0.030)	(0.038)	(0.050)	(0.045)	(0.061)	(0.052)	(0.050)	(0.089)
Period# Road	0.031	0.026	0.028	-0.009	-0.018	0.044	0.007	-0.005	0.108
	(0.028)	(0.029)	(0.054)	(0.060)	(0.059)	(0.090)	(0.052)	(0.051)	(0.121)
Observations	1,288	1,282	817	1,160	1,154	704	1,757	1,746	1,340

Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Control variables included in the analysis are listed in Table 5.2.

Table D.5: Estimated impacts of rural road access on education outcomes: Children aged above 12 at the baseline

	Current attendance			School absenteeism			Primary education		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	-0.026	-0.030	-0.038	-0.059	-0.064	-0.097	-0.147**	-0.108*	-0.082
	(0.066)	(0.061)	(0.099)	(0.068)	(0.065)	(0.083)	(0.071)	(0.061)	(0.068)
Period# Road	0.039	0.052	0.076	0.159*	0.170*	0.161	0.126	0.111	0.105
	(0.085)	(0.090)	(0.179)	(0.092)	(0.097)	(0.129)	(0.078)	(0.080)	(0.084)
Observations	451	449	345	271	270	213	579	577	433

Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Control variables included in the analysis are listed in Table 5.2.

Table D.6: Impact of rural road access on child labor (binary outcome): Children aged between 7 and 12 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.015	0.036	0.036	0.052	0.062	0.114*	0.038	0.073	0.079	-0.004	0.002	-0.005
	(0.046)	(0.040)	(0.079)	(0.054)	(0.049)	(0.059)	(0.056)	(0.053)	(0.099)	(0.009)	(0.010)	(0.010)
Period# Road	0.007	-0.001	0.022	0.050	0.043	-0.028	0.019	0.006	-0.035	0.007	0.006	0.018
	(0.057)	(0.056)	(0.094)	(0.064)	(0.064)	(0.089)	(0.074)	(0.074)	(0.100)	(0.030)	(0.029)	(0.032)
Observations	1,757	1,746	1,340	1,757	1,746	1,340	1,757	1,746	1,340	1,757	1,746	1,340

The table shows how road access affects child labor for children aged above at the baseline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.7: Impact of rural road access on child labor (continuous outcome): Children aged between 7 and 12 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.122	0.370	0.647	0.544	0.673	1.247*	0.292	0.654	0.843	-0.093	-0.078	-0.067
	(0.515)	(0.455)	(0.708)	(0.598)	(0.552)	(0.644)	(0.567)	(0.532)	(0.895)	(0.076)	(0.073)	(0.074)
Period# Road	0.047	-0.034	-0.176	0.415	0.349	-0.429	0.228	0.123	-0.432	0.001	-0.004	-0.006
	(0.655)	(0.645)	(0.832)	(0.726)	(0.719)	(0.959)	(0.746)	(0.746)	(0.900)	(0.100)	(0.099)	(0.088)
Observations	1,757	1,746	1,340	1,757	1,746	1,340	1,757	1,746	1,340	1,757	1,746	1,340

The table shows how road access affects child labor for children aged between 7 and 12 at the baseline. Standard errors clustered at EA level in parentheses . *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.8: Impact of rural road access on child labor (binary outcome): Children aged above 12 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.051	0.036	-0.018	0.014	0.032	0.091	0.163*	0.132	0.041	-0.019	-0.002	-0.131
	(0.062)	(0.061)	(0.073)	(0.067)	(0.056)	(0.062)	(0.087)	(0.087)	(0.099)	(0.024)	(0.025)	(0.093)
Period# Road	-0.079	-0.064	0.037	-0.006	-0.016	-0.046	-0.043	0.000	0.102	0.022	0.001	0.131
	(0.078)	(0.080)	(0.136)	(0.085)	(0.083)	(0.088)	(0.092)	(0.097)	(0.154)	(0.055)	(0.054)	(0.143)
Observations	579	577	433	579	577	433	579	577	433	579	577	433

The table shows how road access affects child labor for children aged above at the baseline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.9: Impact of rural road access on child labor (continuous outcome indicators): Children aged above 12 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.521	0.464	0.263	0.061	0.214	0.947	1.545*	1.334	0.630	-0.002	0.014	-0.841
	(0.667)	(0.625)	(0.719)	(0.748)	(0.643)	(0.693)	(0.890)	(0.878)	(0.974)	(0.104)	(0.116)	(0.725)
Period# Road	-0.761	-0.578	-0.077	-0.230	-0.261	-0.512	-0.211	0.113	0.794	-0.217	-0.250	0.431
	(0.890)	(0.894)	(1.443)	(0.953)	(0.920)	(0.988)	(0.928)	(0.980)	(1.540)	(0.259)	(0.255)	(1.026)
Observations	579	577	433	579	577	433	579	577	433	579	577	433

The table shows how road access affects child labor for children aged above 12 at the baseline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.10: Estimated impacts of rural road access on education outcomes: Upper age limit = 14 at the baseline

	Current attendance			School absenteeism			Primary education		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.028	0.008	0.004	-0.038	-0.024	-0.072	-0.082*	-0.068	-0.061
	(0.023)	(0.027)	(0.037)	(0.052)	(0.046)	(0.059)	(0.050)	(0.048)	(0.054)
Period# Road	0.019	0.018	0.041	-0.001	-0.012	0.063	0.042	0.039	0.069
	(0.029)	(0.028)	(0.044)	(0.061)	(0.059)	(0.090)	(0.057)	(0.056)	(0.068)
Observations	1,633	1,626	1,134	1,436	1,429	916	2,197	2,185	1,657

The table presents the effects of road access on educational outcomes for children aged between 7 and 14 at the baseline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.11: Impact of rural road access on child labor (binary outcome): Upper age limit = 14 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.014	0.027	0.019	0.031	0.018	-0.003	0.051	0.076	0.051	0.003	0.006	-0.001
	(0.043)	(0.039)	(0.050)	(0.053)	(0.049)	(0.062)	(0.055)	(0.054)	(0.073)	(0.009)	(0.010)	(0.014)
Period# Road	0.013	0.003	0.019	0.065	0.060	0.064	-0.002	-0.015	-0.007	0.010	0.007	0.001
	(0.053)	(0.053)	(0.064)	(0.061)	(0.061)	(0.070)	(0.074)	(0.075)	(0.095)	(0.032)	(0.030)	(0.041)
Observations	2,197	2,185	1,657	2,197	2,185	1,657	2,197	2,185	1,657	2,197	2,185	1,657

The table shows how road access affects child labor for children aged between 7 and 14 at the baseline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.12: Impact of rural road access on child labor (continuous outcome): Upper limit = 14 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.100	0.230	0.172	0.284	0.151	-0.092	0.446	0.727	0.498	-0.056	-0.058	-0.081
	(0.483)	(0.443)	(0.559)	(0.595)	(0.551)	(0.694)	(0.555)	(0.531)	(0.726)	(0.063)	(0.063)	(0.098)
Period# Road	0.027	-0.060	0.047	0.597	0.542	0.613	0.008	-0.107	0.013	-0.019	-0.028	0.008
	(0.611)	(0.610)	(0.730)	(0.690)	(0.686)	(0.783)	(0.738)	(0.751)	(0.970)	(0.090)	(0.090)	(0.079)
Observations	2,197	2,185	1,657	2,197	2,185	1,657	2,197	2,185	1,657	2,197	2,185	1,657

The table shows how road access affects child labor for children aged between 7 and 14 at the baseline. Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Control variables included in the analysis are listed in Table 5.2.

Table D.13: Estimated impacts of rural road access on education outcomes: Upper limit = 16 at the baseline

	Current attendance			School absenteeism			Primary education		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.024	0.019	0.033	-0.062	-0.050	-0.068	-0.100**	-0.083*	-0.050
	(0.024)	(0.027)	(0.037)	(0.051)	(0.044)	(0.049)	(0.045)	(0.044)	(0.050)
Period# Road	0.011	0.004	0.004	0.036	0.032	0.113	0.071	0.068	0.066
	(0.030)	(0.031)	(0.042)	(0.059)	(0.058)	(0.078)	(0.052)	(0.052)	(0.063)
Observations	1,883	1,875	1,307	1,598	1,591	1,023	2,515	2,502	1,830

The table presents the effects of road access on educational outcomes for children aged between 7 and 16 at the baseline. Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Control variables included in the analysis are listed in Table 5.2.

Table D.14: Impact of rural road access on child labor (binary outcome): Upper limit = 16 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.022	0.026	0.050	0.035	0.018	0.009	0.058	0.075	0.099	0.002	0.004	0.006
	(0.040)	(0.037)	(0.045)	(0.049)	(0.046)	(0.061)	(0.054)	(0.053)	(0.069)	(0.010)	(0.010)	(0.014)
Period# Road	-0.010	-0.020	-0.059	0.058	0.052	0.033	-0.014	-0.024	-0.097	-0.001	-0.003	-0.022
	(0.050)	(0.049)	(0.054)	(0.057)	(0.056)	(0.066)	(0.068)	(0.069)	(0.084)	(0.030)	(0.029)	(0.043)
Observations	2,515	2,502	1,830	2,515	2,502	1,830	2,515	2,502	1,830	2,515	2,502	1,830

The table shows how road access affects child labor for children aged between 7 and 16 at the baseline. Standard errors clustered at EA level in parentheses . *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.15: Impact of rural road access on child labor (continuous outcome): Upper limit = 16 at the baseline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.143	0.206	0.499	0.317	0.132	0.060	0.483	0.694	0.950	-0.084	-0.089	-0.050
	(0.444)	(0.412)	(0.511)	(0.552)	(0.523)	(0.675)	(0.543)	(0.528)	(0.699)	(0.065)	(0.065)	(0.072)
Period# Road	-0.109	-0.195	-0.802	0.528	0.472	0.213	-0.066	-0.164	-0.938	-0.024	-0.026	-0.075
	(0.572)	(0.563)	(0.621)	(0.641)	(0.633)	(0.739)	(0.692)	(0.702)	(0.852)	(0.095)	(0.094)	(0.113)
Observations	2,515	2,502	1,830	2,515	2,502	1,830	2,515	2,502	1,830	2,515	2,502	1,830

The table shows how road access affects child labor for children aged between 7 and 16 at the baseline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.16: Estimated impacts of rural road access on education outcomes: Spatial panel model

Variables	Current attendance	School absenteeism	Primary education
Road	-0.004	-0.024	-0.085**
	(0.033)	(0.047)	(0.038)
Period# Road	0.045	0.025	0.058
	(0.043)	(0.062)	(0.045)
Controls	Yes	Yes	Yes
Observations	216	216	216

The table shows how road access affects educational outcomes by implementing spatial econometrics technique. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.17: Impact of rural road access on child labor (binary outcome indicators): Spatial panel model

VARIABLES	Child Labour	Domestic Chore	Household Enterprises	Wage Job
Road	0.033	0.041	0.063	0.014
	(0.037)	(0.039)	(0.055)	(0.021)
Period# Road	-0.03	0.003	-0.03	-0.002
	(0.048)	(0.051)	(0.073)	(0.028)
Observations	216	216	216	216

The table shows how road access affects child labor by implementing spatial econometrics technique. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.18: Impact of rural road access on child labor (continuous outcome): Spatial panel model

Variables	Child Labour	Domestic Chore	Household Enterprises	Wage Job
Road	0.367	0.495	0.573	-0.021
	(0.407)	(0.439)	(0.561)	(0.104)
Period# Road	-0.472	-0.125	-0.236	-0.08
	(0.542)	(0.584)	(0.738)	(0.138)
Controls	Yes	Yes	Yes	Yes
Observations	216	216	216	216

The table shows how road access affects child labor by implementing spatial econometrics technique. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.19: Estimated impacts of rural road access on education outcomes: Excluding children within 10km of distance to road at the endline

	Current attendance			School absenteeism			Primary education		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	-0.004	-0.011	-0.026	-0.075	-0.057	-0.079	-0.105**	-0.099**	-0.04
	(0.026)	(0.026)	(0.032)	(0.056)	(0.047)	(0.055)	(0.046)	(0.044)	(0.047)
Period# Road	0.042	0.034	0.066	0.049	0.035	0.145	0.064	0.067	0.058
	(0.034)	(0.035)	(0.046)	(0.065)	(0.063)	(0.09)	(0.052)	(0.051)	(0.067)
Observations	1,755	1,749	1,093	1,457	1,451	850	2,348	2,342	1,763

The table shows how road access affects educational outcomes by excluding children within 10km of distance to road at the endline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.20: Impact of rural road access on child labor (binary outcome): Excluding children within 10km of distance to road at the endline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.021	0.024	-0.03	0.021	0.002	-0.078	0.06	0.074	-0.003	-0.006	0.001	-0.037
	(0.042)	(0.039)	(0.04)	(0.05)	(0.048)	(0.058)	(0.058)	(0.056)	(0.071)	(0.012)	(0.013)	(0.038)
Period# Road	-0.01	-0.02	0.021	0.063	0.059	0.078	-0.016	-0.027	0.025	0.011	0.007	0.012
	(0.05)	(0.049)	(0.061)	(0.057)	(0.056)	(0.072)	(0.071)	(0.071)	(0.112)	(0.031)	(0.029)	(0.052)
Observations	2,348	2,342	1,763	2,348	2,342	1,763	2,348	2,342	1,763	2,348	2,342	1,763

The table shows how road access affects educational outcomes by excluding children within 10km of distance to road at the endline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.21: Impact of rural road access on child labor (continuous outcome): Excluding children within 10km of distance to road at the endline

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.208	0.239	-0.39	0.197	0.004	-0.829	0.545	0.72	-0.123	-0.091	-0.076	-0.397
	(0.463)	(0.436)	(0.474)	(0.559)	(0.542)	(0.632)	(0.592)	(0.563)	(0.738)	(0.089)	(0.089)	(0.348)
Period# Road	-0.165	-0.244	0.026	0.577	0.541	0.615	-0.11	-0.215	0.499	0.009	-0.002	0.156
	(0.571)	(0.559)	(0.721)	(0.649)	(0.638)	(0.818)	(0.716)	(0.724)	(1.204)	(0.108)	(0.107)	(0.287)
Observations	2,348	2,342	1,763	2,348	2,342	1,763	2,348	2,342	1,763	2,348	2,342	1,763

The table shows how road access affects educational outcomes by excluding children within 10km of distance to road at the endline. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.22: Impact of rural road access on educational outcomes: Repeated cross-sectional

Variables	Current attendance	School absenteeism	Primary education
Road	0.020	-0.020	-0.011
	(0.027)	(0.046)	(0.043)
Period# Road	-0.013	0.000	0.008
	(0.040)	(0.070)	(0.058)
Observations	1,662	1,458	2,233

The table shows how road access affects educational outcomes for pooled children aged between 7 and 18. Standard errors clustered at EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Control variables included in the analysis are listed in Table 5.2.

Table D.23: Impact of rural road access on child labor (binary outcome): Repeated cross-sectional

Variables	Child Labour	Domestic Chore	Household Enterprises	Wage Job
Road	0.007	-0.030	0.041	-0.013
	(0.046)	(0.060)	(0.070)	(0.016)
Period# Road	0.081	0.122*	0.057	0.027
	(0.066)	(0.073)	(0.093)	(0.038)
Observations	1,676	1,676	1,676	1,676

The table shows how road access affects child labor for pooled children aged between 7 and 18. Standard errors clustered at EA level in parentheses . *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Control variables included in the analysis are listed in Table 5.2.

Table D.24: Impact of rural road access on child labor (continuous outcome): Repeated cross-sectional

Variables	Child Labour	Domestic Chore	Household Enterprises	Wage Job
Road	0.025	-0.355	0.370	-0.131
	(0.528)	(0.650)	(0.717)	(0.113)
Period# Road	0.840	1.225	0.743	-0.034
	(0.763)	(0.791)	(0.967)	(0.137)
Observations	1,676	1,676	1,676	1,676

The table shows how road access affects child labor for pooled children aged between 7 and 18. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.25: Estimated impacts of rural road access on education outcomes: EA as the unit of analysis

Variables	Current attendance			School absenteeism			Primary education		
	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	-0.009	-0.014	0.001	-0.042	-0.027	-0.059	-0.088**	-0.069	0.004
	(0.033)	(0.033)	(0.046)	(0.049)	(0.050)	(0.060)	(0.041)	(0.042)	(0.042)
Period# Road	0.036	0.034	0.036	0.039	0.037	0.065	0.053	0.051	-0.040
	(0.044)	(0.046)	(0.065)	(0.062)	(0.065)	(0.072)	(0.045)	(0.047)	(0.061)
Observations	210	210	196	209	209	194	210	210	196

The table presents the effects of road access on educational outcomes for children aged between 7 and 18at the EA level. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.26: Impact of rural road access on child labor (binary outcome): EA as the unit of analysis

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.031	0.037	-0.001	0.046	0.036	0.078	0.060	0.072	0.021	0.006	0.008	0.005
	(0.039)	(0.035)	(0.044)	(0.047)	(0.045)	(0.053)	(0.054)	(0.052)	(0.067)	(0.012)	(0.014)	(0.017)
Period# Road	-0.016	-0.020	0.011	0.023	0.021	0.002	-0.025	-0.028	-0.011	0.008	0.005	0.005
	(0.047)	(0.048)	(0.068)	(0.054)	(0.055)	(0.066)	(0.069)	(0.073)	(0.098)	(0.034)	(0.033)	(0.045)
Observations	210	210	144	210	210	144	210	210	144	210	210	144

The table shows how road access affects child labor for children aged between 7 and 18 at the EA level. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.27: Impact of rural road access on child labor (continuous outcome): EA as the unit of analysis

	Child Labour			Domestic Chore			Household Enterprises			Wage Job		
Variables	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.295	0.387	0.241	0.480	0.403	0.879	0.506	0.634	0.265	-0.053	-0.067	0.026
	(0.435)	(0.395)	(0.444)	(0.528)	(0.507)	(0.592)	(0.554)	(0.517)	(0.647)	(0.070)	(0.073)	(0.070)
Period# Road	-0.303	-0.329	-0.276	0.105	0.088	-0.157	-0.163	-0.188	-0.164	-0.024	-0.031	-0.170
	(0.538)	(0.554)	(0.704)	(0.607)	(0.620)	(0.730)	(0.697)	(0.735)	(0.989)	(0.111)	(0.115)	(0.153)
Observations	210	210	144	210	210	144	210	210	144	210	210	144

The table shows how road access affects child labor for children aged between 7 and 18 at the EA level. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.28: Impact of rural road access on child labor for household business: Binary outcome

	Agriculture			Non-agriculture		
Variables	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.031	0.023	0.019	0.055	0.075	0.046
	(0.045)	(0.041)	(0.059)	(0.052)	(0.052)	(0.057)
Period# Road	-0.026	-0.022	-0.011	-0.01	-0.021	0.017
	(0.043)	(0.043)	(0.065)	(0.065)	(0.066)	(0.088)
Observations	2,730	2,715	1,978	2,730	2,715	1,978

The table presents the effects of road access on child labor used for household enterprises (agricultural and non-agricultural enterprises). Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

Table D.29: Impact of rural road access on child labor for household business: Continuous outcome

	Agriculture			non-Agriculture		
Variables	(A)	(B)	(C)	(A)	(B)	(C)
Road	0.474	0.708	0.48	0.286	0.219	0.179
	(0.524)	(0.513)	(0.571)	(0.423)	(0.388)	(0.559)
Period# Road	-0.035	-0.138	0.279	-0.233	-0.204	-0.092
	(0.655)	(0.668)	(0.893)	(0.402)	(0.405)	(0.615)
Observations	2,730	2,715	1,978	2,730	2,715	1,978

The table presents the effects of road access on child labor used for household enterprises (agricultural and non-agricultural enterprises. Standard errors clustered at EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included in the analysis are listed in Table 5.2.

6

CONCLUSION

6.1 CONTRIBUTIONS AND MAIN FINDINGS

The adverse effects of climate change are already being felt on many socioeconomic outcomes at micro and macroeconomy levels, and it is expected that future weather will make existing challenging conditions far worse, especially in developing countries. These countries also fall short when it comes to having resilient and educated populations, which are essential for ending poverty, fostering economic structural transformation, and achieving economic success. As a result, overcoming the challenges that climate change has caused to the agriculture sector and producing skilled human capital are among the main policy challenges that developing countries are facing. This dissertation empirically illustrated how environmental and developmental changes in developing economies affected agricultural production, food consumption, and investments in human capital by focusing on Ethiopia.

In the second chapter, we looked into if and how subsistence smallholder farmers modify their land allocation decision in response to weather variations during the early planting season. We find a positive and significant effect of early planting season temperature on the size of land allocated to maize production. Given that a larger temperature increase is expected in the region because of climate change, the adaptation margin we documented is a nontrivial amount. The findings highlight focusing just solely on annual or growing season temperatures and ignoring within-season temperature variation leaves a significant short-term farmer behavioral response that is important for policy formulation. Farmers' response to early planting season weather variations also provides insight into how expectations may affect the economic behavior of smallholder farmers.

Chapter 3 demonstrates how supporting the smallholder agricultural sector by investing in irrigation infrastructure can be considered a practical strategy to improve diet quality. We also identified increasing access to nutrient-rich crops like vegetables and fruits from own production and encouraging the adoption of productivity-improving technologies to be the main pathway through which irrigation affects diet quality. Producing more fruits and vegetables due to irrigation access can boost the availability of those food items in the local market. If so, irrigation investment offers the potential to increase diet quality at the community level in addition to benefits at the household level.

Better nutrition contributes to improved health outcomes resulting in a more productive and healthy workforce. Another essential component of human capital is education. In Chapter 4, we investigate if investments in the expansion of higher education might raise adolescent females' educational attainment. We showed that universities helped female adolescents to increase their education levels at primary and secondary levels. Given the significant and wide-ranging economic benefits of educating women, including gains that span generations, the spillover effects of universities on the educational achievement of female adolescents can aid in justifying the investment. Somehow related to this, Schultz (2002) argues that investing disproportionate sums of money in women's education is justified by citing a variety of benefits of doing so. Our finding strengthens the argument for the need for public funding of higher education in developing countries where low rates of completion of lower grades are common.

The fifth chapter, which still focused on education, examined if children's labor allocation and educational outcomes are affected by access to roads. By utilizing Ethiopia's recent rural road expansion initiative as a case study, our results demonstrate no fundamental trade-off between school outcomes and the immediate economic prospects made possible by road access. Even though the lack of a trade-off between road access and children's education is an intriguing finding, the fact that there was no significant improvement in academic achievement as a result of access to roads also demonstrates that having a road alone does not encourage the investment of human capital. We found suggestive results that show child labor and lack of interest are the main factors that keep children out of school; thus, these factors require special attention.

6.2 POLICY IMPLICATIONS

Our findings on the impacts of early planting season weather variation on land allocation decisions emphasize the need for a novel policy instrument that takes early planting season weather conditions along with other crucial weather factors into account when designing climate policies in smallholder contexts. Besides, the results on how weather variation affects crop-specific land allocations may help policymakers better understand how some crops may be negatively impacted by climate change, and such changes might affect the diet quality of farming households and their market participation depending on whether the crop they scarified is a cash or a food security crop. Therefore, we contend that policymakers ought to create crop-specific adaptation strategies as opposed to broad national plans. It is also important to underscore the fact that those farmers who considerably rely on short-term weather realization as a tool to develop expectations may incur losses because of sub-optimal resource allocation (Ji & Cobourn, 2021). The overall effects of the adaptation strategy will become clearer with more research that accounts for its margin in calculating the effects of climate change on yield, and other household welfare indicators.

The results on the impacts of irrigation access on diet quality and the possible impact pathways give policymakers and practitioners a complete view of the effects of irrigation on nutrition quality. Therefore, by designing and implementing policies that help to address the problems hindering the adoption of irrigation technology, the diet quality of rural farming households can be significantly improved. This necessitates a collaborative approach among policymakers, farmers, and stakeholders to establish an enabling environment for irrigation development. Policymakers can stimulate farmers by providing subsidies or loans to offset the expenses associated with irrigation equipment and inputs. Numerous studies have shown that agricultural inputs are interdependent and that adopting multiple agricultural technologies generates higher returns than adopting a single innovation. Hence, improving the accessibility of inputs that can be used in combination with irrigation such as pesticides and fertilizers might improve the adaption and profitability of irrigation technologies Moreover, extension agents can play a pivotal role by providing technical assistance and information on the advantages and effective utilization of irrigation. They can provide training while helping farmers to access necessary inputs. Besides, since the main pathway through which irrigation affects diet quality is through own production, extension agents may help advocate what to produce and offer farmers the support they need to enhance their productivity, hence, health.

The result on the spillover effects of universities on the lower level school outcomes also has an interesting policy relevance. Our findings show that universities provide long-term socioeconomic benefits for the local economy by fostering human capital development. We contend that traditional estimates of the return on investment in higher education leave out significant spillover effects that may help the regional economy. As a result, such spillover benefits should be considered when developing educational policy or assessing the effectiveness of public investment.

The result from the investigation of the impacts of rural roads on children's education and employment identified child domestic work and a lack of interest as the main reasons for children not attending school. In this regard, making water and animal feed more accessible and designing a flexible educational system that takes into account times of peak labor demand can improve enrollment and attendance. Poverty, cultural beliefs, poor school, teacher, or curriculum quality, and other factors could all contribute to a lack of interest. As a result, further research is needed to investigate the underlying causes of the lack of interest and the effectiveness of potential remedies.

6.3 RESEARCH LIMITATIONS

In this sub-section, we outline the study's limitations. Chapter 2 examined the impact of early planting season weather variability on land allocation by focusing on maize. Since each crop has different moisture requirements and heat tolerance levels, focusing on a single crop gives empirical advantages. Besides, the paucity of data limits us from extending our study by looking at how these changes in land allocation decisions affected farmer consumption patterns, farm productivity, and profitability.

Due to a similar reason, we did not include educational quality in the human capital measures we used in chapters four and five. Furthermore, a dearth of data precluded us from precisely pinpointing the mechanism through which universities affect educational attainment at lower levels. The availability of the data also impacted the selection of the research country. While we contend that the findings may be generalizable to other countries with comparable characteristics, we also encourage the replication of our study in a different socioeconomic setting. Despite these challenges and limitations, our findings are considerable contributions to the literature and discussion of policy. Despite these challenges and limitations, our findings are considerable contributions to the literature and discussion of policy.

6.4 AREA FOR FUTURE STUDY

There are numerous ways to expand the research presented here. In chapter 2, we present the effects of early planting season weather variation on land allocation decisions. Expanding the analysis into the implications of such decisions on agricultural productivity, production diversification, and revenue helps to view the wider picture. Even though maize is a major crop for smallholder farmers in terms of land use, the number of farmers involved in its production, and the total production, future research should evaluate if growers of other crops behave similarly to adapt to weather variation. Future research can also look into the nutritional effects of irrigation infrastructure at the community level. In chapter four, the effects of universities are discussed with a focus on lower-level educational stages. Any further spillover effects, such as the diffusion of agricultural innovations and lifestyle changes, can also be investigated. Therefore, future studies could look at additional benefits of public spending. This chapter can also be expanded by exploring the mechanisms of how such investment affects lower-level educational outcomes. Future studies may extend the findings in chapters four and five by examining the effects of both rural roads and universities on educational quality using more potent indicators, such as standardized examinations.

REFERENCES

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IMPACT PARAGRAPH

The impact paragraph of this doctoral dissertation is added in compliance with article 22.5 of the "Regulations for obtaining the doctoral degree at Maastricht University" decreed by resolution of the board of deans, dated 1 October 2020.

This study investigated the effects of environmental and developmental changes on decisions relating to agricultural production, diet quality, and the development of human capital. The findings of each chapter in this dissertation have a considerable impact on designing and implementing programs that aim to improve human capital and combat the adverse effects of climate change.

The findings on how early planting season weather variation affects smallholder farmers' land allocation decisions help us understand how climate change affects agricultural output and the efficiency of adaptation investments. The result also helps policymakers fully comprehend the effects of climate change and develop an efficient policy response because disregarding such adaptation margins could result in skewed calculations. Hence, the findings help to attain SDGs Goal 13, which calls for increased resilience and adaptability to climate-related shocks among other things. The expansion of maize, including into less suitable areas at the expense of other crops, may affect agricultural production, crop rotation, commercialization, and diet. Therefore, the result informs and encourages decision-makers about the importance of the development and distribution of seeds for high-value crops that are drought-resistant.

The finding on the role of irrigation to improve the diet quality of smallholder farmers gives donors and decision-makers working to improve nutritional status the assurance to address challenges preventing the expansion of irrigation systems in smallholder-dominated agriculture. Hence, the result will be crucial for future policies and programs that aim to improve the health status of farming households, especially in Africa where there are more agricultural households, less irrigation use, and more people facing food and nutrition insecurity. This will significantly contribute to attaining SDG 2 which aims to promote sustainable agriculture while eradicating all forms of undernourishment, achieving food security, and enhancing nutrition. The impact pathway findings, which demonstrate how irrigation affects nutrition, also serve as a point of departure for all those working to improve the nutritional status in nations like Ethiopia, where under-nutrition and deficiencies in essential micronutrients and vitamins are serious public health issues. Farmers' decisions to grow nutrient-rich food types as a result of access to irrigation may increase the accessibility and affordability of nutrient-rich foods for non-farming households in the village. This provides policymakers with recommendations on how to improve food quality at the community level in addition to the advantages for households.

Our finding on how a government program intended to increase coverage of higher education unintendedly improved educational outcomes for young females at lower educational levels also aids policymakers in improving their estimation of the effectiveness of public investment and helps to justify public spending on higher education. Besides, the documented spillover effect that helps to improve female educational attainment helps in achieving SDG4 which aims to eliminate gender gaps in education and ensure equitable access to all levels of education.

These results from analyzing the trade-off between children's education and road access also provided suggestive information for policymakers regarding factors keeping children out of school. It reveals that domestic child labor and a lack of interest are the top reasons why children skip school. This makes it easier for policymakers and other stakeholders to establish systems for addressing these problems. This might include, improving access to water and animal feeds, and establishing a flexible school system that takes into account peak labor demand seasons.

We have been attempting to reach out to possible beneficiaries of the results of this dissertation using several channels. Chapter 2 is presented at the 31st International Conference of Agricultural Economists and the 96th Annual Conference of the Agricultural Economics Society. The third chapter is presented during the 2020 and 2021 biannual conferences of the African Economic Research Consortium (AERC). Besides, a policy brief is prepared and distributed at the annual senior policy forums organized by AERC. The forums bring together, among others, intellectual leaders, private sector actors, ministers, heads of civil service, and government agencies from Africa to exchange experiences. The fourth chapter is presented at the 2023 CSAE conference in Oxford, while the fifth chapter was presented at the UNU-MERIT internal conference. Chapter 2 has already been published in the *Journal of Agricultural Economics*, and the third chapter made its final distinction in the *Journal of Irrigation and Drainage*.

ABOUT THE AUTHOR

Musa holds a Master of Science degree in Agricultural Economics. Before joining UNU-MERIT in 2018, he was a lecturer and researcher in Ethiopia. Musa's research interest covers smallholder agriculture, climate economics, poverty & inequality dynamics, agricultural innovations & productivity analysis, and human capital development. Musa is an Ethiopian.