ESSAYS IN DEVELOPMENT ECONOMICS

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This dissertation consists of three self-contained papers, which are all related to the welfare consequences of risk and uncertainty.

Chapter one studies the intergenerational effects of maternal early childhood shocks on the human capital outcomes of children. I exploit the 1983-1985 Ethiopian famine as an exogenous source of variation to study the effects of exposure to severe shocks *in utero* and/ or during the first three years after birth on the cognitive, non-cognitive and health capabilities of children of mothers who were exposed to shocks in early childhood. Using data that track children from early childhood through adolescence, I estimate the effects of mothers' early childhood shock over their children's life cycle. I find that the famine had a lasting intergenerational effect. Mothers' early childhood famine exposure reduces their children's height-for-age z-score, schooling, locus of control and self-esteem. These effects are persistent from age one through early adolescence. The main inter-generational transmission channel of the shock is children's maternal human capital endowment. Mothers who suffered the famine in early childhood are shorter and have less schooling. I also find a critical maternal shock duration threshold of three months. These findings point to ineffectiveness of remediation once the damage is done to mothers as young girls. The policy implication is that girls under the age of three with high risk of crossing the critical famine duration

threshold should be targeted for health and nutritional interventions.

In chapter two, coauthored with Christopher B. Barrett, Erin Lentz and Birhanu Ayana, we estimate the causal effects of index insurance coverage on the subjective well-being (SWB) of a poor population in rural southern Ethiopia. Insurance coverage may be welfare enhancing *ex ante* by reducing exposure to risk. Yet, if the insurance policy lapses without payout, but having paid a premium, the buyer will be financially worse off and may experience buyer's remorse *ex post* of the resolution of uncertainty. The *ex ante* and *ex post* well-being effects of insurance may therefore differ, especially in the absence of indemnity payments. We separately identify (1) the *ex ante* SWB effects of current insurance coverage that arise from reducing *ex ante* risk exposure to potential shocks, and (2) the *ex post* buyer's remorse effects of lapsed insurance policies that did not pay out. By exploiting the randomization of incentives to purchase a newly introduced index-based livestock insurance product and three rounds of household panel data, we establish that current coverage generates statistically significant gains in buyer's SWB. The *ex ante* gains more than offset the statistically significant buyer's remorse effect of having lost money on insurance that did not pay out. These results suggest that insurance can have significant impact on SWB and illustrate that failure to control for potential buyer's remorse effects can bias downwards estimates of the welfare gains from insurance coverage.

Chapter three concerns with the determinants of crop diversification in Ugandan agriculture. I use three rounds of the Uganda National Panel Survey (UNPS) data, which collects detailed information on land holding and characteristics, crop

production, agricultural inputs and farm management practices to examine the prime motives for observed crop diversification practices. The findings show that crop diversification is determined by a combination of yield and variance considerations, and that these considerations vary by crop type. Among the main crops in Uganda, inter-cropping of beans and sweet potatoes appears to be primarily driven by average yield considerations while variance (risk) appears to factor prominently in maize inter-cropping decisions. Maize and beans are best suited for inter-cropping, whereas sorghum and matoke yield better results when planted as mono crops. The maize-beans combination is the best crop mix. I also find that crop yields are lower and yield variance higher on larger plots, suggesting the inverse productivity-size phenomenon is present in Ugandan agriculture.

BIOGRAPHICAL SKETCH

Kibrom Tafere Hirfrfot received his B.A. degree in economics in 2004 and M.Sc. degree in international economics in 2008, both from Addis Ababa University, Ethiopia. Between his undergraduate and Masters studies, he worked as a graduate assistant at Haramaya University, Ethiopia. He joined the International Food Policy Research Institute (IFPRI)–Ethiopia Strategy Support Program (ESSP) as a research assistant in October 2008. After almost three years at IFPRI, he began his graduate studies at the Dyson School of Applied Economics and Management, Cornell University in August 2011. He will receive his Doctor of Philosophy degree in December 2017.

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CHAPTER 1

INTRODUCTION

Conditions of risk and uncertainty frame the economic and social behavior of individuals and households in a profound manner. First, households may adopt risk management strategies *ex ante* that they otherwise would not, to minimize risk exposure. These may include altering the composition of their asset portfolio, livelihood sources or agricultural activities, especially the case in rural communities. Farm households may diversify into farm vs. non-farm income sources, crop vs. livestock or specialized vs. diversified crops. Second, households may engage in risk mitigating strategies *ex post* to minimize the (negative) effects of adverse events. These may include selling off assets, reducing consumption, withdrawing children from school to raise supplementary income or reduce the burden of educational expenses, among others [24, 116].

The prospect and experience of random, negative shocks can have considerable impact on the immediate and long-term welfare outcomes of households and their members. The nature and size of the effects of such events depends on the magnitude of the shocks themselves as well as the manner with which households respond to them. If households have sufficient liquid and non-liquid assets to cushion against unforeseen shocks, the effects of shocks could be less than otherwise. In much of the developing world, households lack this critical cushion against shocks. Furthermore, access to credit is limited and agricultural insurance

is almost non-existent.[1] As a result, households are forced to engage in destructive risk mitigating strategies such as selling farm implements, consuming seedlings, reducing consumption to preserve assets [117, 44, 147].

Poor communities in the developing world subsist on quantity and quality of foods well below the required daily macro- and micro-nutrient intakes. Under these circumstances, shock mitigation strategies that involve reduction of consumption or, in extreme cases, radical changes in consumption patterns in response to severe droughts (famines) can lead to adverse childhood welfare (health and schooling), adult health and labor market outcomes, or even have intergenerational consequences. Shocks experienced in childhood tend to have lasting negative impact [46]. Lack of access to food in the formative period (commonly taken as the first 1000 days – *in utero* and two years after birth), affects the expression of the genome and adversely impacts cognitive development and physical health in childhood and later in adulthood [8]. Especially in the case of women, the effects of early exposure could transmitted to their offspring across generational lines.

Financial development plays a crucial role in smoothing welfare over time. Access to credit would allow households to smooth consumption by shifting savings over time – saving during periods of relative surplus and borrowing during periods of relative shortage. Likewise access to insurance would help minimize the effects of shocks. The development of the financial sector is, however, at a very low level in much of the developing world. The limitations associated with con-

[1] There have been increasing efforts in recent years to expand index insurance offerings in several developing countries [120, 123, 57].

ventional insurance products – adverse selection and moral hazard – further complicate the delivery of insurance to rural communities. In recent years, there has been a growing push to expand the availability of index insurance products to fill in this void. The evaluations of the various index insurance products introduced in last decade or so have shown that access to insurance has been instrumental in improving saving, nutrition and consumption [120, 123, 117].

This dissertation straddles the three dimensions of risk and uncertainty outlined above. The first chapter studies the intergenerational impacts of childhood shocks on the human capital of children born to mothers who suffered severe shocks as young girls. The second chapter studies the crop diversification decisions of farm households in a risky environment. More specifically, it focuses on the determinants of crop diversification by distinguishing between return motives as they relate to the desire to take advantage of synergistic relationships between different crops and risk minimization motives in which farm households trade high return for low variability of yield. The chapter makes qualitative distinctions between distributions with greater lower return odds and those with greater high return odds for the same level of variance. The final chapter studies the effects of index insurance on household wellbeing. Self reported measures of well-being – subjective well-being – are used as outcome variables. The chapter examines the well-being effects of an index based livestock insurance product on household well-being. What follows, presents a more detailed introduction of each of the three chapters that make up this dissertation.

1.1 Intergenerational Effects of Early Childhood Shocks on Human Capital: Evidence from Ethiopia

The frequency and intensity of extreme weather events including droughts, heat waves, flooding and storms has increased in the last few decades due to climate change related rises in temperature. This rise in incidence of extreme weather has been associated with increase in the economic and social costs of natural disasters [207]. The adverse effects of natural disasters are likely to be very high in communities that are under-resourced to shoulder the burden of disasters. Rural households in much of the developing world, who primarily depend on agriculture for sustenance, fall in this category. Major shocks to agricultural activities in these communities can have devastating consequences due to loss of productive assets and disruptions in nutrition, health, and schooling, among others. Shocks experienced in early childhood are especially damaging [61, 59].

Explorations of the relationship between early childhood environments and child outcomes date back to the early epidemiological works of [18, 19] on the fetal origins of disease (popularly known as the "fetal origins hypothesis"). Since, there has been a growing interest in economics to study the effects of adverse exposure on various human capital outcomes of children. The evidence so far shows that adverse exposure during the prenatal and postnatal periods negatively affects the health and schooling outcomes of children and their labor market outcomes as adults [187, 62, 148, 5]. Prenatal shock exposure may delay or impair the expres-

sion of parts of the genome that are crucial for cognitive and motor functions and lead to a lasting impact on childhood and adulthood outcomes [169]. Epigenetic and physiological adaptations to nutritional stress during this period and early in the postnatal period may set growth parameters of children, especially girls, and determine their and their offspring's developmental trajectory [8, 166].

This chapter focuses on the intergenerational effects of childhood shocks on human capital. Despite the flourish of interest in the links between early childhood environments and various child and adult outcomes over the last two decades, there is little research on the intergenerational aspect of early childhood shocks. Whether shocks experienced in childhood last across generations; and if so, the transmission mechanisms are not fully understood. This paper presents one of the first estimates of the intergenerational effects of early childhood shocks on human capital. Other recent studies of the intergenerational transmission of shocks include [45] and [46] who examine the intergenerational effects of natural disasters in Latin America on human capital, and [191] who study how parents' exposure to the 1959-1961 Chinese famine affects the cognitive outcomes of their children.

This paper makes important contributions to this emerging literature. First, the focus of this paper is a major drought that was the prime source of a destructive famine in Ethiopia. Though the shock event in focus in the paper is of an extreme nature, drought events tend to be more common. Thus, lessons from this study may have more immediate policy relevance than some of the less frequent shocks

(e.g., earthquakes, volcanoes) that [45] and [46] leverage as exogenous source of variation to identify the intergenerational causal impact of early childhood shocks on human capital. The shock used by [191] is similar to the one this paper. Yet, there is a broad consensus that the Chinese famine was primarily a policy failure rather than a meteorological shock. Further, the data used in this paper are panel in nature and track children from early childhood into adolescence and, thus, permit examining the life cycle effects of shocks.

Building on previous studies documenting that the impacts of natural disasters tend to be greater for girls than boys [46, 191], this chapter focuses on the intergenerational effects of early childhood shocks on the human capital of children born to mothers who suffered severe shocks as young girls. The data come from the Ethiopia Young Lives longitudinal survey, which tracks children from the age of 6-18 months through adolescence. I combine the survey data with weather data from Ethiopia in 1980s. Ethiopia suffered a catastrophic famine in 1983-1985 as rains failed in successive cropping seasons between 1983 and 1985 in most parts of the country, especially in the north. I exploit the geographic variation of the famine and mothers' age at the onset of the famine to explore whether shocks in early childhood have a lasting intergenerational impact on the health, cognitive and non-cognitive human capital of the children as well as identify potential transmission mechanisms. In a previous study in the same study area, [72] find a negative long term impact of the Ethiopian famine on the height of young adults. They, however, do not examine the intergenerational effects of the famine.

I find that the 1983-1985 Ethiopian famine had a negative intergenerational effect on the human capital outcomes of children of mothers who were exposed to the famine *in utero* and/or in their first three years of life after birth. The effect is particularly strong on the health human capital of children. At the mean level of famine intensity and duration, the famine reduces height-for-age (zhfa) by 0.07 standard deviations (about 5%) relative to the World Health Organization (WHO) growth chart reference population. The effect on schooling is slightly smaller, but still statistically significant. At mean famine intensity and duration, the schooling of affected children declines by about 0.05 grades (4%) relative to their unaffected counterparts. The key transmission channels of the shock are maternal human capital outcomes. Mothers exposed to the famine during developmental plasticity are shorter and have less schooling.

1.2 Insuring Wellbeing? Buyer's Remorse and Peace of Mind Effects from Insurance

In low income communities with limited means for private risk management, risk exposure can have dire welfare consequences. In addition to its negative effects on contemporaneous welfare, uninsured risk can lead to poverty traps that may bind households in poverty in perpetuity [178, 21]. There is a widespread recognition that access to insurance in these environments can help preserve assets as well as encourage efficient allocation of productive resources. However, standard

insurance products are routinely unavailable due to moral hazard and adverse selection problems and high transaction costs in infrastructure-poor areas [29]. In response to the lack of standard insurance products, there have been growing efforts in recent years to expand index insurance products in the developing world.

Index insurance addresses some of the key limitations of standard insurance products that limit their expansion in poor communities. It resolves the moral hazard and transaction cost concerns by writing contracts not on realized losses but on an observable exogenous indicator that is believed to be strongly correlated with actual losses. This design feature of index insurance is also the source of its limitation. The exogenous index and actual losses at the household level are not perfectly correlated. As a result, policy holders could experience catastrophic losses that the index may not detect, and thus will not covered by insurance. It is not, therefore, immediately clear whether index insurance is welfare improving. There is little empirical work that indeed index insurance offerings lead to welfare gains to poor rural households [57, 33]. This is further complicated by the fact that *ex ante* well-being effects may differ from *ex post* well-being effects after the resolution of uncertainty.

In this chapter, we use a novel approach to estimate the welfare impacts of an index insurance product that was introduced to southern Ethiopia in 2012. We take advantage of recent innovations in the measurement of subjective wellbeing (SWB) [134] to examine the effects of index based livestock insurance (IBLI) on the SWB of pastoralists in Borana zone of southern Ethiopia. The use of SWB mea-

sures is growing in popularity owing to their potential for deeper insights beyond the traditional asset, income and expenditure based measures [75, 89, 146]. We exploit the experimental design features of IBLI to overcome potential selection issues in insurance uptake. Incentives to purchase IBLI were randomized among the target population through distribution of discount coupons and information extension treatments. This enables us to use an instrumental variables method to identify the causal impacts of IBLI on SWB. Moreover, the distribution of the randomized incentives and the survey were implemented over multiple periods. This allows us to distinguish *ex ante* and *ex post* well-being and isolate the positive peace of mind effects of active insurance coverage from negative buyer's remorse effects of lapsed insurance.

We find that current IBLI coverage – represented by both a discrete measure of uptake and by a continuous measure of purchase volume – generates statistically significant SWB gains. These gains significantly exceed the statistically significant adverse buyer's remorse effects. We also show that the estimated SWB gains from insurance would be biased downwards if one omits controls for lapsed insurance coverage that generates buyer's remorse. The key implication is that IBLI, which has premiums set above actuarially fair rates, improves buyers' SWB even over a period when pastoralists in southern Ethiopia lose money on the policy. The ex ante peace of mind effect dominates any ex post buyer's remorse. In other words, even an insurance policy that does not pay out still improves people's perceptions of their well-being. [12]

1.3 Diversification and Productivity in African Agriculture: Evidence from Uganda

Rainfed agriculture is the prime source of sustenance in rural communities in much of the developing world. As much as 95% of cultivated land in Sub-Saharan Africa and over 60% in East and South Asia and North Africa is rainfed. Under these conditions, rainfall variability can impose significant challenges to rural livelihoods. The threat of weather shocks is further compounded by lack of access to credit and insurance for protecting consumption and assets. Faced with these circumstances, rural households may engage in otherwise inefficient risk management practices *ex ante* and risk mitigating strategies *ex post*. Crop diversification is one such private risk management strategy in which farm households may trade-off lower returns for lower variance.

While there has long been much focus on the income stabilizing role of crop diversification, its potential for increasing productivity through inter-crop synergies is yet to receive similar attention. Crop rotation stabilizes soil fertility [149], whereas inter-cropping boosts productivity by exploiting symbiotic complementarity of crops [50]. Studies of the productivity dynamics associated with crop diversification are primarily conducted on experimental plots, with limited focus on the potential drivers of observed diversification practices as they relate to risk and return. Much of the relevant empirical studies has been in settings where crop production is dominated by a few crops [129] or multiple varieties of a single crop

[76]. In most of Sub-Saharan Africa, farming is a complex multi-crop enterprise, in which farmers engage in the production of several crops on small plots, leading to complex inter-crop dynamics. A fuller understanding of on-farm crop dynamics in such environments requires an analysis of a broad range of crops.

This chapter studies the determinants of crop diversification decisions in Uganda. The results of this paper are crucial for understanding the prime motives for crop diversification with emphasis on devising policies to maximize the gains from diversification and minimize associated downsides. To that end, first it examines the contributions of mean, variance and skewness in crop choice, with a particular focus on determining whether yield and/ or risk are the primary considerations in crop decisions. Second, it investigates whether inter-crop synergies vary with crop plot area to draw implications for optimal farm size and crop mix.

I use the 2009/10, 2010/11 and 2011/12 rounds of the Uganda National Panel Survey (UNPS) data, which were collected by the Uganda Bureau of Statistics (UBOS) under the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS–ISA) project. The surveys contain detailed agriculture modules and collect information on land holding and characteristics, crop production, agricultural inputs and farm management practices. The survey is conducted twice a year to reflect the seasonality in Ugandan agriculture. Thus, in total, this paper uses six rounds of data to examine the drivers of crop choice.

The main findings are: first, the determinants of crop diversification vary by crop type. The prominence of mean and variance considerations differs by

crops. Average yield appears to be the key factor in beans and sweet potatoes inter-cropping with other cereals and tubers, while variance seems to be the main motive for maize intercropping. Second, crop productivity decreases with plot size for all major crops in Uganda. This result is consistent with the inverse farm productivity size relationship. Larger plots are also associated with high yield variance, though this is mitigated by the positive skewness associated with larger plots. Third, maize and beans are most suitable for intercropping, whereas sorghum and matoke are least suitable. When intercropped with other crops, maize reduces yield variance, while beans seem to increase yield. The maize-beans combination represents the best crop mix in Uganda. On the contrary, when intercropped with other crops, matoke and especially sorghum reduce average yield of other crops across the board. Thus, they should be planted as mono crops.

CHAPTER 2

INTERGENERATIONAL EFFECTS OF EARLY CHILDHOOD SHOCKS ON HUMAN CAPITAL: EVIDENCE FROM ETHIOPIA

2.1 Introduction

Climate change-related rise in temperature has increased the frequency and intensity of extreme weather events in the last few decades. The rise in incidence of droughts, heat waves, flooding, and storms has been associated with surge in economic and social costs of natural disasters [207]. In much of the developing world where a significant share of household income is sourced in the agricultural sector, such events have adverse welfare consequences due to loss of productive assets and disruptions in nutrition, health, and schooling, among others. Within the household unit, the effects of weather shocks may differ based on individuals' characteristics. Shocks experienced in early childhood tend to have greater negative impact on human capital and labor market outcomes [12, 148, 59, 3].

Since the early epidemiological studies by [19, 18] on the fetal origins of disease, there has been a growing body of literature in economics exploring the effects of adverse exposure during the prenatal period [62, 6] and at various stages in the postnatal period [187, 63] on health, schooling and labor market outcomes. These studies typically leverage exogenous sources of variation (natural experiments) to circumvent the potential confounding between unob-

served individual and family characteristics and early childhood environments [187, 35, 64, 2, 125, 3, 5].

Much of the literature on early childhood shocks focuses on the prenatal period, which is perhaps the most sensitive period for child development. Disruptions during this period may delay or impair the expression of parts of the genome that are crucial for cognitive and motor functions and lead to a lasting impact on childhood and adulthood outcomes [35, 62, 169, 5, 6]. Recent studies show that the adverse effects of such shocks are greater for females [45, 46, 191, 7]. Irreversible physiological adaptations to nutritional stress during critical prenatal and postnatal periods may set the growth parameters of girls [8, 96], which may predetermine their offspring's developmental trajectory and later life outcomes [166]. This intergenerational aspect of shocks is surprisingly understudied.

This paper presents one of the first estimates of the intergenerational effects of early childhood shocks on human capital. Other recent studies of the intergenerational transmission of shocks include [46], who examine the effects of the 1970 Ancash earthquake in Peru on schooling and child labor. They find that maternal *in utero* shock exposure negatively affects child labor and schooling. [191] study how parents' exposure to the 1959-1961 Chinese famine affects the cognitive outcomes of their children. They find that the daughters of fathers who suffered the famine as young boys perform worse in cognitive tests. In a more recent paper, [45] explores the intergenerational effects of childhood exposure to natural disasters that occurred in Latin America in the 20th century on schooling, health and

labor market outcomes, among others. Early childhood exposure (*in utero* and first two years after birth) to natural disasters is found to have the greatest impact on human capital and adult labor market outcomes. This paper extends this emerging literature to a broad range of human capital measures over children's life cycle in the context of an African country where agriculture is the prime source of sustenance. In such environments, weather shocks can have destructive lasting effect on the human capital of individuals who suffer the shocks directly and their offspring.

Ethiopia suffered a catastrophic famine in 1983-1985 as rains failed in successive cropping seasons between 1983 and 1985 in most parts of the country, especially the northern provinces of Tigray, Wello and Eritrea.[1] The central highlands and western parts of the country were largely unaffected. I exploit the geographic variation of the famine, parents' age at the onset of the famine and unique data that track children from the age of 6-18 months through early adolescence to explore whether shocks in early childhood have a lasting impact on the health, cognitive and non-cognitive human capital of the children of mothers who suffered the shocks as young girls. In a previous study, [72] find a negative longterm impact of same shock on the height of young adults who were 12-36 months old at the peak of the famine. They do not, however, examine the intergenerational effects of the famine.

The analysis in this paper extends beyond the extensive margin and examines

[1] Eritrea has since become an independent state.

variation in famine durations (in months) to determine whether shocks of certain duration are more damaging than others. Understanding the role of famine duration is important for efficient targeting of groups with the greatest need for assistance. The panel nature of the data permits exploring the effects of maternal early childhood shocks on children's human capital over their life cycle. I evaluate the effect size from age 1 through age 12 in a three-year interval. This provides evidence on whether early disadvantages are malleable through remediation efforts, which is crucial for devising effective policies to reduce intergenerational transmission of shocks.

This paper also seeks to determine the intergenerational shock transmission mechanisms. To this end, I focus on children's maternal human capital endowment and parental investments. Maternal human capital is an essential input in children's human capital production. Negative shocks to mothers' human capital may have persistent impact through generations in a complex feedback processes [61, 59, 108]. Likewise, early childhood shocks may impair mothers' adulthood earnings and investments in their children's schooling and health.

This paper makes two important contributions. First, it contributes to the early childhood development literature by extending the study of the impacts of adverse early childhood exposure on childhood and adolescent outcomes to intergenerational transmission of the effects of severe shocks. Second, it provides an indirect test for the intergenerational persistence of poverty. The presence (or absence) of intergenerational persistence of the effects of childhood shocks points to

early conditions (e.g., family income, education) as one of the potential causes (or not) of poverty persistence across generations [30, 137, 34].

I find that the 1983-1985 Ethiopian famine had a negative intergenerational effect on the human capital outcomes of children of mothers who were exposed to the famine *in utero* and/or in their first three years of life after birth. The effect is particularly strong on the health human capabilities of children. At the mean level of famine intensity and duration, the famine reduces height-for-age (zhfa) by 0.07 standard deviations (about 5%) relative to the World Health Organization (WHO) growth chart reference population. The effect on schooling is small, but statistically significant. At mean famine intensity and duration, children's schooling decreases by about 0.05 grades (4%). The key transmission channels of the shock are maternal human capital outcomes. Mothers exposed to the famine during developmental plasticity are shorter and have less schooling.

The rest of this paper is organized as follows. The next section provides a brief background on the Ethiopian famine. Section 3 presents the conceptual framework of the paper. Section 4 discusses the data, the various famine and human capital measures and summary statistics. Section 5 presents the empirical strategy. Section 6 discusses the main results of the paper. Section 7 concludes.

2.2 Background

The agricultural sector is the mainstay of the Ethiopian economy and accounts for 40% of GDP and 80% of employment [209]. It is dominated by subsistent rain-fed smallholder agriculture. The production environment is characterized by increasing land degradation and erratic weather conditions. Variability in the amount and seasonal distribution of precipitation has been a major cause of crop failure and food shortages. The frequency of irregular rainfall patterns and droughts has increased over the recent decades [77, 200]. In some cases, the food shortages associated with droughts have led to catastrophic famines.

In the last half century alone, there have been at least three famines in Ethiopia, of which the 1983-1985 famine is widely considered the worst.[2] Estimates of the number of people killed range between 400,000 and over a million. [74] estimates that between 600,000 and one million people were killed due to the famine. [70] puts the figure closer to 400,000, though he notes that is likely to be a lower bound. [128] argues the true figure of the casualties of the famine is 700,000. Despite the differences in the estimates of famine casualties, the famine's impact has been undoubtedly devastating. In fact, [164] notes that in terms of the number of deaths relative to population size, the 1983-1985 Ethiopian famine ranks as one of the worst in the world in recent history.

[2]For a complete chronology of droughts and famines in Ethiopia, see [204].

2.2.1 Ethiopian 1983-1985 Famine

The rainfall pattern in Ethiopia is characterized by a bi-modal distribution. In the predominantly crop producing central and northern areas of the country, the main rainy season (*meher*) is in June-September and accounts for 85-90% of annual agricultural output nationwide. Some central and eastern highlands also receive rainfall during a short rainy season (*belg*) between March and May. In the southern parts of the country, where the primary source of livelihood is pastoralism, the main rainy season is in March-May, followed by a short rainy season in October-November.

The famine started 1983 when *meher* rains failed in Tigray and Wello. It quickly spread to the rest of the country when the 1984 *belg* rains failed in *belg* growing highland areas in central Ethiopia [70]. The drought condition continued in *meher* 1984 through *belg* 1985. The famine was most severe in 1984. Using historical rainfall data for the 1961-1999 period for the *meher* season, [185] show that 1984 was by far the driest year.[3] Low pre-*meher* rains were followed by early onset of *meher* rains, which quickly dried up. The extended dry spell led to a very short effective growing season and widespread crop failures throughout the country. The famine ended with the return of normal *meher* rains in 1985.

The famine condition was further exacerbated by insurgencies and the govern-

[3]Using annual rainfall data (including both *meher* and *belg* rains) for the 1961-1987 period, [204] report similar results. They show 1984 was the driest year for the whole of Ethiopia, as well as the northern provinces of Wello and Tigray, and Hararghe in the east.

ment's counter-insurgency strategies in northern Ethiopia. To counter the rebel movements, the government had mobilized large military campaigns, which diverted resources from relief effort.[4] The government had also restricted access to relief aid in rebel controlled areas in Tigray and Eritrea [70]. There was limited access to food and medicine to people (especially women and children) severely weakened by the famine in a handful of relief centers in government controlled areas. While the move to relief centers allowed access to much needed food, poor health facilities and hygiene conditions led to the rapid spread of infectious diseases in the centers and the death of thousands. Further, restrictions on the movement of people and goods in the northern provinces constrained migration of able bodied individuals to relatively less affected parts of the country in search of employment and limited commercial imports of food from surplus growing areas, compounding the impacts of the famine.

In terms of age distribution, children under the age of 10 and adults of age 60 and above were disproportionately affected by the famine. [128] shows that among households displaced from the two most famine-affected provinces of Tigray and Wello, about 26% of children under the age of 5 and 14% of children between age 5 and 9 died during the famine. For the 0-4 age group, males were slightly more likely to die (27% vs. 24%). In the 5-9 age bracket, the female mortality rate was much higher than that of males (19% vs. 9%). Likewise, 20% of people in the 60 plus age group perished, with females most affected than males.[5]

[4] In 1984 the government had allocated 46% of the national budget to military spending [203].

[5] Note, however, that these are likely to be upper bound estimates of famine-related excess death as migration often tends to be a last resort option after households exhaust their food re-

Though it is not clear that famine was the sole driver of the high mortality, the fact that compared to 1981, the share of 0-14 and 65+ age groups in the population significantly decreased in 1984-1985 suggests that the famine was perhaps the prime cause of the rise in mortality of these groups [127]. The key implication of the high incidence of famine-related excess mortality among children in the 0-4 age group is that estimates of the impact of the famine are likely to be attenuated downwards. The problem is further compounded by the fact that children in the reference (control) group for the purpose of this paper (age 4-7 at the start of the famine) were also affected, albeit less, by the famine.

2.3 Theoretical Framework

I use the dynamic model of human capital development by [61, 108] and [59] to study the effects of maternal exposure to severe shocks (famine) on the human capital of their offspring. The starting point in this framework is the multidimensional nature of human capital. At any given time t, the human capital vector is given as $\theta_t = (\theta_{c,t}, \theta_{n,t}, \theta_{h,t})$, where θ_c, θ_n, and θ_h are cognitive, non-cognitive/socio-emotional, and health capabilities, respectively. The formation of capabilities (skills) follows a multistage technology in the sense that skills at one stage of the life cycle serve as inputs at a later stage. Investments in skills will, therefore, have lasting effect by increasing the stock of skills, which will be used as inputs in the formation of future skills.

serves and selling off assets [167].

In this framework, early life adverse exposure may have persistent negative impact on outcomes later in life for at least two reasons. First, skills are dynamically self-reinforcing. High cognitive skill in one period leads to higher cognitive skill in a later period, and a higher health capability cross fertilizes (i.e., creates a conductive environment for acquisition of) cognitive skill. Heckman and co-authors refer to this effect as "self-productivity"; it includes own and cross capability effects. Famines affect human capital by reducing the stock of skills available for self-production. Second, shocks reduce the productivity of future investments in human capital, a process called "dynamic complementarity." Shocks to a child's health, for example, will have a negative effect on returns to investment on future learning [61, 59].

There are multiple sensitive periods in a child's life that are crucial to the development of human capital. Some skills are more readily acquired at one stage than another, and some skill deficits are more malleable at one stage than another. The most important period in a child's development is the period *in utero* [5]. Adverse experiences at this stage are known to cause significant damages to birth weight, cognitive ability, later life height and weight, and lead to various diseases [177, 96, 19]. Even within the prenatal period, early exposure may have a different impact than exposure later during pregnancy. [177] shows that exposure to shocks during the first two trimesters has adverse effect on cognitive ability, whereas exposure during the third trimester reduces child height.

The fist three years after birth are also critical for the formation and shaping

of skills that determine later life outcomes. Children who are exposed to shocks during this period tend to perform relatively poorly in school and labor markets [187]. [60] find similar results in a randomized evaluation of the Abecedarian program in the US. They find significant cognitive and non-cognitive gains for children who enrolled in the program early (4 months), but not for those who only experienced the intervention later (age 5). Some studies document even early adolescence years (age 10-12) can be crucial to the development of certain dimensions of human capability. [162] finds a negative relationship between age of acquisition of primary and secondary languages and language proficiency, with the relationship flattening out around the age of 12. Likewise, the fact that IQ scores tend to stabilize around age 10 [184] suggests that the critical period for acquisition of cognitive capability is before age 10. Non-cognitive skills are malleable even after age 20 [65]. Once critical periods are missed, remediation interventions may not reverse the damages already done.

Following [61, 108, 59], the technology summarizing the formation of skill $k \in \{c, n, h\}$ is given as:

$$\theta_{k,t+1} = f_k(\theta_t, I_t, \theta_p, \eta_t) \tag{2.1}$$

where, $\theta_{k,t}$, I_t, θ_p, and η_t denote the stock of skill k at time t, parental investments in children at time t, parental endowments, and shocks at time t. The skill production function, f_k, is monotonically increasing in all of its arguments, twice differentiable, and concave in I. After solving recursively, (2.1) can be rewritten as:

$$\theta_{k,t+1} = f_k(\theta_0; I_0, I_1, ..., I_t; \theta_p; \eta_0, \eta_1, ..., \eta_t) \tag{2.2}$$

where θ_0 is the initial skill endowment of the child and is determined by both genetic and environmental factors. Equation (2.2) shows that the stock of skills at any given time t depends on endowment as well as investments and shocks at different stages in the life cycle. Early shocks are more destructive than shocks in adolescence, and more so for disadvantaged children, since early disadvantages persist through the self productivity and dynamic complementarity processes [108, 60].

For ease of exposition, I divide the developmental periods of a child in two: early childhood, including the period *in utero*, denoted period 0; and late childhood, which constitutes the rest of childhood, denoted period 1. Adulthood is denoted period 2. Following [61], the process of human capital development can be described by an overlapping generations model, in which each individual lives for three periods $t \in [0, 2]$ in a household consisting of an adult and a child–the first two periods ($t = 0$ and $t = 1$) as a child and $t = 2$ as a parent. As shown in Figure 2.1, the adulthood period of the parent coincides with the two childhood periods of the child.[6] In each period, θ_t is stock of skills at the start of time t and I_t and η_t are investments and shocks between t and $t + 1$.

The primary interest of this paper is in childhood outcomes. Thus, I focus on the first two periods of the life cycle. The stock of skills in late childhood can be

[6]The early childhood period is defined as the entire period between conception and second birthday. This is just meant to capture the "first 1,000 days" commonly taken as the most important period for childhood development. The definition can be relaxed as necessary.

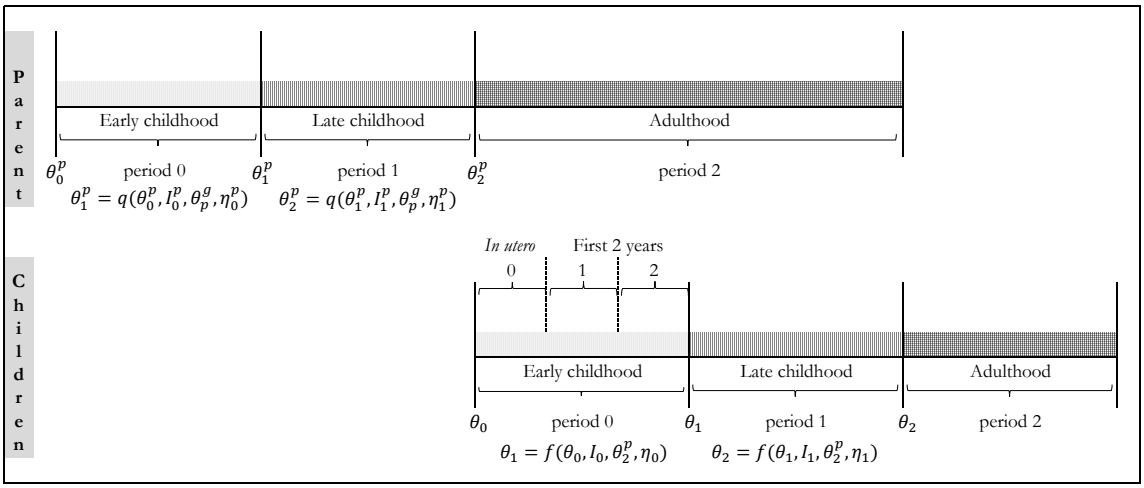

Figure 2.1: Intergenerational evolution of human capital

Note: Figure 2.1 shows the intergenerational human capital production function. A child's human capital at any period t depends on initial endowment and investments through the child's life up to period t.

described by[7]

$$\theta_{k,1} = f_k(\theta_0, I_0, \theta_p, \eta_0) \tag{2.3}$$

where, θ_0, I_0, and η_0 are vectors of skill endowment, parental investments, and shocks on cognitive, non-cognitive, and health capabilities. Parental investments and early childhood skills are endogenous and are affected by shocks. Parental investment in skill k is given as:

$$I_{k,0} = g_k(\theta_0, \theta_p, \eta_0). \tag{2.4}$$

Similarly, parental endowment, $\theta_p = \theta_2^p$ (parents' stock of skills in adulthood), depends on parents' late childhood capabilities, θ_1^p, late childhood investments,

[7] I assume that investments and shocks in adulthood have little impact on human capital. Several empirical studies find small/insignificant returns to investment in adolescence and adulthood (see [60] for discussion).

I_1^p, parental endowment at childhood, θ_g, and late childhood shocks, η_1^p.[8]

$$\theta_p = q(\theta_1^p, I_1^p, \theta_g, \eta_1^p). \tag{2.5}$$

This framework can be used to study the effects of maternal shocks at different stages of the life cycle on the human capital of their children. For analytical ease, I use a compact form of the skills vector, which can easily be extended to look at shocks to a specific skill type.[9]

The effect of a parent's late childhood shock on her offspring's human capital can be stated as:[10]

$$\frac{\partial \theta_{k,1}}{\partial \eta_1^p} = \frac{\partial \theta_{k,1}}{\partial I_0} \frac{\partial I_0}{\partial \theta_p} \frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_{k,1}}{\partial \theta_p} \frac{\partial \theta_p}{\partial \eta_1^p}. \tag{2.6}$$

Early childhood investments in parent's capabilities, I_1^p, is endogenous, i.e., $I_1^p = g(\theta_1^p, \theta_g, \eta_1^p)$. Thus, $\frac{\partial \theta_p}{\partial \eta_1^p}$ in (2.6) can be rewritten as:

$$\frac{\partial \theta_p}{\partial \eta_1^p} = \frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_p}{\partial I_1^p} \frac{\partial I_1^p}{\partial \eta_1^p}. \tag{2.7}$$

Substituting (2.7) in (2.6), we find a decomposable impact of parental childhood

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

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

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

[10] Here, I show only the effect of parents' late childhood shocks on their children's human capital. See Appendix A.1, for results on parental early childhood shocks.

shocks on child outcomes as:

$$\frac{\partial \theta_{k,1}}{\partial \eta_1^p} = \left(\frac{\partial \theta_{k,1}}{\partial I_0} \frac{\partial I_0}{\partial \theta_p} + \frac{\partial \theta_{k,1}}{\partial \theta_p} \right) \left(\frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_p}{\partial I_1^p} \frac{\partial I_1^p}{\partial \eta_1^p} \right)$$

$$= \underbrace{\frac{\partial \theta_{k,1}}{\partial \theta_p} \frac{\partial \theta_p}{\partial \eta_1^p}}_{\text{Self Productivity}} + \underbrace{\frac{\partial \theta_{k,1}}{\partial I_0} \frac{\partial I_0}{\partial \theta_p} \frac{\partial \theta_p}{\partial \eta_1^p} + \frac{\partial \theta_{k,1}}{\partial \theta_p} \frac{\partial \theta_p}{\partial I_1^p} \frac{\partial I_1^p}{\partial \eta_1^p}}_{\text{Mixed channel}} + \underbrace{\frac{\partial \theta_{k,1}}{\partial I_0} \frac{\partial I_0}{\partial \theta_p} \frac{\partial \theta_p}{\partial I_1^p} \frac{\partial I_1^p}{\partial \eta_1^p}}_{\text{Dynamic complementarity}} . \tag{2.8}$$

Equation (2.8) presents a compact solution of the effects of parental shock exposure on a child's human capital k. It includes both direct (effect of a shock to a parent's health in childhood on her child's health) and cross (effect of shocks to a parent's health in childhood on her child's cognitive capabilities) effects. The first term measures the pure self-productivity effect of parental exposure to adverse shocks. Shocks experienced by a parent reduce the parent's capabilities, which in turn reduce a child's human capital through the "skill begets skill" notion. It is, therefore, expected to be negative.

The last term in (2.8) is the pure dynamic complementarity effect. Parents' childhood shock exposure reduces the return on investments in their human capital, and hence the stock of parents' stock of skills at adulthood. Low parental skills (children's parental endowment), in turn, leads to low child capabilities. The sign of the dynamic complementarity effect is, however, not straight forward due to competing mechanisms. Even though $\frac{\partial \theta_{k,1}}{\partial I_0}$ and $\frac{\partial \theta p}{\partial I_1^p}$ are both positive, the signs of $\frac{\partial I_0}{\partial \theta_p}$ and $\frac{\partial I_1^p}{\partial \eta_1^p}$ are ambiguous. First, famine can have general equilibrium wage and

relative price effects [177]. A fall in wage rates reduces the opportunity cost of time invested in child care, and conceivably lead to increase in time investments [187]. By contrast, a rise in the relative price of food may have a negative real income effect and retard investments on children. Second, the income effect of a fall in agricultural outputs during famines may reduce investments in children for farm households. Moreover, parental remediation of adverse exposures can compensate for the effects of a shock if parents invest more in the affected child or reinforce the effect if, rather, investments are directed to the unaffected child to maximize returns. These combine to generate an ambiguous dynamic complementarity effect.

The two middle terms in (2.8) constitute a mixed channel, which emanates from the inter-generational nature of the mechanism driving the effects of shocks. The second term measures the effect of a parent's childhood shock exposure on her child that is transmitted through the child's indirect investment channel. Though $\frac{\partial \theta_{k,1}}{\partial I_0} > 0$ and $\frac{\partial \theta_p}{\partial \eta_1^p} < 0$, the sign of $\frac{\partial I_0}{\partial \theta_p}$ is ambiguous leading to an ambiguous sign for this term. The third term captures the effect of parental shock exposure channeled through the child's indirect parental endowment channel. Its sign is, however, ambiguous since $\frac{\partial I_1^p}{\partial \eta_1^p}$ cannot be readily signed, leaving the mixed channel effect ambiguous. Thus, the theoretical predictions of the impacts of early parental shocks on the human capital of children are not clear.

In this paper I use exogenous exposure to famine in Ethiopia in the early 1980s to identify the causal effects of maternal early childhood shocks on their children's

outcomes. I use rich panel data to estimate the *net* effects of the famine on cognitive and health outcomes of the children of parents who were exposed. The correspondence between a child's human capital and her outcomes can be thought to be defined by the function $h(.)$ [26], which translates human capital stock in a given period t into performance Y in the same period. Measured performance in time t for some dimension j is, thus, $Y_{t,j} = h(\theta_t)$. To identify mechanisms, I estimate the effects on parental cognitive, non-cognitive (socio-emotional) and health outcomes, and other parental inputs such as health, schooling, and food expenditure.

2.4 Data

I use information on mothers' age to recover their birth cohort during the 1983-1985 Ethiopian famine. I combine the birth cohort data with a plausibly exogenous geographic variation in the intensity and duration of drought condition during the famine to identify the causal impacts of maternal famine exposure on the human capital of children. The Ethiopia Young Lives (YL) data track children from early childhood through early adolescence over a 12 year period. In 2002, a baseline survey was conducted on a sample of 2,000 children born in 2001-2002 (6-18 months old) living in 20 sites across Addis Ababa, Amhara, Oromia, Southern Nations and Nationalities Region (SNNPR), and Tigray regions. Follow up surveys were conducted in 2006, 2009, and 2013.[11]

[11] I use the *Rounds 1-4 Constructed Files 2002-2014*, which combine sub-sets of selected variables from Rounds 1-4 of the Young Lives survey [37].

Table 2.1: Summary statistics

	Survey round								
Variables	1	2	3	4	Obs.	Mean	Sd	Min	Max
Child outcomes									
Height-for-age z-score	✓	✓	✓	✓	3459	-1.36	1.26	-4.98	4.92
Child height (cm)	✓	✓	✓	✓	3494	108.89	26.50	55.30	178.00
Child stunted (<-2 SD)	✓	✓	✓	✓	3493	0.30	0.46	0.00	1.00
Child severely stunted (<-3 SD)	✓	✓	✓	✓	3493	0.10	0.30	0.00	1.00
Child schooling (year)			✓	✓	1559	2.29	1.96	0.00	8.00
PPVT score (raw)		✓	✓	✓	2472	46.88	37.33	0.00	196.00
Math score (raw)				✓	1602	8.51	6.14	0.00	28.00
Child education aspiration (year)				✓	851	13.88	2.53	0.00	17.00
Child locus of control		✓	✓	✓	2606	1.94	1.49	0.00	4.00
Child self esteem		✓	✓	✓	2606	1.67	1.30	0.00	4.00
Mother outcomes									
Mother height(cm)		✓			804	158.78	5.81	133.35	178.20
Mother schooling (year)	✓	✓	✓	✓	3187	3.22	4.02	0.00	16.00
Mother's education aspiration for child (year)		✓	✓	✓	2583	15.32	2.44	0.00	18.00
Mother locus of control		✓	✓	✓	2606	2.35	0.91	0.25	4.00
Mother self esteem		✓	✓	✓	2606	2.69	0.65	0.22	4.00
Child and household characteristics									
Child gender (male=1)	✓	✓	✓	✓	3523	0.53	0.50	0.00	1.00
Child age (months)	✓	✓	✓	✓	3523	78.29	49.12	6.02	154.00
Child age order	✓	✓	✓	✓	3523	1.87	1.12	1.00	9.00
Child number of siblings	✓	✓	✓	✓	3523	3.02	1.71	1.00	11.00
Household head age	✓	✓	✓	✓	3521	38.13	11.03	5.00	110.00
Household head gender (male=1)	✓	✓	✓	✓	3522	0.81	0.39	0.00	1.00
Household head schooling (year)	✓	✓	✓	✓	3522	4.70	4.56	0.00	25.00
Household size	✓	✓	✓	✓	3523	5.39	1.83	2.00	15.00
Mother age	✓	✓	✓	✓	3523	28.07	5.02	18.00	47.00
Father age	✓	✓	✓	✓	2989	36.60	7.31	19.00	86.00
Father schooling (year)	✓	✓	✓	✓	2680	5.04	4.40	0.00	18.00
Other controls									
Urban-rural dummy (urban=1)	✓	✓	✓	✓	3523	0.42	0.49	0.00	1.00
Shock index	✓	✓	✓	✓	3523	0.11	0.11	0.00	0.68
Wealth index		✓	✓	✓	3523	0.31	0.18	0.01	0.90

Continued on next page

Table 2.1 – *Continued from previous page*

	Survey round								
Variables	1	2	3	4	Obs.	Mean	Sd	Min	Max
Food expenditure per month (Birr)		✓	✓	✓	3484	96.92	57.50	8.38	744.66
Non-food expenditure per month (Birr)		✓	✓	✓	3484	73.84	130.56	0.26	4,325.19
Total expenditure per month (Birr)		✓	✓	✓	3484	168.07	153.27	9.70	4,280.61
Education expenditure per year (Birr)		✓	✓	✓	3484	493.45	1,456.56	0.00	35,558.00
Health expenditure per year (Birr)		✓	✓	✓	3484	249.40	2,801.31	0.00	144,000.00
Drought measures (external data)									
Negative rainfall deviation (SD)					3523	0.25	1.41	-2.63	2.07
Negative rainfall deviation in early childhood (SD)					3523	0.07	0.89	-2.63	2.07
Mother's # months of famine					3364	3.87	2.00	1.00	7.00
Mother's # months of famine in early childhood					3514	1.10	1.89	0.00	7.00

Note: Check marks in columns 2-5 indicate whether data on a variable in column 1 were collected in survey rounds 1-4. Food, non-food and total expenditure are measured in real 2006 Birr per capita. Education and health expenditures are measured in nominal Birr. The drought measures are limited to growing seasons (as opposed to full year) specific to *weredas*. In *belg* and *meher* growing *weredas*, the drought measures reflect the condition for the two seasons. For *meher*-only growing areas, it covers the *meher* season only.

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

(such as education, health, electricity, telephone etc.), population, religion, and ethnicity, language, political representation, crimes, environmental changes and community networks. Table 2.1 presents a list of key variables and the survey round in which they were collected.

The household survey data are matched with weather (rainfall) data. The weather data are from the National Oceanic and Atmospheric Administration (NOAA) AgMERRA climate dataset, which provides daily time series over the 1980-2010 period [81, 180, 181].[12] The data are originally provided at 0.25 degree (≈25km×25km) resolution. These data are converted to *wereda* level rainfall data by applying weights based on the area size of the grid cell relative to the *wereda*, i.e., percentage of each *wereda*'s area occupied by the grid cell. All grid cells that fully fall within a *wereda* receive equal weights whereas intersected cells (grids that fall between two or more *wereda*s) receive smaller weight proportional to area size.

[12] AgMERRA stands for Agricultural Modern-Era Retrospective analysis for Research and Applications. The AgMERRA dataset provides daily, high-resolution meteorological time series by combining daily resolution data from retrospective analysis with ground level and remotely-sensed observational datasets for temperature, precipitation and solar radiation. It gives particular consideration to agricultural areas, and agronomic factors that affect plant growth such as mean growing season temperature and precipitation, seasonal cycles, inter-annual variability, the frequency and sequence of rainfall events, and the distribution of sub-seasonal extremes, leading to substantial reduction in bias [181].

2.4.1 Measuring Famine Magnitude

The main cause of the famine was an extended drought that lasted several cropping seasons. Thus, the geographic and temporal variation in the drought condition is used as a proxy for the famine. I construct two measures of famine magnitude: the deviation of average rainfall during the 1983-1985 famine from historical average (*rdev*), and the number of months with rainfall shortage of half or higher standard deviations (SD) (*mdry*). While these measures are likely to be correlated, they measure different aspects of a famine condition. *Rdev* measures the intensity of famine (the extent of dryness), whereas *mdry* measures the duration of a dry spell. A famine can be deep (extremely dry weather condition) but of short duration, or vise versa. The nature of interventions called for by the two dimensions of famine may, thus, differ.

Both measures take the seasonality of agriculture in Ethiopia and the geographic variability of rainfall into account. The famine started in the *meher* season of 1983 and ended by the start of *meher* rains of 1985. Some of the *wereda*s covered in the Young Lives survey receive rainfall in both *meher* and *belg* seasons, while others get only *meher* rains. The famine measures are constructed to reflect these realities. Accordingly, the rainfall deviation measure captures *wereda*-specific total monthly rainfall deviations during the *meher* and/or *belg* seasons.

The rainfall deviation measure *rdev* is constructed as:

$$rdev_{m,w,y} = \sum_{Jun-Sep1983}^{Mar-May1985} -\frac{rain_{w,m,y} - \overline{rain}_{w,m}}{sdrain_{w,m}} \tag{2.9}$$

where $rain_{m,w,y}$ is monthly precipitation in *wereda w* in the month of *m* in year *y* in millimeters, ($\overline{rain}_{w,m}$) is historical (1980-2010) average of rainfall in *wereda w* for month *m*, and $sdrain_{w,m}$ is standard deviation of monthly rainfall in *wereda w* in month *m* over the same 1980-2010 period.[13] If a *wereda* receives rainfall in both *meher* and *belg* seasons, the deviation measure would cover *meher* 1983, *belg* 1984, *meher* 1984 and *belg* 1985. If, on the other hand, a *wereda* gets rainfall only during the *meher* season, the relevant measure would cover *meher* 1983 and *meher* 1984.

The famine measure in equation 2.9 captures the *wereda* level famine conditions for everyone in 1983-1985 irrespective of their age. The obvious candidate to capture the differential impacts due to exposure in early childhood is an interaction term between this *wereda*-specific measure and a dummy variable that takes value 1 if the famine took place during early years of childhood. The extent of famine exposure in early childhood, however, varies depending on when the mother was born within the famine period. Using mother's age, I construct an individual specific measure ("interaction term") that better reflects the extent of exposure. A mother born in 1981 would experience the famine at age 2 in 1983, a mother born in 1983 would experience the full famine —*in utero* in 1983, at age 1 in 1984 and age 2 in 1985, whereas a mother born in 1985 would experience the famine only *in utero* in 1985. This measure is essentially the sum of interactions of famine year specific negative rainfall deviation and mother's birth year dummies (see panel (a) of Table 2.2 for details).

[13]To avoid the effect of the outlier famine years, the 1983-1985 period is excluded in computing mean and standard deviation.

Table 2.2: Individual specific famine measure

Birth year	Age at baseline (2002)	*in utero*	Famine exposure	Famine measure
			a) Famine intensity	
1980	23	1980	None	0
1981	22	1981	1983 (age 2)	$\sum_{Jun-Sep1983} -\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}}$
1982	21	1982	1983 (age 1) and 1984 (age 2)	$\sum_{Jun-Sep1983}^{Jun-Sep1984} -\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}}$
1983	20	1983	1983 (age 0 - *in utero*), 1984 (age 1) and 1985 (age 2)	$\sum_{Jun-Sep1983}^{Mar-May1985} -\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}}$
1984	19	1984	1984 (age 0 - *in utero*) and 1985 (age 1)	$\sum_{Jun-Sep1984}^{Mar-May1985} -\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}}$
1985	18	1985	1985 (age 0 - *in utero*)	$\sum_{Mar-May1985} -\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}}$
1986	17	1986	None	0
			b) Famine duration	
1980	23	1980	None	0
1981	22	1981	1983 (age 2)	$\sum_{Jun-Sep1983} 1(\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}} < -0.5)$
1982	21	1982	1983 (age 1) and 1984 (age 2)	$\sum_{Jun-Sep1983}^{Jun-Sep1984} 1(\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}} < -0.5)$
1983	20	1983	1983 (age 0 - *in utero*), 1984 (age 1) and 1985 (age 2)	$\sum_{Jun-Sep1983}^{Mar-May1985} 1(\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}} < -0.5)$
1984	19	1984	1984 (age 0 - *in utero*) and 1985 (age 1)	$\sum_{Jun-Sep1984}^{Mar-May1985} 1(\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}} < -0.5)$
1985	18	1985	1985 (age 0 - *in utero*)	$\sum_{Mar-May1985} 1(\frac{rain_{w,m,y}-\overline{rain}_{w,m}}{sdrain_{w,m}} < -0.5)$
1986	17	1986	None	0

Because *rdev* is defined as a negative deviation, increase in its magnitude can readily be interpreted as worsening of the famine condition. This is essential to maintain consistency in the definition of the famine measures used in this paper. While this intensity measure is a good proxy for the depth of the famine, it does not fully reflect its breadth. The number of months with significant rainfall shortages during the famine period, addresses this duration issue.

The famine duration measure, *mdry*, measures the number of months of famine exposure during the *meher* and/or *belg* growing seasons of 1983-1985. In *meher* and *belg* growing areas, the measure includes famine months in *meher* 1983, *belg* 1984, *meher* 1984 and *belg* 1985. In *meher*-only growing areas, it includes *meher* 1983 and *meher* 1984. The number of famine months is calculated as:

$$\begin{aligned} mdev_{w,m,y} &= \frac{rain_{w,m,y} - \overline{rain}_{w,m}}{sdrain_{w,m}} \\ mdry_{w,y} &= \sum_{Jun-Sep1983}^{Mar-May1985} 1(mdev_{w,m,y} < -0.5) \end{aligned} \tag{2.10}$$

where $mdev_{w,m,y}$ is deviation of *wereda w* rainfall in the month of *m* and year *y* from historical average rainfall for the month measured in standard deviations. The famine measure $mdry_{w,y} \in [0, 14]$ is computed by summing up the dummy variables for each month of the relevant *wereda* specific famine period. The dummy variable for a given month *m* takes the value 1 if rainfall for the month was 0.5 or higher standard deviations below historical average for the month over the 1980-2010 period, excluding 1983-1985, or 0 otherwise. By adding over a maximum of 14 months of the famine, I obtain a measure of local famine duration.[14]

[14]The maximum number of famine months varies depending on whether a *wereda* is *belg* grow-

Like *rdev* above, *mdev* varies between *wereda*s, but not between individuals within a *wereda*. It measures common *wereda* famine duration effects —the number of famine months experienced by everyone in a given *wereda*. The actual famine duration experienced by a mother, however, is likely to vary by the mother's birth year within the famine period. To capture the differential effect of maternal early childhood exposure during the famine, I exploit mothers' birth year and *wereda*-year specific famine months. As shown in panel (b) of Table 2.2, a mother born in 1981 would experience the famine at age 2 in 1983 for the four *meher* growing months between June and September. Depending on the severity of the monthly rainfall deficit, her famine exposure duration would be between 0 and 4. A mother born in 1983 would experience the full famine —*in utero* in 1983, at age 1 in 1984 and age 2 in 1985. The individual specific rainfall deviation would depend on whether the *wereda* gets rainfall in only *meher* or both *belg* and *meher* seasons, and the severity of the monthly rainfall deficit. If for example, she were from a *wereda* with two annual growing seasons and the *wereda* suffered rainfall shortage of $\geq |0.5|$ standard deviations for three months in *meher* 1984 and two months in *belg* 1985, the mother's famine duration would be 5 months (see panel (b) of Table 2.2 for details).

Despite receiving average annual rainfall of over 700 mm, Ethiopia is extremely vulnerable to weather shocks.[15] This is mainly due to the uneven geo-

ing or not. In *meher* and *belg* growing areas, the maximum number of famine months is 14, whereas is *meher*-only growing areas, it is 8 months.

[15]The average rainfall for years between 1901 and 2012 is 736 mm, and for the period covered in this study (1980-2010) it stands at 711 mm per annum [210].

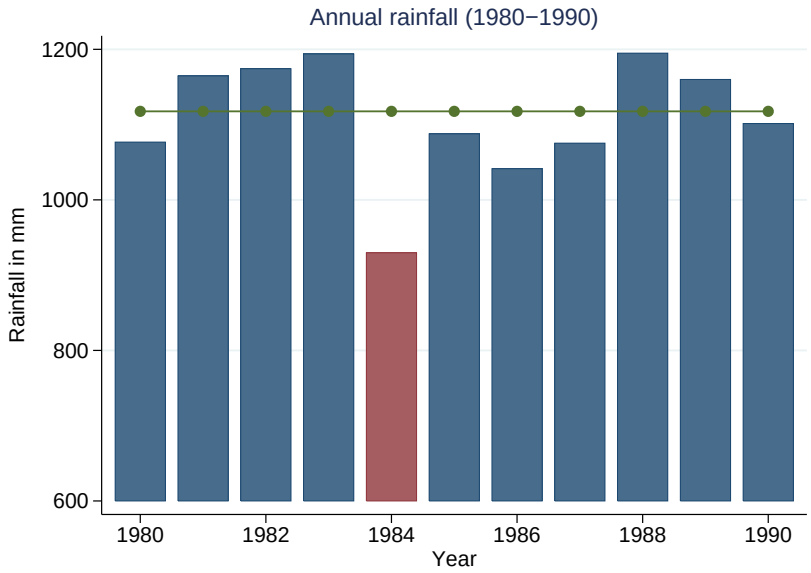

Figure 2.2: Patterns of annual rainfall in 1980-1990

Note: The bars measure the annual rainfall in millimeters for each year. The bar for 1984 is colored in red. The green horizontal line over the bars shows the historical average rainfall for the 1981-2010 period.

graphic distribution of rainfall and its considerable variation over time. Agricultural households who depend on rainfall for their livelihood, and with little means for self-insurance, find it difficult to adapt to drought conditions, especially during consecutive drought years as in the mid 1980s, leading to catastrophic crises. As shown in Figure 2.2, the 1983-1985 Ethiopian famine was associated with annual precipitation falling below historical average for four years in a row. The drop in annual rainfall was especially high in 1984, with rainfall levels of less than 80% of historical average for the whole country.

The geographic variation of rainfall is shown in Figure 2.3. Among the four

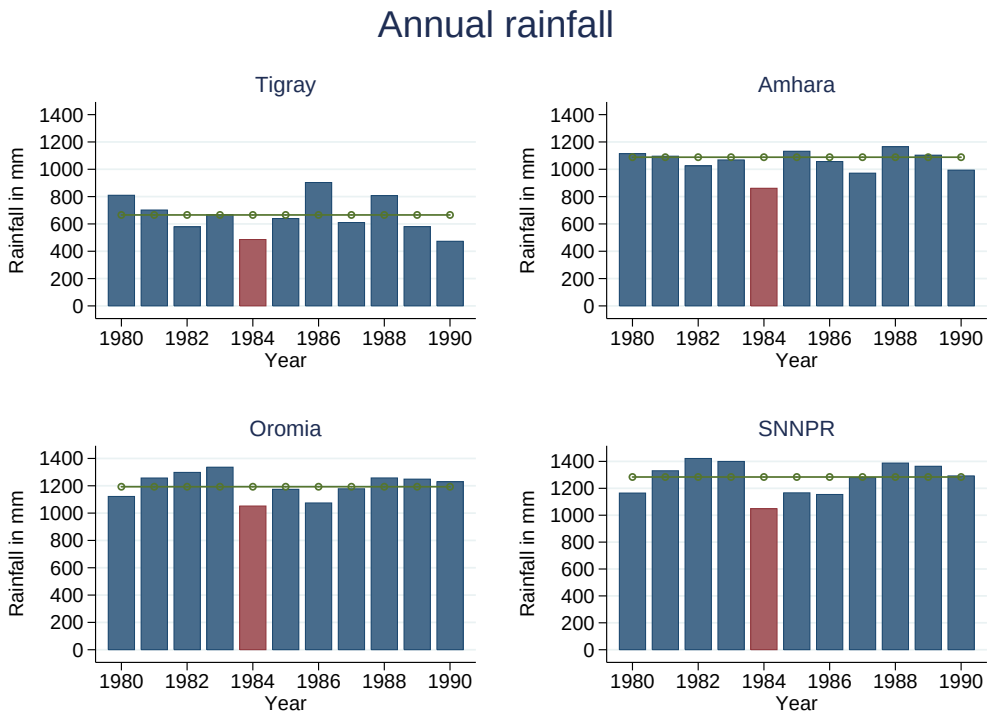

Figure 2.3: Patterns of annual rainfall in 1980-1990 by Region

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

largest regions of Ethiopia, Oromia and SNNPR receive the highest amount of precipitation, whereas Tigray receives the least amount. The average annual precipitation was lowest in 1984 in all four regions. Low rainfall, however, does not necessarily translate into worse outcomes to the extent endogenous adaptation of farming practices and livelihood diversification is possible as a response to historical experiences of rainfall shortages. But, volatility of rainfall in areas with low rainfall, thus, little leverage in terms of minimum water requirements for plant

growth, has been a cause of recurrent disasters. The SNNPR also displays considerable rainfall volatility in the 1980-1990 period.[16]

Figure 2.4 presents the deviation of the average annual rainfall during the famine (1983-1985) from historical average rainfall (1980-2010). The intensity of the famine was greater in the northeastern, southern, and western parts of Ethiopia, which saw rainfall drop of up to 5 standard deviations, on average. The northwestern and central parts of the country were largely spared, with some areas recording higher than normal rainfall. The northern, southern and east-central parts of the country were already getting low rainfall before the famine. The sharp decline in rainfall during the famine in these areas, therefore, had significant effect on peoples' livelihoods. Crop production is the main source of sustenance in most of Ethiopia. Crop failure due to insufficient rains, thus, can have severe lasting consequences. During the 1983-1985 period, repeat exposure of adverse rainfall events led to livelihood collapse in many parts of Ethiopia.[17]

Figure 2.5 reports the number of months with over one standard deviation rainfall shortfall during the famine period. It shows that in most of Ethiopia, rainfall was below historical averages for at least three months in the 1983-85 famine period. Particularly, western and southwestern parts of the country suffered rainfall shortage for up to 16 months. The dry spell (of $\geq |1|$ SD) had relatively short

[16]Like [185] and [203], Appendix Figures A1 and A3, show that the year 1984 had the worst *meher* and *belg* rains. The month of August and April, during which *meher* and *belg* rains peak, respectively, had the worst rainfall in recent history (Appendix Figures A2 and A4).

[17]This, along with other political reasons, prompted the government into the now infamous resettlement program which led to the death of tens of thousands of people [94].

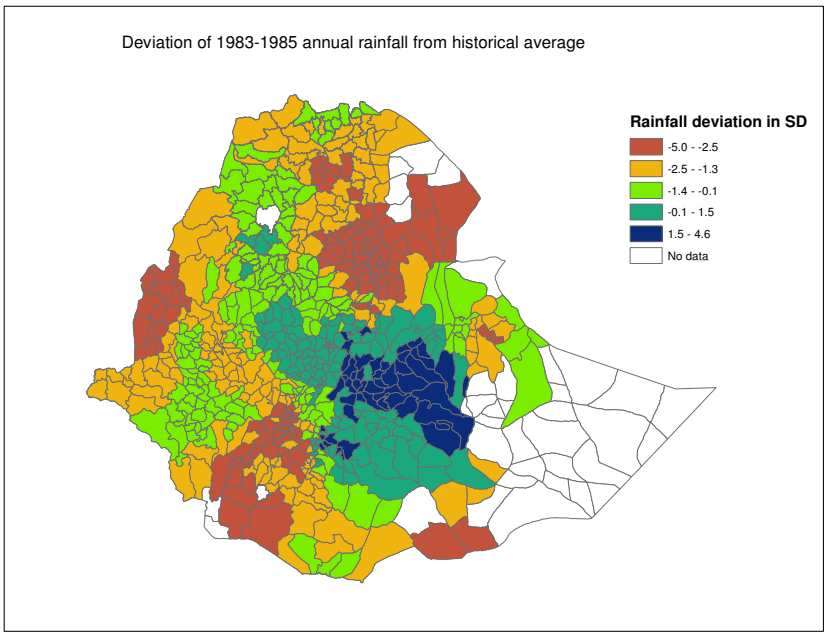

Figure 2.4: Deviation of annual 1983-1985 annual rainfall from historical averages in SD

Note: The figure shows rainfall anomaly during the 1983-1985 famine. The reference period is 1980-2010, excluding the famine years. The blank cells are *woreda*s for which rainfall data is missing.

duration in the central and northern parts of the country. Note, however, that because the northern parts were already receiving low rainfall prior to the famine, the effect of an additional month of dry weather might be more damaging in the north than in the central and western Ethiopia.

The Young Lives study sites are located in geographic areas with varying degrees of famine exposure during the 1983-1985 period . Two sites are located in severely affected *weredas* and six sites are in moderately affected *weredas*. Seven study sites are in *weredas* with no considerable change in rainfall during the

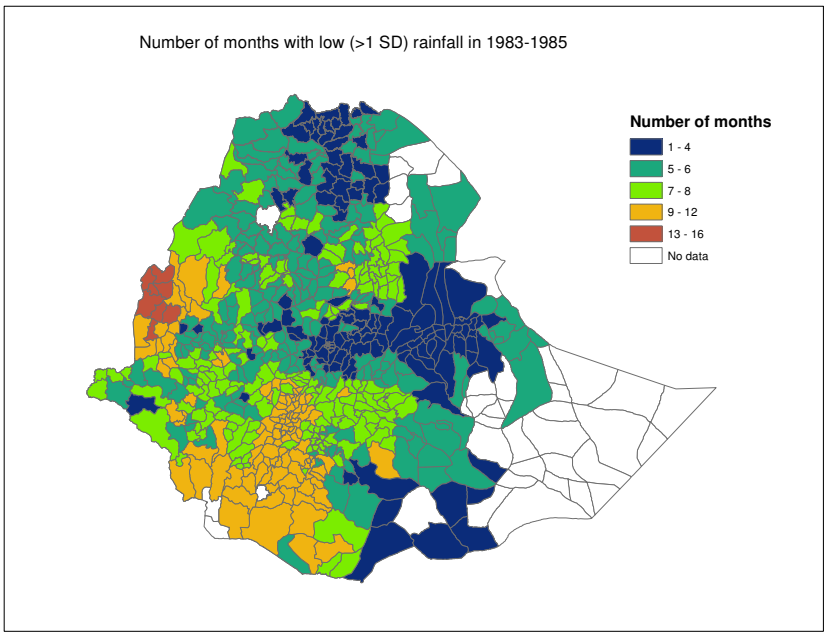

Figure 2.5: Number of months with low rainfall (< -1 SD) in 1983-1985

Note: The figure shows the number of months of rainfall anomaly during the 1983-1985 famine. The reference period is 1980-2010, excluding the famine years. The blank cells are *woreda*s for which rainfall data is missing.

famine period, and the remaining fives sites are in *wereda*s with positive rainfall deviations. I exploit this significant variation in famine intensity and duration to identify the causal impacts of childhood famine exposure of mothers on human capital outcomes of their children.

2.4.2 Measuring Human Capital

In line with the multidimensional nature of human capital [108], I use several measures of cognitive, non-cognitive, and health capabilities of children as outcome

variables. The cognitive capability of children is measured by grade achievement (years of schooling completed) and standardized scholastic aptitude test scores. The Peabody Picture Vocabulary Test (PPVT) is used to measure the receptive vocabulary of children and standardized Math test is used to measure the analytical ability of children. The PPVT measures scholastic (cognitive) ability, not reading ability [80]. The Ethiopia Young Lives PPVT test consists of 204 stimulus words of increasing difficulty and corresponding 204 image plates each containing four black-and-white images. The interviewer reads a stimulus word from a list, and respondents are asked to select one of the four pictures that best describes the word. The starting point (and the level of difficulty) of the test is determined based on the respondent's age.[18] The PPVT raw score is the total number of correct answers by the respondent. Like the PPVT, the Math test is structured in an increasing order of difficulty for different age groups. The raw math score is the total number of correct answers by the respondent.

Since the starting point of the tests and the corresponding level of difficulty varies by age of respondents, raw PPVT and Math scores are not readily comparable across children of different ages. Thus, they do not accurately measure cognitive ability. By accounting for item difficulty, Rasch (logit) transformation of the raw scores provides linearly comparable measures of cognitive ability. This paper uses Rasch PPVT and Math test scores.

Children's non-cognitive human capital is measured by educational aspira-

[18]See [80] for details on how PPVT tests are administered.

tion, locus of control and self-esteem. Educational aspiration is children's stated desired level of schooling if they faced no constraints and could study for as long as they liked, measured at age 12. The locus of control and self-esteem measures are constructed from four-scale responses (0=strongly disagree, 1=disagree, 2=agree, and 3=strongly agree) to various questions on perceptions and attitudes.[19] They are computed as $\theta_{nc} = \frac{\sum_{j=1}^{n} S_j}{n}$, where θ_{nc} is non-cognitive human capital, S_j is the reported score on question j, and n is the total number of questions included in computing each measure. To make the non-cognitive human capital measures comparable across survey rounds, only responses to questions asked consistently in all rounds are included (three questions for locus of control and six for self-esteem). Health human capital is measured by the conventional height-for-age z-score computed based on World Health Organization (WHO) growth charts.

The mechanisms of mother-to-child transmission of famine impacts explored in this paper are child maternal skill endowment, measured by mothers' schooling (cognitive human capital), educational aspirations for child, locus of control and self-esteem (non-cognitive human capital) and height (health human capital) and parental investments. As described by the multidimensional human capital production function in section 3, a mother's early childhood famine exposure is expected to impact negatively her adult human capital and labor market outcomes. These being inputs in her child's human capital production, they may

[19]These scales apply to positively coded questions such as "If I try hard I can improve my situation in life." If a question is rather negatively coded (such as "My teachers treat me worse than other children"), the order of the scores is reversed.

have adverse consequences for the child's human capital. The effect on mothers' labor market outcomes of the famine, if any, may lead to reduced parental investments in children, measured by real total expenditure, and expenditures on schooling and health, all measured in per capita adult equivalent scale. The focus on maternal outcomes is due to previous findings that early childhood shocks affect the adult outcomes of girls more than that of boys, which suggests that maternal channels are likely to be the prime mechanisms of parent-to-child shocks transmission [7, 148, 153].

2.4.3 Descriptive Statistics

Table 2.1 presents summary statistics for key variables used in the analysis sample. The sample covers the children of mothers born between 1978 and 1988, which encompasses mothers born in the three years before the famine (1978-1980), mothers born during the famine (1981-1985) and those born in the three years after the famine (1986-1988). Data on most of the key variables were collected in all four rounds. Data on some variables (e.g. mother's height), however, are available only in some rounds. Columns 2-5 indicate the round(s) in which data on specific variables were collected.

About 42% of the sample households are from urban areas and 81% of households are male headed. The average household head is about 38 years old and has 4.7 years of schooling, while the YL child's mother is 28 years old, 159 cm tall

and has 3.2 years of schooling. The average household size and number of children are 5.4 and 3, respectively. There are slightly more boys in the sample (53%). The average age of children is 78 months and the average child is about 109 cm tall. He/she is typically a second child.[20] The average height-for-age z-score is 1.4 standard deviations below WHO's reference distribution, which indicates the high rate of stunting prevalent in the data. Thirty percent of children are stunted (<-2 SD) of which 10% are severely stunted (<-3 SD).

The average PPVT and Math scores are 47 and 8.5, respectively. The average desired level of schooling (child's educational aspiration) by children is about 14 years, which is equivalent to a diploma post high school completion. The locus of control variable measures the degree to which one feels he/she has control over happenings in one's own life. A high locus of control score represents greater control. The self-esteem variable measures one's overall sense of self-worth. A high self-esteem score indicates greater sense of self-worth. In the sample, the average locus of control and self-esteem scores are 1.9 and 1.7, respectively, with considerable variation across children. Mother's locus of control and self-esteem are similarly measured. The average scores are higher and variance much lower for mothers than children. Mothers' desired level of schooling (educational aspiration) for their children is about 15 years, which amounts to an undergraduate degree.

The average monthly real expenditure per adult equivalent is Birr 155, of

[20] In the baseline, the YL child is a first child. However, over the course of the panel (12 years) sample households had an additional child, on average.

which Birr 90 is spent on food items and rest on non-food items. The average expenditure on education and health per household is Birr 41 and Birr 21, respectively. About 22% of cases (25% of households in round 3 and 19% of households in round 4 participated in the Productive Safety Net Program (PSNP).[21]

2.5 Empirical Strategy

The empirical strategy employed is as follows. First, I estimate the effects of mothers' early childhood famine exposure on the cognitive, non-cognitive and health human capital of their children. Findings of negative impacts point to intergenerational persistence of early childhood conditions. Second, to identify parent-to-child famine transmission mechanisms, I estimate the effects of the famine on the cognitive, non-cognitive and health human capital of mothers who suffered the famine during their developmental plasticity. Negative and statistically significant effects of the famine on mothers' human capital would suggest that children's maternal skill endowment is a key parent-to-child shock transmission channel. To establish this is indeed the case, I re-estimate the children human capital regressions above by including mother human capital outcomes as a regressors. If the child intergenerational famine effects become statistically insignificant with

[21] PSNP is a large nationwide program that provides assistance to food insecure households to mitigate the effects of transitory shocks, while also building resilience to shocks through sustainable community development. It consists of conditional transfers through public works in climate-resilience building activities and unconditional transfers to households lacking in able bodies to engage in public works.

the introduction of the mother's human capital into the child human capital regressions, it confirms that the mother-to-child channel is the prime mechanism of intergenerational shock transmission.

Third, mothers' early childhood shock exposure may also affect child human capital outcomes by reducing the mothers' adult income, which limits the amount they can invest in their children as parents. I use total household expenditure and expenditures on education and health to estimate whether and the extent to which child investments are affected by maternal early childhood shocks. Unless the adulthood earnings of mothers who suffered the famine in early childhood are systematically altered by marriage market outcomes, household expenditures are expected to reflect early childhood experiences of mothers. In this case, parental child investments mediate the parent-to-child famine transmission.

Fourth, to study whether, conditional on famine intensity, the effect of maternal early childhood famine exposure on their children varies by famine duration and to identify critical famine duration thresholds, the child human capital regressions are re-estimated by including dummy variables for each level (month) of famine duration.

Finally, the life cycle effects of maternal early childhood famine exposure on their children's human capital are explored by estimating the child human capital regressions by interacting the birth year specific *wereda* famine duration measure with survey round dummy. The estimates on this interaction term indicate whether the effect of the famine decays over the child's life cycle or not.

The famine event took place prior to survey data collection. The famine measures, thus, do not vary over the survey rounds, which precludes the application of standard fixed effects models to account for time invariant variables that are potentially correlated with regressors. To circumvent this constraint that is imposed by the nature of the data, I employ alternative estimators. The baseline model uses the standard pooled OLS method. This fails to take into account the temporal correlation of observations due to the panel nature of the data. This is addressed using the random effects model. The random effects model, however, relies on the strong assumption that fixed effects are uncorrelated with regressors. To deal with the potential bias due to correlation between regressors and error terms containing time invariant child, parent and *wereda* fixed effects, among others, I turn to Mundlak's fixed effects approach [158] and the Hausman-Taylor random effects estimator [105].

2.5.1 Child Outcomes

To estimate the impacts of mothers' exposure to the 1983-1985 famine on the human capital outcomes of their children, I estimate:

$$\theta^k_{iwvt} = \beta_0 + \beta_1 rdev_w + \beta_2 mom\_rdev_{iwt} + \beta_3 mdry_w + \beta_4 mom\_mdry_{iwt} + \mathbf{\Gamma}'\mathbf{X}_{iwv} + \pi + \lambda_w + \tau_v + \varepsilon_{iwvt} \tag{2.11}$$

where $\theta^k_{i,w,v,t}$ is the human capital outcome $k \in \{c, n, h\}$ of child i in wereda w, survey round v and mother birth year t within the famine cohort. A mother is

considered to be in the famine cohort if she suffered the famine *in utero* and/or in the first three years of life after birth —born 1981-1985. The famine intensity measure $rdev_{w,t}$ is the total monthly rainfall deviation during *meher* and/or *belg* seasons in 1983-1985 from historical monthly averages, in SD. Higher *rdev* represents exposure to more severe famine. It varies between *wereda*s but not between children within each *wereda*. The variable *mom_rdev* is the total rainfall deviation experienced by a mother during her early childhood period in *meher* and/or *belg* seasons in 1983-1985. It is similar in construction to an interaction term between *rdev* and the famine cohort dummy π (=1 if born 1983-1985), but it is a more precise measure as it reflects the birth year of the mother during the famine.

Likewise, *mdry* is the total number of months during *meher* and/or *belg* seasons of the famine years with rainfall half or greater SD below the historical monthly average in a *wereda*. It varies across *wereda*s, but is constant within each *wereda*. Higher *mdry* means longer famine duration in a *wereda*. *Mom_mdry* is the number of months a mother was exposed to rainfall deviation of half or greater SD below the historical monthly average *in utero* and/or during her first three years after birth. It varies across children depending on mother's birth year and *wereda* of residence. Its construction is similar to an interaction term between *mdry* and π, but since it reflects mother's birth year, it offers a more precise birth year-specific measure of early childhood famine exposure duration.

$\mathbf{X}_{i,w,v}$ is a vector of child, parent and household characteristics. It includes household size, household head age, gender and schooling, wealth, income,

shocks, child age, gender, age order, number of siblings, language, ethnicity, religion, and urban-rural dummy.[22] The *wereda* fixed effect, λ_w, controls for time invariant characteristics that are common to all children in the same *wereda*. In empirical estimation, however, I include region controls rather than *wereda* controls as standard errors are cluster bootstrapped at the *wereda* level (see discussion below). The survey round fixed effect τ_v controls for factors that are common to children surveyed in a given round; π is a famine cohort fixed effect and captures common shocks to all children born to parents of the famine cohort and $\varepsilon_{i,w,v,t}$ is a random error term.

β_1 measures the average *wereda* level effect of a one standard deviation increase in famine intensity that is common to all children whose mothers were alive during the famine. Similarly, β_3 measures the average *wereda* level effect of an additional month of famine that is common to all children whose mothers were alive during the 1983-1985 famine. Both β_1 and β_3 are expected to be negative.

The primary coefficients of interest are β_2 and β_4, which measure the *net* differential effects of maternal famine exposure during the early periods of childhood on the human capital outcomes of children and are given as

$$\beta_j = \frac{\partial \theta_{k,1}}{\partial \eta^p_{1,j}}, \qquad j = 2, 4 \tag{2.12}$$

in equation (2.8), where $j \in (mom\_rdev, mom\_mdry)$ stands for the famine measure

[22]The wealth and shocks measures are composite indices constructed from a series of asset and shock indicators, respectively. Wealth index is a simple average of housing quality, consumer durables and access to services, which are all simple indices (mean) of component indicator dummies. The shock index is a simple average of crime, regulations, economic, environmental and family shocks, each of which being a composite measure of indicator dummies of components.

used. The coefficient on *mom_rdev*, β_2, measures the average effect of an increase in negative rainfall deviation; it is expected to be negative. A negative β_2 indicates that higher shortfall in rainfall during the mothers' early childhood is associated with worse human capital outcomes for their children. The coefficient on *mom_mdry*, β_4, measures the average effect on child outcomes of an additional month of maternal famine exposure in early childhood; it too is expected to be negative.[23] To address the potential spatial correlation of famine due to the covariate nature of weather conditions, standard errors are clustered at the *wereda* level. To deal with the small number of clusters (*wereda*s) problem in the data, I use the wild cluster bootstrap approach suggested by [40].

Previous studies show that the intergenerational effects of famine are not the same for males and females. Children born to mothers who experienced the famine *in utero* are likely to suffer more than those born to famine-affected fathers [7, 153, 51]. Moreover, data on fathers are missing for several key variables for a significant number of children. Thus, the intergenerational effects of parental shock exposure on child outcomes are estimated using maternal experiences of the famine.

The key identifying assumption required for consistent estimation of the causal effects of parents' early life famine exposure on the later life outcomes of their children is independence between measures of famine exposure (*rdev* and

[23]Too much rainfall is not desirable for agricultural production. As a robustness check I include a quadratic famine severity term to test if excluding it causes upward bias on β_2. The coefficient on the quadratic famine severity term is statistically insignificant.

mdry) and the error term, after controlling for *wereda*, survey round, and cohort fixed effects, and various child, parent and household characteristics. As long as there were no systematic differences in the growth rates of cognitive, non-cognitive, and health capabilities between villages affected more severely by the 1983-1985 famine and those that were less affected, the parameter estimates β_2 and β_4 are consistent.

2.5.2 Mechanisms

To identify the mechanisms through which maternal early childhood famine exposure affects the human capital of children, I investigate 1) the impact on child maternal endowment —mother's cognitive (years of schooling), non-cognitive (aspirations for child schooling, locus of control and self-esteem) and health human capital (height); 2) parental child investments measured by total expenditure and expenditures on schooling and health. Mothers' human capital serves as an input in child human capital production. Shocks experienced by the mother in early childhood may be transmitted to her child by reducing the parental skill endowment available to the child for skill production. The first set of mechanisms capture this effect. Maternal early childhood shocks may also affect child human capital outcomes by reducing parent's child investments. These, if any, will be reflected in the second set of mechanisms.

Mother Human Capital

I identify the effects of the famine on maternal skill endowment of the child by estimating the equation

$$\theta^{p,k}_{iwvt} = \alpha_0 + \alpha_1 rdev_w + \alpha_2 mom\_rdev_{iwt} + \alpha_3 mdry_w + \alpha_4 mom\_mdry_{iwt} + \mathbf{\Psi'X}_{iwv} + \phi + \delta_w + \kappa_v + \epsilon_{iwvt} \tag{2.13}$$

where $\theta^{p,k}_{iwvt}$ is mother i's human capital k ($k \in \{c, n, h\}$) in *wereda* w, survey round v and birth year t. The rest of the variables are as defined before. α_1 measures *wereda* level common effects of famine intensity, i.e., the average effect of an increase in negative monthly rainfall deviation in a *wereda* on maternal adult human capital outcomes. Similarly, α_3 measures common *wereda* effects of an increase in famine duration on maternal adult human capital outcomes. ϕ is famine cohort dummy taking value 1 if a mother is born during the famine and 0 otherwise, and δ_w and κ_v, capture *wereda* and survey round fixed effects.[24]

The average common *wereda* level effects of a one standard deviation increase in the intensity of the famine and a one month increase in the duration of the famine on the human capital outcomes of mothers who were alive during the famine are given by α_1 and α_3, respectively. Both coefficients are expected to be negative.

The key parameters of interest are α_2 and α_4, which measure the effect of a one standard deviation increase in negative monthly rainfall deviation suffered

[24]Standard errors are wild cluster bootstrapped at the *wereda* level. As a result, in empirical estimation, the *wereda* fixed effects are replaced by region fixed effects.

by the mother in early childhood during the famine on her adult human capital outcomes and the average effect of an additional month of mother's early childhood famine exposure on her adult human capital outcomes, respectively.

The differential effects of mother's early childhood famine exposure captured by α_2 and α_4 are given in equation 2.7 as:

$$\alpha_j = \frac{\partial \theta_p}{\partial \eta^p_{1,j}}, \qquad j = 2, 4 \tag{2.14}$$

where $j \in (mom\_rdev, mom\_mdry)$ stands for the famine measure used.

Parent Investments

The effects of the famine on parents' child investments are estimated in a similar fashion as

$$Y_{iwvt} = \sigma_0 + \sigma_1 rdev_w + \sigma_2 mom\_rdev_{iwt} + \sigma_3 mdry_w + \sigma_4 mom\_mdry_{iwt} + \mathbf{\Omega}'\mathbf{X}_{iwv} + \mu + \varphi_w + \rho_v + e_{iwvt} \tag{2.15}$$

where, Y^m_{iwvt}, $m \in$(total expenditure, education expenditure, health expenditure) is child i's household expenditure m in *wereda* w, survey round v for mother's born in year t of the famine period. μ, φ_w and ρ_v are mother famine cohort dummy (=1 if mother was born in 1983-1985), *wereda* fixed effects and survey round fixed effects, respectively.[25]

[25] *Wereda* fixed effects are replaced by region fixed effects in empirical estimation as standard errors are wild cluster bootstrapped at the *wereda* level.

Coefficients σ_1 and σ_3 measure the average common *wereda* level effects of a one standard deviation increase in famine intensity and a one month increase in famine duration suffered by mothers who were alive during the famine, respectively. The differential average effects of maternal exposure in early childhood on parental child investments are given by σ_2 and σ_4. The coefficient σ_2 measures the effects of a 1 standard deviation increase in negative rainfall deviation experienced by the mother as a child on child investments. Similarly, σ_4 measures the effects of an additional month of maternal famine exposure in early childhood on parental child investments. Both σ_2 and σ_4 are expected to be negative.

2.5.3 Heterogeneous Effects

The effects of maternal early childhood shocks on child human capital outcomes may be non-linear in the sense that famine exposures of certain duration are more harmful than others. If so, identifying critical ranges of maternal early childhood famine duration is essential for optimal targeting of vulnerable groups. To this end, the child human capital regressions are estimated as

$$\theta^k_{iwvt} = \tilde{\beta}_0 + \tilde{\beta}_1 rdev_w + \tilde{\beta}_2 mom\_rdev_{iwt} + \tilde{\beta}_3 mdry_w + \sum_{g=1}^{7} \tilde{\beta}_{4g} D_{igwt} + \tilde{\mathbf{\Gamma}}' \mathbf{X}_{iwv} + \tilde{\pi} + \tilde{\lambda}_w + \tilde{\tau}_v + \tilde{\varepsilon}_{iwvt} \tag{2.16}$$

where, $D_g = \mathbf{1}\{mom\_mdry = g\}$, $g \in \{1, ..., 7\}$ is a dummy variable taking value 1 if the mother suffered famine duration of g months in early childhood, and 0 otherwise. The number of months of mothers' early childhood famine exposure

during the growing seasons of 1983-1985 ranges between 0 and 7. The cohort with no famine exposure, D_0, is the reference group and omitted in the regression. The rest of the variables are as defined before.

The coefficients $\tilde{\beta}_{4g}$ measure the effects of maternal early childhood exposure of famine duration of g months on the human capital outcomes of children. These coefficient estimates are expected to vary non-linearly as the duration of famine exposure changes. The patterns of famine effects measured by $\tilde{\beta}_{4g}$ will be essential for efficient delivery of interventions aiming at minimizing the risk of irreversible intergenerational shock effects. If, for example, the effect of maternal early childhood famine exposure on child outcomes steadily rises for famine durations represented by D_1 through D_g, but accelerates past durations of $g+1$ months, preventing girls' childhood famine exposure duration of $g + 1$ or higher is crucial.

The life cycle effects of maternal early childhood exposure on child human capital outcomes are estimated as

$$\theta^k_{iwvt} = \hat{\beta}_0 + \hat{\beta}_1 rdev_w + \hat{\beta}_2 mom\_rdev_{iwt} + \hat{\beta}_3 mdry_w + \hat{\beta}_{4v} mom\_mdry_{iwt} \times \tau_v + \hat{\mathbf{\Gamma}}' \mathbf{X}_{iwv} + \pi + \hat{\lambda}_w + \hat{\tau}_v + \hat{\varepsilon}_{iwvt}. \tag{2.17}$$

The coefficients on the interaction term $mom_m dry \times \tau_v$, $\hat{\beta}_{4v}$ where $v \in \{1, ..., 4\}$, measure the effects of mothers' early childhood famine exposure on the human capital outcomes of their children at various stages in the life cycle. $\hat{\beta}_{41}$ measures the effect of the famine when the children were 6-18 months old, and $\hat{\beta}_{44}$ measures the effect of the famine on children at age 12. The estimates provide evidence on

the malleability (or lack of) of the different skill types over time to intergenerational shocks.

2.6 Results

2.6.1 Child Outcomes

This section presents estimates of the intergenerational effects of mother's early childhood exposure to the 1983-1985 Ethiopian famine on three dimensions of children's human capital: health, cognitive and non-cognitive (socio-emotional).

Table 2.3 presents regression results for children's health capability as measured by height-for-age z-score (zhfa). The choice of zhfa as a measure of child health is due to the established literature showing that height-for-age is a good summary measure of childhood nutrition and environmental factors [101, 47, 48]. Estimates from pooled OLS (POLS), random effects (RE), Mundlak's pseudo fixed effects (MFE) and Hausman-Taylor random effects (HT) estimators are presented. In all models, controls for household characteristics including household size, household head age, gender and schooling, wealth, income (expenditure), shocks, and urban-rural dummy; child characteristics including age, gender, birth order, number of siblings, language, ethnicity and religion; mother birth cohort dummy (=1 if famine cohort) and survey round dummy variables are included. Standard errors are wild cluster bootstrapped at the *wereda* level.

Table 2.3: Effects of maternal famine exposure on children's health

	(1)	(2)	(3)	(4)
Dependent variable: zhfa	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	-0.015	-0.011	-0.011	0.005
	(0.067)	(0.099)	(0.089)	(0.062)
Rain shortage × famine cohort	-0.083***	-0.087**	-0.080**	-0.096*
	(0.032)	(0.043)	(0.040)	(0.053)
Famine months (#)	0.043	0.041	0.039	0.057
	(0.043)	(0.094)	(0.072)	(0.038)
Famine months × famine cohort	-0.040***	-0.042	-0.038	-0.047*
	(0.015)	(0.028)	(0.029)	(0.024)
Famine cohort (famine=1)	0.047	0.017	0.043	0.025
	(0.060)	(0.084)	(0.082)	(0.087)
Household size	0.019	0.008	-0.000	0.012
	(0.021)	(0.022)	(0.024)	(0.015)
Age of household head	0.000	-0.002	-0.005	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)
Gender of household head (male=1)	0.033	0.118**	0.123**	0.169**
	(0.061)	(0.049)	(0.057)	(0.072)
Household head schooling	0.005	-0.003	-0.010	-0.018
	(0.007)	(0.008)	(0.009)	(0.011)
Urban/rural (urban=1)	-0.257**	-0.148	-0.366	-0.013
	(0.111)	(0.239)	(0.235)	(0.111)
Shock index	-0.150	-0.128	-0.101	-0.110
	(0.236)	(0.167)	(0.200)	(0.237)
Wealth index	1.092***	0.714***	0.251	0.337
	(0.215)	(0.244)	(0.295)	(0.218)
Gender of child (male=1)	-0.211***	-0.223***	-0.231***	-0.206***
	(0.045)	(0.056)	(0.061)	(0.064)
Age of child (months)	-0.030***	-0.026***	-0.026**	-0.022***
	(0.008)	(0.010)	(0.012)	(0.008)
Child birth order	-0.052*	-0.034	-0.016	-0.032*
	(0.028)	(0.021)	(0.016)	(0.018)
Number of siblings of child	-0.011	-0.032	-0.058	-0.037*

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Table 2.3 – *Continued from previous page*

Dependent variable: zhfa	POLS	RE	Mundlak	Hausman-Taylor
	(0.022)	(0.020)	(0.038)	(0.022)
Ethnicity	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes
Observations	3,259	3,259	3,259	3,259
R-squared	0.110	0.108	0.118	
Number of children	838	838	838	838

Cluster bootstrap standard errors in parentheses in (1)-(3) and bootstrap standard errors in (4): *** p<0.01, ** p<0.05, * p<0.1.

Note: "Rain shortage" and "Famine months" stand for negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. Columns (3) and (4) present results using Mundlak (1978) estimator and Hausman-Taylor (1981) estimator, respectively. Ethnicity, religion, region and survey round are all vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Column (1) shows POLS regression results. Both the intensity of the famine experienced by mothers in early childhood and the number of months of famine exposure during the mothers' developmental plasticity are statistically significant at the 1% significance level. These findings show that maternal severe shocks exposure during sensitive developmental periods leaves lasting adverse health impacts on her children. The estimated coefficients indicate that a one standard deviation increase in famine intensity reduces child zhfa by 0.08, while an extra month of famine exposure reduces child zhfa by about 0.04. To put this in context, at the average negative rainfall deviation of 0.25 standard deviations and 1.1

months of famine duration, the effect of the famine on child zhfa is about 0.07 (approximately 5%) decrease in zhfa. As expected, the *wereda* level famine intensity measure shows that the children of mothers who were alive during the famine have lower zhfa. Yet, the effect is not statistically significant. Similarly, the common *wereda* level famine duration is statistically insignificant. Once the common *wereda* level, and mother birth year-specific famine intensity and duration measures are controlled for, whether a mother was born during the 1983-1985 famine period or not appears to have no discernible impact on children's health human capital. The consistency of the these estimates depends on the strong assumption of independence of observations, which is unlikely to hold in a panel data setting.

Column (2) presents RE estimates of the same model. The mother birth year-specific famine intensity and duration estimates are comparable to the POLS estimates. The famine intensity measure is statistically significant while the duration measure is not. As in the POLS model, the common *wereda* famine intensity and duration effects as well as mother famine cohort dummy are statistically insignificant. RE estimates are, however, inconsistent if the individual effects in the error term are correlated with regressors. The coefficient estimates will be biased if, for example, mothers' location of birth, which is associated with the intensity of famine she was exposed to, is correlated with grandparents' economic status. That is, if the mother's place of birth was pre-determined by grandparents location choice where poor households self-select into disease (e.g. malaria) vulnerable or food insecure areas, omitting these location specific factors in the regression will bias the estimated effects of the famine on child zhfa.

Table 2.4: Effects of maternal famine exposure on children's schooling

	(1)	(2)	(3)	(4)
Dependent variable: child grade	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	0.187	0.213	0.197*	0.275***
	(0.188)	(0.135)	(0.115)	(0.081)
Rain shortage × famine cohort	-0.020	-0.023	0.000	-0.037
	(0.039)	(0.038)	(0.031)	(0.061)
Famine months (#)	0.270*	0.287*	0.249*	0.345***
	(0.157)	(0.156)	(0.136)	(0.055)
Famine months × famine cohort	-0.042**	-0.043***	-0.046***	-0.051*
	(0.017)	(0.013)	(0.013)	(0.027)
Famine cohort (famine=1)	-0.038	-0.032	-0.030	-0.009
	(0.052)	(0.050)	(0.054)	(0.106)
Household size	0.008	0.006	0.002	0.004
	(0.028)	(0.024)	(0.036)	(0.029)
Age of household head	-0.001	-0.001	-0.003	-0.002
	(0.003)	(0.003)	(0.007)	(0.005)
Gender of household head (male=1)	0.293***	0.281***	0.284***	0.263**
	(0.084)	(0.101)	(0.097)	(0.116)
Household head schooling	0.038***	0.038***	0.029***	0.028
	(0.008)	(0.006)	(0.007)	(0.028)
Urban/rural (urban=1)	0.082	0.133	-0.097	0.304*
	(0.317)	(0.452)	(0.409)	(0.181)
Shock index	0.333	0.800*	1.298**	2.078***
	(0.601)	(0.439)	(0.518)	(0.516)
Wealth index	1.037***	1.015***	-0.008	0.836*
	(0.282)	(0.268)	(0.504)	(0.451)
Gender of child (male=1)	-0.169**	-0.174**	-0.179**	-0.165**
	(0.075)	(0.070)	(0.080)	(0.068)
Age of child (months)	0.055***	0.053***	0.031	0.076***
	(0.010)	(0.009)	(0.026)	(0.022)
Child birth order	0.027	0.021	0.005	0.013
	(0.021)	(0.016)	(0.024)	(0.033)
Number of siblings of child	-0.103***	-0.108***	-0.148***	-0.112***

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Table 2.4 – *Continued from previous page*

Dependent variable: child grade	POLS	RE	Mundlak	Hausman-Taylor
	(0.031)	(0.034)	(0.057)	(0.038)
Ethnicity	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes
Observations	1,501	1,501	1,501	1,501
R-squared	0.679	0.678	0.679	
Number of children	829	829	829	829

Cluster bootstrap standard errors in (1)-(3) and bootstrap standard errors in (4) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: "Rain shortage" and "Famine months" stand for negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. Columns (3) and (4) present results using Mundlak (1978) estimator and Hausman-Taylor (1981) estimator, respectively. Ethnicity, religion, region and survey round are all vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Columns (3) and (4) report results from MFE and HT estimators, both of which address the limitations of the RE results above. The MFE addresses the potential bias resulting from correlation between regressors and the error term by controlling for the averages of time varying variables in the regression [158], whereas the HT estimator employs step-wise generalized least squares [105]. The coefficient of mother birth year-specific famine intensity is negative and statistically significant under both estimators. The mother birth year-specific famine duration has a negative but statistically insignificant coefficient in the MFE model. The effect sizes are comparable to the of POLS and RE estimates. The stability of the coeffi-

cients across estimators gives confidence as to the reliability of the estimates of the effects of early childhood maternal famine exposure on children's health capability. The common *wereda* famine intensity and duration effects, and mother famine cohort dummy are statistically insignificant under both estimators.

Table 2.4 shows the effects of maternal early childhood famine exposure on the cognitive capabilities of children–child schooling. Column (1) reports POLS results. RE, MFE and HT results are reported in columns (2)-(4). Both the intensity of the famine mothers suffered in early childhood and the duration of the famine have the expected signs (the only exception is famine intensity in MFE). The coefficients of famine intensity are negative, but statistically insignificant. Maternal famine exposure duration has a negative and statistically significant effect on children's grade achievement in all models. The POLS results show that an additional month of maternal early childhood famine exposure reduces child schooling by about 0.04 grades. At the average duration of 1.1 months, this translates to about 0.05 less child years of schooling. The estimated effects are comparable across the various estimators.

The common *wereda* level famine intensity and duration measures have positive and statistically significant coefficients in the MFE and HT models. The results are inconsistent with the hypothesized impacts of famine intensity and duration. These seemingly puzzling results may partly be explained by a range of post-famine emergency development activities. The coefficient of mother famine cohort dummy is negative in all models suggesting that children of mothers born

during the famine have less schooling. Yet, the effects are statistically insignificant.[26]

Table 2.5 provides estimates of the effects of maternal early childhood famine exposure on children's non-cognitive human capital. Column (1) reports results for children's educational aspirations using OLS. The estimated coefficients on maternal early childhood famine intensity and duration as well as *wereda* famine intensity and duration have the expected negative sign. All of the estimates, however, are statistically insignificant. Columns (2)-(5) present estimates of the effects of maternal famine exposure on children's locus of control. The duration of maternal early childhood famine exposure has negative and statistically significant effect on locus of control, whereas the coefficients on famine intensity are statistically indistinguishable from zero. These findings suggest that forward looking attitude of children is shaped more by experiences of long episodes of adverse events than short but deep shock events to parents in their early childhood.These results are consistent with the theory of learned helplessness, in which mothers' early experiences of adverse shocks leads to increased probability of interpreting events as beyond one's control [53]. Mothers' diminished locus of control could then be passed on to their children [157]. Columns (6)-(9) report the effects of early childhood maternal shocks on child self esteem. The results show that the famine had no statistically significant effect on children's self esteem.

[26]Maternal early childhood famine exposure does not appear to have statistically significant effect on child test scores (see Table A1). The estimates from POLS, RE, MFE and HT models of the intergenerational effects of the famine using on child PPVT and Math test scores show no discernible impact.

Table 2.5: Effects of maternal famine exposure on children's non-cognitive human capital

	aspirations	locus of control				self esteem			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.: education aspirations, locus of control & self esteem	OLS	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	0.012	0.015	0.015	0.019	0.016	0.013	0.014	0.016	0.014
	(0.299)	(0.038)	(0.033)	(0.030)	(0.022)	(0.047)	(0.043)	(0.048)	(0.021)
Rain shortage × famine cohort	-0.138	0.002	0.002	0.003	0.001	0.016	0.016	0.016	0.017
	(0.120)	(0.015)	(0.010)	(0.011)	(0.017)	(0.014)	(0.011)	(0.011)	(0.017)
Famine months (#)	-0.263	0.006	0.005	0.010	0.008	-0.024	-0.022	-0.021	-0.024*
	(0.306)	(0.026)	(0.040)	(0.034)	(0.016)	(0.035)	(0.035)	(0.041)	(0.014)
Famine months × famine cohort	-0.043	-0.013**	-0.013**	-0.012**	-0.014*	-0.008	-0.008	-0.008	-0.008
	(0.051)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	(0.006)	(0.008)
Famine cohort (famine=1)	0.143	0.047	0.047**	0.037*	0.050	0.032	0.033	0.030	0.037
	(0.223)	(0.031)	(0.022)	(0.021)	(0.032)	(0.030)	(0.029)	(0.031)	(0.031)
Household size	0.073	-0.010	-0.010	-0.004	-0.006	-0.009	-0.009	-0.015	-0.008
	(0.058)	(0.010)	(0.008)	(0.013)	(0.009)	(0.009)	(0.007)	(0.015)	(0.010)
Age of household head	-0.011**	0.002	0.002	0.001	0.001	0.0004	0.000	0.002	0.001
	(0.006)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Gender of household head (male=1)	0.345*	0.027	0.027	0.029	0.042	0.064***	0.064***	0.061***	0.060*
	(0.185)	(0.030)	(0.023)	(0.026)	(0.039)	(0.025)	(0.024)	(0.023)	(0.034)
Household head schooling	-0.037**	-0.001	-0.001	-0.003	-0.002	0.001	0.001	-0.001	0.007
	(0.017)	(0.004)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)	(0.006)
Urban/rural (urban=1)	0.874*	-0.033	-0.033	-0.078	0.019	0.084	0.081	0.041	0.104**
	(0.454)	(0.059)	(0.108)	(0.099)	(0.050)	(0.073)	(0.076)	(0.087)	(0.052)
Shock index	-1.343	-0.162	-0.163	-0.166	-0.167	-0.256	-0.252*	-0.235	-0.308

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Table 2.5 – *Continued from previous page*

Dep. var.: education aspirations, locus of control & self esteem	OLS	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
	(1.852)	(0.222)	(0.183)	(0.187)	(0.180)	(0.231)	(0.135)	(0.163)	(0.194)
Wealth index	1.769***	0.072	0.073	-0.222	-0.156	0.372***	0.369***	0.059	0.157
	(0.686)	(0.117)	(0.110)	(0.153)	(0.138)	(0.115)	(0.131)	(0.133)	(0.138)
Gender of child (male=1)	-0.024	-0.031	-0.031	-0.031	-0.030	-0.042*	-0.040***	-0.041***	-0.042**
	(0.142)	(0.026)	(0.020)	(0.023)	(0.021)	(0.022)	(0.015)	(0.016)	(0.019)
Age of child (months)	0.062***	-0.001	-0.001	0.006**	0.000	0.002	0.002	0.006*	0.002
	(0.022)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.005)
Child birth order	-0.022	0.000	0.000	0.001	0.001	0.013	0.013	0.011	0.013
	(0.062)	(0.013)	(0.012)	(0.016)	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)
Number of siblings of child	0.018	0.015	0.015*	0.049**	0.014	-0.004	-0.004	0.001	-0.003
	(0.096)	(0.013)	(0.009)	(0.021)	(0.012)	(0.012)	(0.009)	(0.022)	(0.013)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	813	2,484	2,484	2,484	2,484	2,484	2,484	2,484	2,484
R-squared	0.164	0.879	0.880	0.880		0.862	0.861	0.863	
Number of children	813	838	838	838	838	838	838	838	838

Cluster bootstrap standard errors in (1)-(4), (6)-(8) and bootstrap standard errors in (5) & (8) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: "Rain shortage" and "Famine months" stand for negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. PPVT is a short-form for Peabody Picture Vocabulary Test. Columns (3) and (7) present results using Mundlak (1978) estimator, while columns (4) and (8) presents results of the Hausman-Taylor (1981) estimator. Ethnicity, religion, region and survey round are all vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

The results presented in Tables 2.3-2.5 show that mother's early childhood exposure to the 1983-1985 Ethiopian famine has had a lasting negative impact on children's health, cognitive and non-cognitive human capital. The results also show that the duration of mother's early childhood famine exposure matters more to child human capital outcomes than famine intensity. This is understandable in the context of the study area. In many parts of Ethiopia the pre-famine conditions were such that rural households were already food insecure for parts of the year. In these settings, exposure to extended period of famine chips away at any chance of recovery from early disadvantages during the narrow critical developmental period, absent outside relief aid or assistance through informal social networks. The results are robust to model specification and estimation strategy, which gives credence to the estimated effects.

2.6.2 Mechanisms

Maternal Human Capital Outcomes

Table 2.6 presents estimates of the effects of the 1983-1985 famine on the health and cognitive human capital outcomes of mothers who suffered the famine in early childhood. Column (1) reports OLS estimates of maternal health (as measured by mothers' adult height) impacts. Both the intensity of famine experienced in early childhood and its duration have statistically significant effect on mothers' adult height. A one standard deviation increase in famine intensity reduces mothers'

height by about 0.6 centimeters, while an extra month of famine exposure leads to 0.25 centimeters decrease in height. These results indicate that at the mean famine intensity and duration, mothers who experienced the famine in early childhood are about 0.43 centimeters shorter than those that experienced it later. The maternal height effect found in this paper is less than that reported by [72], who use self-reported binary drought measure to identify the effect of the famine on the height of survivors of the famine.[27] The *wereda* level famine intensity and duration effects are positive but statistically insignificant, whereas the famine dummy has the expected sign but is statistically insignificant.

Columns (2)-(5) report the effects of the famine on mothers' schooling using POLS, RE, MFE and HT estimators. The POLS estimates of maternal early childhood famine intensity and duration measures as well as the *wereda* famine intensity and duration measure have the expected negative sign. Increase in the intensity of famine suffered before age three by one standard deviation leads to a 0.44 grades drop in mothers' schooling. Early childhood famine exposure duration and *wereda* famine intensity and duration are statistically insignificant. Mothers in the famine cohort have less schooling compared to their non-famine counterparts. Disruptions caused by the famine appear to have left irreparable impact on mothers' schooling. The RE, MFE and HT model results in column (3)-(5) show comparable early childhood famine intensity impacts on mothers' schooling.

[27] [72] report that people who suffered the famine between the age of 12-36 months are 5.3 centimeters shorter than the reference group. This is an estimate of "average treatment effect on treated", and not "average treatment effect". The corresponding figure in this paper is about 1.1 centimeters, which is still less than the [72] estimates.

Table 2.6: Effects of maternal famine exposure on maternal health and schooling

	Health	Schooling			
	(1)	(2)	(3)	(4)	(5)
Dep. var.: mother height & schooling	OLS	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	0.391	-0.187	0.026	-0.032	0.078
	(3.565)	(0.129)	(0.314)	(0.196)	(0.171)
Rain shortage × famine cohort	-0.614***	-0.437***	-0.512***	-0.451***	-0.537***
	(0.168)	(0.080)	(0.133)	(0.127)	(0.163)
Famine months (#)	0.639	-0.003	-0.041	-0.033	-0.045
	(7.048)	(0.099)	(0.406)	(0.309)	(0.106)
Famine months × famine cohort	-0.230*	-0.028	-0.068	-0.012	-0.069
	(0.122)	(0.043)	(0.074)	(0.072)	(0.095)
Famine cohort (famine=1)	-0.094	-0.677***	-0.350	-0.810***	-0.316
	(0.517)	(0.180)	(0.233)	(0.270)	(0.320)
Household size	-0.130	-0.116***	-0.030	-0.029	-0.031*
	(0.098)	(0.044)	(0.020)	(0.020)	(0.016)
Age of mother	0.019	-0.099***	-0.037*	-0.028	-0.033*
	(0.117)	(0.030)	(0.021)	(0.018)	(0.018)
Gender of household head (male=1)	-0.738*	0.109	-0.007	-0.024	-0.003
	(0.434)	(0.162)	(0.052)	(0.052)	(0.073)
Urban/rural (urban=1)	-0.033	1.295***	3.510***	0.319	3.766***
	(9.958)	(0.447)	(1.003)	(0.859)	(0.439)
Shock index	3.663	0.755	0.363***	0.389**	0.376**
	(3.249)	(0.652)	(0.133)	(0.156)	(0.187)
Wealth index	2.924	8.940***	0.917***	0.423***	0.453**
	(1.945)	(0.702)	(0.208)	(0.158)	(0.219)
Ethnicity	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes
Observations	766	2,995	2,995	2,995	2,995
R-squared	0.078	0.473	0.408	0.523	

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Table 2.6 – *Continued from previous page*

Dep. var.: mother height & schooling	OLS	POLS	RE	Mundlak	Hausman-Taylor
Number of mothers	766	835	835	835	835

Cluster bootstrap standard errors in (1)-(4) and bootstrap standard errors in (5) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: "Rain shortage" and "Famine months" stand for negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. Columns (3) and (4) present results using Mundlak (1978) estimator and Hausman-Taylor (1981) estimator, respectively. Ethnicity, religion, region and survey round are all vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Estimates of the effects of early childhood famine exposure on the non-cognitive human capital of mothers are given in Table 2.7. Columns (1)-(4) report locus of control results, whereas columns (5)-(8) report self-esteem results. The locus of control regression results show that the *wereda* level famine intensity and duration effects are negative and statistically significant, which indicates that mothers who were alive during the famine in more severely affected areas report lower locus of control as adults. There is, however, no especial effect due to exposure in early childhood (as opposed to later in life). These effects are fairly consistent across the four estimators. The coefficient of famine cohort dummy is negative, but statistically insignificant.

Table 2.7: Effects of famine exposure on mother's non-cognitive human capital

	locus of control				self-esteem			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: mothers' locus of control & self esteem	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	-0.083*	-0.083***	-0.075***	-0.093***	0.037	0.038	0.036	0.043*
	(0.043)	(0.025)	(0.025)	(0.027)	(0.037)	(0.038)	(0.042)	(0.024)
Rain shortage × famine cohort	0.015	0.015	0.012	0.017	-0.008	-0.009	-0.006	-0.010
	(0.019)	(0.021)	(0.022)	(0.023)	(0.021)	(0.012)	(0.013)	(0.017)
Famine months (#)	-0.056*	-0.056***	-0.047***	-0.061***	0.035	0.036	0.031	0.042***
	(0.033)	(0.017)	(0.017)	(0.019)	(0.030)	(0.035)	(0.050)	(0.014)
Famine months × famine cohort	-0.005	-0.005	-0.003	-0.004	-0.007	-0.007	-0.008	-0.008
	(0.011)	(0.010)	(0.010)	(0.011)	(0.006)	(0.008)	(0.009)	(0.008)
Famine cohort (famine=1)	-0.019	-0.019	-0.025	-0.045	0.040	0.041	0.043	0.047
	(0.051)	(0.047)	(0.047)	(0.060)	(0.034)	(0.028)	(0.028)	(0.043)
Household size	0.037***	0.037***	0.029*	0.042***	0.016*	0.017**	0.026**	0.022**
	(0.011)	(0.011)	(0.016)	(0.013)	(0.009)	(0.007)	(0.013)	(0.009)
Age of mother	-0.001	-0.001	-0.003	-0.004	-0.000	-0.000	0.000	0.001
	(0.007)	(0.007)	(0.007)	(0.010)	(0.006)	(0.005)	(0.005)	(0.007)
Age of household head	-0.006***	-0.006***	-0.009***	-0.007***	-0.002*	-0.002**	-0.002	-0.003**
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Gender of household head (male=1)	0.124***	0.124***	0.136***	0.163***	0.183***	0.183***	0.181***	0.206***
	(0.042)	(0.037)	(0.038)	(0.049)	(0.033)	(0.025)	(0.028)	(0.041)
Household head schooling	0.009**	0.009**	0.008**	0.000	0.004	0.004*	0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)	(0.006)
Urban/rural (urban=1)	-0.074	-0.074	-0.084	-0.023	-0.123	-0.122	-0.156	-0.065

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Table 2.7 – *Continued from previous page*

Dep. var.: mothers' locus of control & self esteem	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
	(0.095)	(0.051)	(0.054)	(0.070)	(0.080)	(0.107)	(0.123)	(0.057)
Shock index	-0.315	-0.314*	-0.485**	-0.494**	-0.324	-0.315***	-0.189	-0.180
	(0.305)	(0.188)	(0.209)	(0.228)	(0.201)	(0.114)	(0.136)	(0.171)
Wealth index	0.185	0.185	-0.005	0.112	0.540***	0.536***	0.325**	0.375**
	(0.125)	(0.120)	(0.201)	(0.198)	(0.110)	(0.092)	(0.152)	(0.148)
Household expenditure (real)	0.00002	0.00002	-0.00002	-0.00002	0.00005***	0.00005**	0.00003	0.00003*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of children	-0.012	-0.012	-0.031	-0.018	-0.002	-0.002	-0.009	-0.006
	(0.013)	(0.013)	(0.030)	(0.016)	(0.010)	(0.009)	(0.027)	(0.014)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,484	2,484	2,484	2,484	2,484	2,484	2,484	2,484
R-squared	0.501	0.500	0.504		0.426	0.426	0.429	
Number of mothers	838	838	838	838	838	838	838	838

Cluster bootstrap standard errors in (1)-(3) and bootstrap standard errors in (4) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: "Rain shortage" and "Famine months" stand for negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. Columns (3) and (4) present results using Mundlak (1978) estimator and Hausman-Taylor (1981) estimator, respectively. Ethnicity, religion, region and survey round are all vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

The self-esteem regressions, on the other hand, produce no statistically significant causal relationship between maternal shock exposure and adult self-esteem under POLS, RE and MFE. The *wereda* level HT results are slightly inconsistent with expectations in that they are positive and statistically significant.[28]

To ascertain that mothers' adult human capital is indeed the main parent-to-child shock transmission channel, the effects on child human capital in Table 2.3 are re-estimated after partialling out the direct famine effects on mothers' human capital. To that end, I include mothers' health, cognitive and non-cognitive human capital in the child human capital regressions. Table 2.8 reports the new POLS estimates. The negative effects of maternal early childhood shocks on child zhfa reported in Table 2.3 become much smaller and statistically insignificant once mothers' human capital outcomes are controlled for. The coefficients on mothers' health (adult height) and schooling are positive and statistically significant. This points to maternal human capital, especially maternal health, being the prime parent-to-child health shock transmission pathway.

The results for the other human capital dimensions, however, rather suggest that maternal human capital does not play significant role in the intergenerational transmission of shocks to cognitive and non-cognitive human capital. The estimates in Tables 2.4 and 2.5 change little due to the inclusion of maternal human capital in the child human capital regressions. These results seem to suggest the

[28]Regression results of the effects of maternal early childhood famine exposure on mothers' educational aspirations for their children produced no statistically significant impacts. The use of alternative estimators makes no discernible difference to the estimated impacts. These results are given in Table A2.

main intergenerational transmission channels of the effects of the famine on child cognitive and non-cognitive outcomes are perhaps parental child investments. The next section explores these potential channels.

In terms of policy, the implication is that prevention of early childhood shock exposure of girls needs to be given the utmost attention to minimize lasting intergenerational impacts. A large body of evidence lends support to interventions of this nature. This is due childhood zhfa (height) being a good predictor of not only adult health but also of cognitive, non-cognitive and labor market outcomes [151, 148, 111, 47, 3]. The targeting of girls for early intervention, however, poses an ethical dilemma about gender fairness. Practical implementation will require finding the right balance between efficiency and fairness.

Table 2.8: Effects of maternal famine exposure on child human capital after controlling for direct mother human capital effects

	(1) Zhfa	(2) Years of Schooling	(3) PPVT	(4) Math	(5) Educational aspirations	(6) Locus of control	(7) Self-esteem
Rain shortage (SD)	-0.023	0.255	1.432	-0.026	0.164	0.015	0.003
	(0.079)	(0.192)	(2.971)	(0.480)	(0.260)	(0.039)	(0.045)
Rain shortage × famine cohort	-0.036	-0.033	-1.334	0.042	-0.108	0.006	0.010
	(0.032)	(0.043)	(0.954)	(0.277)	(0.119)	(0.016)	(0.015)
Famine months (#)	0.044	0.352**	0.770	-0.190	-0.111	0.016	-0.025
	(0.046)	(0.158)	(1.975)	(0.424)	(0.312)	(0.027)	(0.034)
Famine months × famine cohort	-0.018	-0.049**	0.223	0.039	0.025	-0.023***	-0.016*
	(0.016)	(0.020)	(0.524)	(0.126)	(0.077)	(0.008)	(0.009)
Famine cohort (famine=1)	0.051	-0.040	-2.440	-0.366	-0.067	0.100***	0.050
	(0.061)	(0.070)	(1.822)	(0.416)	(0.250)	(0.033)	(0.033)
Household size	0.002	0.026	-0.006	0.150	0.131*	-0.005	-0.007
	(0.019)	(0.035)	(0.418)	(0.116)	(0.076)	(0.011)	(0.009)
Age of household head age	0.002	-0.004	0.069	0.015	0.002	0.000	-0.001
	(0.003)	(0.004)	(0.068)	(0.020)	(0.007)	(0.001)	(0.001)
Gender of household head (male=1)	0.003	0.280***	-0.059	0.526	-0.039	0.049	0.073**
	(0.054)	(0.089)	(1.141)	(0.346)	(0.212)	(0.031)	(0.032)
Household head schooling	-0.000	0.035***	0.478**	0.186***	-0.028	-0.003	-0.001
	(0.006)	(0.008)	(0.212)	(0.041)	(0.024)	(0.004)	(0.003)
Urban/rural (urban=1)	-0.319**	-0.081	3.722	3.161***	0.732	-0.004	0.124
	(0.126)	(0.273)	(4.108)	(0.900)	(0.539)	(0.075)	(0.080)
Shock index	-0.305	0.499	-23.600**	-2.975**	-0.186	-0.142	-0.237

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Table 2.8 – *Continued from previous page*

	Zhfa	Years of Schooling	PPVT	Math	Educational aspirations	Locus of control	Self-esteem
	(0.284)	(0.593)	(11.390)	(1.430)	(1.370)	(0.214)	(0.213)
Wealth index	0.665***	1.186***	14.040**	4.891***	1.751**	0.039	0.161
	(0.214)	(0.335)	(6.712)	(1.151)	(0.825)	(0.131)	(0.118)
Household expenditure (real)	0.000	0.000	0.000	0.000	-0.000*	-0.000***	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Gender of child (male=1)	-0.160***	-0.174**	-1.093	0.042	0.031	-0.038	-0.044*
	(0.041)	(0.080)	(0.925)	(0.237)	(0.149)	(0.028)	(0.022)
Age of child (months)	-0.011*	0.064***	1.191***	0.188***	0.048**	0.001	0.003
	(0.007)	(0.009)	(0.215)	(0.032)	(0.024)	(0.003)	(0.002)
Child birth order	-0.036	0.021	-1.413**	-0.261*	-0.030	0.002	0.014
	(0.025)	(0.020)	(0.590)	(0.137)	(0.064)	(0.014)	(0.013)
Number of siblings of child	0.002	-0.126***	-0.435	-0.231	-0.011	0.019	-0.007
	(0.022)	(0.032)	(0.548)	(0.147)	(0.094)	(0.013)	(0.012)
Mother height (cm)	0.040***	-0.002	0.005	-0.008	-0.027	0.000	-0.002
	(0.004)	(0.006)	(0.089)	(0.020)	(0.019)	(0.002)	(0.001)
Mother schooling	0.016**	-0.007	0.326	0.068	0.003	0.005	0.002
	(0.008)	(0.009)	(0.209)	(0.047)	(0.029)	(0.004)	(0.004)
Mother's child schooling aspiration	-0.012	0.063***	0.688**	0.180***	0.273***	0.000	-0.000
	(0.010)	(0.024)	(0.268)	(0.065)	(0.036)	(0.008)	(0.005)
Mother locus of control	0.042	0.053	2.119**	0.554***	0.335**	0.026	-0.009
	(0.035)	(0.056)	(1.065)	(0.209)	(0.158)	(0.028)	(0.019)
Mother self-esteem	0.004	-0.127**	2.744**	-0.187	0.268**	0.075**	0.216***
	(0.041)	(0.064)	(1.186)	(0.253)	(0.122)	(0.035)	(0.032)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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Table 2.8 – *Continued from previous page*

	Zhfa	Years of Schooling	PPVT	Math	Educational aspirations	Locus of control	Self-esteem
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,085	1,225	2,013	1,260	645	2,090	2,090
R-squared	0.169	0.699	0.594	0.507	0.238	0.890	0.875

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: This table presents pooled OLS estimates of the effects of maternal famine exposure on child human capital outcomes after direct maternal human capital effects are controlled for. "Rain shortage" and "Famine months" are total negative monthly rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. Ethnicity, religion, region and survey round are all vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Parental Investments

Tables 2.9 and 2.10 present the effects of maternal early childhood famine exposure on parental child investments. Table 2.9 reports the results of household expenditure regressions using alternative estimators. The results show that the 1983-1985 famine had no statistically discernible impact on the household expenditure of mothers who were affected as young girls. This may be because mothers are not the main income earners in the majority of households in the data. In 86% of households, males are household heads and tend to be the main breadwinners of the family.

The effects of maternal early famine exposure on education and health expenditures are reported in Table 2.10. The results are similar to the total expenditure regressions above. Maternal early childhood famine exposure has no statistically significant effect on the amount of money households spend on education and health. The common *wereda* level famine intensity and duration measures are positive and weakly statistically significant in the health regressions using HT model, however. These results suggest that parental investments are unlikely to be key parent-to-child famine transmission channel.

Table 2.9: Effects of maternal famine exposure on household expenditure

Dependent variable: real expenditure	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	27.002	45.278	38.683	126.842
	(69.804)	(388.766)	(426.076)	(143.395)
Rain shortage × famine cohort	7.448	5.502	10.875	6.246
	(28.382)	(36.237)	(39.477)	(77.606)
Famine months (#)	7.736	12.773	-0.853	14.993
	(36.612)	(232.486)	(250.203)	(118.103)
Famine months × famine cohort	3.808	5.121	4.084	13.161
	(8.824)	(11.419)	(10.516)	(35.035)
Famine cohort (famine=1)	13.917	3.572	12.876	-50.645
	(36.446)	(46.311)	(48.369)	(140.578)
Household size	113.177***	103.321***	79.836***	83.488***
	(15.187)	(18.657)	(17.167)	(18.782)
Age of household head	3.357	4.321	6.499	6.227
	(2.316)	(3.206)	(5.894)	(5.749)
Gender of household head (male=1)	86.449*	115.270*	108.056*	166.509***
	(48.646)	(63.884)	(63.019)	(57.446)
Household head schooling	39.100***	39.666***	33.141*	41.038*
	(6.870)	(10.315)	(20.080)	(22.115)
Urban/rural (urban=1)	427.142***	452.334	423.727	573.010
	(110.720)	(342.440)	(364.689)	(434.739)
Shock index	-277.371	-71.435	114.352	272.732**
	(227.579)	(207.091)	(203.111)	(132.515)
Ethnicity	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes
Observations	2,484	2,484	2,484	2,484
R-squared	0.208	0.206	0.212	
Number of children	838	838	838	838

Cluster bootstrap standard errors in (1)-(3) and bootstrap standard errors in (4) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table 2.9 presents the effects of maternal famine exposure on real total expenditure. "Rain shortage" and "Famine months" are total monthly negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. Columns (3) and (4) present Mundlak (1978) pseudo fixed effects and Hausman-Taylor (1981) results, respectively. Ethnicity, religion, region and survey round are vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Table 2.10: Effects of maternal famine exposure on household education expenditure

	Education expenditure				Health expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: education expenditure	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	140.370	145.772	139.465	126.841	277.650	277.650	282.006	293.584*
	(90.446)	(330.682)	(342.798)	(143.395)	(203.787)	(188.302)	(176.055)	(177.777)
Rain shortage × famine cohort	-12.412	-13.777	-0.209	6.246	-11.280	-11.280	-9.062	-13.858
	(30.204)	(45.940)	(49.616)	(77.606)	(40.364)	(43.813)	(48.342)	(40.230)
Famine months (#)	6.275	8.967	-6.907	14.993	160.111	160.111	154.517*	174.168*
	(54.815)	(185.996)	(184.379)	(118.103)	(119.340)	(115.072)	(81.252)	(103.400)
Famine months × famine cohort	16.992	16.802	18.810	13.161	-25.468	-25.468	-24.644	-26.056
	(15.243)	(20.510)	(20.589)	(35.035)	(42.291)	(32.658)	(32.328)	(36.797)
Famine cohort (famine=1)	-91.652*	-95.571	-79.241	-50.645	-78.052	-78.052	-30.855	-73.767
	(54.850)	(87.335)	(94.632)	(140.578)	(74.125)	(68.853)	(75.744)	(107.934)
Household size	106.723***	102.509**	58.889	83.488***	-21.963	-21.963	-176.780	-26.568
	(37.755)	(45.015)	(70.694)	(18.782)	(39.909)	(48.146)	(195.239)	(61.155)
Age of household head	1.013	0.592	-4.509	6.227	8.565	8.565	7.096	9.074
	(3.358)	(3.847)	(5.298)	(5.749)	(8.532)	(7.717)	(8.414)	(5.820)
Gender of household head (male=1)	2.486	4.210	24.557	166.509***	-32.220	-32.220	-20.689	-59.599
	(57.262)	(73.421)	(79.982)	(57.446)	(131.730)	(130.496)	(133.546)	(357.166)
Household head schooling	67.629***	67.020***	30.844	41.038*	51.958	51.958	45.610	59.271
	(12.708)	(16.241)	(18.937)	(22.115)	(40.425)	(36.026)	(32.040)	(63.097)
Urban/rural (urban=1)	377.814**	390.176	335.266	573.010	364.510	364.510	346.457	346.965
	(156.169)	(347.026)	(349.357)	(434.739)	(292.867)	(281.229)	(276.970)	(452.655)
Shock index	-203.551	-45.706	346.682	272.732**	1,246.987**	1,246.987**	1,457.608**	1,705.817**

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Table 2.10 – *Continued from previous page*

Dependent variable: education expenditure	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
	(306.470)	(364.737)	(376.441)	(132.514)	(537.269)	(585.130)	(694.513)	(750.214)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,484	2,484	2,484	2,484	2,484	2,484	2,484	2,484
R-squared	0.189	0.189	0.194		0.016	0.016	0.02	
Number of children	838	838	838	838	838	838	838	838

Cluster bootstrap standard errors in (1)-(3) and (5)-(7) and bootstrap standard errors in (4) and (8) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table 2.10 presents the effects of maternal famine exposure on annual household education and health expenditures. "Rain shortage" and "Famine months" are total monthly negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. The results under "Mundlak" and "Hausman-Taylor" columns obtained using Mundlak (1978) pseudo fixed effects and Hausman-Taylor (1981) estimators, respectively. Ethnicity, religion, region and survey round are vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

2.6.3 Heterogeneous Effects

While exposure to extended famine periods is expected to be more damaging, it is not obvious whether increase in famine duration leads to increasing or decreasing effects on child human capital outcomes, at the margin. Critical shifts in famine effect regimes, if any, provide crucial input in the design of efficient interventions. To this effect, each additional month of maternal early childhood famine exposure is allowed to have a unique effect. Results for health, cognitive and non-cognitive human capital of children using POLS are reported in Table 2.11.[29]

The estimates in column (1) show that the effects of maternal early childhood famine exposure on children's height-for-age z-score depends non-linearly on the duration of exposure. Famine impacts are generally increasing in famine duration. The effects of the famine become worse for famine durations of four months and higher. Similar results are obtained for child schooling. As shown in column (2), the maternal early childhood famine exposure effects increase with the length of famine duration. The estimated coefficients jump at famine duration of four months. To test the statistical significance of the difference in coefficient size between famine durations less than four months and four months and higher, I re-estimate the model by including a dummy variable that takes value 1 for famine duration of four months and higher. The results confirm that the differences the coefficients are indeed statistically significant (-0.193(**) for height-for-

[29]Estimates from RE, MFE and HT models are given in Table A3 in the Appendix. The findings are consistent with POLS estimates.

age z-score and -0.289(***) for child schooling).[30] The effects on test scores (PPVT and Math) and non-cognitive human capital are, however, statistically insignificant. These results point to a critical maternal famine exposure threshold of about three months, beyond which the effects of the famine become severe.

Table 2.12 reports the life cycle effects of maternal early childhood famine exposure on the human capital outcomes of children using POLS.[31] Column (1) reports results for height-for-age z-score. Height-for-age is measured in the data from age one through age 12 in about three year intervals. The results show that the effects of maternal childhood shocks are greater (and statistically significant) in early childhood (age one) and early adolescence (age 12). While the effect is negative throughout, it is statistically insignificant at ages five and eight. The estimated effect size drops off after year one, but gradually rises though age 12. These findings suggest that the effect of early intergenerational disadvantages on health does not decay but worsen over the child's life cycle, which points to the likely ineffectiveness of remediation efforts in late childhood.

[30]These results can be obtained upon request.
[31]See Table A4 in the Appendix for RE, MFE and HT model estimates.

Table 2.11: Heterogeneous effects of maternal famine exposure duration on child human capital

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	zhfa	child schooling	PPVT	Math	locus of control	self-esteem
Rain shortage (SD)	-0.023	0.178	0.834	-0.456	0.020	0.019
	(0.069)	(0.191)	(2.878)	(0.421)	(0.037)	(0.047)
Rain shortage × famine cohort	-0.088**	-0.062	-0.231	0.156	0.002	0.021
	(0.041)	(0.041)	(0.877)	(0.239)	(0.020)	(0.019)
Famine months (#)	0.037	0.266*	0.402	-0.440	0.008	-0.024
	(0.044)	(0.158)	(1.785)	(0.311)	(0.024)	(0.034)
1 Famine month × famine cohort	0.016	0.050	-2.490	-0.089	0.002	-0.032
	(0.110)	(0.105)	(1.751)	(0.580)	(0.036)	(0.043)
2 Famine months × famine cohort	-0.143	-0.050	1.406	-0.640	-0.024	-0.023
	(0.090)	(0.133)	(1.841)	(0.395)	(0.038)	(0.045)
3 Famine months × famine cohort	-0.055	-0.039	2.375	0.946	-0.057	-0.001
	(0.083)	(0.146)	(3.749)	(0.641)	(0.043)	(0.054)
4 Famine months × famine cohort	-0.234*	-0.340**	0.506	1.904***	-0.068	-0.098
	(0.133)	(0.146)	(2.990)	(0.581)	(0.058)	(0.066)
5 Famine months × famine cohort	-0.022	-0.509***	6.053	0.236	-0.087	0.019
	(0.171)	(0.191)	(3.687)	(0.878)	(0.078)	(0.053)
6 Famine months × famine cohort	-0.251*	-0.129	4.770	0.829	0.015	0.061
	(0.151)	(0.266)	(4.842)	(0.607)	(0.065)	(0.119)
7 Famine months × famine cohort	-0.312***	-0.310	0.649	-0.176	-0.115**	-0.078
	(0.107)	(0.225)	(4.179)	(0.703)	(0.055)	(0.071)
Famine cohort (famine=1)	0.045	-0.057	-1.857	-0.780**	0.047	0.033
	(0.064)	(0.057)	(1.251)	(0.318)	(0.032)	(0.031)
Household size	0.018	0.011	0.159	0.143*	-0.010	-0.008
	(0.021)	(0.028)	(0.418)	(0.082)	(0.010)	(0.009)
Age of household head	0.000	-0.003	0.027	-0.007	0.002	0.000
	(0.002)	(0.003)	(0.059)	(0.014)	(0.001)	(0.001)
Gender of household head (male=1)	0.044	0.377***	2.024	1.111***	0.025	0.067***
	(0.059)	(0.084)	(1.339)	(0.307)	(0.026)	(0.024)
Urban/rural (urban=1)	-0.245**	0.133	4.558	3.367***	-0.032	0.088
	(0.110)	(0.342)	(4.437)	(0.711)	(0.057)	(0.072)
Shock index	-0.174	0.253	-34.256***	-5.366***	-0.168	-0.276
	(0.237)	(0.605)	(11.729)	(1.579)	(0.219)	(0.223)
Wealth index	1.145***	1.402***	26.610***	7.790***	0.064	0.384***
	(0.201)	(0.304)	(6.111)	(0.910)	(0.101)	(0.103)

Gender of child (male=1)	-0.212***	-0.172**	-0.944	-0.005	-0.032	-0.044**
	(0.043)	(0.075)	(0.919)	(0.234)	(0.025)	(0.022)
Age of child (months)	-0.030***	0.056***	1.167***	0.184***	-0.001	0.001
	(0.008)	(0.010)	(0.203)	(0.029)	(0.003)	(0.002)
Child birth order	-0.054*	0.025	-1.444**	-0.278**	0.000	0.013
	(0.028)	(0.020)	(0.610)	(0.116)	(0.013)	(0.015)
Number of siblings of child	-0.010	-0.108***	-0.475	-0.263**	0.015	-0.005
	(0.022)	(0.030)	(0.598)	(0.114)	(0.013)	(0.012)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,259	1,501	2,394	1,541	2,484	2,484
R-squared	0.111	0.675	0.590	0.476	0.879	0.862
Number of children	838	838	838	838	838	838

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table 2.11 presents the heterogeneous effects of maternal famine exposure duration on child human capital using POLS. "Rain shortage" and "Famine months" are total monthly negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. "# Famine month × famine cohort" represents the effects of maternal early childhood famine exposure duration of # months on children's human capital. Ethnicity, religion, region and survey round are vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Table 2.12: Child life-cycle effects of maternal early childhood famine exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	zhfa	child schooling	PPVT	Math	locus of control	self-esteem
Rain shortage (SD)	-0.018	0.166	0.384	-0.401	0.016	0.012
	(0.066)	(0.185)	(2.811)	(0.414)	(0.038)	(0.048)
Rain shortage × famine cohort	-0.084**	-0.024	-0.663	-0.002	0.002	0.016
	(0.033)	(0.038)	(0.717)	(0.221)	(0.016)	(0.014)
Famine months (#)	0.042	0.263*	0.325	-0.420	0.006	-0.024
	(0.043)	(0.158)	(1.770)	(0.311)	(0.026)	(0.035)
Famine month × famine cohort × round 1	-0.075**	-	-	-	-	-
	(0.033)	-	-	-	-	-
Famine month × famine cohort × round 2	-0.016	-	0.004	-	-0.009	0.002
	(0.021)	-	(0.531)	-	(0.007)	(-0.026)
Famine month × famine cohort × round 3	-0.031	-0.025	1.029	0.062	-0.021**	-0.026**
	(0.021)	(0.278)	(1.137)	(0.117)	(0.010)	(0.011)
Famine month × famine cohort × round 4	-0.040**	-0.055*	-0.140	0.065	-0.009	0.001
	(0.020)	(0.031)	(0.459)	(0.137)	(0.011)	(0.012)
Famine cohort (famine=1)	0.045	-0.062	-1.652	-0.718**	0.047	0.032
	(0.061)	(0.052)	(1.304)	(0.323)	(0.030)	(0.029)
Household size	0.018	0.010	0.116	0.127	-0.010	-0.009
	(0.021)	(0.028)	(0.413)	(0.079)	(0.010)	(0.009)
Age of household head	0.000	-0.003	0.028	-0.006	0.002	0.000
	(0.002)	(0.003)	(0.061)	(0.014)	(0.001)	(0.001)
Gender of household head (male=1)	0.048	0.381***	2.031	1.092***	0.025	0.068***
	(0.058)	(0.083)	(1.354)	(0.302)	(0.026)	(0.024)
Urban/rural (urban=1)	-0.254**	0.128	4.286	3.291***	-0.033	0.083
	(0.111)	(0.342)	(4.438)	(0.714)	(0.057)	(0.073)
Shock index	-0.183	0.310	-33.366***	-5.275***	-0.163	-0.265
	(0.233)	(0.620)	(11.654)	(1.552)	(0.219)	(0.224)
Wealth index	1.143***	1.406***	27.243***	8.130***	0.063	0.381***
	(0.202)	(0.298)	(6.151)	(0.889)	(0.100)	(0.104)
Gender of child (male=1)	-0.210***	-0.163**	-0.982	-0.060	-0.031	-0.041*
	(0.045)	(0.076)	(0.909)	(0.234)	(0.025)	(0.022)
Age of child (months)	-0.030***	0.056***	1.174***	0.177***	-0.001	0.002
	(0.008)	(0.009)	(0.203)	(0.029)	(0.003)	(0.002)
Child birth order	-0.054*	0.022	-1.460**	-0.272**	0.001	0.013
	(0.028)	(0.020)	(0.620)	(0.115)	(0.013)	(0.015)

Number of siblings of child	-0.011	-0.110***	-0.377	-0.271**	0.015	-0.004
	(0.022)	(0.030)	(0.589)	(0.108)	(0.013)	(0.012)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,259	1,501	2,394	1,541	2,484	2,484
R-squared	0.111	0.675	0.590	0.476	0.879	0.862

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table 2.12 shows the evolution of the life cycle effects of maternal early childhood famine exposure on the child human capital. "Rain shortage" and "Famine months" are total monthly negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. "Famine month × famine cohort × round #" represents the effects of the famine on child human capital measured in survey round #. Ethnicity, religion, region and survey round are vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

The evolution of the effects of the famine on children's schooling displays a similar pattern. However, data on child schooling were collected only in rounds 3 and 4 as the Young Lives children were too young to enroll in school in rounds 1 and 2. The results shown in column (2) indicate that the famine effect worsens over time. The life cycle effects on test scores are statistically insignificant, however. In the locus of control and self-esteem regressions, on the other hand, the famine effect is statistically significant at age eight.

The results presented thus far point to the limited malleability of health and cognitive (grade completed) human capital through late remediation once the damage is done to mothers in early childhood. This effect is especially greater for children born to mothers who were exposed to the famine as young girls for over three months. This has a crucial policy implication to the timing and targeting of

interventions. To maximize the impacts of interventions in communities that are vulnerable to severe shocks, emphasis should be placed on reaching young girls before they are exposed to shocks of three months or longer.

2.6.4 Selective Migration

Migration is one of the traditional risk coping strategies during periods of crisis in rural Ethiopia [82, 83]. Migration decisions are usually made at the household level, with household members moving in search of alternative income sources such as wage labor to supplement agricultural incomes or to live with better off close relatives to relieve food shortages in the original household [92]. In rare cases, whole households leave their villages after exhausting other options, which may include consuming seedling stocks, selling off livestock and other assets including farm implements. During the 1983-1985 famine, there were both voluntary and involuntary household relocations. Some households saw no future in their villages and voluntarily relocated to start afresh in remote settlement camps organized by the government. The number of voluntary settlers were short of the government's plan. As a result, it resorted to involuntary resettlement measures to move households from the famine areas to fertile remote areas in the south and western Ethiopia [92].

These movements pose serious identification challenges, as they are almost certainly not random. In fact, [83] show that rural out-migration between 1984

and 1994 was higher among vulnerable communities. If the nature of migration during the famine was such that the poorest and most vulnerable stayed in their villages, the estimated coefficients would overestimate the true impact of the famine. This would be the case if the poor cannot access the capital required for costly migration. In previous studies, [98] find that internal migration decreased in Ecuador during droughts, perhaps due to the relative poverty of internal migrants. Likewise, [109] find that the rural-urban migration of women in Burkina Faso decreased during droughts. On the contrary, if out-migration is a last resort option such that the very desperate who can no longer make ends meet at their place of origin leave, the true impact of the famine would be underestimated. In what follows, I address the potential selective migration problem by 1) reviewing results from previous studies, 2) providing the institutional and environmental context during and after the famine and 3) conducting a robustness check using retrospective data on mother's history of village residence.

The data used in this study does not track mothers' place of birth. As a result, the unbiasedness of the famine impact estimates depends on the assumption that there was no systematic relocation of mothers from their village of birth. That is, there was no statistically significant difference in the baseline migration history of the mothers born during and before/ after the famine as observed in the 2002 baseline. As noted above, however, drought is one of the prime disruptive events in much of the developing world, and tends to affect the most vulnerable more. Moreover, in addition to migrations during the famine, migrations that happen in the intervening period between the famine and the baseline can also bias esti-

mates of the famine impacts if they were systematic (non-random) in nature. It is also feasible that a mother may have moved during the famine or in the period after, but had returned to the place of origin by the time the baseline survey was conducted. The survey includes a question on the duration of stay at the place where the household was first interviewed. I address the identification issues due to potential selective migration by limiting the estimation sample to mothers who have lived at the interview location since, at least, the famine period.

Relative to the scale of the crisis, out-migration during the famine was modest. [92] reports that only a third of the famine affected population moved out of their villages while two-thirds stayed at home. Several factors contributed to restrict the movement of people from the famine areas to the rest of the country. First, due to insurgencies in Eritrea and Tigray in the north, the government had imposed restrictions on the movement of people. People leaving their villages were required to get permits from their Peasants' Association, making migration prohibitively difficult [27]. Second, availability of emergency food aid in some of the most affected villages encouraged people to stay in their villages. Though the delivery food aid in the famine affected areas was delayed due to logistical and political reasons and the number of beneficiaries was low, relief aid played a crucial role in retaining people in their villages. The bulk of food aid began to arrive in late 1984. In total, there were 195 food distribution posts, 20 large shelters and 41 intensive feeding centers for malnourished children and mothers by November 1984 [1].

Third, after coming to power in 1974, the military government (Derg) abolished the old feudalistic land tenure system and in February 1975 issued a land reform proclamation that nationalized all rural land and prohibited private ownership of land and the hiring of labor for agricultural activities. The proclamation bestows upon landholders usufruct rights with no rights to sell, lease, sharecrop or transfer the land [124]. To carry out the provisions of the proclamation, Peasant Associations were formed at the locality (*chika*) level within a minimum area of 800 hectares. The rights over rural land were tied to membership in Peasant Associations and residence within the area. This is believed to have restricted the movement of households from the famine ravaged areas [54]. There were no major changes in land policy following the fall of the Derg in 1991. Land is still owned by the state with landholders entitled to usufruct rights. Some of the restrictions on leasing and mortgaging rural land have been relaxed. However, these are unlikely to have had appreciable impact on mobility of rural households [27, 67].

Much of the rural out-migration in Ethiopia takes place for economic or marriage reasons. Men tend to move for economic reasons more, while women primarily move for marriage reasons. During periods of crisis economic migration increases with able bodied men moving in search of opportunities to supplement rural incomes [83]. The potential selective migration due to economic reasons, thus, is lower for women [99]. Marriage related movement of women, however, poses a major challenge. If the famine altered the composition of the women who leave their parents' homes for marriage, the estimated famine impacts could be

biased. To test if there is a systematic difference in the likelihood of migration between mothers in the famine cohort and non-famine cohort, I regress a migration dummy variable on famine cohort dummy and a range of control variables including mother's age, husband's age, region, religion, ethnicity and urban-rural dummy. The result shows that there was no statistically significant difference in likelihood of migration between mothers affected by the famine as young girls and those who were not.[32] Moreover, under the 1975 land proclamation women and other minority groups were for the first time given the right for access to land. This combined with the requirement of residence in the community where the farm is located may have limited the distance women move for marriage reasons.

The evidence thus far suggests that potential selective migration concerns are likely very low in the setting I study. To further corroborate this, I conduct robustness checks using data on mothers who have not moved from their community. Table A5 in the appendix presents the pooled OLS regression results of the effects of early childhood maternal famine exposure on the human capital outcomes of their children for a sub-sample of mothers who have lived in the study for at least 15 years by the 2002 baseline. This ensures that the mothers included in the sample had reached reproductive age by the baseline. Like the rest of the analysis sample used in the rest of the paper, the sample was further trimmed to include only mothers born between 1978 (three years before the famine) and 1988 (three years after the famine).

[32]These regression results could be obtained upon request.

The results are consistent with the main results reported in Tables 2.3-2.5. Overall, both the intensity and duration of famine experienced by mother in early childhood have negative impact on their children's human capital. The impact is particularly strong for zhfa and children's grade achievement. Increase in the duration of maternal famine exposure reduces children's non-cognitive human capital, though the effects are statistically insignificant. Likewise, the effect of the famine on children's schooling aspirations and self locus of control is negative, but statistically insignificant.

2.6.5 Selective Fertility and Mortality

Selective fertility could be an identification challenge if the mothers in the sample were affected as young girls by selective fertility behavior due to the famine. That is, if grandparents of the Young Lives children had changed their fertility behavior in response to, for example, increase in child mortality and morbidity, scarcity of food and other resources or slack labor due to limited agricultural activities. If fertility increases, competition for food and medication would rise and expose the Young Lives children's mothers to greater scarcity *in utero* and as young girls than they otherwise face. In this case the estimated famine impacts may overestimate the true impact of the famine. On the contrary, if fertility declines as grandparents seek to increase food intake per household members or to avoid the trauma of losing children, the Young Lives mothers would be exposed to lesser shocks as young girls than they otherwise would. This would lead to underestimation of

the true impact of the famine.

The empirical strategy used in this paper accounts for the potential selective fertility problems outlined above. The effects of changes in fertility behavior due to the famine, if any, would be observed on the famine cohort (mothers born between 1981 and 1985) and not the non-famine cohort. The cohort dummy included in all of the regression equations, thus, would control for the effect of such changes in fertility behavior. If, rather, the fertility changes are not limited to the 1981-1985 cohort but vary over time, the effects of these changes on the human capital outcomes of children would be absorbed by parents' age which is also included in all of the regression equations.

Previous studies of the effects of the famine on fertility find no change or temporary decline in fertility. [82] shows that the fertility rate of ever-married women remained stable between 1975 and 1989 for 15-49 years old cohorts of women. There was a sharp decline in fertility in the 1990s, but this is unlikely to have any effect on the cohorts of mothers in Young Lives baseline in 2002. [144] find that probabilities of conception temporarily decline during the famine (1985) but rebound afterwards. Likewise, [127] shows that fertility declined in 1984-1985 among famine victims compared to the pre-famine (1981) fertility rate in one of the famine affected areas (Wello). These results appear to suggest that the famine impacts estimated in this paper may be underestimated.

Selective mortality causes another identification challenge. Granted the very high mortality rates associated with the famine, the mothers who survived the

famine as young girls and were observed in the baseline are likely to have experienced less severe famine or have greater tolerance to the hazards related to the famine. In this sense, selective mortality may underestimate the true impact of the famine on the human capital outcomes of children. [127] finds that the likelihood of childhood (ages 0-4) mortality during the famine was uncorrelated with observable household and village characteristics, which suggests perhaps that the likelihood of mothers' being observed in the Young Lives baseline in 2002 may not be correlated with grandparent characteristics. Despite the potential downward bias, the statistically significant findings of negative intergenerational impact of the famine gives greater credence to the findings in this paper.

2.7 Conclusions

This paper investigates the intergenerational effects of maternal early childhood famine exposure on the human capital outcomes of children. The 1983-1985 Ethiopian famine is used as an exogenous source of variation to identify the effects of exposure to severe shocks during developmental plasticity on the health, cognitive and non-cognitive human capital of children whose mothers suffered the famine as young girls. There is paucity of empirical work in this area. This is one of the first papers to look at the intergenerational effects of severe shocks [46, 191]. The paper explores the potential parent-to-child shock transmission channels. In particular, it determines whether the effects of a mother's famine exposure on the

human capital of her offspring decay over time. It also identifies critical famine duration thresholds.

I find that maternal early childhood famine exposure has a negative effect on children's health (height-for-age z-score), cognitive (number of years of schooling) and non-cognitive (locus of control) human capital. At the sample average famine intensity and duration, the 1983-1985 famine led to a 5% decrease in height-for-age z-score and a 0.05 grades decrease in the number of years of schooling of children born to mothers affected by the famine *in utero* and/ or before age three. The main parent-to-child shock transmission channel is found to be children's maternal human capital endowment. Mothers who were exposed to the famine early in childhood are about 0.5 centimeters shorter. This estimate is considerably less than that obtained by [72] for Ethiopia. Mothers' schooling decreases by about 0.5 grades due to the famine.

The effect of the famine on children's height-for-age z-score and schooling depends non-linearly on maternal famine exposure duration. While the adverse impacts of the famine worsen with increase in famine duration, it sharply rises after three months of famine. This suggests existence of a critical maternal famine duration threshold at about three months of famine exposure. The effects of the famine on height-for-age z-score and schooling persist through children's life cycle from age one through early adolescence (age 12). In fact, the negative effect sizes become greater over time. This seems to suggest remediation may not be effective in mitigating the impacts of maternal early childhood famine exposure

on child human capital.

The findings of the paper point to a few policy implications. First, shocks experienced early in childhood have impacts that last through generations. To minimize the adverse effects of shocks, health and nutritional interventions to children in the developmental plasticity is crucial. Since the effects of the famine are primarily channeled through maternal outcomes ([46, 191] find similar results), young girls should be targeted for intervention during natural disasters. This is further reinforced by the persistence of the effects of shocks through children's life cycle. Second, for optimum intervention, the focus should be on girls under three years old with the highest likelihood of crossing the critical famine duration threshold of three months. That is, primacy should be given to girls who have suffered just under three months of severe shock in the delivery of assistance.

CHAPTER 3

INSURING WELLBEING? BUYER'S REMORSE AND PEACE OF MIND EFFECTS FROM INSURANCE

3.1 Introduction

Uninsured risk exposure in low-income rural communities is widely believed to cause serious welfare losses and to distort behaviors, potentially even resulting in poverty traps [178, 156, 44, 71, 21, 183]. However, standard insurance products are routinely unavailable due to moral hazard and adverse selection problems and high transaction costs in infrastructure-poor areas [29]. In response to the lack of affordable standard insurance products, there has been a significant push to expand index insurance offerings in the developing world over the past decade.[1]

Index insurance attempts to mitigate adverse selection, moral hazard and high transaction cost concerns by writing contracts not on policyholders' realized losses but, instead, on a low-cost, observable indicator – the 'index' – believed to be strongly correlated with actual losses. There is, however, little empirical evidence demonstrating that index insurance generates welfare gains for poor, rural households.[2] Indeed, the low uptake of index insurance products in a range of countries suggests that perhaps many prospective buyers believe index insurance

[1] See [49] for an extensive discussion of these issues as they apply to a setting very similar to the one we study, and [154, 188] and [119] for broader reviews.

[2] [117, 123] and [120, 121] are notable recent exceptions.

does not deliver welfare gains [95, 33, 57].[3] Index insurance uptake may even cause welfare losses for buyers for at least two reasons. First, high commercial loadings by insurers can drive premium rates above actuarially fair levels. Second, when the index does not closely track policyholders' actual losses, the imperfect correlation creates "basis risk" that can result in uninsured losses despite the purchase of insurance. This can lead to uninsured catastrophic loss despite a premium payment; as a result, index insurance will not stochastically dominate remaining uninsured [120].

Estimating the welfare effects of insurance coverage is complicated because insurance produces two potentially opposite effects on the welfare of buyers. Holding insurance before the resolution of uncertainty generates *ex ante* well-being effects. Insurance may increase *ex ante* welfare for risk averse agents prior to the realization of stochastic events that may otherwise impose substantial losses. These *ex ante* well-being effects of insurance may differ from, and be partly offset by, the *ex post* well-being effects of lapsed insurance that did not pay any indemnity. *Ex post* effects arise after the resolution of uncertainty. The same insurance that is *ex ante* welfare improving may prove *ex post* welfare reducing, in a later period, once the risk has passed and a purchaser realizes with perfect hindsight that she

[3] [95] report that take-up rate of a rainfall insurance product in Andhra Pradesh, India was very low, at just 4.6 percent. They argue this might reflect the short history of the product. Similarly, Cole et al. (2013) find that the take-up rate of livestock insurance among the untreated general population in Andhra Pradesh and Gujarat, India, is close to zero. [33] argues that there is low demand for index insurance because better-off farmers have already self-insured through diversification of their portfolios and informal social networks, while the poor face liquidity constraints that limit their participation. [123], on the contrary, find that at an actuarially fair price, almost half of the farmers in their sample from northern Ghana demand index insurance and purchase coverage for more than 60 percent of their acreage.

could have foregone the premium payment without consequence. In this case, the buyer has "lost" her premium and would have been unambiguously better off financially had she not bought insurance coverage after all. If insurance purchase is positively correlated over time, this then raises the possibility that buyer's remorse can confound valuation of insurance coverage, biasing downwards estimates of the value of current insurance coverage following periods without indemnity payments, when insurance purchase lost the insuree money.

In this paper we take a novel approach to estimating the welfare impact of insurance on a poor, rural population, exploring whether index insurance coverage improves subjective well-being (SWB) and disentangling the potentially distinct effects of current and lapsed insurance coverage. The analysis of gains from insurance coverage has typically relied on either relatively weak tests of stochastic dominance or strong assumptions about utility functions [206, 88, 102, 69]. Recent innovations in SWB measurement, however, permit relaxation of many of the strong assumptions on which such analyses rely. Further, measures of SWB often yield deeper insights beyond the traditional income and expenditure based well-being measures [173, 134]. Indeed, conventional measures of well-being may underestimate the true value of a program. A program can have significant effects on SWB even if it does not generate observable material or physical impacts [75, 89, 146]. As a result, SWB measures have become increasingly popular in welfare assessment [91, 55, 84, 97, 174, 122, 134].

Several features of our data enable us to estimate the *ex ante* and *ex post* SWB

effects of index insurance. First, the project's experimental design enables us to use an instrumental variables method to overcome potential selection issues in index-based livestock insurance (IBLI) uptake. We exploit the randomization of incentives to purchase IBLI, newly introduced in southern Ethiopia by a commercial underwriter in August 2012. The novelty of the product obviates the potential confounding of past, unobserved experience with IBLI on buyers' reported SWB. Second, three-round panel data enable us to control for time-invariant household unobservable characteristics that might affect both SWB and IBLI uptake. Third, no indemnity payouts occurred during this period.[4] Without indemnity payments, we exploit the considerable intertemporal variation in households' IBLI uptake to isolate the causal effect of IBLI on SWB. We use coverage active during a survey round to capture *ex ante* welfare effects and coverage that had lapsed by the time of the survey to capture *ex post* impacts. These data offer an unprecedented opportunity to estimate the SWB effects of insurance that arise purely from *ex ante* risk reduction and to disentangle them from *ex post* buyer's remorse effects.

We find that current IBLI coverage improves SWB. Lapsed IBLI contracts that did not pay indemnities have a negative effect on SWB, consistent with the buyer's remorse hypothesis. Although both effects are statistically significant, the welfare gains of current coverage significantly exceed the adverse buyer's remorse effects. Our results are robust to a range of alternative estimators, corrections to address concerns on the measurement of SWB, variable definitions, model specifications

[4]The first IBLI indemnity payments – on 509 contracts yielding total payments of ETB 526,000 (approximately $26,225) – occurred in October-November 2014, after the period covered by our data.

and variations in the relevant panel sub-samples analyzed. Further, we show that the estimated SWB gains from insurance are downwardly biased if one omits control for lapsed insurance coverage that generates buyer's remorse.

The implication is that, despite premiums set above actuarially fair rates, IBLI improves buyers' SWB even over a period when pastoralists in southern Ethiopia lose money on the policy. The *ex ante* peace of mind effect dominates any *ex post* buyer's remorse. In other words, even an insurance policy that does not pay out still improves people's perceptions of their well-being.

The remainder of the paper is organized as follows. The next section presents the study setting and discusses IBLI and its contract design. Section 3 discusses the sampling and experimental design. Section 4 reports summary statistics of the data. Section 5 introduces our estimation strategy. Section 6 details our vignette correction strategy, following best current practice in the SWB literature. Section 7 reports our main results. Section 8 presents a range of robustness checks. Section 9 concludes.

3.2 Study Setting

The study area is Borana zone of Oromia region in southern Ethiopia. It is a vast pastoralist land mass consisting mainly of arid and semi-arid agro-ecological zones with a bimodal rainfall pattern and four distinct seasons: long rainy (March-

May), long dry (June-September), short rainy (October-November), and short dry (December-February) seasons. Mobile pastoralism is the primary source of income and sustenance, with limited cereals cultivation for own consumption. Cyclical movement of livestock in search of forage and water characterizes the livestock production system in the zone [58, 28].

There are widespread concerns that more frequent droughts, perhaps associated with climate change, are making pastoralism more tenuous (Barrett and Santos 2014). Catastrophic droughts in the 1980s and 1990s resulted in herd losses of over 35% [73, 147]. These catastrophic droughts, which are covariate within a community, also put pressure on informal social insurance mechanisms, such as *iqub* (rotating savings and credit associations (ROSCAs)) membership. Informal community networks facing high and widespread herd losses can no longer sufficiently mitigate the effects of shocks and are in decline [147, 182]. Formal insurance might effectively transfer drought risk out of the pastoral system to underwriters, thereby cushioning pastoralists against catastrophic herd loss shocks. However, conventional indemnity insurance can be prohibitively costly to establish and sustain in this environment. Droughts that trigger payouts could bankrupt under-diversified insurers. Moral hazard and adverse selection problems and associated high monitoring costs, as well as high transaction costs in infrastructure-poor areas compound the challenges of delivering standard insurance products [29].

IBLI was developed for precisely such an environment. Originally designed

for and successfully piloted in the neighboring region of northern Kenya beginning in January 2010, IBLI makes indemnity payouts based on an observable, exogenous index of rangeland conditions, as reflected in Normalized Difference Vegetation Index (NDVI) measures generated by remote sensors on satellite platforms. An IBLI policy provides indemnity payouts when pasture vegetation falls below a contractually stipulated threshold level that reflects the onset of drought conditions that typically lead to excess livestock mortality [49].

IBLI was piloted in 2012 in eight *woredas*[5] of Borana zone located directly across the border from the Kenyan region where IBLI first piloted. The index for IBLI Borana is calculated at the *woreda* level as a cumulative deviation of periodic NDVI readings for each IBLI sales period.[6] Accordingly, the IBLI premium rate differs across *woredas* and by livestock species but is the same for all buyers insuring the same livestock species within a *woreda*, irrespective of individual loss experience. The *woreda* specific premium rates are applied to the value of herd that an IBLI buyer chooses to insure to establish the total amount that must paid for IBLI coverage.

[5] *Woreda* is a third-level administrative division in Ethiopia, below region and zone. The eight woredas of Borana zone covered in our sample are Arero, Dhas, Dillo, Dire, Miyo, Moyale, Teltele, and Yabello.

[6] For a more detailed discussion of the construction of the IBLI Borana index, see [114].

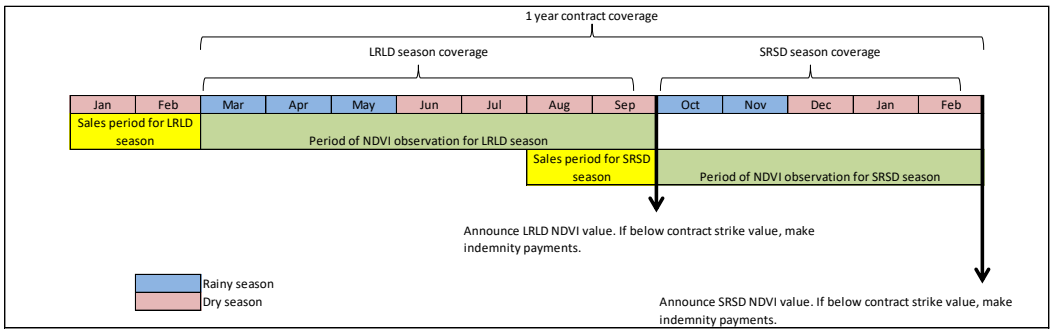

Figure 3.1: Temporal structure of IBLI contracts

Note: IBLI contracts are sold in two sales periods in January-February and August-September prior to the long rains, long dry season (LRLD) and short rains, short dry (SRSD) seasons, respectively. LRLD indicates the long rains, long dry season. The contracts cover a full year from March to February (January-February contracts) or October to September (August-September contracts).

IBLI contracts are sold in two sales periods prior to the start of the short and long rainy seasons. The first IBLI contracts were sold in August-September 2012 (sales period 1). Contract sales were repeated in January-February 2013 (sales period 2), August-September 2013 (sales period 3) and January-February 2014 (sales period 4). The duration of contract coverage is 12 months. A contract sold in January 2014 covers March 2014-February 2015, while one sold in August 2013 covers October 2013-September 2014. Households can augment their coverage by acquiring new contracts in subsequent sales periods. Index readings for each sales period are announced and indemnity payments made to policyholders, if the contractually stipulated strike rate is triggered, at the end the season (See Figure 3.1).

As with all index insurance products, the substantial basis risk associated with IBLI could leave livestock loss uninsured due to imperfect correlation between

the drought predicted by the index and losses experienced at the household level [120]. Animal losses due to covariate shocks that are not covered by IBLI, such as animal disease unrelated to rangeland conditions, as well as idiosyncratic shocks such as wildlife predation or injury, are common.

Nonetheless, recent impact evaluations of the original IBLI pilot in northern Kenya find income and productivity gains, on average, for IBLI policyholders [120, 121]. But in that setting, significant indemnity payouts had occurred in the second year in which contracts were sold following the catastrophic 2011 regional drought, so average indemnity payouts substantially exceeded average premium expenses. Those results could, therefore, be purely the result of stochastic ordering of loss events and associated indemnity payments. Those indemnity payouts had sizable behavioral and welfare effects [117]. Because there were no indemnity payments in southern Ethiopia, our study isolates the welfare effects of insurance that arise purely from reduced *ex ante* risk exposure, that is, just the peace of mind effects that arise from buyers' risk aversion, abstracted from the complication of indemnity payments. The Ethiopia IBLI pilot and associated data enable us to get at these important issues in a novel way that sheds considerable light more generally on the value of insurance coverage.

3.3 Data

3.3.1 Research Design

A baseline survey (R1) was designed and fielded in February-March 2012 before IBLI was developed or announced. Data on a broad range of household characteristics, livestock and other assets, livelihood activities, consumption, social networks, expectations and subjective well-being were collected. A year later, following sales period 2, a follow-up survey round (R2) of the original sample households was fielded in March-April 2013. Following sales period 4, a third round (R3) of survey data was then conducted in March 2014 from the same respondents as the first two survey rounds. We therefore have pre-experiment baseline data (R1), followed by two survey rounds (R2 and R3) with the same respondents. In R2, IBLI contracts purchased in sales periods 1 and 2 were in force. In R3 contracts from sales period 1 and 2 had lapsed but contracts purchased in sales periods 3 and 4 were in force (Figure 3.2).

The sampling was clustered at the *reera* level.[7] *Reeras* were purposively selected based on geographic distribution, variation in market access, and agro-ecological variation across the eight *woredas* of Borana zone in our sample. Inaccessible *reeras* were excluded for logistical reasons. In each *reera*, households were grouped into three livestock holding classes (high, medium and low), measured

[7] *Reera* is the fourth level administrative division in Oromia region below zone, *woreda*, and *kebele*.

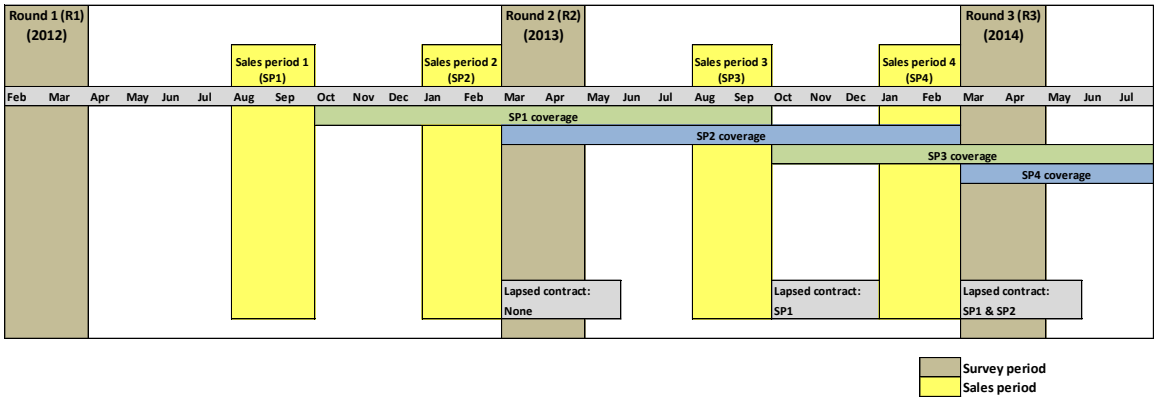

Figure 3.2: Timeline of IBLI survey and sales periods

Note: Figure 3.2 shows active and lapsed contracts through the three survey rounds used in this study. IBLI contracts cover a full year. The August-September contracts lapse after 12 months at the end of September. Likewise, January-February contracts lapse at the end of February.

in tropical livestock units (TLU).[8] Fifteen percent of households were randomly selected in each *reera* such that a minimum of 25 households were selected with a balanced representation of the three TLU classes (terciles). In the event 15 percent of households in a *reera* yields less than 25 households, neighboring *reeras* were combined to form a bigger study site, resulting in a total of 17 study sites [113].

The baseline sample included 515 households. In R2, 476 of the original (baseline) households were re-interviewed. Households that had dropped out were replaced by households from the same study site and TLU class. If replacements could not be found in the same TLU class, households in the adjacent TLU class were picked. Thus, 32 new replacement households were surveyed from the orig-

[8]TLU is a measure used to aggregate livestock across species in relation to a common average metabolic weight such that 1 TLU = 1 cattle = 0.7 camels = 10 goats or sheep, collectively called 'shoats'.

inal population lists for a total of 508 households in R2. In R3, 500 R2 households and 14 replacement households were surveyed. In selecting replacements in R3 priority was given to original households (those sampled in R1 but missed in R2). Of the 14 R3 replacements, 10 were original households and 4 were new households.

Seven households had missing SWB measures or key independent variables and were dropped from the sample. The final estimation sample includes 550 unique households and 1,530 observations (515 in R1, 504 in R2 and 511 in R3), of which 465 households were surveyed in all three rounds, 50 households were surveyed in two rounds (8 in R1 and R2, 12 in R1 and R3, and 30 in R2 and R3), and 35 households were surveyed only once. A detailed treatment of potential attrition bias in the data and relevant corrections is presented in the Appendix.

To encourage IBLI uptake, various combinations of premium discount coupons and information interventions through audio tapes of a poem or comic books were randomly implemented in each of IBLI sales period (Table 3.1). Information was delivered via caricature representation of IBLI in comic books or audio tapes of a poem about IBLI recited in the local language, Oromifa, to subsamples of respondents in sales period 1 and 2.[9] The encouragement design in

[9]In the comic book information treatment, a randomly selected sub-sample of respondents was provided with a caricature representation of the IBLI product prepared by the underwriter, Oromia Insurance Company (OIC). The contents of the material were first read to the sample households, then they were encouraged to look/read through it as many times as they wished. In the audio tape information treatment, development agents (DAs) were asked to play a tape that explains IBLI in Oromifa to a randomly selected sub-sample of respondents (for more details on the information interventions see [113].

sales periods 3 and 4 did not include information intervention. All four sales periods included randomized distribution of premium discount coupons.

Prior to each sales period, all communities received a basic briefing that described the IBLI product. In each study site, 80 percent of respondents were randomly selected to receive discount coupons that would allow them to purchase IBLI at a discounted price for up to 15 TLUs. Discount coupon recipients were evenly distributed across discount levels of 10, 20, 30, 40, 50, 60, 70, and 80 percent. The remaining 20 percent of respondents did not receive discount coupons.[10]

The two information treatments – comic book and audio tape – were randomized in six sites each (in 12 of the 17 study sites, overall), with no overlap in assignment. Within the sites selected for information treatment, about 50 percent of respondents were randomly selected for treatment. In total, 20 percent of respondents received information treatment. The randomized assignment of respondents into information treatments and discount coupons with varying discount levels was implemented independently for each sales period. By creating exogenous variation in IBLI uptake and in the effective premium faced by prospective buyers, IBLI's randomized encouragement design allows a rigorous analysis of the causal impacts of IBLI on SWB.

All sample households in our study sites had opportunities to insure against drought-related livestock loss. Yet, only 22 percent and 21 percent of households

[10]As part of a separate project, however, 10 respondents received IBLI coverage for up to 15 TLUs free of charge (100 percent discount) in each sales period.

surveyed in R2 and R3, respectively, reported buying IBLI coverage. In both R2 and R3, IBLI purchases were lower in the January-February sales period than in the August-September sales period. Of the 504 households surveyed in R2, 130 purchased IBLI in sales period 1 and 94 in sales period 2. Similarly, of the 514 households surveyed in R3, 150 purchased IBLI in sales period 3, but only 62 in sales period 4. This difference might arise due to seasonality in household liquidity.[11] Or this may simply reflect the seasonality arising due to the initial launch of IBLI in August-September 2012, combined with the contracts' 12 month duration.

Because IBLI contracts cover a full year but policies are sold in two sales periods each year, households can augment their coverage or allow contracts to lapse. Of the 130 IBLI buyers in sales period 1, 23 buyers augmented coverage further by buying additional policies in sales period 2, 53 allowed their policy to lapse after a year, and 77 extended their coverage in sales period 3. The remaining 71 buyers in sales period 2 were first time buyers. Likewise, 73 of the 94 IBLI buyers in sales period 2 allowed their contracts to lapse and 21 renewed their contract in sales period 4. Among the 150 households who bought IBLI policies in sales period 3, 33 households bought additional coverage in sales period 4. The considerable intertemporal variation in households' IBLI coverage, combined with the experimental design behind the IBLI pilot, enable us to disentangle the causal effects of current and lapsed insurance policies on respondents' SWB.

[11] Extended dry conditions often lead to stress sales and collapse of livestock markets, which in turn limits ability to raise the necessary liquidity to insure against shocks [22, 147].

3.3.2 Descriptive statistics

Table 3.1 reports baseline treatment-control covariate balance tests on assignment to premium discount coupon in sales periods 1 and 2. There is very little pre-treatment difference in subjective well-being, wealth, expected livestock loss, various household characteristics, and group membership between those who purchased insurance and those who did not, confirming that the randomization was successful.[12] Detailed variable definitions are provided in Appendix Table B2.

To complement these results, we also conducted formal joint orthogonality tests and found that selection into treatment is uncorrelated with observable household characteristics (Appendix Table B3). Joint significance tests from pooled OLS (linear probability model) regression of treatment dummies (discount coupon, audio tape and comic book) for the August-September and January-February sales periods on household income, livestock and non-livestock assets, expectations of future rangeland conditions, and various individual and household characteristics suggest that treatments are randomly assigned. We cannot reject the joint null of zero partial correlation of all covariates in these regressions. Apart from the discount coupon regression in the August-September sales period, pre-treatment differences in covariates between treatment and control households are statistically insignificant in almost all cases.

[12]Covariate balance tests on comic book and poet audio tape information treatments and discount coupon receipts in sales periods 3 and 4 also show that treatment assignment was indeed random. Findings are available upon request.

Table 3.1: Test of treatment-control covariate balance at baseline

	Sales period 1 assignments			Sales period 2 assignments		
	(1)	(2)	(3)	(4)	(5)	(6)
	Discount Coupon	No Discount Coupon	Difference (Discount– No Discount)	Discount Coupon	No Discount Coupon	Difference (Discount– No Discount)
Subjective well-being (SWB)	2.869	2.924	-0.055	2.878	2.887	-0.010
	(0.058)	(0.102)	(0.126)	(0.057)	(0.112)	(0.125)
SWB relative to Borana pastoralists	2.855	2.866	-0.012	2.886	2.746	0.140
	(0.047)	(0.088)	(0.103)	(0.046)	(0.096)	(0.102)
Vignette corrected SWB	3.570	3.741	-0.172	3.556	3.793	-0.238
	(0.076)	(0.145)	(0.167)	(0.075)	(0.146)	(0.165)
Vignette corrected SWB relative to Borana pastoralists	3.628	3.760	-0.132	3.626	3.765	-0.139
	(0.072)	(0.139)	(0.159)	(0.073)	(0.132)	(0.158)
Number of TLUs owned	14.197	17.048	-2.851	14.058	17.529	-3.471
	(1.097)	(2.104)	(2.424)	(0.942)	(3.027)	(2.405)
Non-livestock assets ('000 Birr)	2.672	3.034	-0.363	2.761	2.684	0.078
	(0.197)	(0.495)	(0.464)	(0.204)	(0.448)	(0.461)
Annual income ('000 Birr)	20.357	20.106	0.251	19.734	22.512	-2.778
	(2.322)	(2.087)	(4.736)	(1.846)	(5.888)	(4.701)
Expected TLU loss (max=52)	15.252	17.019	-1.767*	15.784	14.933	0.852
	(0.448)	(0.888)	(0.996)	(0.443)	(0.935)	(0.991)
Gender of household head (Male=1)	0.774	0.818	-0.044	0.773	0.821	-0.049
	(0.021)	(0.039)	(0.046)	(0.021)	(0.038)	(0.045)
Age of household head (years)	49.850	49.500	0.350	49.607	50.444	-0.838
	(0.902)	(1.75)	(1.997)	(0.914)	(1.658)	(1.983)
Household size (#)	6.324	5.895	0.430	6.189	6.425	-0.237
	(0.126)	(0.205)	(0.271)	(0.120)	(0.257)	(0.269)
Non-working age hh members (#)	3.567	3.231	0.337*	3.480	3.576	-0.097
	(0.091)	(0.163)	(0.198)	(0.087)	(0.197)	(0.197)
Female hh members (#)	3.122	3.010	0.113	3.064	3.236	-0.173
	(0.078)	(0.135)	(0.169)	(0.075)	(0.162)	(0.168)
Iqub (ROSCAs) membership (%)	0.095	0.058	0.037	0.092	0.064	0.028
	(0.015)	(0.023)	(0.031)	(0.015)	(0.025)	(0.032)
Observations	411	104	515	409	106	515

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 3.2 reports summary statistics on key dependent and independent variables by insurance status.[13] The top four rows show that households who had IBLI coverage in R2 and/or R3 report higher SWB – by any of the four different measures discussed in the next section – compared to their counterparts who have had no IBLI coverage in any of the survey rounds. Rows 5-9 show that IBLI purchase is strongly positively correlated with the discount coupon and information treatments. In each sales period, about 93 percent of IBLI contract holders had received discount coupons.[14] Similarly, households who received information treatments (comic book or audio tape) were more likely to buy IBLI. As expected, higher discount rates are strongly correlated with IBLI uptake. These simple descriptive statistics suggest that the random, exogenous assignment of discount coupons and information treatments are suitable predictors of IBLI adoption.

[13]Table 3.2 presents the averages of the variables in R2 and R3, during which IBLI was available for purchase.

[14]Since survey rounds 2 and 3 were preceded by two sales periods each, a household who purchased IBLI in sales period 2 but had received discount coupon in sales period 1 is reported to have received discount coupon for the survey round, hence the slightly higher figures in Table 2.

Table 3.2: Summary statistics - round 2 and 3 values (pooled), by insurance status

	(1) Insured	(2) Uninsured	(3) Difference (Insured - Uninsured)
Subjective well-being (SWB)	3.192	3.049	0.143**
	(0.041)	(0.036)	(0.056)
SWB relative to Borana pastoralists	3.250	3.138	0.112**
	(0.038)	(0.034)	(0.053)
Vignette corrected SWB	4.079	3.714	0.365***
	(0.068)	(0.058)	(0.092)
Vignette corrected SWB relative to Borana pastoralists	4.100	3.792	0.308***
	(0.065)	(0.057)	(0.089)
Encouragement design			
Discount coupon	0.932	0.524	0.408***
	(0.013)	(0.020)	(0.027)
Audio tape	0.110	0.039	0.071***
	(0.016)	(0.008)	(0.016)
Cartoon	0.165	0.085	0.081***
	(0.019)	(0.011)	(0.020)
Value of discount coupon (%) SP1	0.353	0.164	0.188***
	(0.016)	(0.010)	(0.018)
Value of discount coupon (%) SP2	0.278	0.171	0.107***
	(0.016)	(0.011)	(0.082)
Number of TLUs owned	20.592	17.323	3.269*
	(1.671)	(1.050)	(1.874)
Non-livestock assets ('000 Birr)	4.975	4.630	0.344
	(0.480)	(0.460)	(0.702)
Annual income ('000 Birr)	20.932	19.180	1.753
	(2.048)	(1.168)	(2.188)
Expected TLU loss (max=52)	13.077	12.989	-0.089
	(0.410)	(0.362)	(0.566)
Gender of household head (Male=1)	0.774	0.807	-0.033
	(0.021)	(0.016)	(0.026)
Age of household head (years)	50.341	51.884	-1.542

	(0.915)	(0.726)	(1.176)
Household size (#)	6.561	6.745	0.183
	(0.125)	(0.105)	(0.167)
Non-working age hh members (#)	3.619	3.754	0.134
	(0.090)	(0.071)	(0.115)
Female hh members (#)	3.276	3.330	0.055
	(0.074)	(0.065)	(0.101)
Iqub (ROSCAs) membership (%)	0.058	0.053	0.005
	(0.012)	(0.009)	(0.015)
Observations	381	639	1020

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Insured and uninsured households are not distinguishable by observable characteristics, apart from number of TLU owned, which is weakly statistically significant. The value of non-livestock assets, annual income, expected livestock loss, gender and age of household head, household size and composition, and membership in *iqub* groups vary insignificantly between those that purchased insurance and those who did not. These findings on observable characteristics do not rule out potential differences based on unobservable characteristics. However, so long as such unobservable differences are time invariant, we can control for them using a fixed effects estimator. Concerns that time varying characteristics may determine IBLI adoption nonetheless remain. We exploit the random assignment of discount coupon and information treatments, each strongly correlated with IBLI uptake, to address these concerns.

3.4 Estimation strategy

A key challenge in evaluating policy interventions where respondents can voluntarily "opt-in" is that selection into the program may not be random. Rather, participation could be systematically correlated with respondents observable and unobservable characteristics. Peoples' SWB is likely correlated with their subjective assessment of risk, their planning horizons, and other unobserved factors that influence insurance uptake. The experimental design features of IBLI's impact evaluation, including randomized exposure to various information treatments and randomized distribution of premium discount coupons, allow us to address the selection bias associated with insurance uptake choices. We first estimate selection into IBLI using randomized encouragement treatments as instruments. We then estimate the effect of instrumented IBLI on SWB. This approach allows us to derive unbiased and consistent causal estimates of IBLI's impact on SWB.

IBLI uptake by household i in village v, sales period s, and survey round t is estimated using the linear probability model (LPM)[15] as:

$$Pr(IBLI_{ivt} = 1) = \omega + \gamma_s D_{ivst} + \phi_s A_{ivst} + \mu_s C_{ivst} + \eta_s P_{ivst} + \zeta X_{ivt} + \kappa_t + \tau_i + \varepsilon_{ivt} \quad (3.1)$$

The randomly assigned treatments include dummy variables for receiving a randomly assigned premium discount coupon (D) in the first sales period (August-September 2012), the second sales period (January-February 2013), or

[15]To avoid the "forbidden regression" problem associated with non-linear models such as logit or probit, we use an LPM to predict an endogenous dichotomous variable in the first stage of an instrumental variables (IV) regression [14, 208].

both; dummy variables for receiving randomly assigned extension treatments in either audio tape (A) or comic book (C) form in the first, the second or both sales periods, and a *woreda* specific continuous measure of the randomly discounted IBLI premium rate (P) in the first and second sales periods. These are all randomly assigned to households and should have no direct effect on SWB, only an indirect effect through their impact on inducing IBLI uptake. The lone possible exception is P, since price variation has a (very modest) real income effect conditional on someone purchasing IBLI and thus could plausibly have some direct effect on SWB. A series of covariates, X, that may influence the uptake of IBLI are included as controls, including household herd size and income, expectation of livestock death, gender, age and educational attainment of household head and household composition. Household fixed effects (FE), τ, which control for, among other things, time invariant optimism or pessimism of individual respondents and survey round fixed effects, κ, are also included.

We use the randomized coupon distribution and information treatments to instrument for the purchase of IBLI coverage in the first stage estimation. When applied to R2 data, equation (3.1) predicts current uptake, $\widehat{IBLI}_{iv2}$, based on purchases in sales periods 1 and 2. There were no lapsed contracts in R2. When applied to R3 data, it predicts current uptake, $\widehat{IBLI}_{iv3}$, based on purchases in sales periods 3 and 4. We use the $\widehat{IBLI}_{iv2}$ predicted value to capture lapsed contracts in R3.

In the second stage of our estimation, the predicted IBLI coverage is used to

estimate the causal effect of IBLI on SWB in the second stage of our estimation. SWB includes ordinal responses to the question "on which step do you place your current economic condition," ranging from 1 (very bad) to 5 (very good). The construction of our SWB measure and related robustness checks are discussed in more detail below. The second stage ordered logit regression includes predicted IBLI uptake, number of TLUs owned (TLUO), predicted lapsed IBLI uptake the probability of having acquired an IBLI contract that has lapsed (IBLIL), a series of controls X, household fixed effects χ, and survey round fixed effect λ.

$$SWB_{ivt} = \alpha + \beta\widehat{IBLI}_{ivt} + \theta TLUO_{ivt} + \sigma\widehat{IBLIL}_{ivt} + \delta X_{ivt} + \lambda_t + \chi_i + \epsilon_{ivt} \tag{3.2}$$

The coefficient estimate on predicted IBLI uptake, $\widehat{\beta}$ measures the effect of IBLI coverage on the extensive margin – the ordered log-odds estimate of possessing IBLI contract(s) on SWB. We expect that effect to be positive, reflecting the welfare gains from insurance in a risky setting. The coefficient estimate on $\widehat{IBLIL}_{ivt}$, σ measures the effect on SWB of an IBLI contract that was in force in R2 but had lapsed in R3. Since contracts in force are controlled for, this coefficient estimate isolates the *ex post* SWB effect of insurance that did not pay, i.e., buyer's remorse, and it is expected to be negative ($\hat{\sigma} < 0$).

A finding that $\hat{\beta} > |\hat{\sigma}|$ indicates that even if insurance does not pay out, in expectation, the positive peace of mind effect exceeds the negative buyer's remorse effect, and hence IBLI improves expected welfare. If policy purchases – and therefore current and lapsed policies – are correlated over time, failure to include lapsed contracts in equation (3.2) would lead to omitted relevant variable

bias of the β estimate, presumably downwards due to negative buyer's remorse effects.

To capture the intensive margin of IBLI coverage, i.e., the marginal effect of increasing the volume of IBLI uptake by a unit, we re-estimate equation (3.1) replacing the IBLI uptake dummy variable with volume of TLUs insured (TLUI). The first stage equation for the negative censored continuous variable TLUI is estimated using Tobit as:

$$TLUI_{ivt} = \tilde{\omega} + \tilde{\gamma}_s D_{ivst} + \tilde{\phi}_s A_{ivst} + \tilde{\mu}_s C_{ivst} + \tilde{\eta}_s P_{ivst} + \tilde{\zeta} X_{ivt} + \tilde{\kappa}_t + \tilde{\tau}_i + \tilde{\varepsilon}_{ivt} \tag{3.3}$$

We construct predicted values for current and lapsed IBLI coverage using the same approach as we did for the discrete uptake variable earlier. The second stage ordered logit regression then includes predicted TLU insured and predicted lapsed TLU insured instead of predicted IBLI uptake to identify the causal effect of buying an additional TLU of IBLI coverage on SWB.

$$SWB_{ivt} = \tilde{\alpha} + \tilde{\beta}\widehat{TLUI}_{ivt} + \tilde{\theta} TLUO_{ivt} + \tilde{\sigma}\widehat{TLUL}_{ivt} + \tilde{\delta} X_{ivt} + \tilde{\lambda}_t + \tilde{\chi}_i + \tilde{\epsilon}_{ivt} \tag{3.4}$$

The second stage regression equations of both IBLI uptake (equation 3.2) and quantity of TLU insured (equation 3.4) include generated regressors. Conventional standard errors of the estimated coefficients would be biased downwards. To account for the lower variation in the predicted uptake and volume of TLUs insured, we estimate the standard errors using a bootstrapping method where both the first and second stage are included for every bootstrap sample. Further,

to account for spatial correlation of observations estimated standard errors are clustered at the village (*reera*) level in all regressions.

There are at least two possible mechanisms through which IBLI coverage could influence SWB. The first effect is the gross non-monetary benefits or costs associated with coverage, represented by the coefficient estimate on the instrumented IBLI, $\hat{\beta}$, net of instrumented lapsed IBLI, $\hat{\sigma}$, ($\hat{\beta} + \hat{\sigma}$), or the coefficient estimate on instrumented TLU insured, $\hat{\hat{\beta}}$, multiplied by the number of TLUs insured net of the coefficient on instrumented lapsed TLU insured, $\hat{\hat{\sigma}}$, multiplied by the number of lapsed TLUs insured, ($\hat{\hat{\beta}} \times \widehat{TLUI}_t + \hat{\hat{\sigma}} \times \widehat{TLUL}_t$). Purchasing insurance may reduce stress about possible adverse outcomes, which could lead to higher levels of SWB ($\hat{\beta} > 0$), while greater coverage may lead to higher SWB ($\hat{\hat{\beta}} > 0$). Conversely, if the basis risk on the product is high such that IBLI uptake is more like a lottery ticket than a conventional indemnity insurance policy, IBLI uptake could increase stress and reduce SWB ($\hat{\beta} < 0$). For the same reason, greater IBLI coverage may cause higher stress and lower SWB ($\hat{\hat{\beta}} < 0$).

The second influence on SWB arises from the net monetary benefit or cost of IBLI coverage on SWB. If net income or wealth influences SWB, as many studies suggest [91, 97], then IBLI will also affect SWB through the premium amount paid for IBLI, which reduces net income or wealth, and any indemnity payment received in the event that the IBLI policy pays out, which increases net income or wealth, *ceteris paribus*. This effect is captured by the coefficient estimate on the number of TLUs owned, $\hat{\hat{\theta}}$, multiplied by the net flow of funds associated with

the period-specific net indemnity payments (indemnity receipts minus premium payments) associated with the predicted IBLI uptake volume, converted into TLU units at prevailing livestock prices, NI.[16]

We therefore estimate the aggregate effect of IBLI on SWB as:

$$\Delta\widehat{SWB}_{ivt} = \hat{\hat{\beta}}/s \times \widehat{TLUI}_{ivt} + \hat{\hat{\sigma}}/s \times \widehat{TLUL}_{ivt} + \hat{\hat{\theta}}/s \times NI_{ivt} \tag{3.5}$$

The point estimate $\hat{\hat{\beta}}$ in equation (3.5) reflects the SWB benefit of a unit of free IBLI with no indemnity payment. Likewise, the coefficient estimate $\hat{\hat{\sigma}}$ measures the SWB loss due to a unit of free IBLI that has expired without payout. Note, however, that $\hat{\hat{\beta}}$, $\hat{\hat{\sigma}}$ and $\hat{\hat{\theta}}$ measure effects on SWB in log-odds scales while SWB is measured in ordinal Likert scale. It is necessary to harmonize the units in which these coefficients and SWB are measured before one can calculate the overall effect of IBLI on SWB. We use the fact that the logistic and Normal distributions are similar, except at the tails of the distribution, to convert the coefficients from log-odds units to Normal equivalent deviates. The effects measured in log-odds and their corresponding standard errors can be converted to approximate effects in Normal equivalent deviates by dividing by the standard deviation of the logistic distribution $s = \pi/\sqrt{3}$ [104, 52].

Given that during R2 and R3 there were no indemnity payments but respondents paid for IBLI, our estimates provide a lower bound, reflecting the SWB

[16] $NI = \frac{\text{Indemnity per TLU–Premium per TLU}}{\text{Price per TLU}} \times \widehat{TLUI}$ is the TLU equivalent wealth gained or lost due to IBLI purchase.

associated with insurance coverage in the absence of any payout, i.e., a period in which insurance represents an unambiguous financial loss. A finding that $\Delta\widehat{SWB}_{ivt} > 0|NI_{ivt} < 0$ would therefore represent a strong finding with respect to the welfare effects of index insurance in this setting.[17]

3.5 SWB and vignette correction

Subjective measures of welfare are becoming increasingly popular but pose methodological challenges [133, 173]. Respondents may have different reference points when answering a subjective question, making interpersonal comparisons problematic. To address any latent heterogeneity problems that might hinder interpersonal comparisons of subjective welfare, we adjust the subjective measures of well-being using hypothetical vignettes that provide an explicitly standardized reference point for all respondents' comparisons in order to bring objective and subjective assessments into alignment [198, 134].[18]

Interpersonal comparisons using SWB data can be challenging due to potential unobserved heterogeneity in respondents' reference points, which may depend

[17] Estimates for $\Delta\widehat{SWB}$ are obtained by evaluating equation (5) at the average TLUs insured and NI. The price per TLU is obtained by weighting livestock prices from Haro Bake livestock market (the largest livestock market in Borana zone) with the TLU conversion units of each species (Table B1).

[18] As discussed further below, we test the robustness of our core results by re-estimating our model for direct (unadjusted) SWB responses and for responses to a similar SWB question that asks people about their well-being relative to other Borana pastoralists. The core findings prove stable.

on socio-economic conditions, and other observable and unobservable characteristics. Such latent heterogeneity in subjective well-being measures may render interpersonal comparisons meaningless and invalidate inference from subjective welfare regressions [131, 198, 25, 174].

[131], [132], [198] and [25] suggest an approach for correcting latent heterogeneity problems that involves measuring the interpersonal incomparability of responses itself. Respondents are asked to assess their own circumstances relative to a set of hypothetical individuals described by short vignettes on the same scale. Responses to the hypothetical vignettes are then used to construct an interpersonally comparable welfare measure as respondents' reference points have been exogenously standardized. The validity of this approach relies on two key assumptions: response consistency, and vignette equivalence. Response consistency requires that each respondent use response categories for a particular concept in the same way when self-assessing as when assessing hypothetical individuals. Vignette equivalence is the assumption that each respondent perceives the level of the variable represented by a particular vignette on the same unidimensional scale. That is, the variable being measured by vignettes should have a consistent meaning among respondents [131].

Following [131], the reported SWB measures are corrected using a simple non-parametric approach. For notational ease, we momentarily suppress the village and time dimensions of the data. Suppose SWB_i is the categorical self-assessment for respondent $i (i = 1, ..., n)$, and V_{ij} is the categorical survey response for respon-

dent i on vignette $j(j = 1, ..., J)$. For respondents with identical vignette ordering (i.e. $V_{i,j-1} < V_{ij}$) the vignette adjusted measure of subjective well-being is given as:[19]

$$VSWB_i = \begin{cases} 1 & \text{if} \quad SWB_i < V_{i1} \\ 2 & \text{if} \quad SWB_i = V_{i1} \\ 3 & \text{if} \quad V_{i1} < SWB_i < V_{i2} \\ . & . \\ . & . \\ 2J+1 & \text{if} \quad SWB_i > V_{iJ} \end{cases} \tag{3.6}$$

The hypothetical vignettes used in this study involve households that fall in one of three well-being rungs: low, middle and high, which were constructed in consultation with local field researchers knowledgeable about the local socio-economic conditions in the study area. The lowest (poor), middle, and highest (rich) rungs were represented by a family that "*has no livestock and does not eat meat except on special occasions*," a family that "*has a dozen of shoats* [goat and sheep], *but no camel or cattle and can eat meat only once a month*," and a family that"*has a lot of shoats and several camels and cattle and can eat meat whenever they choose*," respectively.

The cross tabulation of SWB measures and vignette corrected SWB measures

[19]In our data, rescaling of self-assessments relative to vignettes does not generate vector responses, which are associated with inconsistent vignette ordering or correspondence of self-assessment with more than one vignette responses. As a result, the standard class of econometric methods for ordered dependent variables is suitable for our analysis.

in Appendix Table B4 shows that vignette corrected SWB measures largely mirror SWB, particularly at the lower end of the scale. For example, in panel (a), out of the 120 observations with SWB score of one (very bad), 27 are rescaled to one and 93 to two on the vignette adjusted SWB. Similarly, of the 88 observations with SWB scores of five (very good), none is rescaled one, and only five to two on the vignette adjusted SWB. We observe similar correspondence between SWB relative to Borana pastoralists and its vignette corrected equivalence in panel (b).

To test the robustness of our results to potentially unstable responses, we re-estimate the model using alternative SWB measures vignette corrected SWB relative to Borana pastoralists and SWB relative to Borana pastoralists. The SWB relative to Borana pastoralists variable is similar to the SWB measure, but respondents are asked to gauge their life relative to other Borana pastoralists. The anchoring of subjective well-being questions reduces the likelihood that respondents may have different reference groups in mind when responding [173].

3.6 Results

We first discuss the estimated vignette-corrected SWB effects of IBLI on the extensive margin, followed by discussion of results on the intensive margin. Table 3.3 presents the first stage panel fixed effects LPM estimates of equation (3.1) (columns 1-2) and panel random-effects (RE) Tobit model of equation (3.3) (columns 3-4). Column 1 shows results from a basic model with just random-

ized discount coupon and audio tape and comic book information extension treatments in sales periods 1 and 2. In column 2, in addition to the randomized discount coupon and information treatments in column 1, we include a broad range of household characteristics, wealth measures, IBLI knowledge, expectations of livestock loss, membership in *iqub*, and survey round fixed effects.

The parameter estimates of both models show that randomized treatments had positive effects on IBLI uptake and, thus, can serve as suitable instruments. Receiving a discount coupon and the amount of the discount were especially strong predictors of IBLI uptake. Receiving a discount coupon in sales period 1 increases the probability of buying IBLI policy by over 20 percent. This effect is even greater for the discount coupon in sales period 2 – it increases the odds of buying IBLI by about 24 percent. Moreover, having received discount coupons in sales period 1 increases the probability of buying coverage for recipients of discount coupons in sales period 2. Besides the price effect of discount coupons, which is captured by the coefficient estimates on discount values, the discount coupon had informational value, offering holders a physical reminder of the insurance product. Conditional on the amount of discount received and other covariates, receiving a discount coupon had an independent positive effect on IBLI uptake.

Table 3.3: First stage estimates of IBLI uptake and volume of TLUs insured

	LPM estimates of IBLI uptake		Tobit estimates of volume of TLUs insured	
	(1)	(2)	(3)	(4)
Discount: SP1 only	0.103**	0.108**	3.124***	2.731***
	(0.044)	(0.043)	(0.764)	(0.773)
Discount: SP2 only	0.165***	0.173***	2.988***	2.931***
	(0.046)	(0.044)	(0.765)	(0.768)
Discount: SP1 & SP2	0.084*	0.085*	2.402***	2.036**
	(0.046)	(0.043)	(0.823)	(0.824)
Value of discount (%) SP1	0.183***	0.181***	3.737***	4.050***
	(0.056)	(0.055)	(0.892)	(0.892)
Value of discount (%) SP2	-0.007	-0.011	3.296***	2.957***
	(0.065)	(0.061)	(0.908)	(0.912)
Poet tape: SP1 only	0.043	0.063	0.363	0.963
	(0.092)	(0.087)	(1.031)	(1.041)
Poet tape: SP2 only	0.114	0.131*	2.823***	2.803***
	(0.073)	(0.070)	(0.977)	(0.979)
Poet tape: SP1 & SP2	0.129**	0.098	0.836	0.553
	(0.063)	(0.065)	(1.256)	(1.268)
Comic book: SP1 only	0.078	0.063	0.945	0.820
	(0.059)	(0.061)	(0.891)	(0.896)
Comic book: SP2 only	0.068	0.079	1.586*	1.231
	(0.061)	(0.064)	(0.923)	(0.926)
Comic book: SP1 & SP2	0.200***	0.217***	2.632***	2.522***
	(0.073)	(0.071)	(0.787)	(0.812)
IBLI premium: SP1	-	-	0.286	-3.236
			(4.189)	(18.438)
IBLI premium: SP2	0.243	0.017	2.425	4.598
	(0.211)	(1.014)	(2.947)	(20.238)
IBLI knowledge		0.007		0.508***
		(0.006)		(0.129)
Expected TLUs loss		-0.001		-0.004
		(0.002)		(0.023)
Number of TLUs owned		0.002*		0.019**

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Table 3.3 – *Continued from previous page*

	LPM estimates of IBLI uptake		Tobit estimates of volume of TLUs insured	
	(1)	(2)	(3)	(4)
		(0.001)		(0.008)
Asset index		0.131		0.303
		(0.128)		(0.253)
Annual income ('000 Birr)		-0.0001		-0.005
		(0.0002)		(0.005)
Household head gender (Male=1)		-0.241*		0.592
		(0.136)		(0.638)
Household head age		0.002		-0.041
		(0.016)		(0.081)
Household age squared		-0.0001		0.0003
		(0.0001)		(0.001)
Household size		0.075***		-0.009
		(0.027)		(0.193)
Household head schooling		-0.003		-0.176
		(0.008)		(0.124)
Iqub membership		-0.070		-1.353*
		(0.049)		(0.748)
Household composition	No	Yes	No	Yes
Round dummy	No	Yes	No	Yes
Constant	0.086	0.482	-8.403***	-8.332***
	(0.132)	(0.902)	(2.280)	(3.488)
Wald test for joint significance of instruments (χ^2)	72.4	197.7	58.6	255.9
P-value	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,015	1,015	1,015	1,015
Number of households	520	520	520	520

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Table 3.3 – *Continued from previous page*

	LPM estimates of IBLI uptake		Tobit estimates of volume of TLUs insured	
	(1)	(2)	(3)	(4)

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

Note: SP1 stands for sales period 1 and SP2 stands for sales period 2. Columns (1) and (2) show LPM estimates of IBLI uptake. The dependent variable IBLI uptake is a dummy variable that takes value 1 if a household buys IBLI and 0 otherwise. Standard errors are clustered at the panel-Reera level. Columns (3) and (4) show Tobit model estimates of volume of TLUs insured. The dependent variable TLUs insured is a non-negative continues variable. IBLI premium for SP1 did not vary between R2 and R3. Thus, it is dropped in the FE LPM regression results in columns (1) and (2). The controls for household composition include number of household members by age group and gender: all/male/female #members≤5, #mem>5&≤15,#mem>15&≤64, and #mem≥65.

Randomized provision of audio tape and comic book information treatments also had a positive, albeit weaker, effect on IBLI uptake. The audio tape treatment had a positive and statistically significant effect in sales period 2. The comic book treatment, however, had an effect on IBLI uptake only when offered in both sales periods, suggesting the effectiveness of repeated exposure to this informational approach. Both Sargan ($\chi^2(24) = 75.36$, $prob > \chi^2 = 0.000$) and Basmann ($\chi^2(24) = 79.17$, $prob > \chi^2 = 0.000$) over-identification tests fail to reject the null hypothesis that our instruments are valid. The Wald test for joint significance of all instruments also strongly rejects the null of jointly insignificant instruments ($\chi^2(9) = 137.8$, $prob > \chi^2 = 0.000$). Thus, this first stage appears to successfully instrument for endogenous IBLI uptake.

IBLI uptake relates to our control variables in the expected ways. Uptake is

positively correlated with knowledge about IBLI and wealth (livestock and non-livestock assets), but only number of TLUs owned is statistically significant. Income and *iqub* membership are negatively but statistically insignificantly correlated with IBLI uptake. The later suggests that *iqub* may crowd out IBLI. We also find that male headed households are less likely to buy IBLI and that larger households are more likely to buy IBLI.[20]

We find similar results when estimating a Tobit model for volume of TLUs insured to study IBLI uptake at the intensive margin (columns 3-4, Table 3.3). Receiving discount coupons and the size of the discount carried by the coupon are strong predictors of the volume of TLUs insured. The audio and comic book information treatments were also found to be positively, but relatively weakly, related to the volume of IBLI coverage. The number of TLUs owned is positively related to volume of coverage. In line with the IBLI uptake results in columns 1 and 2, we find that IBLI knowledge influences the volume of uptake. Respondents with more correct answers to questions about the particulars of the IBLI contract are more likely to buy IBLI, a result consistent with ambiguity aversion [93]. *Iqub* membership reduces the volume of TLUs insured, as such traditional institutions lower the demand for other forms of insurance.

[20] As a robustness check, we also estimate a probit selection model. The results are strongly consistent with the LPM (Table B5).

Table 3.4: Ordered logit regression: Vignette adjusted SWB estimates using IBLI uptake and volume of TLUs insured

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: SWB	panel (a)					
Predicted IBLI/ TLUs insured	0.816***	0.713***	0.859***	0.137***	0.138***	0.144***
	(0.264)	(0.256)	(0.290)	(0.041)	(0.040)	(0.041)
Predicted lapsed IBLI/ TLUs insured	-0.454**	-0.439**	-0.442**	-0.077**	-0.071**	-0.074**
	(0.191)	(0.197)	(0.198)	(0.030)	(0.031)	(0.030)
Number of TLUs owned	0.015**	0.012*	0.012*	0.015**	0.012*	0.012*
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Asset Index		0.283**	0.239**		0.325***	0.289***
		(0.114)	(0.120)		(0.102)	(0.101)
Annual income ('000 Birr)		0.003	0.004		0.003	0.003
		(0.002)	(0.002)		(0.002)	(0.002)
Household head gender (Male=1)			0.733**			0.617*
			(0.358)			(0.334)
Household head age			-0.042			-0.037
			(0.040)			(0.038)
Household head age squared			0.0004			0.0003
			(0.0003)			(0.0003)
Household size			-0.224**			-0.193**
			(0.090)			(0.085)
Household head schooling			0.055			0.058
			(0.051)			(0.053)
	panel (b)					
Predicted IBLI/ TLUs insured						
prob(SWB=1)	-0.042***	-0.037***	-0.044***	-0.007***	-0.007***	-0.007***
	(0.014)	(0.014)	(0.015)	(0.002)	(0.002)	(0.002)
prob(SWB=2)	-0.033***	-0.029***	-0.035***	-0.006***	-0.006***	-0.006***
	(0.011)	(0.011)	(0.012)	(0.002)	(0.002)	(0.002)
prob(SWB=3)	-0.025***	-0.021**	-0.026***	-0.004***	-0.004***	-0.004***
	(0.009)	(0.008)	(0.009)	(0.001)	(0.001)	(0.001)
prob(SWB=4)	0.005**	0.005*	0.007*	0.001*	0.001*	0.001*
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
prob(SWB=5)	0.052***	0.045***	0.055***	0.009***	0.009***	0.009***

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Table 3.4 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.018)	(0.017)	(0.019)	(0.003)	(0.003)	(0.003)
prob(SWB=6)	0.027***	0.023***	0.028***	0.005***	0.004***	0.005***
	(0.009)	(0.009)	(0.009)	(0.001)	(0.001)	(0.001)
prob(SWB=7)	0.015***	0.013**	0.016***	0.003***	0.003***	0.003***
	(0.005)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
Predicted lapsed IBLI/ TLUs insured						
prob(SWB=1)	0.024**	0.023**	0.023**	0.004**	0.004**	0.004**
	(0.010)	(0.011)	(0.011)	(0.002)	(0.002)	(0.002)
prob(SWB=2)	0.018**	0.018**	0.018**	0.003**	0.003**	0.003**
	(0.008)	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)
prob(SWB=3)	0.014**	0.013**	0.013**	0.002**	0.002**	0.002**
	(0.006)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)
prob(SWB=4)	-0.003*	-0.003	-0.003*	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.0003)	(0.0003)	(0.0004)
prob(SWB=5)	-0.029**	-0.028**	-0.028**	-0.005**	-0.005**	-0.005**
	(0.013)	(0.013)	(0.013)	(0.002)	(0.002)	(0.002)
prob(SWB=6)	-0.015**	-0.014**	-0.014**	-0.003**	-0.002**	-0.002**
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
prob(SWB=7)	-0.009**	-0.008**	-0.008**	-0.001**	-0.001**	-0.001**
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Number of TLUs owned						
prob(SWB=1)	-0.001**	-0.001*	-0.001*	-0.001**	-0.001*	-0.001*
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
prob(SWB=2)	-0.001**	-0.0005*	-0.0005*	-0.001**	-0.0005*	-0.0005*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
prob(SWB=3)	-0.0004**	-0.0004*	-0.0004	-0.0005**	-0.0004*	-0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prob(SWB=4)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.00001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
prob(SWB=5)	0.001**	0.001*	0.001*	0.001**	0.001*	0.001*
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
prob(SWB=6)	0.0005**	0.0004*	0.0004*	0.0005**	0.0004*	0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prob(SWB=7)	0.0003**	0.0002*	0.0002*	0.0003**	0.0002*	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Household composition	No	No	Yes	No	No	Yes

Continued on next page

Table 3.4 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Round dummy	No	No	Yes	No	No	Yes
Observations	1,530	1,530	1,530	1,530	1,530	1,530
Number of households	550	550	550	550	550	550

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Panel (a) reports the effects of IBLI uptake and volume of TLUs insured on vignette adjusted SWB in log-odds units. Panel (b) reports the marginal effects for the main results in panel (a) – IBLI/ TLUs insured, lapsed IBLI/ TLUs insured and number of TLUs owned. The marginal effects estimates in panel (b) show the effects of these variables on the probability of reporting one of the seven unique scales of SWB. In column 3 for example, IBLI uptake reduces the probability of reporting SWB=1 by 4.4% and increases the probability of reporting SWB=7 by 1.6%. A unit increase in TLUs owned reduces the probability of reporting SWB=1 by 0.1% and increases the probability of reporting SWB=7 by 0.02%.

Table 3.4 reports second stage ordered logit regression results of the effects of IBLI on vignette corrected SWB. Panel (a) shows the effects of IBLI in log-odds units. While these results are concise and more convenient for presentation purposes, their interpretation may not be straight forward. In panel (b), we present the corresponding marginal effects of the main results in panel (a). Columns 1-3 show the extensive margin effects of IBLI uptake on SWB. Since randomized discount coupon and information treatments were used as instruments for the potentially endogenous IBLI uptake in stage one, the coefficient on $\widehat{IBLI}$ measures the causal effect of IBLI on SWB. We find that IBLI has a strong positive effect on SWB, presumably because insurance coverage reduces risk exposure for risk averse buyers. The full model in column 3 shows that IBLI uptake increases the log-odds of reporting higher SWB by 0.86. That is, IBLI buyers are 2.4 ($\approx e^{0.86}$) times more likely to report higher SWB than lower SWB. The probability estimates in panel (b) make this point more clear. IBLI reduces the probability of

reporting lower SWB ($SWB \leq 3$) by 11 percent and increases the probability of reporting higher SWB ($SWB \geq 5$) by 11 percent. Our results are robust to the inclusion of income, wealth, a range of demographic and household characteristics, and household composition variables.

At the time of the R3 survey implementation, IBLI policies from sales period 1 and sales period 2 had already lapsed without payout. Thus, the coefficient estimate on $\widehat{IBLIL}$ captures the negative *ex post* SWB effect of having bought an insurance policy that did not pay out. Indeed, the negative and statistically significant coefficient estimate on $\widehat{IBLIL}$ indicates buyer's remorse. Having bought an IBLI contract that lapsed without pay out reduces the log-odds of reporting high SWB by 0.42, which indicates that buyers of lapsed IBLI contracts are 1.5 ($\approx 1/e^{-0.44}$) times more likely to report lower SWB than higher SWB. In probability units, having bought a lapsed IBLI contract increases the probability of reporting low SWB ($SWB \leq 3$) by 5 percent and decreases the probability of reporting high SWB ($SWB \geq 5$) by 5 percent. More importantly, the magnitude of the $\widehat{IBLIL}$ coefficient is statistically significantly smaller than that of $\widehat{IBLI}$. This suggests that people are comforted by insurance coverage, and the positive *ex ante* effect trumps the negative *ex post* regret they feel once they realize that they paid for insurance that, in retrospect, they did not ultimately need.

As expected, SWB is positively correlated with various wealth measures. Both livestock and non-livestock assets are positively related to SWB. Male headed households are more likely to report higher SWB than their female headed coun-

terparts. Household size is negatively correlated with SWB.

We find similar results for the volume of TLUs insured (columns 4-6). Vignette corrected SWB is increasing in the predicted number of TLUs insured. In the full model in column 6, a unit increase in the volume of TLUs insured increases the log-odds of reporting higher SWB by 0.14, which translates to 1.15 times more likelihood of reporting higher SWB than lower SWB. The corresponding column in panel (b) shows that an additional unit of TLUs insured reduces the probability of reporting low SWB ($SWB \leq 3$) by 2 percent and increases the probability of reporting high SWB ($SWB \geq 5$) by 2 percent. Yet, as IBLI policies lapse without paying, the more TLUs one had insured, the greater the buyer's remorse one experiences. A unit increase in lapsed TLUs insured reduces the log-odds of reporting higher SWB by 0.07. An IBLI buyer with a unit more lapsed TLUs insured is 1.08 times more likely to report lower SWB than higher SWB. That is, an additional unit of lapsed TLUs insured increases the probability of reporting low SWB ($SWB \leq 3$) by 0.9 percent and reduces the probability of reporting high SWB ($SWB \geq 5$) by 0.8 percent. As is the case with IBLI uptake, the positive effect of greater volume of TLUs insured statistically significantly exceeds the negative remorse it causes when the contract fails to pay out. We also find that livestock and non-livestock wealth are positively correlated with SWB, while household size is negatively correlated with SWB.

Appendix Table B9 presents the regression results from estimating equations (3.2) and (3.4) using only currently active IBLI policies. Omission of $\widehat{IBLIL}$ leads

to a considerably smaller, yet still statistically significant, point estimate on $\widehat{IBLI}$. This finding underscores the prospective omitted relevant variable bias on the *ex ante* SWB impact estimate that arises due to autocorrelation in insurance demand if one does not separately control for lapsed policies. In other words, econometric estimates of the gains from insurance will likely underreport the welfare effects of insurance coverage if the research design does not permit the researcher to disentangle the *ex ante* and *ex post* effects of insurance.

The net aggregate SWB effect of IBLI is presented in Table 3.5. The estimated $\Delta\widehat{SWB}$ is positive and statistically significant in the number of TLU insured. The point estimate suggests that insuring an extra TLU increases vignette corrected SWB by 0.2 points, although these units have no specific informational content given the ordinal nature of the dependent variable. But this magnitude indicates that, assuming a constant marginal SWB effect of IBLI, insuring about five TLUs bumps a household up by one rung on the SWB Likert scale, from, for example, "very bad" to "bad" or "good" to "very good", on average. So, even insurance policies that did not pay out generate SWB gains. Given the actual financial losses experienced by households that purchased insurance policies in these poor communities in southern Ethiopia, this finding is important and reassuring.

Table 3.5: The aggregate effect of IBLI on SWB

Variables	(1)	(2)	(3)
ΔSWB_{ivt}	0.197***	0.202***	0.213***
	(0.072)	(0.071)	(0.073)
Observations	1,530	1,530	1,530

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

3.7 Robustness checks

We complete several robustness checks to test whether our findings are sensitive to various specifications and variable definitions. First, we re-estimate our model for vignette corrected SWB relative to Borana pastoralists, a refinement of our dependent variable (Appendix Table B6). The results are consistent with our main findings, suggesting response stability – that the phrasing of questions had little impact. As in the model for vignette adjusted SWB in Table 3.4, buying IBLI leads to higher SWB scores. The estimated coefficients on predicted IBLI as well as lapsed IBLI in the two models are comparable. As expected, the coefficients on predicted lapsed IBLI are negative and statistically significant. But, the positive effect of possessing IBLI policies is significantly higher than the negative buyer's remorse effect. The number of TLUs owned is positively related to SWB. As before, greater household size is associated with lower SWB. Non-livestock assets and gender are, however, statistically insignificant. The results of the regression

of SWB relative to Borana pastoralists on the volume of TLUs insured are also consistent with our main results in Table 3.4. The positive effect of active contracts exceeds the negative buyer's remorse effect of lapsed coverage. The difference is statistically significant.

We then estimate our model using raw SWB, which has not been vignette corrected, for IBLI uptake and volume of TLUs insured (Table B7). The results are consistent with our main findings – SWB increases with IBLI uptake/ volume of TLUs insured, and livestock and non-livestock wealth. Lapsed IBLI contracts cause remorse, hence negatively impact well-being. Male household heads are more likely to report higher SWB than female household heads. However, the coefficients on predicted IBLI and predicted TLUs insured are not statistically different from the absolute value of the corresponding coefficients on lapsed predicted IBLI uptake and predicted TLUs insured.

We also estimate our model for the balanced panel subsample to verify that the differential weighting of households in the unbalanced panel sample does not influence our estimates. Results for the balanced panel household sub-sample are presented in Tables B8. Again, we find that all of the estimated coefficients are consistent with our main results in Table 3.4. Predicted IBLI coverage and TLU insured increase vignette adjusted SWB, while lapsed contracts reduce it. The magnitudes of the positive effects of IBLI remain significantly higher than the negative estimated buyer's remorse effects, and comparable to what we find in Table 3.4. As before, SWB rises with wealth and decreases with household size.

Male household heads report higher SWB.

The multiple robustness checks we conduct strongly suggest that the positive *ex ante* SWB effects of IBLI coverage, and the negative *ex post* SWB effects of buyer's remorse in response to a lapsed policy that did not pay out, are robust to both definitions of subjective well-being measures, various specifications, and variations in the relevant panel sub-sample. The effects of wealth, gender and household size are also consistent throughout. These results give us more confidence in the robustness of our results.

3.8 Conclusions

Interest in the study of subjective well-being (SWB) has increased in recent years, as has research on index insurance in rural areas of the developing world. To date, much of the SWB research in low-income countries has focused on the relationship between SWB and income or assets. There is limited understanding of how institutional factors, access to services, or policy-related issues influence SWB, if at all [84]. Furthermore, few studies link policy-related variables, such as uptake of index based livestock insurance (IBLI), with changes in SWB [122]. This study addresses that important gap in the literature while simultaneously making an important contribution to disentangling the *ex ante* and *ex post* welfare effects of insurance by isolating the buyer's remorse effect that arises from lapsed insurance policies. Empirically, we demonstrate that index insurance such as IBLI, which re-

duces the drought-related risk faced by pastoralists in southern Ethiopia has the potential to impact not only material well-being – e.g., by replacing lost assets and reducing adverse coping behaviors – but also to improve non-material well-being, by providing valuable peace of mind for risk averse buyers even if they can reasonably anticipate experiencing buyer's remorse if a policy lapses without payout.

We use three rounds of annual household panel data collected between 2012 and 2014, bracketing the introduction of IBLI in southern Ethiopia, and randomized encouragements to buy the product to identify the causal effect of IBLI on SWB. We separate out the *ex ante* SWB effects of current coverage from the *ex post* buyer's remorse effect, exploiting the fact that some households had purchased IBLI in the second survey round and those policies had lapsed by the third survey round. We also show that if buyer's remorse effects exist and there is any persistence in insurance purchases, such that current and lapsed coverage are positively correlated, then ignoring lapsed policies results in downwardly biased estimates of the well-being effects of insurance.

We find that current IBLI coverage has a strongly positive and statistically significant effect on SWB. We also find statistically significant evidence of a buyer's remorse effect. The negative buyer's remorse effect is considerably smaller in magnitude than the positive effect of IBLI coverage, however, suggesting that the comfort people derive from insurance coverage more than compensates for any regret they suffer once they realize they did not need coverage. Therefore, in our

survey sample, insurance purchase is *ex ante* optimal, on average.

This could reflect the nature of the sample we study. Pastoralists in southern Ethiopia's Borana Zone face decline in informal social insurance institutions at a time when pastoral livelihoods are becoming more risky. As a result, Borana pastoralists may experience greater well-being as a result of having access to index insurance, even if it did not pay out in the short-term. These results suggest that for people with precarious livelihoods, even an imperfect, commercially priced insurance policy that does not pay out can leave them feeling better off.

Our findings also show that estimations of the welfare effects of insurance ought not ignore potential *ex post* impacts. Prior purchases of insurance may induce buyer's remorse once a buyer realizes that, in retrospect, costly insurance proved unnecessary. Survey-based SWB measures can capture all of these prospective effects without resorting to strong assumptions about the arguments and functional form of utility functions.

SWB measures seem especially appropriate to establishing the impacts of commercial insurance. Commercial insurance policies, including IBLI, intrinsically involve a tradeoff between material and non-material well-being if policies are priced above actuarially fair premium rates so as to cover the costs of and ensure a profit margin for the underwriter. Theory suggests that actuarially fair insurance is welfare enhancing, regardless of whether it pays out, because most people are risk averse and insurance mitigates risk. But when insurance is not actuarially fair, and perhaps especially if it offers incomplete coverage, as is inevitably the

case with index insurance products subject to basis risk, the *ex ante* expected monetary loss (because premiums exceed expected indemnity payments over time) and the *ex post* buyer's remorse that might result if no insurable loss occurs, might negate the oft-assumed benefits of insurance.

CHAPTER 4

DIVERSIFICATION AND PRODUCTIVITY IN AFRICAN AGRICULTURE: EVIDENCE FROM UGANDA

4.1 Introduction

Climate change related rises in the incidence of adverse weather conditions increased the risk of destructive disruptions to the livelihoods of rural households who rely on rain-fed agriculture for sustenance. In much of the developing world, the threat of whether shocks on livelihoods is further compounded by lack of access to credit and insurance for protecting consumption and assets. Under these circumstances, households engage in otherwise inefficient risk management practices *ex ante* and risk mitigating strategies *ex post*. Indeed, in much of Sub-Saharan Africa, where small holder agriculture is the primary source of livelihood for 80% of rural households, private risk bearing is commonplace [85].[1] Crop diversification is one of such private risk management strategies where farmers trade-off returns for lower output variance.

The productivity of agricultural systems depends on physical factors such as temperature and precipitation and the micro-climate near the earth's surface. Random variations in limiting physical factors may lead to fluctuations in farm pro-

[1]There have been increasing recent efforts to avail institutional insurance products to rural communities. Examples of such efforts include livestock and crop index insurance products in Ethiopia [72] and Ghana [123], and livestock index insurance in Kenya [117, 121]. However, these are relatively new insurance instruments and their coverage is limited to small geographic areas.

ductivity and household income. Likewise, the micro-climate influences plant processes such as photosynthesis and transpiration and disease resistance [9, 150]. Planting multiple crops that respond differently to different environmental conditions mitigates the effects of random changes in growing conditions. There are multiple ways in which diversified cropping systems can reduce variability in yield. First, diversification improves system resilience by increasing the range of crops that can thrive under varying environmental conditions [160]. Thus, it reduces the likelihood of complete crop failures due to unpredictable rainfall and temperature.

Second, diversification may serve as a biological constraint on the spread of plant pathogens. Pathogen transmission may be regulated by the plant diversity and functional composition. Variability in host density associated with increase in diversity reduces the spread of pathogens, especially if the pathogen attacks a narrow host range [179, 155]. Diversity may also change the micro-climatic conditions of the host plant and lead to modification of the host plant's traits [212] allowing it to develop induced resistance to pathogens [159].

Third, diversity may limit pest infestations and weed invasions. Diversification may restrict the range of crops that a herbivore can feed or lay eggs on and force it to expend greater time and energy in search of acceptable hosts, which limits its reproduction. Further, this also reduces the time it has to cause crop damage [176, 13]. Companion plants in diversified systems provide beneficial arthropods with fertile habitats and food sources. This promotes competition and enhanced

predation of harmful pests by beneficial arthropods and reduces the density of herbivores, stabilizing productivity.

Increase in crop diversity reduces weed population by slowing weed emergence relative to crop emergence and stunting weed growth and seed production through resource competition, allelopathy and predation. Shading by tall stature crops reduces weed leaf nitrogen concentration, photosynthetic surface area, soil temperature and biomass production [143, 145, 193]. This is especially true for late emerging weeds. Early emerging crops in a diverse system may form a tight canopy, intercepting incoming light and shade-out weed emergence [107].

By carefully selecting crop mixes, it is also possible to restrict weed growth through allelopathy (addition of phytotoxicants into the micro environment). Allelopathic chemicals released by crops may serve as weed growth regulators and natural herbicides [171, 38, 195]. Weed species may be more susceptible to phytotoxic influences of other crops because of differences in seed mass. Large-seeded crops may have superior advantage over small-seeded weeds [140, 135]. Besides allelopathic effects, crop diversity creates a rich habitat for insects, rodents and birds, thereby facilitating weed seed predation before it germinates [112, 197, 168].

In addition to stabilizing output, crop diversification also increases productivity through spatial, temporal and chemical inter-crop synergies. Diversity improves biotic and abiotic resource capture, conversion, growth and allocation, especially if there is greater functional difference among component crops [165, 142, 150]. Differences in the timing of crop emergence, development and

maturity increases the efficiency of water, sunlight, nitrogen and other nutrients use [199]. Early maturing crops may improve the productivity of late maturing crops through reduced competition for resources, improved soil fertility due to increase in soil organic matter from enhanced nutrient and carbon rhizodeposition and crop residue and improved soil water retention [66, 110, 79]. Likewise, spatial differences in resource use such as nitrogen sourcing (soil vs. atmospheric) of legumes and cereals, or differences in rooting depth, which determines extraction depth of water and nutrients, increases productivity. Leguminous crops are known to improve soil nitrogen content through their ability to extract atmospheric nitrogen, thereby reducing inter-specific competition for soil nitrogen [165, 9, 23]. Allelopathic effects of crops on herbivores and weeds may also reduce competition for resources and pest attacks and improve the productivity of component crops [141, 10].

The inter-crop dynamics associated with crop diversification has drawn a great deal of interest in the economics literature, though the focus has often been on risk management and mitigation roles of diversity [201, 4, 196, 43, 56]. More recently, however, there is a growing interest in the productivity effects of diversity [50, 129, 163]. Much of the evidence on productivity gains from crop diversification is from studies conducted on experimental plots [106, 68]. Studies on the relationship between diversification and productivity in observed on-farm practices are, however, surprisingly limited. To the extent that observed cropping patterns reflect the social and economic context in which agricultural production takes place, understanding the key incentives and constraints that shape farmers'

production decisions is crucial for effective policy prescriptions.

The existing literature on observed crop diversification tends to focus on production environment dominated by a few crops [129] or multiple varieties of a single crop [76]. In much of Sub-Saharan Africa, crop production is often a multi-crop enterprise in which farmers produce multiple crops on small plots using traditional methods following natural rainfall cycles. This leads to complex below-ground and above-ground inter-crop dynamics, which depend on crop type, crop management practices and environmental factors. A better understanding of on-farm crop dynamics in this setting would require an approach that covers a broad range of crops.

In order to devise appropriate policies to effect a desired change in the rural economy, policy makers would need to have clarity on the prime motives for farmers' observed crop diversification. If risk management is the prime driver of an otherwise inefficient crop mix choice by farmers, interventions through crop insurance provisions would be relevant. If increasing productivity by exploiting inter-crop synergy is the main determinant of farmers' cropping choices, perhaps relaxing constraints to such ventures through input and output market interventions might be required. All of these point to the need to comprehend farmers cropping decision processes. This paper studies the contributions of observed crop diversification practices to productivity and risk management. The linear moments model in [15] is adapted to examine the relationship between crop diversification and crop yield and yield variance. A third moment of yield (skew-

ness) – a measure of downside risk aversion – is included to distinguish between random low draws from random high draws.[2]

This paper has two main objectives. First, it examines the contributions of mean, variance and skewness in crop choice, with a particular focus on determining whether yield and/ or risk are the primary considerations in crop decisions. Second, it studies whether crop complementarity effects (yield and variance) vary with crop plot area.

To this end, I use three rounds of the Uganda National Panel Survey data, which track a nationally representative sample of 2,356 households over a five year period between 2009/10–2013/14. The surveys cover a broad range of topics encompassing household characteristics, education, health, labor market status, assets, income and consumption, shocks and food security, infrastructure and services, agriculture, and access to various services. Each survey round covers two farming seasons. Thus, a total of six data rounds are used in the analysis.

The results of the paper, though not causal, provide suggestive evidence that crop diversification decisions in Uganda are mainly derived by yield considerations. Mixed cropping is associated with increase in the average yield of all crops except sorghum. I find little evidence that variance reduction is a prime motive in farmers' crop diversification decisions. Nor is there strong evidence that

[2]Output variance is undesirable to the extent it leads to low outcomes. For a constant variance, a distribution with positive skewness (greater probability of high yield) is preferable. Including the third moment of yield addresses this qualitative difference in the observations at the tail ends of yield distribution.

skewness considerations are important in crop diversification decisions, though increase in land allocations to some crops appears to be associated with increase in yield skewness of other crops.

The yield gains associated with crop diversification arise only on small plots. There are significant yield gains to farms in the bottom farm size quantile. These gains vanish for farms in the third or higher quantiles. I also find that productivity decreases with plot size for all major crops in Uganda. This result is consistent with the inverse farm productivity-size relationship. Larger plots are also associated with high yield variance. This is, however, mitigated by positive skewness, hence greater probability of high yield draws, associated with larger plots.

The rest of this paper is organized as follows. The next section presents the conceptual framework of the study. Section 3 discusses the data and presents summary statistics. Section 4 introduces the empirical strategy. Section 5 discusses the main results. Section 6 concludes.

4.2 Conceptual Framework

Consider a multi-output farm household making crop production decision to maximize the expected utility of end of farming season income y. Suppose the production technology of crop j is given by $q_j = h(x_j, x_{-j}, v_j)$, where q_j is output quantity of crop j, x_j is a vector of inputs allocated to crop j, and v_j is a random

error term distributed $v_j \sim N(0, \sigma^2_{vj})$. The output level q_j depends on the quantity of inputs used in crop j and other crops $-j$ due to synergistic and competitive relationships between crops. The interdependence of crop yields arises because of cross-sectional nutrient, disease/ pest, water and sunlight complementary/ rival effects and inter-temporal nitrogen carry-over in multi-crop systems. The random variable v_j reflects crop yield uncertainty. There are two sources of uncertainty: the production technology, which is known only up to a joint density $F(q_1, q_2, ..., q_k)$, and factors beyond the farm household's control, such as rainfall.

The farm household's utility maximizing problem can be specified as:

$$\max_{q_1,...,q_k} E\{u[y(q,p)]\} = \int u[y(q,p)]dF(q) \tag{4.1}$$

where $u(.)$ is von Neumann-Morgenstern utility function, $q = (q_1, q_2, ..., q_k)$ is a vector of output quantities and $p = (p_1, p_2, ..., p_k)$ is a vector of exogenous prices. The function $u(y)$ is continuously differentiable, strictly increasing and concave ($u'(.) > 0, u''(.) < 0$) and marginal utility is convex, $u'''(.) > 0$. In the expected-utility framework, the concavity of the utility function is sufficient for risk aversion. The general notion of risk aversion involves the spread of the probability weight from the center irrespective of the "placement" of the risk. Any mean-variance preserving transformation of a distribution obtained by shifting probability weight from one tail to the other will have the same risk aversion as the original distribution. The notion of "downside risk aversion"[3] concerns with the distribution of probability weight around the tails of a distribution [152]. For the same mean and

[3]The concept of downside risk aversion is equivalent to the concept of "prudence" defined by [130].

variance, a distribution is said to have more downside risk if it has more dispersion around the left tail (skewed to the left). This is equivalent to positive third derivative of the utility function $u'''(.) > 0$ [152, 130].

Following [170], the expected utility $E[u(y)]$ can be written as:

$$E[u(y)] = u[E(y) - \pi] \tag{4.2}$$

where $\pi > 0$ is a risk premium measuring the maximum amount one is willing to forgo to avoid risk exposure. The certainty equivalent $\phi = E(y) - \pi$ is the minimum amount one is willing to accept for the risky prospect y, with $u'(\pi) < 0$.

In equation (4.2), the marginal utility effect of producing crop j, $\frac{\partial E[u(y)]}{\partial q_j}$ has two components: marginal expected income effect $\frac{\partial E(y)}{\partial q_j}$ and marginal risk effect $\frac{\partial \pi}{\partial q_j}$. Since $u'(.) > 0$, the farm household makes crop production decisions to maximize expected income and reduce risk, which depend on crop yield and yield risk, for given inputs (especially land area) and exogenous prices. In a multi-cropping system, this return-risk relationship is complex. Some crops may increase/decrease the expected yield of other crops or increase/decrease variance. The equilibrium condition involves equating the utility weighted difference in marginal expected income effect and marginal risk effect across crops:

$$q_j^* = \left\{ q_j : \frac{\partial E(y)}{\partial q_j} - \frac{\partial \pi}{\partial q_j} = \frac{\partial E(y)}{\partial q_{-j}} - \frac{\partial \pi}{\partial q_{-j}}, \ \forall \ j, -j \in k \right\}. \tag{4.3}$$

Using Taylor series approximation, the components of (4.2) can be restated as:

$$
\begin{aligned}
E[u(y)] &= u(\mu) + \frac{u''(\mu)}{2}E[(y-\mu)^2] + \frac{u'''(\mu)}{6}E[(y-\mu)^3] \\
u[E(y) - \pi] &= u(\mu) - \pi u'(\mu),
\end{aligned}
\tag{4.4}
$$

where $E(y) = \mu$ is expected income. After simple rearrangement, (4.4) yields

$$
\begin{aligned}
\pi &= -\frac{1}{2}\frac{u''(\mu)}{u'(\mu)}E[(y-\mu)^2] - \frac{1}{6}\frac{u'''(\mu)}{u'(\mu)}E[(y-\mu)^3] \\
&= -\frac{1}{2}\frac{u''(\mu)}{u'(\mu)}E[(y-\mu)^2] - \frac{1}{6}\frac{u'''(\mu)}{u''(\mu)}\frac{u''(\mu)}{u'(\mu)}E[(y-\mu)^3].
\end{aligned}
\tag{4.5}
$$

Define variance as $\sigma_y^2 = E[(y-\mu)^2]$ and skewness as $\sigma_y^3 = E[(y-\mu)^3]$. Thus, (4.5) can be written more intuitively as:

$$
\pi = \frac{1}{2}r_2\sigma_y^2 - \frac{1}{6}r_2 r_3 \sigma_y^3 \tag{4.6}
$$

where $r_2 = -\frac{u''(\mu)}{u'(\mu)}$, is the Arrow-Pratt absolute risk aversion coefficient and $r_3 = -\frac{u'''(\mu)}{u''(\mu)}$ is Kimball's absolute prudence, which measures an individual's aversion to downside risk [130]. By strict concavity of $u(.)$, $r_2 > 0$ and by convexity of $u'(.)$, $r_3 > 0$. Equation (4.6) produces interesting insights. First, the relationship between risk premium and risk aversion depends on the shape of the distribution of income. For a symmetric or negatively skewed distribution ($\sigma_y^3 \leq 0$), more risk averse individuals have higher risk premium, $\frac{\partial \pi}{\partial r_2} > 0$. If income is positively skewed ($\sigma_y^3 > 0$), however, risk aversion is risk premium increasing only if $r_3 < \frac{3\sigma_y^2}{\sigma_y^3}$. Second, $\frac{\partial \pi^2}{\partial r_2 \partial r_3} < 0$ if $\sigma_y^3 > 0$ indicating that prudence, defined as the propensity to prepare oneself in the face of uncertainty [130], reduces the effect of risk aversion

on the risk premium one requires to engage in risky prospects if income is positively skewed. The opposite is true if income has negatively skewed distribution, $\sigma_y^3 < 0$.

Applying the identity $\phi = \mu - \pi$ to (4.6) yields

$$\phi = \mu - \frac{1}{2} r_2 \sigma_y^2 + \frac{1}{6} r_2 r_3 \sigma_y^3 \tag{4.7}$$

which summarizes certainty equivalent as the sum of three terms: expected income, variance, and skewness. Thus, the farm household's problem can be expressed as the maximization of the certainty equivalent.

$$\max_{q_1,\ldots,q_k} \phi = \mu - \frac{1}{2} r_2 \sigma_y^2 + \frac{1}{6} r_2 r_3 \sigma_y^3 \tag{4.8}$$

The expected utility effect of the household's crop production decision $\frac{\partial E[u(y)]}{\partial q_j}$ is, therefore, congruent to the effects of crop choice on the certainty equivalence ϕ, $\frac{\partial \phi}{\partial q_j}$. Thus, expected utility is positively related to expected income and skewness, and negatively related to variance. That is, the production of a particular crop j is desirable in so far as it increases expected income and the odds of higher random income, and reduces income variance.

[15] provides a simple moment based approach for analyzing the return-risk dynamics described in (4.8).[4] It allows recursive component-by-component anal-

[4]The point of departure in the moment based approach is that the probability distribution of output is fully described by its moments. The production behavior of farm households under uncertainty can, thus, be summarized by the relationship between inputs and moments of output [15]. The first three moments are generally thought to sufficiently approximate the distribution of random variables [78].

ysis of the effects of mean, variance and skewness on the production decisions of farm households. This comes in handy when the production system concerns joint production of multiple crops. The moment based approach starts with a general parameterization of the probability distribution of output rather than the production function. Since the range of values of crop output is finite, the sufficient condition for unique characterization of the probability distribution is satisfied and all moments exist [15].

Suppose q_j is output j of a farm household, $x_j = (x_{j0}, x_{j1}, ..., x_{jm})$ is input vector where $x_{j0} = 1$, $\alpha_j = (\alpha_{j0}, \alpha_{j1}, ..., \alpha_{jm})$ and $\beta_j = (\beta_{j0\lambda}, \beta_{j1\lambda}, ..., \beta_{jm\lambda})$ are vectors of coefficients, u_j and $\varepsilon_{j\lambda}$ are random error terms, and $f(.)$ and $g_\lambda(.)$ are linear functions of x_j. The stochastic mean function is defined as:

$$q_j = f(x_j, \alpha_j) + u_j, \qquad E(u_j) = 0, i = 1, ..., n. \tag{4.9}$$

The first moment of output naturally follows as:

$$E(q_j) = \mu_{j1} = f(x_j, \alpha_j). \tag{4.10}$$

Higher moments are defined as

$$\mu_{j\lambda} = E(q_j - \mu_{j1})^\lambda = E(u_j^\lambda), \qquad \lambda \geq 2. \tag{4.11}$$

The probability distribution of output is assumed to be linear in moments with higher order residual terms of the form

$$u_j^\lambda = g_\lambda(x_j, \beta_{j\lambda}) + \varepsilon_{j\lambda}, \qquad E(\varepsilon_{j\lambda}) = 0. \tag{4.12}$$

Under some regularity assumptions, consistent estimates of $\hat{\alpha}_j$ and $\hat{\beta}_{j\lambda}$ can be obtained using least square estimator [15]. Since variance and skewness are linear functions of inputs, however, the residuals of the mean function are heteroskedastic and standard errors are inefficient. Equations (4.10) and (4.11) can be estimated separately or as a system of equations using Generalized Least Square (GLS), which addresses heteroskedasticity problems.

The mean function in (4.10) is concave and increasing in inputs. Thus, its partial derivatives with respect to inputs are all expected to be positive ($\partial\mu_{j1}/\partial x_j = \alpha_j > 0$). On the other hand, the effects of inputs on the variance and skewness of output are empirical questions. If an input is variance increasing (decreasing), $\partial\mu_{j2}/\partial x_j = \beta_{i2} > 0(< 0)$. Likewise, if an input is skewness increasing (decreasing), $\partial\mu_{j3}/\partial x_j = \beta_{j3} > 0(< 0)$.

4.3 Data

This paper uses the Uganda National Panel Survey (UNPS) data, which were collected by the Uganda Bureau of Statistics (UBOS) under the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS–ISA) project.[5] The UNPS collected four rounds of nationally representative panel data on 2,356

[5]The LSMS–ISA project implements multi-topic nationally representative panel household data in eight Sub-Saharan Africa countries: Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania, and Uganda. In collaboration with national statistics offices, it collects comprehensive data on household characteristics, agriculture, non-farm enterprises, and access to various services, among others.

households in 2009/10, 2010/11, 2011/12 and 2013/14. Data from the first three rounds of the survey are used in this paper. The survey covers a broad range of topics encompassing household characteristics, education, health, labor market status, assets, income and consumption, shocks and food security, infrastructure and services, agriculture, and access to various services.

Uganda is divided into four regions (Central, Western, Eastern and Southern) and, as of 2009/10, 80 districts and one city (Kampala). All 80 districts and Kampala were covered in UNPS. Selection of survey households follows stratified re-sampling of households who were part of the Uganda National Household Survey (UNHS) in 2005/06. Stratification was implemented at the urban/rural and district level, with strata of representativeness defined at Kampala City, other Urban Areas, Central Rural, Eastern Rural, Western Rural and Northern Rural. Within each strata, Enumeration Areas (EAs) were randomly selected from a pool of EAs covered in UNHS. Households were, then, randomly selected from each selected EA.

The UNPS 2009/10 round started with 2,975 households distributed over 318 EAs, of which 88% were original UNHS 2005/06 households and the remaining 12% were split–off households.[6] In terms of geographic distribution, 74% of the 2009/10 sample households were rural and 26% urban. In the 2010/11 and

[6]UNPS set out to track 3,123 households from 322 EAs, from which 643 households (20% of sample) were selected for split-off tracking. It managed to track 2,607 original and 368 split-off households, for a total of 2,975 households (UNPS Wave I report 2011, p. 13-14). Split-off households are UNHS 2005/06 household members who have since moved to different locations and were tracked in the UNPS.

2011/12 follow up rounds, 83% of households were tracked and re-interviewed.[7] In response to attrition, sampling weights have been adjusted in the later rounds.

The surveys were conducted over a 12 month period in two visits to each sample household in every round. This design reflects the seasonality associated with production and consumption due to the two cropping seasons (January to June and July to December) in Uganda. During each visit, detailed data on household assets including size and characteristics of parcels and plots, crops planted, farming practices, input use, and harvest were collected.

Households are tracked between farming seasons and survey periods, whereas parcels are tracked between farming seasons within a survey year but not between survey years. Plots change both between farming periods and survey years. Thus, the plot level data were aggregated to the parcel level for panel tracking purposes. This aggregation may lead to loss of interesting within and between plot yield dynamics. However, there is no such concern for single plot parcels, which account for the majority of parcels in 2011/12 (57%), or mono crop plots. Moreover, the fact that average parcel size in Uganda is small (0.4 hectares) indicates the potential underestimation of inter-crop synergies is minimal. Because of these tracking limitations of the data, the empirical analysis is done at the parcel level.

The plot level data do not distinguish between intercrops (mixed, row, relay etc.) and specialized partitioned sub-plots. Thus, mixed stand is defined in this

[7]The reasons for leaving the sample includes migration to unknown location, household disintegration, death of whole household, and refusal to respond.

paper as the production of multiple crops on a parcel irrespective of cropping patterns at the plot level. That is, a parcel that consists of two plots, each specialized in a single crop is considered a mixed stand parcel as is a parcel that consists of two plots, each planted with multiple crops. A parcel is considered pure stand if it is planted with a single crop, which may include single plot parcels and parcels consisting of multiple plots, all planted with the same crop. While this definition is not precise, it captures some of the below-ground and above-ground dynamics between crops. In the case of a parcel made up of multiple specialized sub-plots, for example, this dynamics could result from trapping, repelling and predation. A crop planted on a plot may attract insects and birds that attack pests and weed harmful to crops planted on adjacent plots. This same process may enhance cross-pollination and seed fertilization.

4.3.1 Descriptive Statistics

In this paper, I focus on the eight most important crops in Uganda: maize, sorghum, beans, groundnuts, sweet potatoes, cassava and matoke (plantains). These crops account for roughly 75% of land area planted in the 2011/12 survey round. As shown in Table 4.1, there is no single dominant crop. Rather, a few crops, each with significant land share, characterize crop production in Uganda. The main crops are maize, beans and matoke, with a combined land share of 40%, while coffee comes out least with about 5% of land area allocation. This combined with the fact that over 60% of parcels are inter-cropped points to the considerable

crop diversification in Ugandan agriculture (see Table 4.5). Moreover, these crops encompass a broad range of crop categories – cereals, legumes and tubers – and offer rich diversity to capture inter-crop dynamics.

Table 4.1: Land shares allocated to crops (%) in 2011/12

Crops	Cropping season 1	Cropping season 2
Maize	0.13	0.14
Sorghum	0.04	0.04
Beans	0.13	0.14
Groundnuts	0.08	0.04
Sweet potatoes	0.07	0.09
Cassava	0.08	0.09
Matoke	0.13	0.16
Coffee	0.04	0.06
All	0.75	0.76

Note: This table shows the share of cultivated land allocated to different crops in 2011/12 by cropping season. Cropping season 1 stands for the January–June/August farming season and cropping season 2 covers the August/September–December farming season.

Tables 4.2–4.4 present household and land (parcel) summary statistics for 2011/12. The 2011/12 sample households are predominantly rural, with 83% of households residing in rural areas. About 92% households are male headed, of which 98% are married. On average, the household head is 41 years old and has 6.4 years of schooling. The average age of the spouse is 35 and he/she has aver-

age schooling of 5.3 years. Average household size is 6, while dependency ratio, defined as the ratio of number of household members younger than 15 or older than 64 to working age members (15-64), is very high at 124%. In total, 28% of households report experiencing some shock in 2011/12, the most common being drought, which 20% households experienced, followed by flooding at 6%.

Table 4.2: Household characteristics in 2011/12

Variables	mean	std. error	obs.
Urban/rural (rural=1)	0.83	0.018	2,850
HH head gender (male=1)	0.92	0.010	2,850
HH head age	40.83	0.569	2,833
HH head marital status (married=1)	0.98	0.003	2,845
HH head schooling	6.41	0.159	2,835
HH size	5.84	0.110	2,850
HH dependency ratio	1.24	0.030	2,850
Spouse age	34.49	0.500	1,918
Spouse schooling	5.27	0.155	2,835
Shocks: drought	0.20	0.019	2,809
Shocks: flood	0.06	0.011	2,809
Shocks: erosion	0.01	0.003	2,809
Shocks: pest	0.02	0.006	2,809

Note: This table presents household summary statistics for the 2011/12 UNPS survey round. For ease of presentation the shorthand HH is used for "household". The marriage dummy treats divorced/separated, widow/widower and never married as single. It also doesn't distinguish between monogamous and polygamous marriage.

Farm parcels display considerable variation in terms of ownership, remoteness, soil quality and topography. The majority of land is owner operated and

within an hour walking distance from homestead. The soil in three-quarters of parcels is sand loam or sandy clay loam.[8] The soil type on a parcel, to a great extent, determines the suitability of the parcel for growing a variety of crops. Generally, sandy soils tend to be low in organic matter and native fertility, low in ability to retain moisture but allow greater movement of water and air. At the other end of the spectrum, clays are more fertile and have high water retention but poor aeration and can crack when dry, damaging crop roots.

Soil type is strongly linked to topography. Topography affects the formation of soils through its influence on micro-climate, vegetation and water runoff.[9] In the UNPS sample, over 85% of parcels have flat or gentle slope orientation allowing the parent material in the soil to stay in place and develop. This is reflected in the subjective assessment of soil quality where 99% parcels are reported to have "good" or "fair" quality soil. Rain-fed agriculture is by far the dominant mode of crop production.

On average, a household operates 2 parcels, each consisting of 2 plots, on a total cultivated land area of 0.8 hectares (see Table 4.5). Multiple cropping is the most common system with 61% of total land area planted, the remaining 39% being pure-stand. At 0.45 hectares, multi-crop parcels tend to be considerably larger than pure-stand parcels, which average 0.27 hectares.

[8]The difference between these soil types is in the composition of sand, silt and clay, which differ in terms of particle size (sand, >63 micrometer (0.001mm); silt >2 micrometer; and clay <2 micrometer).

[9]Summary statistics on farm slope and elevation are given in Table 4.4.

Table 4.3: Land (parcel) characteristics

Variables	proportion	std. error	obs.
Land ownership			
Owned	0.77	0.012	4,781
Use rights only	0.23	0.012	4,781
Distance from homestead to parcel			
Less than 15 minutes	0.53	0.013	4,781
15 - 30 minutes	0.17	0.011	4,781
30 - 60 minutes	0.17	0.013	4,781
1 - 2 hours	0.09	0.008	4,781
Over 2 hours	0.04	0.008	4,781
Soil type			
Sand loam	0.44	0.020	4,781
Sandy clay loam	0.31	0.020	4,781
Black clay	0.18	0.014	4,781
Other	0.07	0.009	4,781
Soil quality			
Good	0.63	0.017	4,781
Fair	0.36	0.017	4,781
Poor	0.02	0.003	4,781
Topography			
Hilly	0.09	0.014	4,781
Flat	0.49	0.022	4,781
Gentle slope	0.37	0.018	4,781
Steep slope	0.04	0.006	4,781
Valley	0.02	0.003	4,781
Water source			
Irrigated	0.01	0.002	4,781
Rain-fed	0.98	0.004	4,781
Swamp/ wetland	0.01	0.003	4,781

Note: This table shows parcel summary statistics for the 2011/12 UNPS round. All variables are self reported. The distance variable measures time to parcel by foot (walking).

Table 4.4: Agro-ecology and "connectedness" of homestead in 2011/12

Variables	mean	std. error	Obs.
Distance to major road (km)	7.26	0.448	2,740
Distance to pop. center +20,000 (km)	21.96	1.001	2,740
Distance to nearest market (km)	28.45	1.039	2,740
Slope (%)	7.35	0.438	2,740
Elevation (m)	1,234.42	15.325	2,740
Annual rainfall (mm)	1,293.70	9.958	2,740

Note: This table presents various measures of proximity of homestead to services in kilometers *km*. It also presents measured land characteristics at homestead. *m* and *mm* stand for meter and millimeter, respectively.

Table 4.5: Land characteristics in 2011/12 at the parcel level

Variables	Mean	Std. error	Unit	Obs.
Parcels per HH (#)	2.06	0.049	Parcel	4,781
Plots per parcel (#)	1.94	0.051	Parcel	4,781
Plots per HH (#)	3.65	0.084	Parcel	4,781
Cropping system				
Pure stand (%)	0.39	0.015	Parcel	4,495*
Inter-cropped (%)	0.61	0.015	Parcel	4,495*
Total land area (ha)	0.80	0.022	Household	2,163
Parcel area (ha)	0.39	0.013	Parcel	3,886
Pure stand (ha)	0.27	0.011	Parcel	4,495*
Inter-cropped (ha)	0.45	0.015	Parcel	4,495*

Note: *For 625 parcels, the cropping system has changed from pure stand to inter-cropped between cropping seasons one and two. These are counted twice (once fore each cropping system) in computing these statistics.

Table 4.6 shows average crop yield by cropping system. For each crop, yield is higher under multi-crop systems. It is particularly high in the case of maize, beans, and groundnuts with multi-crop parcel yields almost twice as much as pure-stand. As shown in Table 4.7, some of the yield differential can be explained by differences in input use. Except for labor (both household and hired), more inputs are used per hectare on multi-crop parcels than pure-stand parcels.

4.3.2 Yield and cropping patterns

This section describes the yield patterns of major crops in Uganda under different cropping systems and crop-mix conditions. For presentation purposes, I focus on the most important crop – maize. Figure 4.1 shows the distribution of maize, beans, cassava and matoke yield under pure stand and multi-crop (mixed stand) systems.[10] The top left panel presents average maize yield for pure stand (solid line) and mixed stand (long dash) parcels. The average maize yield under mixed stand is substantially higher than pure stand yield. Maize yield distribution under mixed stand has less density around the mode and fatter tails, suggesting higher variance. From simple inspection, it is clear that the higher variance is due to positive maize yield skewness. Likewise, the beans yield distribution panel (top right) shows that mixed stand parcels generate greater yield but are riskier. The relatively higher variance is, however, primarily due to positive skewness of

[10] A complete set of yield distributions for all seven crops in the analysis sample is shown in Figures C1 and C2.

Table 4.6: Crop yield by cropping system

Crops	Pure stand	Mixed stand	Difference Pure-Mixed
Maize	12.74	25.84	-13.10***
	(1.225)	(1.469)	(1.810)
Sorghum	6.48	8.34	-1.86**
	(0.579)	(0.840)	(0.944)
Beans	5.79	10.92	-5.13***
	(0.465)	(0.385)	(0.582)
Groundnuts	6.20	10.27	-4.07***
	(0.703)	(0.665)	(0.903)
Sweet potatoes	30.21	42.55	-12.34***
	(2.018)	(2.076)	(2.538)
Cassava	24.06	38.45	-14.39***
	(2.273)	(2.364)	(3.140)
Matoke	48.50	53.61	-5.11*
	(4.192)	(2.826)	(3.595)

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows output per hectare measured in quintals for each of the seven crops in the analysis sample. It shows that yield is significantly different between pure stand and mixed stand cropping systems.

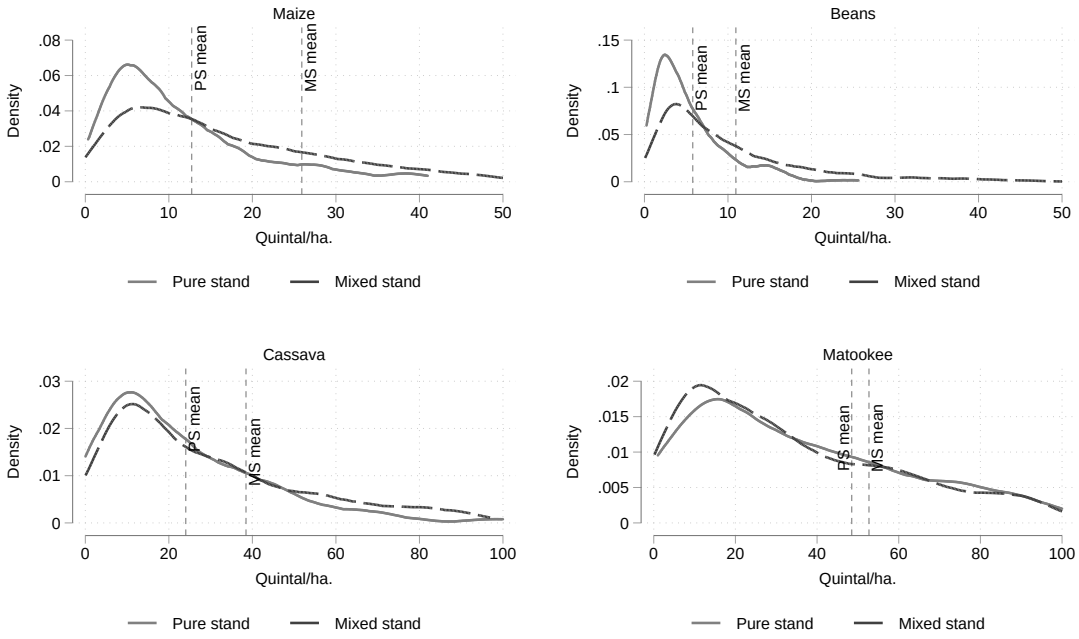
Table 4.7: Inputs per hectare in 2011/12

Variables	Pure stand	Mixed stand	Difference Pure-Mixed
Parcel area (ha)	0.273	0.442	-0.169***
	(0.011)	(0.015)	(0.012)
Used organic fertilizer (%)	0.037	0.073	-0.036***
	(0.007)	(0.009)	(0.008)
Used inorganic fertilizer (%)	0.010	0.028	-0.017**
	(0.004)	(0.008)	(0.008)
Used pesticides (%)	0.031	0.059	-0.028***
	(0.006)	(0.007)	(0.009)
Organic fertilizer (kg)	52.598	61.356	-8.843
	(16.467)	(9.070)	(16.141)
Inorganic fertilizer (kg)	1.252	0.817	0.432
	(0.529)	(0.383)	(0.646)
Pesticides (kg)	0.157	0.200	-0.043
	(0.042)	(0.046)	(0.056)
Labor days: total	207.589	186.894	20.316**
	(9.678)	(6.078)	(9.295)
Labor days: HH member	196.626	176.623	19.643**
	(9.260)	(6.035)	(8.838)
Labor days: hired	8.665	7.470	1.179
	(1.188)	(0.631)	(1.265)

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents input use by cropping systems. The figures shown in rows 5-10 are quantity of input used per hectare.

mixed stand yield.



Note: For presentation purposes, maize and beans yield are trimmed at 50Q/ha whereas cassava and matookee yield are trimmed at 100Q/ha.

Note: Figure 4.1 shows the distribution of maize, beans, cassava and matoke yield by cropping system. The solid line shows yield when each crop is planted as pure stand while the dashed-line shows yield for mixed stand. The vertical dashed lines are the average yield level for pure stand (PS mean) and mixed stand (MS mean). The mixed stand doesn't distinguish between any specific sets of crop combinations. If two more crops are planted on a parcel, the cropping system is considered mixed stand. It also doesn't distinguish between inter-cropping and multiple specialized plots on a parcel.

Figure 4.1: Distribution of yield by cropping system

The distribution of cassava and matoke yield in the bottom half of Figure 4.1 do not display as sharp a contrast between pure stand and mixed stand parcels as the top half. The mean cassava yield is higher under mixed stand system with fatter and longer tail compared to pure-stand.[11] Bar the slight difference in average

[11]For presentation purposes, the graph is shown for output less than 100 quintal per hectare. In

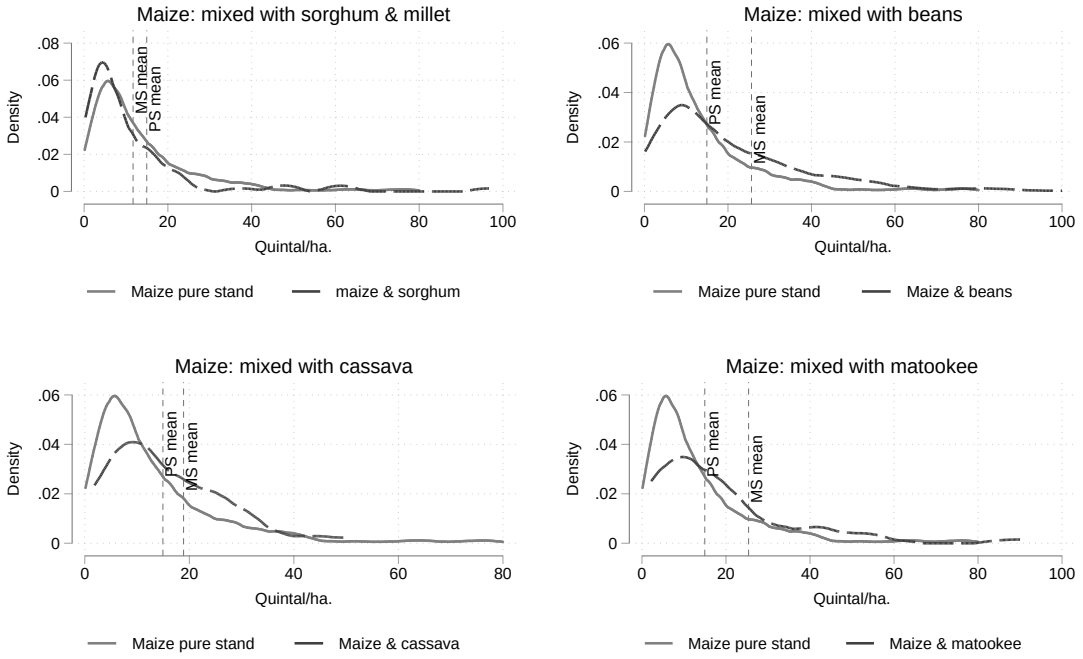
yield, mixed stand matoke yield is practically indistinguishable from pure stand. Overall, these results show that mixed stand parcels have greater yield but also involve higher variance, perhaps primarily due to higher skewness.

Figure 4.2 presents maize yield distribution under different crop-mix conditions.[12] The top left panel suggests that pure stand stochastically dominates mixed stand of maize and sorghum. The mass of the distribution shifts to the left while variance remains about the same. The situation is completely different in the maize-beans top right panel. Compared to pure stand, the maize yield distribution shifts to the right under maize-beans mixed stand systems: mean yield is higher and variance lower. With the maize-cassava mixed stand in the bottom left panel, it is difficult to make a conclusive assessment based on visual inspection. Based purely on mean and variance, though mixed stand appears superior to pure stand, the likelihood of very high yields, albeit with greater risk, are reduced with mixed stand system. For the maize-matoke mix, mixed stand is unambiguously superior to pure stand, it involves higher yield but similar variance.

The change in maize yield as the diversity of crop-mix changes is summarized in Figure 4.3. It shows that, the maize-beans mix trumps not only pure stand maize or maize-sorghum mix, but also the maize, sorghum and beans mix. Though variance appears higher, albeit positively skewed, average yield is much higher for the maize-beans mix as shown by the fact that its yield distribution lies

the complete graph, the distribution of mixed stand cassava yield is considerably longer than that of pure stand.

[12]Figure C3 presents the yield distribution of maize under various crop-mixes for greater number of the major crops in the analysis sample.



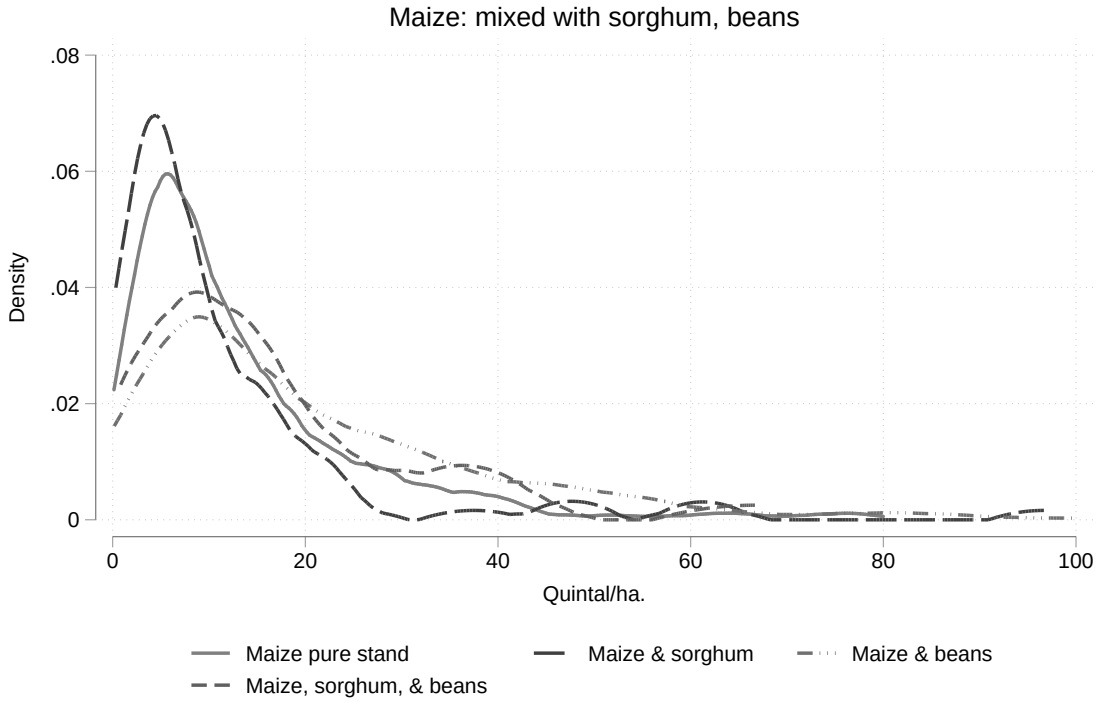
Note: For presentation purposes, yield is trimmed at 100Q/ha in all panels.

Note: Figure 4.2 shows maize yield under different crop mix conditions. Panel (1) compares the distribution of pure stand maize yield with with maize-sorghum mixed stand. In panel (2) pure stand maize yield is compared with maize yield from a maize-beans mixed stand. Panels (3) and (4) present the pure stand maize yield vs. the two main root crops in Uganda –cassava and matoke, respectively. Mixed stand includes inter-cropping as well as specialized plots in multi-crop parcels.

Figure 4.2: Distribution of maize yield under pure stand and various dual-crop mixed stand

above and to the right of the three-crop mix for much of the range of values of yield.[13]

[13] Appendix Figure C4 expands this to show maize yield under various crop combinations and diversity intensities.



Note: The distribution of maize yield under changing of corp mix conditions are presented in Figure 4.3. It compares the evolution of maize yield as maize parcels are mixed gradually with sorghum, beans, and finally both sorghum and beans. The definition of mixed stand doesn't distinguish between inter-cropping and multi-crop parcels with specialized plots.

Figure 4.3: Maize yield under changing and diverse crop-mixes

4.4 Empirical Strategy

The empirical estimation strategy proceeds in two steps. First the mean equation is estimated using $q_{ijkt} = f(x_{ijkt}, \alpha_k) + u_{ijkt}$, where i, j, k, and t represent household, parcel, crop and panel round, respectively, and u is a random error term with mean zero. The residual from equation $\hat{u}_{ijkt} = q_{ijkt} - f(x_{ijkt}, \hat{\alpha}_k)$ is then used to estimate the parameters of the higher order moments as $\hat{u}^{\lambda}_{ijkt} = g(x_{ijkt}, \beta_{k\lambda}) + \varepsilon_{ijkt\lambda}$, $\lambda =$

2, 3 and $E(\varepsilon_{ijkt\lambda}) = 0$. A good approximation of the mean equation is especially crucial since the higher order residual terms are correlated with inputs x_{ijkt} [15]. Thus, to estimate the moment functions for each crop k, the production function is specified as

$$\begin{aligned} \ln q_{ijt} &= \alpha_0 + \sum_{m=1}^{m} \alpha_m \ln x_{ijmt} + \mathbf{w}'_{it}\boldsymbol{\gamma} + \mathbf{z}'_{jt}\boldsymbol{\delta} + \pi_t + \eta_v + u_{ijt} \\ \hat{u}^{\lambda}_{ijt} &= \beta_{0\lambda} + \sum_{m=1}^{m} \beta_{m\lambda} \ln x_{ijmt} + \mathbf{w}'_{it}\boldsymbol{\theta}_{\lambda} + \mathbf{z}'_{jt}\boldsymbol{\phi}_{\lambda} + \pi_{t\lambda} + \eta_{v\lambda} + \varepsilon_{ijt\lambda}, \quad \lambda = 2, 3 \end{aligned} \tag{4.13}$$

where q is output per hectare (yield), x_m is quantity of input m, $\mathbf{w}$ is a vector of household characteristics, $\mathbf{z}$ is a vector of parcel characteristics, π is time dummy, η is village fixed effect, and u and ε are random error terms.

The inputs x_m include conventional inputs such as land, labor, fertilizer, pesticides, and seeds. Crop yields are measured in grain equivalent quintal per hectare. Labor is measured in total labor days by household members and hired workers with no regard to gender and age. Fertilizer is measured in kilograms (kg). It includes both organic (manure, compost and seaweed) and inorganic/chemical (nitrogen, phosphate, potash and mixed complex) fertilizers. Pesticides are measured in kg and include insecticides, fungicides, fumigants, herbicides and rodenticides. Seed is measured in Ugandan Shillings, because data on seed quantity are available only for the 2011/12 round.[14]

[14]Using a dummy variable for the type of seeds used (1 if improved seeds, and 0 otherwise) doesn't have much effect on the broad findings. Likewise data on draught animals used aren't available for all rounds. This, however, doesn't appear to be a major problem as only 8% of households report using animals for draught power in 2011/12, and is thus dropped.

To reflect the interdependence of crop productivity in multi-crop systems, which characterize agriculture in Uganda, land allocations to other crops are included in (4.13). This allows output to be complementary with some crops and rival with others.[15] The set of household level controls included are age, gender, schooling and marital status of the household head, spouse schooling, household size, and average age and schooling of the household. The parcel specific variables in $\mathbf{z}$ are elevation, soil type, soil quality, topography, a dummy variable for water source (1 if the parcel is irrigated, and 0 otherwise), and precipitation. Time (round $\times$ cropping season) dummy is included to control for factors such as government policy, which are common to all parcels within a period but vary over time. Village dummies are included to control for factors that have a common effect on productivity within a village but vary across villages, such as access to inputs, credit, and extension services, and administrative bureaucracy.

By construction, u_{ij} in (4.13) is correlated with higher moments of q, thus, heteroskedastic. Estimation of the parameters of the model by ordinary least squares (OLS) would lead to suspect inference. To address this problem, parameters of the model are estimated using generalized least squares (GLS) type estimator, which allows an arbitrary correlation between error terms and non-linear functions of the regressors. Joint production in multi-output systems further complicates the estimation challenge since crop production decisions are likely correlated, leading to violation of the classical assumption $E(u_{ijk}, u_{ijl}) = 0$. As a result, equation-by-

[15]For example, legumes such as peas and soybeans are known to have symbiotic nitrogen-fixing bacteria, whereas potatoes are known to reduce soil productivity. The productivity of cereals may, thus, vary depending on other jointly produced crops.

equation estimation of (4.13) would lead to inefficient estimates. I address this issue by estimating the model by a system estimator that allows contemporaneous correlation of errors across equations. Further, for a given crop, errors are likely to be correlated over time due to observed and unobserved omitted variables. However, since the unit of analysis in this paper, parcel, cannot be tracked over time, distributed lag models cannot be employed to account for potential error correlation. To address this issue, errors are allowed to be correlated arbitrarily over time. The model is estimated using system generalized method of moments (GMM) estimator. Standard errors are clustered at the EA level.

The production function in (4.13) is specified as a log-linear model, allowing a straight forward interpretation of estimated coefficients. In the yield function, coefficients measure input elasticity of yield. Likewise, in the variance and skewness equations, estimated coefficients are input elasticities of variance and skewness. In transforming level variables into logs, I use inverse hyperbolic sine transformation to circumvent the challenges imposed by the relatively large number of zero values for inputs in the sample.[16]

The choice of log-linear production function is due to its relative ease of estimation for a relatively large system such as this, despite its well known limitations [100]. As a robustness check, I estimate a restricted translog production function

[16]The inverse hyperbolic sine transformation is defined as: $\log(x) \approx \log(x + \sqrt{(x^2 + 1)})$.

of the form

$$\ln q_{ijt} = \alpha_0 + \sum_{m=1}^{m} \alpha_m \ln x_{ijmt} + \sum_{m=1}^{m}\sum_{l=1}^{m} \alpha_{ml} \ln x_{ijmt} \ln x_{ijlt} + \mathbf{w}'_{it}\boldsymbol{\gamma} + \mathbf{z}'_{jt}\boldsymbol{\delta} + \pi_t + \eta_v + u_{ijt}$$

$$(\hat{u}_{ijt})^{\lambda} = \beta_{0\lambda} + \sum_{m=1}^{m} \gamma_{m\lambda} \ln x_{ijmt} + \sum_{m=1}^{m}\sum_{l=1}^{m} \beta_{ml\lambda} \ln x_{ijmt} \ln x_{ijlt} + \mathbf{w}'_{it\lambda}\boldsymbol{\theta}_{\lambda} + \mathbf{z}'_{jt}\boldsymbol{\phi}_{\lambda} + \pi_{t\lambda} + \eta_{v\lambda} + \varepsilon_{ijt\lambda},$$

$$\lambda = 2, 3. \tag{4.14}$$

Restriction on interaction terms is necessary due to the large number of crops in the system (seven). Only conventional inputs are allowed to interact to capture potential complementarity and rivalry between inputs in production, while land allocations for other crops enter linearly. The results are consistent with the estimated coefficients of the log-linear model in (4.13) and are reported in the appendix.

4.5 Results

4.5.1 Mean equations

Table 4.8 presents elasticity estimates of the mean function. The estimated system of equations achieves high goodness of fit for all seven equations with R^2 upwards of 0.65. Average crop yield is positively related to labor input for each of the seven crops. This may indicate that greater labor input would allow better farm management at different stages of crop production. During land preparation, it would

enable repeat tillage to turn deep soils and bring fresh nutrients to the surface as well as allow better aeration. More labor days for weeding, attending to crops, and keeping out pest birds and other animals during the vegetative and reproductive cycles of crop growth may increase yield. Later on, greater availability of labor may enable timely harvesting (cutting), threshing, winnowing and storing of crop and reduce waste. The estimated elasticities are also large. A one percent increase in labor days is associated with 0.9% increase in mean maize yield and 0.8% increase in mean sorghum, beans and groundnuts yield. Likewise, a one percent increase in labor days is associated with over one percent increases in average cassava and matoke yield. These results point to the potential for productivity gains through conventional input intensification.

Table 4.8: GMM estimates of mean yield elasticities

Dependent variable: log crop yield	(1) Maize	(2) Sorghum	(3) Beans	(4) Groundnuts	(5) Sweet potatoes	(6) Cassava	(7) Matoke
Log labor (days)	0.941***	0.759***	0.754***	0.764***	1.199***	1.161***	1.163***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Log fertilizer (kg)	0.070***	0.045***	0.070***	0.127***	-0.011	0.062***	0.044***
	(0.015)	(0.010)	(0.008)	(0.024)	(0.020)	(0.015)	(0.006)
Log seed value (USh)	0.037***	0.028***	0.033***	0.040***	0.055***	0.001	0.030**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.007)	(0.015)
Log pesticides (kg)	-0.196***	-1.023***	-0.061	-0.560***	-0.282***	0.398***	0.046
	(0.056)	(0.255)	(0.077)	(0.127)	(0.105)	(0.087)	(0.075)
Log maize plot (ht)	-1.983***	-0.023	0.385***	0.161***	0.309***	0.094**	0.482***
	(0.064)	(0.018)	(0.046)	(0.028)	(0.047)	(0.044)	(0.052)
Log sorghum plot (ht)	-0.079	-2.278***	0.046	0.126**	0.146	0.018	0.036
	(0.108)	(0.058)	(0.095)	(0.056)	(0.095)	(0.088)	(0.105)
Log beans plot (ht)	0.452***	0.001	-2.639***	0.241***	0.371***	0.204***	0.464***
	(0.066)	(0.022)	(0.074)	(0.034)	(0.058)	(0.054)	(0.064)
Log groundnuts plot (ht)	0.504***	0.136***	0.668***	-1.358***	0.069	0.169**	0.334***
	(0.085)	(0.029)	(0.075)	(0.060)	(0.075)	(0.070)	(0.083)
Log sweet potatoes plot (ht)	0.711***	0.031	0.546***	0.159***	-2.575***	0.431***	0.555***
	(0.078)	(0.026)	(0.068)	(0.040)	(0.094)	(0.064)	(0.075)
Log cassava plot (ht)	0.101	0.014	0.218***	0.104***	0.314***	-2.043***	0.308***
	(0.065)	(0.022)	(0.057)	(0.034)	(0.057)	(0.070)	(0.063)
Log matoke plot (ht)	0.371***	-0.011	0.578***	0.168***	0.318***	0.223***	-1.418***
	(0.049)	(0.017)	(0.043)	(0.025)	(0.043)	(0.040)	(0.058)
Log total land area (ht)	-0.073***	0.014***	-0.098***	-0.031***	0.013	-0.023**	-0.122***

Continued on next page

Table 4.8 – *Continued from previous page*

Dependent variable: squared residual (u^2)	Maize	Sorghum	Beans	Groundnuts	Sweet potatoes	Cassava	Matoke
	(0.011)	(0.004)	(0.010)	(0.006)	(0.010)	(0.009)	(0.011)
Parcel slope (%)	-0.001	0.001	0.001	0.003***	-0.002	-0.004***	-0.004***
	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parcel elevation (m)	-0.0003***	-0.00001	-0.0002***	-0.0002***	-0.00005	-0.0001**	0.0003***
	(0.0001)	(0.00001)	(0.00005)	(0.00003)	(0.00005)	(0.00004)	(0.00005)
Rainfall ('000 mm)	-0.042	0.070***	0.186***	0.062**	0.192***	0.099**	0.234***
	(0.055)	(0.019)	(0.048)	(0.028)	(0.048)	(0.045)	(0.053)
Constant	0.332***	-0.064	-0.016	-0.025	-0.215**	0.075	-0.389***
	(0.121)	(0.041)	(0.106)	(0.063)	(0.107)	(0.099)	(0.117)
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,774	18,774	18,774	18,774	18,774	18,774	18,774
R^2	0.675	0.771	0.646	0.702	0.743	0.740	0.778

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

Note: This table presents the elasticity estimates of yield (mean) equation. The dependent variables are log crop yields in quintals. All regressors listed above are in logs and the units in which each regressor is measured is given in parenthesis. The amount of fertilizer used includes both organic and inorganic fertilizer. *kg*, *ht*, *m* and *mm* stand for kilogram, hectare, meter and millimeter, respectively. Household characteristics include household (hh) head gender, age, marital status, years of schooling, household size, hh average years of schooling, spouse years of schooling, hh average age, distance to major road, population center of 20,000, and nearest market. Parcel characteristics include agro-ecology, soil type, soil quality, water source (irrigation=1) and topography.

Fertilizer use is positively correlated with the average yield of all crops except sweet potatoes, whose coefficient is small and statistically insignificant. Elasticity estimates for fertilizer range between 0.04 for matoke and 0.13 for groundnuts. Similarly, improved seed use is positively correlated with crop yield. A one percent increase in expenditure on seed is associated with between 0.03% and 0.06% increase in yield for all crops except cassava. The coefficient for seed in the cassava equation is positive but statistically insignificant. Admittedly, it is difficult to distinguish the effects of increase in quantity from the effects of quality (improved vs. traditional seeds) using seed value data. However, estimates using dummy variables for improved seed application show positive correlation between improved seed use and yield for all crops (results could be obtained upon request). Surprisingly, it appears that pesticide use is negatively correlated with average yield for most crops. This might be due to selection in pesticide use. That is, if a significant fraction of pesticide application takes place on plots that have already been infested with pests, the average yield on these plots could be lower, despite pesticide use.

The elasticity estimates of crop plot size are negative and statistically significant for all crops. The coefficients are also large – a one percent increase in land area is associated with over one percent fall in crop yield. These results are consistent with the large evidence on inverse productivity-size relationship [186, 42, 20, 136]. This point is further supported by the negative and statistically significant coefficients of total parcel area in five of the seven crops. The only exception is sorghum, whose coefficient is positive and significant. The cross-

equation land allocations in each equation also show that there is considerable complementarity among crops.

Maize yield is positively and statistically significantly correlated with the amount of land allocated to beans, groundnuts, sweet potatoes and matoke. The correlations with sorghum and cassava are statistically insignificant. The positive correlation between maize yield and land allocated to beans and groundnuts reflects the well known symbiotic relationship between cereals and legumes. The potential mechanisms include differences in the growth cycles of these crops and the ability of legumes to fix soil nitrogen. Beans and groundnuts emerge more quickly than maize, promoting a more efficient use of nutrients and sunlight during the sensitive early growth stages. Legumes benefit from N-fixing *rhizobia* bacteria to transform atmospheric nitrogen into a biologically useful form (NH_3) for plant growth. Limited amount of surplus nitrogen is released into the environment during nitrogen fixation and more when the bacteria die, improving soil nutrition while also reducing competition with non-legumes (maize) for inorganic fertilizer [189, 139]. Increase in land allocation to sweet potatoes is associated with increase in maize yield, potentially because sweet potato vines provide mulch for maize, preserving moisture and reducing weed infestation [11, 115].

Sorghum does not appear to have strong complementary or rival relationship with other crops. The only exception is groundnut. The gains in sorghum yield in a sorghum-groundnut mix could be attributed to improved radiation interception in a sorghum-groundnut mixed stand than in sole-cropped sorghum [103, 194],

strong nitrogen fixation by groundnuts [202] and weed suppression (eg. *Striga hermonthica*) [41]. The average yield of beans is positively correlated with land allocation for maize, groundnuts, sweet potatoes, cassava and matoke. Similarly, groundnuts, sweet potatoes, cassava and matoke display strong complementarity with other constituent crops. The average yield for each crop is positively correlated with land allocations of other crops, except sorghum.[17] The potential mechanisms include increase in efficiency of resource use (e.g. light), nitrogen fixation and the associated lower competition for nutrients, and weed suppression ([39]; and references therein).

These results reflect the positive productivity gains from mixed cropping of cereals and legumes established in the literature [118, 211]. In addition to the nitrogen fixing ability of legumes, morphological differences between cereals and legumes allows different spatial and temporal use of environmental resources by the cereals-legume mix components and greater nutrient intake [205]. Legumes have shorter formative phase, lower canopy structure and shallow root systems compared to cereals. Cereals have higher canopy structure and their root system grows to a greater depth than those of legumes. As a result, competition for nutrients, radiation, and water between component crops during pick growth phases is limited.

There is mixed evidence on productivity gains from cereals-tubers mix. There are no cereal or cassava yield gains from mixed cropping of maize or sorghum

[17]Several previous studies find negative or no relationship between sorghum and legumes (see [175, 138]).

with cassava. This is perhaps due to the nutrient (nitrogen and potassium) intensive nature of cassava and lack of nutrient complementarity between cereals and cassava. The legumes-cassava mix, on the other hand, increases the productivity of both legumes and cassava. Legumes are compatible with cassava in terms of growth pattern, canopy structure and nutrient demand. Legumes can largely satisfy their nitrogen needs but require phosphorous, while cassava requires potassium and nitrogen [172]. The evidence from previous studies on the yield effects of cereals-tubers and legumes-tubers intercrops is largely consistent with these findings [11, 36].

4.5.2 Variance equations

Table 4.9 presents estimates of the variance system of equations. Yield variance is positively correlated with labor inputs for all crops. This could be the case if labor inputs are greater on farms that are infested with weeds, pests and other pathogens. In Uganda, where the use of herbicides and pesticides is very low, farmers rely on traditional labor intensive methods. Weed and pests are known to cause yield variability. While greater labor inputs may mean greater resources for weed and pest management, labor inputs would be positively correlated with crop yield if observed increases in labor are associated more with mitigating the effects of infestation rather than prevention. [20] argues that food security concerns may induce small holders into using more labor as a risk mitigation strategy.

Table 4.9: GMM estimates of yield variance elasticities

Dependent variable: squared residual (u^2)	(1) Maize	(2) Sorghum	(3) Beans	(4) Groundnuts	(5) Sweet potatoes	(6) Cassava	(7) Matoke
Log labor (days)	0.289***	0.252***	0.190***	0.295***	0.414***	0.397***	0.276***
	(0.017)	(0.010)	(0.013)	(0.014)	(0.020)	(0.018)	(0.020)
Log fertilizer (kg)	0.015	-0.082***	0.019	0.119**	0.154**	0.193***	-0.063***
	(0.041)	(0.023)	(0.020)	(0.057)	(0.061)	(0.044)	(0.018)
Log seed value (USh)	0.093***	0.051***	0.043***	0.068***	0.019	0.035*	0.031
	(0.007)	(0.005)	(0.004)	(0.005)	(0.018)	(0.019)	(0.045)
Log pesticides (kg)	-0.303*	-0.850	-0.333*	-0.629**	-0.368	-0.372	1.225***
	(0.158)	(0.565)	(0.187)	(0.302)	(0.315)	(0.249)	(0.230)
Log maize plot (ht)	0.205	0.001	0.753***	0.131**	0.228	-0.026	0.773***
	(0.179)	(0.040)	(0.111)	(0.066)	(0.139)	(0.124)	(0.159)
Log sorghum plot (ht)	0.083	-0.387***	0.031	-0.014	-0.312	-0.346	-0.077
	(0.299)	(0.129)	(0.227)	(0.134)	(0.282)	(0.252)	(0.322)
Log beans plot (ht)	0.239	-0.014	-0.040	0.248***	0.242	-0.014	0.208
	(0.182)	(0.050)	(0.177)	(0.082)	(0.172)	(0.153)	(0.197)
Log groundnuts plot (ht)	0.805***	0.259***	0.610***	0.913***	-0.340	-0.084	0.057
	(0.236)	(0.065)	(0.179)	(0.143)	(0.223)	(0.198)	(0.255)
Log sweet potatoes plot (ht)	0.804***	-0.023	0.470***	0.097	1.517***	0.520***	0.746***
	(0.214)	(0.059)	(0.162)	(0.096)	(0.282)	(0.180)	(0.231)
Log cassava plot (ht)	-0.328*	0.006	0.021	0.010	0.202	1.938***	0.027
	(0.180)	(0.049)	(0.136)	(0.080)	(0.170)	(0.200)	(0.193)
Log matoke plot (ht)	0.695***	-0.065*	0.732***	0.090	0.323**	0.129	1.465***
	(0.136)	(0.037)	(0.104)	(0.061)	(0.129)	(0.114)	(0.178)
Log total land area (ht)	-0.194***	0.024***	-0.225***	-0.046***	0.084***	0.016	-0.165***

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Table 4.9 – *Continued from previous page*

Dependent variable: squared residual (u^2)	Maize	Sorghum	Beans	Groundnuts	Sweet potatoes	Cassava	Matoke
	(0.031)	(0.008)	(0.023)	(0.014)	(0.029)	(0.026)	(0.033)
Parcel slope (%)	0.203***	-0.006	0.172***	0.095***	0.011	-0.051	0.242***
	(0.044)	(0.012)	(0.033)	(0.020)	(0.041)	(0.037)	(0.047)
Parcel elevation (m)	-1.078***	0.004	-0.292*	-0.348***	-0.507***	-0.288*	-0.669***
	(0.206)	(0.057)	(0.156)	(0.093)	(0.195)	(0.174)	(0.222)
Rainfall ('000 mm)	0.723***	0.138***	0.749***	0.435***	0.691***	0.372***	1.048***
	(0.168)	(0.047)	(0.128)	(0.075)	(0.159)	(0.142)	(0.182)
Constant	7.722***	0.116	1.846*	2.501***	4.311***	3.152***	4.837***
	(1.430)	(0.394)	(1.084)	(0.642)	(1.353)	(1.204)	(1.541)
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,774	18,774	18,774	18,774	18,774	18,774	18,774
R^2	0.073	0.115	0.062	0.145	0.082	0.100	0.064

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents the elasticity estimates of yield (mean) equation. The dependent variables are squared residuals from the mean equation. All regressors listed above are in logs and the units in which each regressor is measured is given in parenthesis. The amount of fertilizer used includes both organic and inorganic fertilizer. *kg*, *ht*, *m* and *mm* stand for kilogram, hectare, meter and millimeter, respectively. Household characteristics include household (hh) head gender, age, marital status, years of schooling, household size, hh average years of schooling, spouse years of schooling, hh average age, distance to major road, population center of 20,000, and nearest market. Parcel characteristics include agro-ecology, soil type, soil quality, water source (irrigation=1) and topography.

Fertilizer use is associated with rise in yield variance for sorghum and matoke but increase in the variance of groundnuts, sweet potatoes and cassava yield. Various studies show that fertilizer is variability increasing input [17, 190]. In the presence of uncertainty about soil quality, risk averse farmers are likely to over-apply fertilizers as insurance against crop loss [16, 126]. Generally, sorghum and matoke are planted on marginal land. Perhaps, as opposed to the other crops, fertilizer under-application due to farmers' subjective distribution of marginal product of fertilizer may explain the negative relationship between fertilizer and sorghum and matoke yield variance [16]. Likewise, farmers' erroneous perceptions of the distribution of marginal product of seeds relative to experimental distributions and consequent over-application may explain the positive correlation between crop yield variance and the value of seeds used [190]. Pesticides, as expected, appear to be crop yield variance reducing.

For the majority of the crops, increase in land area is associated with increase in yield variance. The elasticity estimates are especially large for sweet potatoes, cassava and matoke. A one percent increase in plot area is associated with over 1.5% increase in yield variance. The potential explanations for the high variances includes high transaction costs [32, 31] and supervision costs [86, 192] as farm size increases. Yield variance for sorghum, on the contrary, appears to be negatively correlated with plot area. Estimates for maize and beans are statistically insignificant.

The cross-equation elasticity estimates show that there is little gain in terms

of reduced yield variance from mixed cropping. For the majority of crops, crop mixes that include sweet potatoes and matoke are associated with increase in yield variance. Similarly, groundnut mix with maize, sorghum or beans tends to have higher yield variance. The maize mix with beans, groundnuts or matoke also has high yield variance. The only crop mixes that appear to have lower yield variance are the maize-cassava and the sorghum-matoke mixes.

4.5.3 Skewness equations

Table 4.10 presents elasticity estimates of the skewness system of equations. The coefficients on own plot size are positive and statistically significant for all crops in the system, except sorghum. The large skewness associated with larger plots points to the potential trade-off that farmers face in land allocation decisions given the positive (negative) correlation between land area and yield skewness (average yield), respectively. The aversion to yield variance by risk averse farmers relates to the potential for low yield draws from distributions with wide spread. For a constant variance, positively skewed distributions are rather preferred. The results in Table 4.10, suggest that increase in land area may increase the likelihood of high yield levels, which speaks to the importance of including a third moment of yield in estimating risk parameters. The potential explanations include economies of scale [129] and lumpy nature of some agricultural technologies which limits their economic feasibility on small plots [87, 161].

Table 4.10: GMM estimates of yield skewness elasticities

Dependent variable: cubic residual (u^3)	(1) Maize	(2) Sorghum	(3) Beans	(4) Groundnuts	(5) Sweet potatoes	(6) Cassava	(7) Matoke
Log labor (days)	-0.707***	-0.029	-0.467***	-0.229***	-0.493***	-0.882***	-1.321***
	(0.081)	(0.040)	(0.056)	(0.054)	(0.090)	(0.081)	(0.097)
Log fertilizer (kg)	-0.062	-0.039	-0.009	-0.269	-0.380	-0.101	0.010
	(0.200)	(0.090)	(0.086)	(0.226)	(0.278)	(0.194)	(0.090)
Log seed value (USh)	0.183***	0.114***	0.078***	0.145***	-0.084	-0.087	-0.562**
	(0.035)	(0.018)	(0.018)	(0.018)	(0.080)	(0.085)	(0.224)
Log pesticides (kg)	-1.256	-0.147	-0.916	0.183	1.718	0.131	-0.878
	(0.766)	(2.192)	(0.801)	(1.197)	(1.443)	(1.102)	(1.135)
Log maize plot (ht)	2.922***	0.0003	2.031***	0.624**	0.935	-0.270	2.658***
	(0.867)	(0.157)	(0.474)	(0.261)	(0.636)	(0.547)	(0.789)
Log sorghum plot (ht)	0.265	-0.194	-0.281	0.458	-1.212	-1.375	-1.334
	(1.451)	(0.499)	(0.969)	(0.532)	(1.293)	(1.113)	(1.603)
Log beans plot (ht)	0.789	-0.060	2.823***	0.996***	0.272	-0.340	0.471
	(0.882)	(0.195)	(0.757)	(0.326)	(0.790)	(0.678)	(0.981)
Log groundnuts plot (ht)	2.134*	0.847***	0.800	1.210**	-1.642	-0.589	-0.767
	(1.145)	(0.252)	(0.766)	(0.568)	(1.021)	(0.877)	(1.266)
Log sweet potatoes plot (ht)	2.230**	-0.209	1.140	0.393	3.981***	1.052	1.848
	(1.041)	(0.229)	(0.693)	(0.381)	(1.290)	(0.797)	(1.150)
Log cassava plot (ht)	-1.503*	-0.024	-0.329	0.064	-0.215	7.602***	0.163
	(0.873)	(0.191)	(0.579)	(0.319)	(0.780)	(0.885)	(0.960)
Log matoke plot (ht)	1.658**	-0.204	1.327***	0.393	0.762	0.430	7.548***
	(0.661)	(0.145)	(0.443)	(0.243)	(0.589)	(0.506)	(0.881)
Log total land area (ht)	-0.758***	0.105***	-0.767***	-0.198***	0.256*	-0.006	-0.839***

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Table 4.10 – *Continued from previous page*

Dependent variable: squared residual (u^2)	Maize	Sorghum	Beans	Groundnuts	Sweet potatoes	Cassava	Matoke
	(0.149)	(0.033)	(0.099)	(0.055)	(0.133)	(0.114)	(0.165)
Parcel slope (%)	1.267***	-0.003	0.756***	0.366***	0.180	-0.164	0.804***
	(0.213)	(0.047)	(0.142)	(0.078)	(0.190)	(0.163)	(0.235)
Parcel elevation (m)	-5.060***	0.116	-0.210	-1.339***	-1.252	-1.425*	0.438
	(1.002)	(0.221)	(0.668)	(0.368)	(0.895)	(0.768)	(1.106)
Rainfall ('000 mm)	3.863***	0.534***	3.513***	1.386***	2.619***	1.661***	5.329***
	(0.816)	(0.181)	(0.545)	(0.300)	(0.729)	(0.626)	(0.904)
Constant	33.655***	-0.570	-0.380	9.191***	10.512*	13.439**	-2.572
	(6.946)	(1.534)	(4.627)	(2.550)	(6.200)	(5.323)	(7.661)
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,774	18,774	18,774	18,774	18,774	18,774	18,774
R^2	0.019	0.010	0.019	0.014	0.010	0.012	0.019

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents the elasticity estimates of yield (mean) equation. The dependent variables are cubed residuals from the mean equation. All regressors listed above are in logs and the units in which each regressor is measured is given in parenthesis. The amount of fertilizer used includes both organic and inorganic fertilizer. *kg*, *ht*, *m* and *mm* stand for kilogram, hectare, meter and millimeter, respectively. Household characteristics include household (hh) head gender, age, marital status, years of schooling, household size, hh average years of schooling, spouse years of schooling, hh average age, distance to major road, population center of 20,000, and nearest market. Parcel characteristics include agro-ecology, soil type, soil quality, water source (irrigation=1) and topography.

The inter-crop dynamics in the skewness system of equations is very limited, with maize at the center of much of it. Groundnuts, sweet potatoes and matoke land allocations are positively correlated with maize yield skewness, whereas cassava land allocation is negatively correlated with maize yield skewness. Likewise, increase in maize land allocation is associated with rise in beans, groundnuts and matoke yield skewness. The results show that yield skewness explains some of the variation in yield variance shown in Table 4.9. Failure to recognize the qualitative difference between positively and negatively skewed yield distributions in the analysis of crop choice may lead to overestimating the role of yield variance on farmers' decisions and unwarranted emphasis on policies focused at reducing risk.

4.5.4 Robustness checks

To confirm that the results in sections 5.1–5.3 are not outcomes of the log-linear functional form chosen for the analysis, I conduct robustness checks using the more flexible translog functional form. The choice of the log-linear function in the main text as opposed to the translog function is due to the relatively large number of crops in the system, with each individual equation containing a large number of variables. Thus, the robustness checks are conducted using a restricted translog function that allows interaction only among conventional inputs: labor, fertilizer, seed, pesticides and land allocations to maize, sorghum, beans, groundnuts, sweet potatoes, cassava and matoke.

Tables C1-C3 present the mean, variance and skewness system of equations estimates using translog production function. The reported figures are marginal effects – elasticity estimates evaluated at the average values of interacting variables. That is, the estimate on labor x_m in Table C1 of 1.303 is $\gamma_m + \sum_m \gamma_{ml} \times \bar{x}_l$, where $\bar{x}_l$ the average value of labor (for the quadratic term) and other conventional inputs (for the interaction terms). In the mean system of equations, the results of translog functional form are broadly similar to that of the log-linear model. There are, however, some key differences. The coefficients on land allocations for maize, sorghum and beans are negative and statistically significant in their corresponding equations, whereas the coefficients for groundnuts, sweet potatoes, cassava and matoke are positive. Moreover, land allocations to other crops are statistically insignificant for groundnuts, sweet potatoes and matoke.

The pattern is similar for the variance and skewness systems of equations. In the variance system of equations in Table C2, the own land allocations for all crops except sorghum are positive and statistically significant. Compared to the log-linear model, there is even less inter-crop dynamics under the translog functional form. Similarly, the results of the skewness system of equations for the translog model presented in Table C3 mirror the results of the log-linear model. Along the diagonal of the land allocation matrix, the coefficients on own land allocation are all positive and statistically significant, but the off-diagonal elements are, for the most part, statistically insignificant. Overall, the results for the translog model show that there is synergistic relationship between the different crops in the maize, beans and cassava equations but very little complementarity elsewhere. As

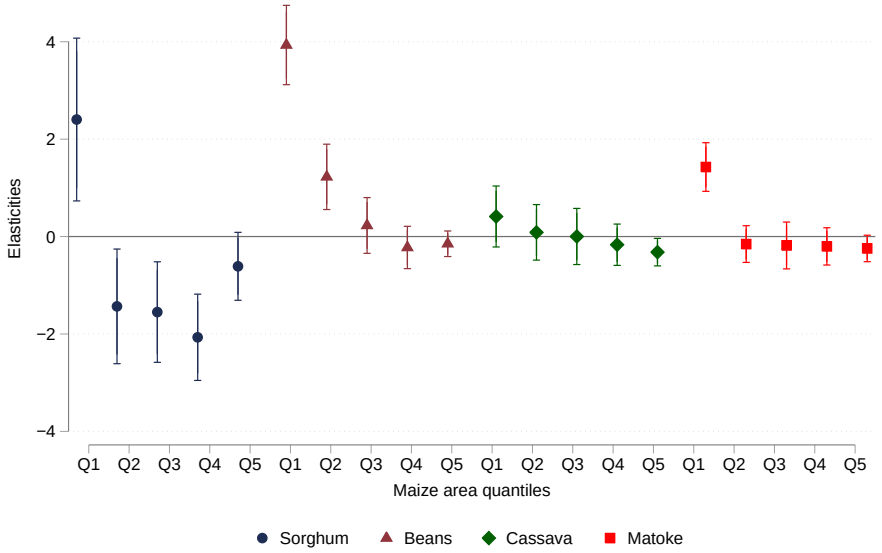
with the log-linear model, the results point to the need to include yield skewness in estimating risk parameters as some of the yield variance is explained by upside risk, which is not necessarily undesirable.

4.5.5 Plot heterogeneous effects

Figures 4.4-4.7 present estimates of the land area elasticity of yield by quantiles (Q) of plot size of the four major crops in Uganda: maize, beans, cassava and matoke.[18] The results for maize are summarized in Figure 4.4. It shows that there is considerable variation in maize yield response to mixed-cropping on plots of different sizes. Yield gains are largest for small plots. Indeed, mixed-cropping with the other three major crops is associated with maize yield gain for the smallest maize plots of about 0.03 hectares. Maize yield gains dramatically fall for the maize-sorghum mix and completely disappear for the maize-matoke mix as maize plot area increases. The maize yield gains associated with the maize-sorghum mix are negative for Q2-Q5, which suggests that the negative elasticity estimates of sorghum area in the maize equation in Tables 4.8 is perhaps due to negative correlations for relatively larger maize plots (0.06-0.6 hectares). The elasticity estimates for the maize-beans mix are rather positive and large for median or smaller maize plots (< 0.2 hectares). As plot area increases, the maize yield response gradually

[18]These estimates are based on parcels with non-zero output levels. In Figure 4.4, for example, the maize plot size quantiles are created conditional on positive quantities of maize on the parcel for the cropping season. If maize output on a parcel is zero because maize was not planted on it, it was left fallow or there was complete crop loss, the parcel is dropped from the analysis.

declines and settles around zero for Q4 and Q5, which explains the positive and statistically significant results found in the maize equation in Table (4.8). There is no appreciable variation in maize yield for the maize-cassava mix as maize plot area increases. Likewise, there is little variation in maize yield for the maize-matoke mix as maize plot area increases aside, from Q1. For Q2-Q5, the maize yield elasticity estimates are stable at around zero throughout.

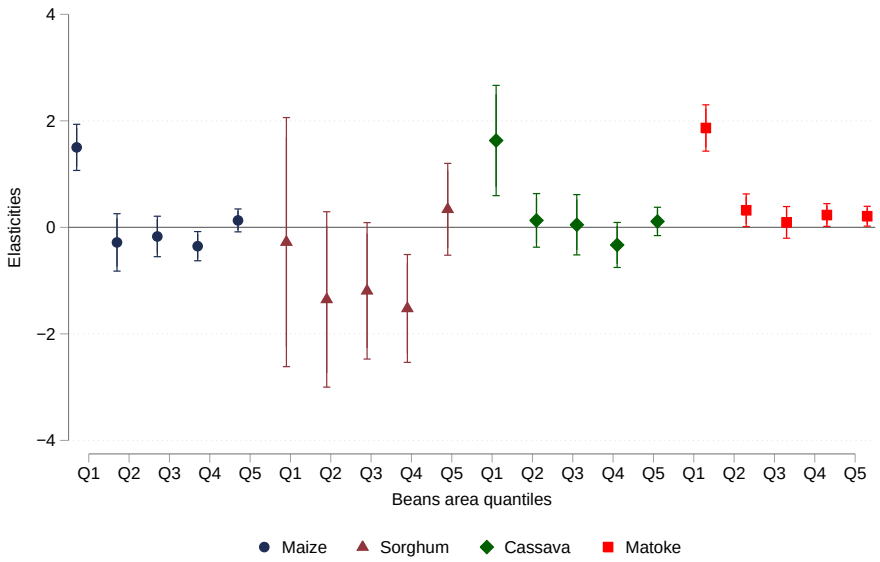


This figure shows average maize yield on plots with maize and sorghum, maize and beans, maize and cassava, and maize and matoke mix by quantiles of maize plot. Q1 is the lowest quantile and Q5 the highest quantile.

Figure 4.4: Average maize yield under mixed-cropping by quantiles of maize plot

The plot area elasticity of beans yield is shown in Figure 4.5. As in the case with maize, there are large gains associated with mixed-cropping beans with other crops on small beans plots. The elasticity estimates on plot allocations for maize,

cassava and matoke range between 1.5 and 2. With the exception of matoke, there is little mixed-cropping associated beans yield gain for larger beans plots (> 0.07 hectares). The beans-sorghum mix, rather, seems to have low beans yield at all levels of beans plot area. The beans yield elasticities are estimated with large variance, thus not statistically different from zero, which may explain the statistically insignificant coefficient on sorghum plot area in the beans equation in Table 4.8.

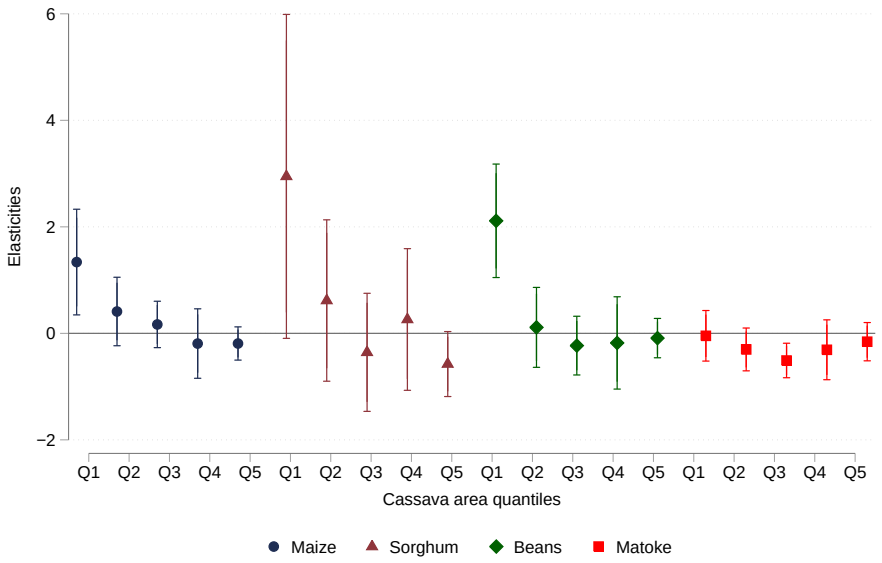


This figure shows average beans yield on plots with beans and maize, beans and sorghum, beans and cassava, and beans and matoke mix by quantiles of beans plot. Q1 is the lowest quantile and Q5 the highest quantile.

Figure 4.5: Average beans yield under mixed-cropping by quantiles of beans plot

Figure 4.6 shows the average cassava yield levels on diversified plots by cassava plot quantiles. The cassava yield follows a fairly similar pattern to that of maize and beans. The average cassava yield associated with the cassava-maize,

cassava-sorghum and cassava-beans mix is greater on small cassava plots (Q1), gradually decreasing as the cassava plot area increases (Q2-Q5). For the cassava-matoke mix, however, there is no appreciable variation in cassava yield for the full range of cassava plot area size.

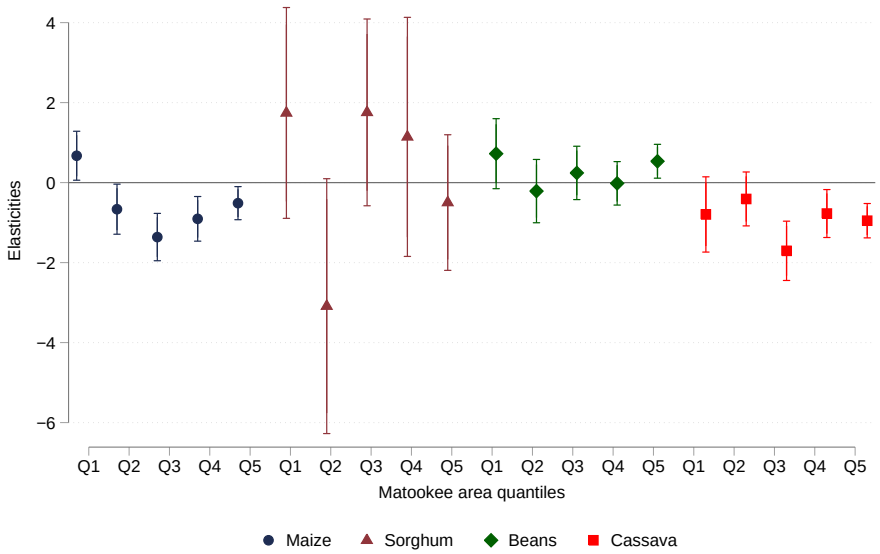


This figure shows average cassava yield on plots with cassava and maize, cassava and sorghum, cassava and beans, and cassava and matoke mix by quantiles of cassava plot. Q1 is the lowest quantile and Q5 the highest quantile.

Figure 4.6: Average cassava yield under mixed-cropping by quantiles of cassava plot

With the exception of the matoke-maize mix, there are no clear non-linear relationships between mixed-cropping associated matoke yield gains and matoke plot area (Figure 4.7). In the maize-matoke mix, the average matoke yield decreases as matoke plot area rises (Q1-Q3) and picks up afterwards (Q4-Q5). While there is some matoke yield variability in the other crop mixes containing matoke,

the estimated elasticities are for the most part statistically insignificant.



This figure shows average matoke yield on plots with matoke and maize, matoke and sorghum, matoke and beans, and matoke and cassava mix by quantiles of matoke plot. Q1 is the lowest quantile and Q5 the highest quantile.

Figure 4.7: Average matoke yield under mixed-cropping by quantiles of matoke plot

4.6 Conclusions

In this paper I find results that suggest the determinants of crop diversification in Uganda are not uniform across crops. It rather appears that both yield and variance considerations come into play to various degrees for different crops. Yield (return) seems to be the key deriver of inter-cropping of beans and sweet potatoes with other cereals and tubers, while variance seems to be the main factor behind

maize inter-cropping with other crops. I do not find strong evidence that skewness considerations figure prominently in farmers crop diversification decisions.

I find strong evidence that productivity decreases with plot size for all major crops in Uganda. This result is consistent with the much discussed inverse farm productivity-size relationship. Larger plots are also associated with high yield variance. Yet, this undesirable feature masks the greater opportunities presented by high variance—high skewness yield distributions. This is precisely the case in Ugandan agriculture—large plots are associated with positive skewness, and hence greater probability of high yield draws.

In terms of best crop mixes, maize, beans and sweet potatoes are most suitable for inter-cropping. The main benefit from inter-cropping maize with other crops is reduced yield variance. For beans and sweet potatoes, gains accrue in terms of increase in yield. The maize-beans combination is the best mix both in yield and variance terms. On the contrary, sorghum and matoke appear to be ill-fit for different reasons. When inter-cropped with other crops, sorghum seems to reduce yield of other crops across the board. While there is benefit in the form of reduced variance, this is subsumed by skewness reduction. In the case of matoke, on the other, its yield level suffers with no apparent gain in variance reduction or increase in skewness.

The fact that both yield and variance considerations appear to be important in crop diversification choices of farmers in rural Uganda calls for an appropriate mix of input and insurance market interventions. Improving access to modern

agricultural inputs would enhance yield. The results in Table 4.8 show that there is substantial gain to be had from fertilizer use and suggestive evidence that improved seeds increase crop yield. Further studies on the yield and variance effects of crop diversification at different levels of improved inputs use would shed better light on this dynamics. Due to limited modern inputs use, this paper doesn't attempt such an analysis. Provision of formal crop insurance would reduce incentives for inefficient self-insurance such as when farmer inter-crop other cereals and tubers with sorghum to take advantage of the considerable variance reduction in brings about.

APPENDIX A

CHAPTER 1 OF APPENDIX

A.1 Derivation of the effects of parents' early childhood shock on children's human capital

The effect of parental shocks early in childhood on their offspring's human capital can be written as:

$$\begin{aligned}\frac{\partial \theta_{k,1}}{\partial \eta_0^p} &= \frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p}\frac{\partial \theta_p}{\partial \eta_0^p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\frac{\partial \theta_p}{\partial \eta_0^p} \\ &= \left(\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\right)\frac{\partial \theta_p}{\partial \eta_0^p}.\end{aligned} \tag{A1}$$

Early childhood investments in parent's capabilities, I_1^p, is endogenous, i.e., $I_1^p = g(\theta_1^p, \theta_g, \eta_1^p)$. Thus, $\frac{\partial \theta_p}{\partial \eta_0^p}$ in (2.16) can be rewritten as:

$$\begin{aligned}\frac{\partial \theta_p}{\partial \eta_0^p} &= \frac{\partial \theta_p}{\partial \theta_1^p}\frac{\partial \theta_1^p}{\partial \eta_0^p} + \frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\frac{\partial \theta_1^p}{\partial \eta_0^p} \\ &= \left(\frac{\partial \theta_p}{\partial \theta_1^p} + \frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\right)\frac{\partial \theta_1^p}{\partial \eta_0^p}\end{aligned} \tag{A2}$$

Since θ_1^p itself is endogenous, $\frac{\partial \theta_1^p}{\partial \eta_0^p}$ can be expressed as:

$$\frac{\partial \theta_1^p}{\partial \eta_0^p} = \frac{\partial \theta_1^p}{\partial \eta_0^p} + \frac{\partial \theta_1^p}{\partial I_0^p}\frac{\partial I_0^p}{\partial \eta_0^p}. \tag{A3}$$

Thus,

$$\frac{\partial \theta_p}{\partial \eta_0^p} = \left(\frac{\partial \theta_p}{\partial \theta_1^p} + \frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\right)\left(\frac{\partial \theta_1^p}{\partial \eta_0^p} + \frac{\partial \theta_1^p}{\partial I_0^p}\frac{\partial I_0^p}{\partial \eta_0^p}\right). \tag{A4}$$

Substituting (A1) in (2.16), we find a decomposable impact of parental childhood shocks on child outcomes as:

$$\begin{aligned}
\frac{\partial \theta_{k,1}}{\partial \eta_0^p} &= \left(\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\right)\left(\frac{\partial \theta_p}{\partial \theta_1^p} + \frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\right)\left(\frac{\partial \theta_1^p}{\partial \eta_0^p} + \frac{\partial \theta_1^p}{\partial I_0^p}\frac{\partial I_0^p}{\partial \eta_0^p}\right) \\
&= \underbrace{\frac{\partial \theta_{k,1}}{\partial \theta_p}\frac{\partial \theta_p}{\partial \theta_1^p}\frac{\partial \theta_1^p}{\partial \eta_0^p}}_{\text{Self Productivity}} + \underbrace{\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p}\frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\frac{\partial \theta_1^p}{\partial I_0^p}\frac{\partial I_0^p}{\partial \eta_0^p}}_{\text{Dynamic complementarity}} \\
&\quad + \underbrace{\left[\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p}\left(\frac{\partial \theta_p}{\partial \theta_1^p} + \frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\right) + \frac{\partial \theta_{k,1}}{\partial \theta_p}\frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\right]\frac{\partial \theta_1^p}{\partial \eta_0^p}}_{\text{Mixed channel}} \\
&\quad + \underbrace{\left[\left(\frac{\partial \theta_{k,1}}{\partial I_0}\frac{\partial I_0}{\partial \theta_p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\right)\frac{\partial \theta_p}{\partial \theta_1^p} + \frac{\partial \theta_{k,1}}{\partial \theta_p}\frac{\partial \theta_p}{\partial I_1^p}\frac{\partial I_1^p}{\partial \theta_1^p}\right]\frac{\partial \theta_1^p}{\partial I_0^p}\frac{\partial I_0^p}{\partial \eta_0^p}}_{\text{Mixed channel}}.
\end{aligned} \tag{A5}$$

A.2 Figures

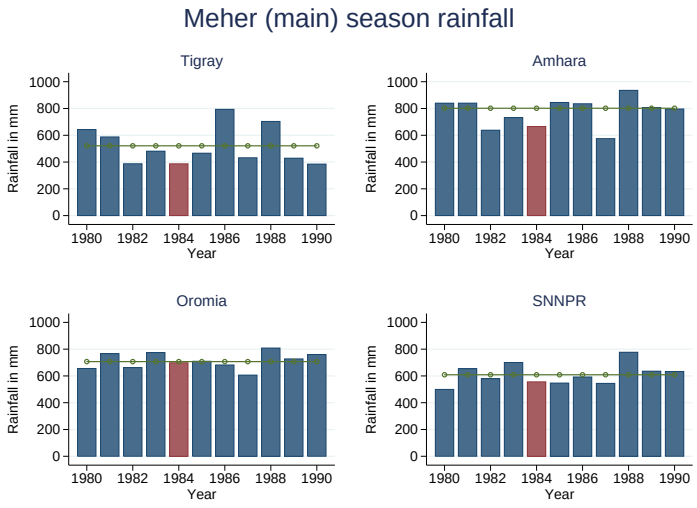


Figure A1: Patterns of Meher rains 1980-1990

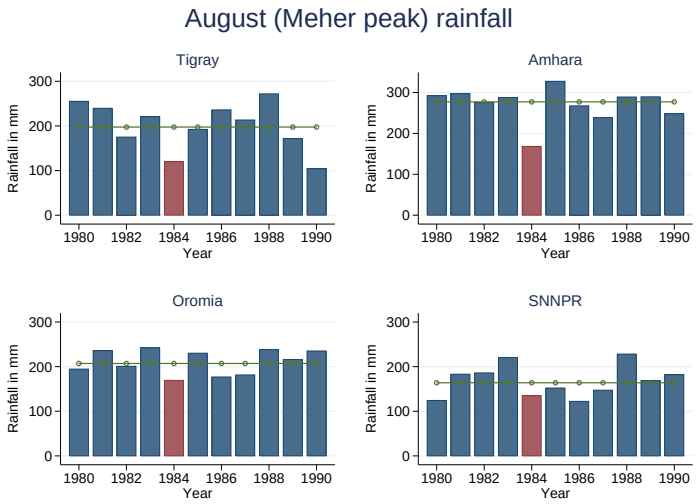


Figure A2: Patterns of August rains 1980-1990

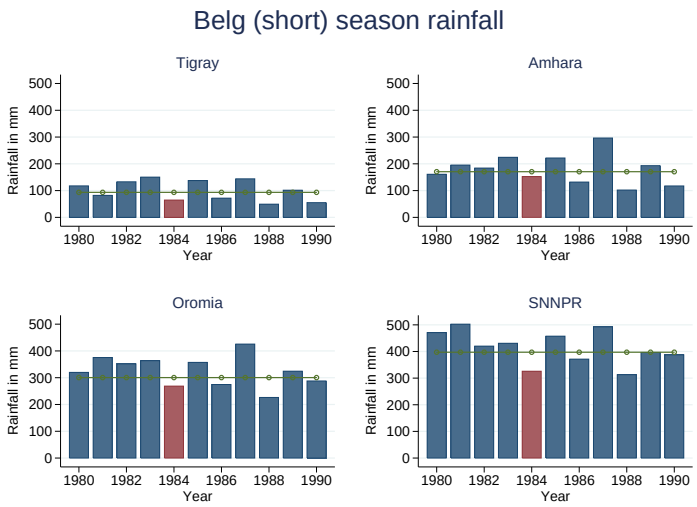


Figure A3: Patterns of Belg rains 1980-1990

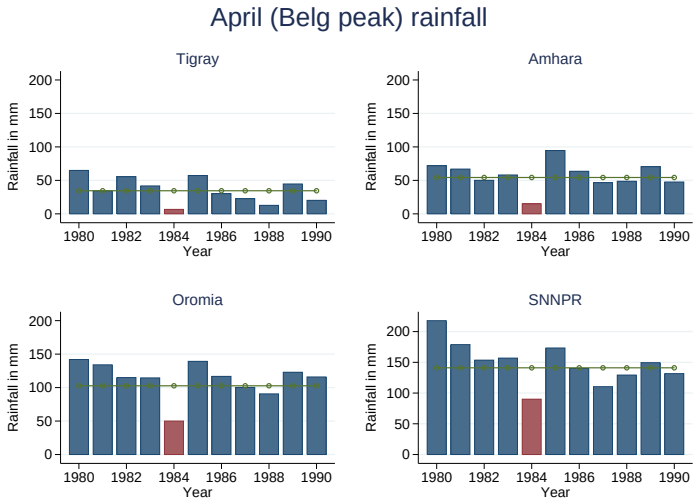


Figure A4: Patterns of April rains 1980-1990

A.3 Tables

Table A1: Effects of maternal famine exposure on test scores

	PPVT score				Math score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: PPVT & Math test scores	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	0.731	0.735	0.784	0.709	-0.280	-0.211	-0.288	-0.066
	(2.959)	(1.226)	(1.253)	(0.910)	(0.383)	(0.385)	(0.337)	(0.282)
Rain shortage × famine cohort	-0.606	-0.608	-0.530	-0.693	0.010	-0.026	0.041	-0.059
	(0.729)	(0.580)	(0.519)	(0.756)	(0.224)	(0.211)	(0.188)	(0.244)
Famine months (#)	0.428	0.434	0.444	0.551	-0.376	-0.305	-0.426	-0.051
	(1.845)	(1.458)	(1.655)	(0.586)	(0.276)	(0.570)	(0.490)	(0.190)
Famine months × famine cohort	0.323	0.322	0.344	0.241	0.065	0.047	0.045	-0.020
	(0.493)	(0.629)	(0.611)	(0.360)	(0.105)	(0.138)	(0.138)	(0.116)
Famine cohort (famine=1)	-1.239	-1.235	-1.086	-1.199	-0.602**	-0.525	-0.554	-0.369
	(1.309)	(1.430)	(1.501)	(1.355)	(0.305)	(0.425)	(0.418)	(0.433)
Household size	0.118**	0.118	0.566	0.502	0.126	0.127**	0.125	0.201**
	(0.399)	(0.317)	(0.484)	(0.445)	(0.077)	(0.063)	(0.120)	(0.101)
Age of household head	0.078	0.078	0.008	0.052	0.007	0.007	0.015	0.002
	(0.063)	(0.059)	(0.147)	(0.061)	(0.014)	(0.012)	(0.023)	(0.017)
Gender of household head (male=1)	0.102	0.102	0.255	1.896	0.594*	0.391	0.400	0.615
	(1.370)	(1.179)	(1.103)	(1.844)	(0.323)	(0.327)	(0.333)	(0.500)
Household head schooling	0.753***	0.753***	0.575***	0.412	0.220***	0.200***	0.143***	-0.020
	(0.190)	(0.108)	(0.106)	(0.333)	(0.039)	(0.046)	(0.043)	(0.119)
Urban/rural (urban=1)	3.516	3.513	0.487	8.103***	3.023***	3.294***	2.006**	4.859***
	(4.015)	(4.840)	(4.916)	(2.487)	(0.718)	(1.064)	(0.851)	(0.728)
Shock index	-31.914***	-31.900***	-31.557***	-33.739***	-4.959***	-2.739***	-0.770	1.030
	(11.405)	(9.245)	(10.437)	(8.383)	(1.571)	(1.009)	(1.053)	(1.705)
Wealth index	19.869***	19.859***	-4.944	1.563	5.978***	5.292***	0.585	2.252

Continued on next page

Table A1 – *Continued from previous page*

Dep. var.: PPVT & Math test scores	POLS	RE	Mundlak	Hausman-Taylor	POLS	RE	Mundlak	Hausman-Taylor
	(5.071)	(4.714)	(6.978)	(6.910)	(0.891)	(0.946)	(1.277)	(1.535)
Gender of child (male=1)	-1.044	-1.039	-1.061	-0.972	-0.080	-0.088	-0.112	0.016
	(0.914)	(0.705)	(0.712)	(0.980)	(0.238)	(0.252)	(0.245)	(0.302)
Age of child (months)	1.146***	1.146***	1.388***	1.300***	0.172***	0.167***	0.223**	0.369***
	(0.200)	(0.089)	(0.202)	(0.225)	(0.029)	(0.029)	(0.095)	(0.092)
Child birth order	-1.313**	-1.315***	-0.961***	-1.355***	-0.249**	-0.191**	-0.118	-0.143
[-0.2cm]	(0.612)	(0.408)	(0.356)	(0.466)	(0.119)	(0.090)	(0.079)	(0.117)
Number of siblings of child	-0.269	-0.270	-1.244	-0.540	-0.240**	-0.242**	-0.191	-0.279*
	(0.616)	(0.433)	(0.873)	(0.505)	(0.111)	(0.112)	(0.242)	(0.144)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,394	2,394	2,394	2,394	1,541	1,541	1,541	1,541
R-squared	0.589				0.489			

Cluster bootstrap standard errors in (1)-(3), (5)-(7) and bootstrap standard errors in (4) & (8) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: "Rain shortage" and "Famine months" stand for negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. PPVT is a short-form for Peabody Picture Vocabulary Test. Columns (3) and (7) present results using Mundlak (1978) estimator, while columns (4) and (8) presents results of the Hausman-Taylor (1981) estimator. Ethnicity, religion, region and survey round are vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Table A2: Effects of maternal famine exposure on mothers' educational aspirations for children

Dep. var.: mothers' educational aspirations for children	(1) POLS	(2) RE	(3) Mundlak	(4) Hausman-Taylor
Rain shortage (SD)	-0.163	-0.150	-0.153	-0.171
	(0.237)	(0.182)	(0.160)	(0.112)
Rain shortage × famine cohort	0.044	0.046	0.055	0.034
	(0.069)	(0.055)	(0.051)	(0.088)
Famine months (#)	-0.017	-0.012	-0.015	-0.008
	(0.146)	(0.187)	(0.146)	(0.075)
Famine months × famine cohort	0.004	0.003	0.008	-0.005
	(0.046)	(0.037)	(0.044)	(0.039)
Famine cohort (famine=1)	-0.028	-0.012	-0.033	-0.013
	(0.169)	(0.122)	(0.157)	(0.223)
Household size	0.021	0.028	0.098*	0.068*
	(0.038)	(0.031)	(0.053)	(0.039)
Age of mother	-0.002	-0.002	-0.006	0.002
	(0.018)	(0.014)	(0.015)	(0.035)
Age of household head	-0.009*	-0.008	-0.009	-0.013*
	(0.005)	(0.005)	(0.014)	(0.007)
Gender of household head (male=1)	0.093	0.029	0.052	0.261
	(0.097)	(0.084)	(0.096)	(0.173)
Urban/rural (urban=1)	0.325	0.314	0.123	0.740***
	(0.337)	(0.538)	(0.532)	(0.244)
Shock index	0.275	0.329	0.468	0.278
	(0.986)	(0.505)	(0.533)	(0.822)
Wealth index	2.183***	1.911***	0.740	0.838
	(0.444)	(0.352)	(0.609)	(0.684)
Household expenditure (real)	4.26e-06	-7.20e-06	-0.00001	7.94e-06
	(0.000)	(0.000)	(0.000)	(0.000)
Gender of child (male=1)	-0.143	-0.142	-0.145	-0.131
	(0.104)	(0.105)	(0.101)	(0.099)
Age of child (months)	-0.003	-0.004	-0.006	0.004
	(0.012)	(0.011)	(0.015)	(0.022)

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Table A2 – *Continued from previous page*

Dep. var.: mothers' educational aspirations for children	POLS	RE	Mundlak	Hausman-Taylor
Child birth order	0.028	0.039	0.107**	0.056
	(0.055)	(0.042)	(0.054)	(0.061)
Number of children	-0.014	-0.016	-0.024	-0.059
	(0.043)	(0.031)	(0.085)	(0.056)
Ethnicity	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes
Observations	2,461	2,461	2,461	2,461
R-squared	0.177	0.178	0.183	
Number of mothers	838	838	838	838

Cluster bootstrap standard errors in (1)-(3) and bootstrap standard errors in (4) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: "Rain shortage" and "Famine months" stand for negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. POLS and RE stand for pooled OLS and random effects, respectively. Columns (3) and (4) present results using Mundlak (1978) estimator and Hausman-Taylor (1981) estimator, respectively. Controls included in all four models are household characteristics (household size, household head age, gender and schooling, wealth, income, shocks), child characteristics (age, gender, age order, number of siblings, language, ethnicity, religion), mother famine cohort dummies, urban-rural dummy, and survey round dummies. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Table A3: Heterogeneous effects of maternal famine exposure duration on children's human capital

	Panel (a): Cognitive human capital								
Dependent variables	child schooling			PPVT			Math		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	0.206	0.189	0.274***	0.834	0.884	1.158	-0.351	-0.429	-0.102
	(0.183)	(0.141)	(0.084)	(1.700)	(1.468)	(0.945)	(0.450)	(0.357)	(0.298)
Rain shortage × famine cohort	-0.069*	-0.044	-0.089	-0.231	-0.164	-0.222	0.108	0.203	0.084
	(0.040)	(0.035)	(0.068)	(0.631)	(0.688)	(0.876)	(0.269)	(0.269)	(0.279)
Famine months (#)	0.287	0.247	0.350***	0.402	0.374	0.710	-0.342	-0.482	-0.058
	(0.187)	(0.159)	(0.056)	(1.746)	(1.531)	(0.598)	(0.440)	(0.351)	(0.191)
1 Famine month × famine cohort	0.079	0.130	0.102	-2.490**	-2.027	-2.917*	-0.141	-0.041	-0.154
	(0.124)	(0.113)	(0.129)	(1.250)	(1.459)	(1.674)	(0.670)	(0.692)	(0.510)
2 Famine months × famine cohort	-0.074	-0.106	-0.081	1.406	1.293	1.367	-0.699	-0.819**	-0.779
	(0.117)	(0.108)	(0.162)	(1.038)	(1.028)	(2.027)	(0.430)	(0.403)	(0.648)
3 Famine months × famine cohort	-0.051	-0.065	-0.037	2.375	1.932	3.017	0.960	0.844	1.124
	(0.143)	(0.165)	(0.172)	(2.408)	(3.123)	(2.277)	(0.701)	(0.786)	(0.705)
4 Famine months × famine cohort	-0.371**	-0.375**	-0.356	0.506	0.256	1.641	1.865***	1.845**	2.144**
	(0.183)	(0.171)	(0.222)	(3.594)	(3.539)	(3.394)	(0.718)	(0.846)	(0.932)
5 Famine months × famine cohort	-0.501***	-0.465***	-0.584***	6.053	5.339	5.566	-0.034	-0.064	-0.516
	(0.168)	(0.134)	(0.222)	(3.825)	(3.361)	(3.622)	(1.000)	(1.219)	(1.026)
6 Famine months × famine cohort	-0.164	-0.176	-0.261	4.770	4.705	4.923	0.597	0.754	0.222
	(0.171)	(0.133)	(0.286)	(3.040)	(2.965)	(3.631)	(0.677)	(0.690)	(0.991)
7 Famine months × famine cohort	-0.318	-0.359	-0.403*	0.649	1.336	-0.997	-0.273	-0.254	-0.960
	(0.200)	(0.229)	(0.225)	(4.711)	(5.065)	(3.234)	(0.762)	(0.799)	(0.989)

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Table A3 – *Continued from previous page*

	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Famine cohort (famine=1)	-0.046	-0.037	-0.021	-1.857	-1.540	-1.733	-0.678	-0.673*	-0.493
	(0.055)	(0.055)	(0.106)	(1.420)	(1.411)	(1.425)	(0.421)	(0.406)	(0.434)
Household size	0.009	0.007	0.009	0.159	0.585	0.587	0.145**	0.129	0.210**
	(0.025)	(0.033)	(0.028)	(0.322)	(0.457)	(0.442)	(0.059)	(0.109)	(0.099)
Age of household head	-0.004	-0.005	-0.003	0.027	-0.027	0.024	-0.005	0.004	0.003
	(0.003)	(0.007)	(0.004)	(0.059)	(0.142)	(0.057)	(0.010)	(0.022)	(0.015)
Gender of household head (male=1)	0.364***	0.340***	0.336***	2.024*	1.631	3.043*	0.809***	0.684**	0.693
	(0.097)	(0.087)	(0.096)	(1.118)	(1.090)	(1.584)	(0.264)	(0.299)	(0.468)
Urban/rural (urban=1)	0.196	-0.109	0.373**	4.558	0.494	9.377***	3.675***	2.010***	4.758***
	(0.411)	(0.463)	(0.154)	(4.921)	(5.280)	(2.343)	(0.812)	(0.679)	(0.601)
Shock index	0.782	1.322**	2.080***	-34.256***	-31.898***	-33.990***	-2.874**	-0.573	1.008
	(0.554)	(0.584)	(0.517)	(10.246)	(11.961)	(8.348)	(1.166)	(1.211)	(1.709)
Wealth index	1.331***	-0.037	0.933**	26.610***	-5.481	2.150	6.523***	0.395	2.325
	(0.312)	(0.485)	(0.450)	(4.895)	(6.900)	(6.930)	(0.981)	(1.359)	(1.529)
Gender of child (male=1)	-0.176**	-0.184**	-0.168**	-0.944	-1.030	-0.837	0.005	-0.042	0.083
	(0.069)	(0.081)	(0.069)	(0.675)	(0.788)	(0.991)	(0.239)	(0.245)	(0.295)
Age of child (months)	0.054***	0.032	0.079***	1.167***	1.411***	1.326***	0.180***	0.230***	0.369***
	(0.009)	(0.024)	(0.020)	(0.102)	(0.223)	(0.208)	(0.027)	(0.073)	(0.088)
Child birth order	0.018	0.005	0.012	-1.444***	-0.996***	-1.423***	-0.206**	-0.125	-0.155
	(0.015)	(0.023)	(0.033)	(0.367)	(0.356)	(0.465)	(0.090)	(0.079)	(0.117)
Number of siblings of child	-0.113***	-0.151***	-0.115***	-0.475	-1.297	-0.711	-0.270**	-0.157	-0.275**
	(0.038)	(0.054)	(0.037)	(0.445)	(0.904)	(0.501)	(0.115)	(0.239)	(0.138)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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Table A3 – *Continued from previous page*

	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Observations	1,501	1,501	1,501	2,394	2,394	2,394	1,541	1,541	1,541
Number of children	829	829	829	838	838	838	824	824	824
	Panel (b): Health and non-cognitive human capital								
Dependent variables	zhfa			locus of control			self-esteem		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	-0.006	-0.007	0.011	0.020	0.023	0.022	0.019	0.021	0.019
	(0.121)	(0.118)	(0.066)	(0.034)	(0.029)	(0.024)	(0.043)	(0.049)	(0.023)
Rain shortage × famine cohort	-0.094*	-0.092*	-0.096*	0.002	0.004	0.001	0.021	0.022	0.021
	(0.052)	(0.047)	(0.058)	(0.015)	(0.016)	(0.020)	(0.013)	(0.014)	(0.020)
Famine months (#)	0.045	0.042	0.055	0.008	0.012	0.010	-0.024	-0.024	-0.023
	(0.103)	(0.096)	(0.040)	(0.035)	(0.030)	(0.017)	(0.036)	(0.040)	(0.015)
1 Famine month × famine cohort	0.023	0.049	0.011	0.002	0.006	-0.003	-0.032	-0.035	-0.035
	(0.163)	(0.149)	(0.131)	(0.037)	(0.034)	(0.045)	(0.031)	(0.033)	(0.037)
2 Famine months × famine cohort	-0.129	-0.118	-0.128	-0.024	-0.025	-0.025	-0.023	-0.027	-0.023
	(0.127)	(0.122)	(0.136)	(0.033)	(0.031)	(0.043)	(0.040)	(0.037)	(0.036)
3 Famine months × famine cohort	-0.057	-0.059	-0.040	-0.057*	-0.061	-0.051	-0.001	-0.007	0.004
	(0.102)	(0.102)	(0.143)	(0.033)	(0.040)	(0.054)	(0.033)	(0.045)	(0.057)
4 Famine months × famine cohort	-0.223	-0.244	-0.211	-0.068	-0.069	-0.059	-0.098	-0.101	-0.089
	(0.217)	(0.235)	(0.183)	(0.066)	(0.064)	(0.062)	(0.085)	(0.078)	(0.065)
5 Famine months × famine cohort	-0.027	-0.010	-0.038	-0.087	-0.070	-0.097	0.019	0.008	0.017
	(0.226)	(0.210)	(0.219)	(0.058)	(0.058)	(0.082)	(0.046)	(0.039)	(0.095)
6 Famine months × famine cohort	-0.245	-0.246	-0.245	0.015	0.020	0.012	0.061	0.066	0.064

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Table A3 – *Continued from previous page*

	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
	(0.211)	(0.215)	(0.259)	(0.058)	(0.051)	(0.092)	(0.054)	(0.051)	(0.072)
7 Famine months × famine cohort	-0.361***	-0.309**	-0.396**	-0.115*	-0.104	-0.129**	-0.078	-0.071	-0.089
	(0.133)	(0.125)	(0.197)	(0.063)	(0.071)	(0.063)	(0.056)	(0.062)	(0.064)
Famine cohort (famine=1)	0.016	0.048	0.021	0.047*	0.038	0.050	0.033	0.032	0.034
	(0.093)	(0.089)	(0.091)	(0.024)	(0.024)	(0.032)	(0.033)	(0.031)	(0.032)
Household size	0.007	-0.000	0.011	-0.010	-0.004	-0.006	-0.008	-0.014	-0.007
	(0.023)	(0.024)	(0.015)	(0.007)	(0.013)	(0.009)	(0.007)	(0.015)	(0.009)
Age of household head	-0.002	-0.004	-0.002	0.002	0.002	0.002	0.000	0.002	0.000
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Gender of household head (male=1)	0.111***	0.103**	0.127**	0.025	0.023	0.036	0.067***	0.057**	0.079***
	(0.043)	(0.048)	(0.064)	(0.022)	(0.023)	(0.033)	(0.024)	(0.023)	(0.029)
Urban/rural (urban=1)	-0.148	-0.359*	-0.052	-0.032	-0.077	0.014	0.088	0.047	0.129***
	(0.209)	(0.210)	(0.106)	(0.092)	(0.093)	(0.047)	(0.067)	(0.081)	(0.048)
Shock index	-0.139	-0.109	-0.125	-0.168	-0.162	-0.165	-0.276*	-0.246	-0.310
	(0.174)	(0.213)	(0.238)	(0.188)	(0.196)	(0.180)	(0.147)	(0.181)	(0.194)
Wealth index	0.692***	0.245	0.317	0.064	-0.220	-0.161	0.384***	0.066	0.168
	(0.266)	(0.306)	(0.218)	(0.090)	(0.135)	(0.137)	(0.108)	(0.148)	(0.137)
Gender of child (male=1)	-0.218***	-0.227***	-0.207***	-0.032	-0.032	-0.031	-0.044***	-0.045***	-0.043**
	(0.054)	(0.058)	(0.065)	(0.022)	(0.022)	(0.022)	(0.016)	(0.016)	(0.019)
Age of child (months)	-0.026***	-0.026**	-0.023***	-0.001	0.006**	0.000	0.001	0.006	0.002
	(0.009)	(0.013)	(0.008)	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.004)
Child birth order	-0.034	-0.015	-0.032*	0.000	0.001	0.001	0.013	0.011	0.012
	(0.022)	(0.015)	(0.018)	(0.011)	(0.016)	(0.013)	(0.012)	(0.014)	(0.014)
Number of siblings of child	-0.032	-0.059	-0.034	0.015*	0.049**	0.014	-0.005	0.001	-0.006
	(0.021)	(0.039)	(0.022)	(0.009)	(0.021)	(0.012)	(0.009)	(0.021)	(0.012)
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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Table A3 – *Continued from previous page*

	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,259	3,259	3,259	2,484	2,484	2,484	2,484	2,484	2,484
Number of children	838	838	838	838	838	838	838	838	838

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table A3 presents the heterogeneous effects of maternal famine exposure duration on children's human capital using random effects, Mundlak's pseudo fixed effects and Hausman-Taylor estimators. "Rain shortage" and "Famine months" are total monthly negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. Ethnicity, religion, region and survey round are vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Table A4: Life-cycle effects of maternal famine exposure duration on children's human capital

	Panel (a): Cognitive human capital								
Dependent variables	child schooling			PPVT			Math		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	0.199	0.187	0.265***	0.384	0.526	0.512	-0.289	-0.341	-0.061
	(0.185)	(0.152)	(0.082)	(1.629)	(1.516)	(0.909)	(0.487)	(0.375)	(0.279)
Rain shortage × famine cohort	-0.027	-0.000	-0.039	-0.663	-0.532	-0.697	-0.048	0.037	-0.051
	(0.035)	(0.029)	(0.062)	(0.552)	(0.554)	(0.765)	(0.211)	(0.198)	(0.240)
Famine months (#)	0.286	0.248	0.347	0.325	0.335	0.548	-0.322	-0.443	-0.050
	(0.199)	(0.174)	(0.056)	(1.984)	(1.963)	(0.588)	(0.631)	(0.509)	(0.186)
Famine months × famine cohort× round 1	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-
Famine months × famine cohort× round 2	-	-	-	0.004	-	-0.068	-	-	-
	-	-	-	(0.541)	-	(0.183)	-	-	-
Famine months × famine cohort× round 3	-0.023	-0.029	-0.009	1.029	1.008	0.284	-	-	-0.003
	(0.026)	(0.030)	(0.009)	(1.112)	(1.145)	(0.237)	-	-	(0.038)
Famine months × famine cohort× round 4	-0.061**	-0.061**	-0.018**	-0.140	-0.063	-0.058	0.035	0.046	-0.005
	(0.028)	(0.029)	(0.008)	(0.482)	(0.549)	(0.089)	(0.131)	(0.141)	(0.032)
Famine cohort (famine=1)	-0.053	-0.045	-0.022	-1.652	-1.396	-1.076	-0.622	-0.624	-0.390
	(0.052)	(0.055)	(0.104)	(1.461)	(1.516)	(1.359)	(0.444)	(0.435)	(0.422)
Household size	0.009	0.004	0.013	0.116	0.607	0.468	0.133**	0.125	0.206**
	(0.026)	(0.036)	(0.028)	(0.330)	(0.462)	(0.449)	(0.058)	(0.113)	(0.100)
Age of household head	-0.004	-0.005	-0.004	0.028	-0.032	0.027	-0.005	0.005	0.003
	(0.003)	(0.007)	(0.004)	(0.060)	(0.147)	(0.059)	(0.011)	(0.021)	(0.015)

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Table A4 – *Continued from previous page*

	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Gender of household head (male=1)	0.367***	0.343***	0.337***	2.031*	1.636	2.816*	0.797***	0.671**	0.620
	(0.097)	(0.088)	(0.100)	(1.193)	(1.149)	(1.654)	(0.272)	(0.297)	(0.503)
Urban/rural (urban=1)	0.190	-0.109	0.364**	4.286	0.281	8.779***	3.626***	1.943**	4.813***
	(0.448)	(0.467)	(0.157)	(5.446)	(5.339)	(2.345)	(0.932)	(0.840)	(0.608)
Shock index	0.834	1.372**	2.103***	-33.366***	-31.546**	-33.108***	-2.829**	-0.672	1.034
	(0.581)	(0.632)	(0.593)	(10.550)	(12.461)	(8.307)	(1.168)	(1.180)	(1.701)
Wealth index	1.338***	0.004	0.947**	27.243***	-5.243	4.404	6.787***	0.524	2.228
	(0.316)	(0.514)	(0.454)	(5.152)	(6.655)	(6.985)	(0.985)	(1.321)	(1.541)
Gender of child (male=1)	-0.166**	-0.175**	-0.163**	-0.982	-1.036	-0.993	-0.052	-0.093	0.021
	(0.075)	(0.084)	(0.068)	(0.676)	(0.785)	(0.990)	(0.247)	(0.249)	(0.293)
Age of child (months)	0.054***	0.032	0.081***	1.174***	1.422***	1.297***	0.173***	0.229***	0.374***
	(0.009)	(0.026)	(0.022)	(0.104)	(0.216)	(0.220)	(0.028)	(0.085)	(0.081)
Child birth order	0.015	0.002	0.008	-1.460***	-1.025**	-1.398***	-0.206**	-0.119	-0.158
	(0.017)	(0.029)	(0.034)	(0.405)	(0.411)	(0.464)	(0.085)	(0.080)	(0.118)
Number of siblings of child	-0.115***	-0.146**	-0.120***	-0.377	-1.289	-0.568	-0.276***	-0.193	-0.273*
	(0.036)	(0.058)	(0.038)	(0.444)	(0.936)	(0.510)	(0.105)	(0.244)	(0.142)
Observations	1,501	1,501	1,504	2,394	2,394	2,398	1,541	1,541	1,545
Number of children	829	829	829	838	838	838	824	824	824

Panel (b): Health and non-cognitive human capital

Dependent variables	zhfa			locus of control			self-esteem		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Rain shortage (SD)	-0.007	-0.003	0.001	0.016	0.020	0.016	0.012	0.015	0.011
	(0.106)	(0.100)	(0.061)	(0.035)	(0.032)	(0.022)	(0.047)	(0.052)	(0.021)

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Table A4 – *Continued from previous page*

	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
Rain shortage × famine cohort	-0.088**	-0.081**	-0.090*	0.002	0.003	0.001	0.016	0.016	0.016
	(0.043)	(0.040)	(0.052)	(0.011)	(0.011)	(0.017)	(0.011)	(0.011)	(0.017)
Famine months (#)	0.046	0.046	0.051	0.006	0.011	0.008	-0.024	-0.023	-0.024*
	(0.101)	(0.088)	(0.038)	(0.042)	(0.038)	(0.016)	(0.041)	(0.047)	(0.014)
Famine months × famine cohort× round 1	-0.078*	-0.074	-0.079**	-	-	-	-	-	-
	(0.045)	(0.046)	(0.034)	-	-	-	-	-	-
Famine months × famine cohort× round 2	-0.017	-0.012	-0.009	-	-	-0.005*	-	-	0.000
	(0.026)	(0.025)	(0.013)	-	-	(0.003)	-	-	(0.004)
Famine months × famine cohort× round 3	-0.038	-0.035	-0.013	-0.021***	-0.020**	-0.008*	-0.026**	-0.026**	-0.009**
	(0.025)	(0.026)	(0.009)	(0.008)	(0.008)	(0.004)	(0.011)	(0.011)	(0.004)
Famine months × famine cohort× round 4	-0.040	-0.034	-0.010*	-0.009	-0.008	-0.003	0.001	0.002	0.000
	(0.025)	(0.027)	(0.006)	(0.012)	(0.013)	(0.003)	(0.011)	(0.011)	(0.003)
Famine cohort (famine=1)	0.022	0.050	0.023	0.047*	0.038*	0.054*	0.032	0.030	0.036
	(0.091)	(0.084)	(0.087)	(0.024)	(0.023)	(0.032)	(0.031)	(0.032)	(0.031)
Household size	0.007	-0.001	0.010	-0.010	-0.004	-0.006	-0.009	-0.015	-0.009
	(0.023)	(0.025)	(0.015)	(0.008)	(0.014)	(0.009)	(0.007)	(0.015)	(0.010)
Age of household head	-0.002	-0.004	-0.002	0.002	0.002	0.002	0.000	0.002	0.000
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Gender of household head (male=1)	0.114***	0.105**	0.132**	0.025	0.024	0.036	0.068***	0.059**	0.082***
	(0.043)	(0.051)	(0.065)	(0.023)	(0.025)	(0.033)	(0.023)	(0.023)	(0.029)
Urban/rural (urban=1)	-0.157	-0.362	-0.070	-0.033	-0.077	0.014	0.083	0.042	0.127***
	(0.230)	(0.224)	(0.107)	(0.104)	(0.094)	(0.047)	(0.076)	(0.089)	(0.048)
Shock index	-0.170	-0.151	-0.170	-0.163	-0.167	-0.174	-0.265*	-0.250	-0.322*
	(0.180)	(0.226)	(0.235)	(0.193)	(0.204)	(0.179)	(0.155)	(0.186)	(0.193)
Wealth index	0.698***	0.249	0.330	0.063	-0.225	-0.169	0.381***	0.047	0.153
	(0.258)	(0.307)	(0.217)	(0.097)	(0.147)	(0.136)	(0.120)	(0.151)	(0.137)
Gender of child (male=1)	-0.217***	-0.225***	-0.211***	-0.031	-0.031	-0.031	-0.041***	-0.043***	-0.041**

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Table A4 – *Continued from previous page*

	RE	Mundlak	Hausman-Taylor (RE)	RE	Mundlak	Hausman-Taylor	RE	Mundlak	Hausman-Taylor
	(0.058)	(0.064)	(0.064)	(0.022)	(0.022)	(0.021)	(0.015)	(0.015)	(0.019)
Age of child (months)	-0.026***	-0.026**	-0.024***	-0.001	0.006**	0.001	0.002	0.006*	0.002
	(0.009)	(0.013)	(0.008)	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.005)
Child birth order	-0.034	-0.016	-0.032*	0.001	0.002	0.002	0.013	0.013	0.013
	(0.022)	(0.017)	(0.018)	(0.013)	(0.017)	(0.013)	(0.014)	(0.016)	(0.014)
Number of siblings of child	-0.032	-0.059	-0.036	0.015	0.049**	0.014	-0.004	-0.001	-0.004
	(0.022)	(0.040)	(0.022)	(0.009)	(0.022)	(0.012)	(0.009)	(0.023)	(0.013)
Observations	3,259	3,259	3,266	2,484	2,484	2,488	2,484	2,484	2,488
Number of children	838	838	838	838	838	838	838	838	838

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table A4 shows the life-cycle effects of maternal famine exposure on children's human capital using random effects, Mundlak's pseudo fixed effects and Hausman-Taylor estimators. "Rain shortage" and "Famine months" are total monthly negative rainfall deviation during the 1983-1985 famine and the number of months a mother was exposed to the famine, respectively. Ethnicity, religion, region and survey round are vectors of dummy variables. The sample included in these results excludes mothers born before 1978 (three years before famine) and after 1988 (three years after the famine).

Table A5: Effects of maternal famine exposure on children's human capital

Dependent variables	(1) zhfa	(2) child schooling	(3) child aspirations	(4) locus of control	(5) self-esteem
Rain shortage (SD)	-0.047	0.154	-0.008	0.005	-0.003
	(0.070)	(0.199)	(0.569)	(0.045)	(0.049)
Rain shortage × famine cohort	-0.066*	0.029	-0.122	-0.012	0.003
	(0.039)	(0.053)	(0.166)	(0.018)	(0.015)
Famine months (#)	0.046	0.302*	-0.339	0.001	-0.030
	(0.041)	(0.173)	(0.514)	(0.031)	(0.037)
Famine months × famine cohort	-0.036***	-0.053**	-0.074	-0.008	-0.010
	(0.014)	(0.026)	(0.074)	(0.007)	(0.009)
Famine cohort (famine=1)	0.019	0.050	0.259	-0.006	0.021
	(0.057)	(0.069)	(0.295)	(0.037)	(0.031)
Household size	0.019	0.003	0.070	-0.006	-0.011
	(0.021)	(0.032)	(0.071)	(0.012)	(0.010)
Age of household head	-0.001	-0.001	-0.017***	0.002	0.001
	(0.002)	(0.004)	(0.006)	(0.002)	(0.001)
Gender of household head (male=1)	0.051	0.293***	0.631***	0.022	0.080***
	(0.072)	(0.090)	(0.234)	(0.037)	(0.030)
Household head schooling	0.005	0.039***	-0.052***	0.001	0.002
	(0.007)	(0.012)	(0.018)	(0.004)	(0.004)
Urban/rural (urban=1)	-0.176	-0.069	1.187*	-0.051	0.082
	(0.132)	(0.319)	(0.643)	(0.073)	(0.088)
Shock index	-0.237	0.239	-2.476	-0.172	-0.501**
	(0.278)	(0.678)	(2.089)	(0.260)	(0.244)
Wealth index	1.071***	1.060***	1.825**	0.036	0.249*
	(0.248)	(0.316)	(0.736)	(0.132)	(0.143)
Gender of child (male=1)	-0.187***	-0.175*	-0.186	-0.015	-0.048*
	(0.054)	(0.099)	(0.199)	(0.030)	(0.026)
Age of child (months)	-0.024***	0.057***	0.071***	-0.002	-0.002
	(0.008)	(0.010)	(0.027)	(0.003)	(0.003)
Child birth order	-0.001	0.037	0.090	0.023	0.030**
	(0.030)	(0.037)	(0.088)	(0.016)	(0.014)
Number of siblings of child	-0.023	-0.086**	-0.038	0.002	-0.004

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Table A5 – *Continued from previous page*

Dependent variables	zhfa	child schooling	child aspirations	locus of control	self-esteem
	(0.027)	(0.037)	(0.111)	(0.014)	(0.012)
Ethnicity	Yes	Yes	Yes	Yes	Yes
Religion	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes
Survey round	Yes	Yes	Yes	Yes	Yes
Constant	-1.117***	-5.389***	5.439	-0.023	0.029
	(0.273)	(1.100)	(4.474)	(0.223)	(0.214)
Observations	2,280	1,046	569	1,742	1,742
R-squared	0.121	0.673	0.204	0.877	0.861

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table A5 shows the effects of maternal early childhood famine exposure on their children's human capital using pooled OLS. The estimation sample consists of mothers who lived at the interview site for at least 15 years by the 2002 baseline. Like the rest of the estimation sample, mothers born before 1978 (three years before famine) and after 1988 (three years after the famine) have been excluded.

APPENDIX B

CHAPTER 2 OF APPENDIX

B.1 Tables

Table B1: Annual IBLI premium and out of pocket payments

	Aug-Sept 2012; Jan-Feb 2013; Aug-Sept 2013							Jan-Feb 2014						
	Premium (Birr)						Out of pocket pay per	Premium (Birr)						Out of pocket pay per
Woreda	(%)	Cattle	Camel	Goat/ Sheep	TLU	TLUs insured	TLU (Birr)*	(%)	Cattle	Camel	Goat/ Sheep	TLU	TLUs insured	TLU (Birr)*
Dillo	9.8	488	1,463	68	739	1.3	450	8.6	516	860	69	606	0.4	324
Teltele	8.7	436	1,307	61	660	3.1	385	7.7	462	770	62	543	3.3	236
Yabello	7.5	377	1,131	53	571	3.1	289	6.7	402	670	54	472	2.1	240
Dire	9.5	475	1,424	66	719	1.6	413	8.4	504	840	67	592	1.7	296
Arero	8.6	429	1,287	60	650	2.9	333	7.6	456	760	61	536	4.1	300
Dehas	9.4	468	1,404	66	709	3.0	343	8.3	498	830	66	585	4.0	234
Miyo	11.1	553	1,658	77	837	0.9	442	9.8	588	980	78	691	2.5	414
Moyale	11.1	553	1,658	77	837	1.2	566	9.8	588	980	78	691	0.0	-
Overall		461	1,382	65	698	2.3	384		489.4	815.7	65	575	2.4	279

Source: Source: ILRI, 2013 and own calculation

Note:* Average out of pocket payment per TLU by actual buyers.

Table B2: Variable definitions

General information	Description
Round 1	Baseline conducted: March/April, 2012
Round 2	Conducted: March/April, 2013
Round 3	Conducted: March 2014
Sales period 1	August-September 2012; contract active- October 2012-September 2013; Encouragement design- discount coupon, poet tape, comic book
Sales period 2	January-February 2013; contract active- March 2013-February 2014; Encouragement design- discount coupon, poet tape, comic book
Sales period 3	August-September 2013; contract active- October 2013-September 2014; Encouragement design- discount coupon only
Sales period 4	January-February 2014; contract active- March 2014-February 2015; Encouragement design- discount coupon only
Variable	Definition
SWB	An ordinal scale of respondents' stated perception of their economic condition on a Likert scale ranging from 1=very bad to 5= very good. It is the answer to the question "On which step do you place your present economic conditions?"
SWB relative to Borana pastoralists	Response the question "In general, how do you rate your living conditions compared to those of other Borana pastoralists?" 1=much worse;...; 5=much better

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Table B2 – *Continued from previous page*

General information	Description
Discount coupon	A dummy variable taking value 1 if a household received discount coupon and 0 otherwise.
Audio tape	A dummy variable taking value 1 if a household received additional information treatment via audio tape and 0 otherwise.
Comic book	A dummy variable taking value 1 if a household received additional information via comic book and 0 otherwise.
Value of discount coupon	The amount of discount received, in percentages, which ranges between 0 and 100%.
Number of TLU owned	A standardized measure of livestock holding. It is obtained by multiplying number of livestock by the relevant TLU conversion unit for each livestock type. The conversion units used are TLU=1 for cattle, TLU=1.4 for camel, and TLU=0.1 for goats and sheep, collectively called shoats.
Non-Livestock assets	Value of non-livestock assets in Birr. It includes assets such as bed frame, mattress, chair, table, bicycle, motorcycle, car, cellphone, computer, television, radio, wheelbarrow, grind mill, axe, spade, sickle, hoe, watch, jewelry etc.

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Table B2 – *Continued from previous page*

General information	Description
Expected TLU loss	Constructed from a set of questions that ask responds how many of 20 livestock (by type) they expect to die in the coming year. These figures are converted to common TLUs. Thus, results should be read against a total of 52 tropical livestock units. The questions used are "what is the number out of 20 X do you expect to die over the March 2013 to February 2014 period?" X here stands for livestock types.
Insurance premium	Insurance premium per TLU. Insurance premium vary by livestock type and Woreda. Some household in the sample also received discount. To reflect this variation, premium is calculated as:
	$(1 - \%discount) \times (cattlepremium \times 1 + camelpremium \times 1.4 + shoatspremium \times 0.1)/3$.
Cash income	Includes cash income (in 1,000 Birr) from sale of livestock and livestock products, crop sales, wages and salaries, business and trading (petty trading, motorcycle services etc), cash for work (bush clearing, pond digging etc), mining etc.
Net transfers	The value of annual net cash transfers (during the four seasons: long dry, long rainy, short dry and short rainy). It includes both cash and in kind transfers. It is the difference between transfers received and transfers given.
Value of food aid	The value of annual food aid (in 1,000 Birr) received by households. It is calculated by multiplying the value of monthly food aid by the number of months food aid is received.

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Table B2 – *Continued from previous page*

General information	Description
Non-food assistance	The value of annual non-food assistance (in 1,000 Birr). It includes value of annual should feeding, supplementary feeding, income from employment program, and non-food aid. The value of non-food aid consists of non-food aid from government, NGOs, and PSNP program e.g., water, fodder, vaccination, cash transfers via PSNP.
Annual Income	The sum of annual cash income, value of auto-consumption, net transfers, food aid, and non-food assistance in 1,000 Birr.
Price per TLU	The average price of a TLU equivalent calculated by weighting prices for shoats, cattle, and camel at Haro Bake livestock market in Borana zone by each species' TLU conversion unit. More specifically, we used Birr 700 for shoats price, Birr 5,000 for cattle price and Birr 15,000 for camel price. The TLU conversion unit for shoats is 0.1, for cattle 1 and camel 1.4. Thus, price per TLU=0.1700 + 15,000 + 1.415,000 = Birr 7,571.4.
Asset Index	An index constructed from the current value of non-livestock assets using the principal component factor (PCF) method.
Household size	The number of people who live in the same homestead including people who are away temporarily for less than eight months.
Number of non-working age household members	Includes household members 14 years old and under and 65 years and above.

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Table B2 – *Continued from previous page*

General information	Description
Iqub membership	*Iqub* is an informal rotating saving and credit organization (ROSCA). The variable takes value 1 if a household member is a member of Iqub, and 0 otherwise.

Table B3: Joint orthogonality test for selection into treatment

	Aug-Sep sales period			Jan-Feb sales period		
	(1) Discount coupon	(2) Comic book	(3) Audio tape	(4) Discount coupon	(5) Comic book	(6) Audio tape
Expected TLU loss	-0.002	0.001	0.001	0.001	-0.0003	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of TLUs owned	-0.001**	0.001	-0.0003	-0.001	-0.0004	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Asset index	0.010	-0.033	-0.038**	0.012	-0.030	-0.029
	(0.014)	(0.021)	(0.018)	(0.014)	(0.021)	(0.018)
Annual income ('000 Birr)	0.0002	0.0005	-0.00003	0.0002	0.0004	-0.0004
	(0.0004)	(0.001)	(0.0004)	(0.0004)	(0.001)	(0.0004)
Household head gender (Male=1)	-0.077**	-0.0004	-0.018	-0.043	-0.009	-0.044
	(0.034)	(0.048)	(0.041)	(0.034)	(0.049)	(0.042)
Household head age	-0.0004	-0.0001	-0.0002	0.00004	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household size	0.018*	0.020	0.011	0.008	0.002	0.019
	(0.010)	(0.014)	(0.012)	(0.010)	(0.014)	(0.012)
Household head schooling	0.005	0.006	-0.006	0.002	0.014	-0.010
	(0.007)	(0.010)	(0.009)	(0.007)	(0.010)	(0.009)
Number of females in household	-0.024**	-0.017	-0.010	-0.010	0.003	-0.014
	(0.012)	(0.017)	(0.015)	(0.012)	(0.018)	(0.015)
Number of working age household members	-0.010	-0.022	0.013	-0.017	0.006	0.004
	(0.013)	(0.019)	(0.016)	(0.013)	(0.019)	(0.017)
Iqub membership	0.056	0.111*	-0.039	0.015	-0.010	-0.020
	(0.049)	(0.065)	(0.055)	(0.049)	(0.066)	(0.056)
Constant	0.909***	0.130	0.078	0.868***	0.084	0.070
	(0.058)	(0.083)	(0.071)	(0.059)	(0.084)	(0.072)
Observations	968	473	473	968	473	473
Prob > F	0.144	0.463	0.411	0.729	0.840	0.129
R-squared	0.016	0.023	0.024	0.008	0.014	0.035

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Table B3 – *Continued from previous page*

	Discount coupon	Comic book	Audio tape	Discount coupon	Comic book	Audio tape

Standard errors cluster bootstrapped at the Reera level in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Table A3 presents joint tests of orthogonality for the treatment variables. Prior to sales period 1 (Aug-Sep 2012) and sales period 2 (Jan-Feb 2013), discount coupons as well as audio tape and comic book information treatments were distributed to randomly selected sub-sample of survey households. Similarly, prior to sales period 3 (Aug-Sep 2013) and sales period 4 (Jan-Feb 2014) discount coupons were distributed to randomly selected households. Columns 1-3 and 4-6 show the linear probability model (LPM) regressions of assignment into discount coupon, comic book and audio tape treatment in the Aug-Sep and Jan-Feb sales periods, respectively, on lagged household characteristics using a pooled sample from rounds 2 and 3. Note that the sample includes baseline households who were re-interviewed in R2 and R2 households re-interviewed in R3. The joint orthogonality test (F-test) is reported in the second bottom row.

Table B4: Comparison of uncorrected SWB and vignette corrected SWB

a) SWB Vs. vignette corrected SWB

	Vignette corrected SWB							
SWB	1	2	3	4	5	6	7	Total
Very bad (1)	27	93	0	0	0	0	0	120
Bad (2)	31	30	115	74	15	0	0	265
Neither good nor bad (3)	65	22	147	224	221	5	5	689
Good (4)	29	7	23	85	183	34	9	370
Very good (5)	0	5	0	8	0	58	17	88
Total	152	157	285	391	419	97	31	1532

b) SWB relative to Borana pastoralists Vs. vignette-corrected SWB relative to Borana pastoralists

	Vignette corrected SWB relative to Borana households							
SWB relative to Borana households	1	2	3	4	5	6	7	Total
Much worse (1)	13	51	0	0	0	0	0	64
Worse (2)	28	32	145	88	21	0	1	315
Same (3)	67	19	154	181	194	5	6	626
Better (4)	31	15	27	92	266	59	13	503
Much better (5)	0	2	0	2	0	13	7	24
Total	139	119	326	363	481	77	27	1532

Table B5: Probit model estimates of IBLI uptake

Dependent variable: IBLI uptake	(1)	(2)
Discount: SP1 only	1.865***	1.633***
	(0.308)	(0.309)
Discount: SP2 only	1.861***	1.754***
	(0.367)	(0.350)
Discount: SP1 & SP2	1.661***	1.445***
	(0.393)	(0.368)
Value of discount (%) SP1	0.956**	0.955**
	(0.390)	(0.406)
Value of discount (%) SP2	0.163	0.030
	(0.367)	(0.350)
Poet tape: SP1 only	0.672	0.827
	(0.709)	(0.712)
Poet tape: SP2 only	1.381***	1.336***
	(0.337)	(0.317)
Poet tape: SP1 & SP2	0.237	0.115
	(0.461)	(0.429)
Comic book: SP1 only	0.770	0.777*
	(0.478)	(0.434)
Comic book: SP2 only	0.344	0.121
	(0.426)	(0.427)
Comic book: SP1 & SP2	0.921*	0.799
	(0.508)	(0.535)
IBLI premium: SP1	2.725	-0.846
	(1.738)	(8.931)
IBLI premium: SP2	1.905	4.095
	(1.640)	(10.080)
IBLI knowledge		0.232***
		(0.055)
Expected TLUs loss		-0.001
		(0.012)
Number of TLUs owned		0.006
		(0.004)
Asset index		0.028

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Table B5 – *Continued from previous page*

Dependent variable: IBLI uptake	(1)	(2)
		(0.097)
Annual income ('000 Birr)		-0.001
		(0.002)
Household head gender (Male=1)		-0.216
		(0.230)
Household head age		-0.022
		(0.026)
Household age squared		0.0002
		(0.0002)
Household size		0.008
		(0.057)
Household head schooling		-0.025
		(0.048)
Iqub membership		-0.362
		(0.282)
Household composition	No	Yes
Round dummy	No	Yes
Constant	-4.647***	-4.191**
	(1.684)	(1.779)
Observations	1,015	1,015
Number of households	520	520

Cluster bootstrap standard errors in parentheses:

*** p<0.01, ** p<0.05, * p<0.1.

Table B6: Ordered logit regression: Estimates for vignette adjusted SWB relative to Borana pastoralists using IBLI uptake and volume of TLUs insured

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: SWB relative to Borana pastoralists	panel (a)					
Predicted IBLI/ TLUs insured	0.942***	0.930***	1.070***	0.179***	0.179***	0.188***
	(0.269)	(0.273)	(0.290)	(0.040)	(0.040)	(0.041)
Predicted lapsed IBLI/ TLUs insured	-0.351*	-0.336*	-0.364*	-0.075**	-0.072**	-0.080**
	(0.200)	(0.199)	(0.201)	(0.033)	(0.032)	(0.033)
Number of TLUs owned	0.010**	0.009*	0.009*	0.010**	0.009**	0.009**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Asset index		0.044	-0.006		0.103	0.060
		(0.141)	(0.145)		(0.123)	(0.120)
Annual income ('000 Birr)		0.002	0.002		0.001	0.002
		(0.001)	(0.001)		(0.001)	(0.001)
Household head gender (Male=1)			0.593			0.436
			(0.366)			(0.337)
Household head age			-0.044			-0.037
			(0.041)			(0.038)
Household head age squared			0.0004			0.000
			(0.0003)			(0.000)
Household size			-0.232**			-0.187**
			(0.093)			(0.088)
Household head schooling			0.071			0.077*
			(0.045)			(0.046)
	panel (b)					
Predicted IBLI/ TLUs insured						
prob(SWB=1)	-0.043***	-0.043***	-0.049***	-0.008***	-0.008***	-0.009***
	(0.013)	(0.013)	(0.014)	(0.002)	(0.002)	(0.002)
prob(SWB=2)	-0.031***	-0.031***	-0.036***	-0.006***	-0.006***	-0.006***
	(0.009)	(0.010)	(0.010)	(0.002)	(0.002)	(0.002)
prob(SWB=3)	-0.037***	-0.037***	-0.042***	-0.007***	-0.007***	-0.007***
	(0.012)	(0.012)	(0.012)	(0.002)	(0.002)	(0.002)

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Table B6 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
prob(SWB=4)	0.002	0.002	0.003	0.0004	0.0004	0.001
	(0.002)	(0.002)	(0.003)	(0.0004)	(0.0005)	(0.001)
prob(SWB=5)	0.067***	0.066***	0.077***	0.013***	0.013***	0.013***
	(0.020)	(0.021)	(0.021)	(0.003)	(0.003)	(0.003)
prob(SWB=6)	0.027***	0.027***	0.030***	0.005***	0.005***	0.005***
	(0.008)	(0.009)	(0.009)	(0.001)	(0.001)	(0.001)
prob(SWB=7)	0.015***	0.015***	0.017***	0.003***	0.003***	0.003***
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Predicted lapsed IBLI/ TLUs insured						
prob(SWB=1)	0.016*	0.016*	0.017*	0.003**	0.003**	0.004**
	(0.009)	(0.009)	(0.009)	(0.001)	(0.001)	(0.001)
prob(SWB=2)	0.012*	0.011*	0.012*	0.002**	0.002**	0.003**
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
prob(SWB=3)	0.014*	0.013*	0.014*	0.003**	0.003**	0.003**
	(0.008)	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)
prob(SWB=4)	-0.001	-0.001	-0.001	-0.0002	-0.0002	-0.0002
	(0.001)	(0.001)	(0.001)	(0.0002)	(0.0002)	(0.0003)
prob(SWB=5)	-0.025*	-0.024*	-0.026*	-0.005**	-0.005**	-0.006**
	(0.014)	(0.013)	(0.014)	(0.002)	(0.002)	(0.002)
prob(SWB=6)	-0.010*	-0.010*	-0.010*	-0.002**	-0.002**	-0.002**
	(0.006)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
prob(SWB=7)	-0.006*	-0.005*	-0.006*	-0.001**	-0.001**	-0.001**
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Number of TLUs owned						
prob(SWB=1)	-0.0004**	-0.0004*	-0.0004*	-0.0005**	-0.0004*	-0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prob(SWB=2)	-0.0003**	-0.0003*	-0.0003*	-0.0003**	-0.0003*	-0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prob(SWB=3)	-0.0004**	-0.0004*	-0.0003*	-0.0004**	-0.0004*	-0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prob(SWB=4)	0.00002	0.00002	0.00003	0.00002	0.00002	0.00003
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
prob(SWB=5)	0.001**	0.001*	0.001*	0.001**	0.001*	0.001*
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
prob(SWB=6)	0.0003**	0.0003*	0.0003*	0.0003**	0.0003*	0.0003*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

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Table B6 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
prob(SWB=7)	0.0002*	0.0001*	0.0001*	0.0002**	0.0001*	0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.00007)	(0.00007)	(0.00008)
Household composition	No	No	Yes	No	No	Yes
Round dummy	No	No	Yes	No	No	Yes
Observations	1,530	1,530	1,530	1,530	1,530	1,530
Number of households	550	550	550	550	550	550

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Panel (a) reports the effects of IBLI uptake and volume of TLUs insured on vignette adjusted SWB relative to Borana pastoralists in log-odds units. Panel (b) reports the marginal effects for the main results in panel (a) – IBLI/ TLUs insured, lapsed IBLI/ TLUs insured and number of TLUs owned. The marginal effects estimates in panel (b) show the effects of these variables on the probability of reporting one of the seven unique scales of SWB. In column 3 for example, IBLI uptake reduces the probability of reporting SWB=1 by 4.9% and increases the probability of reporting SWB=7 by 1.7%. A unit increase in TLUs owned reduces the probability of reporting SWB=1 by 0.4% and increases the probability of reporting SWB=7 by 0.1%

Table B7: Ordered logit regression: Estimates for SWB using IBLI uptake and volume of TLUs insured

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: SWB	panel (a)					
Predicted IBLI/ TLUs insured	0.759***	0.597**	0.646**	0.126***	0.128***	0.126***
	(0.250)	(0.238)	(0.282)	(0.041)	(0.041)	(0.034)
Predicted lapsed IBLI/ TLUs insured	-0.724***	-0.734***	-0.730***	-0.136***	-0.133***	-0.135***
	(0.223)	(0.230)	(0.233)	(0.033)	(0.034)	(0.022)
Number of TLUs owned	0.034***	0.030***	0.029***	0.034***	0.030***	0.029***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
Asset index		0.205**	0.187**		0.231***	0.213***
		(0.086)	(0.089)		(0.080)	(0.055)
Annual income ('000 Birr)		0.003	0.002		0.003	0.002
		(0.003)	(0.003)		(0.003)	(0.002)
Household head gender (Male=1)			0.406**			0.346***
			(0.191)			(0.131)
Household head age			0.023			0.025
			(0.021)			(0.020)
Household head age squared			-0.0002			-0.0003
			(0.0002)			(0.0003)
Household size			-0.066			-0.051
			(0.055)			(0.043)
Household head schooling			-0.019			-0.017
			(0.032)			(0.024)
	panel (b)					
Predicted IBLI/ TLUs insured						
prob(SWB=1)	-0.051***	-0.040**	-0.043**	-0.008***	-0.009***	-0.008***
	(0.017)	(0.016)	(0.018)	(0.003)	(0.003)	(0.003)
prob(SWB=2)	-0.077***	-0.060**	-0.064**	-0.013***	-0.013***	-0.013***
	(0.026)	(0.025)	(0.027)	(0.004)	(0.004)	(0.004)
prob(SWB=3)	-0.003	-0.002	-0.003	-0.0005	-0.0003	-0.0005
	(0.006)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
prob(SWB=4)	0.098***	0.077**	0.083**	0.016***	0.016***	0.016***
	(0.033)	(0.031)	(0.034)	(0.005)	(0.005)	(0.005)
prob(SWB=5)	0.032***	0.025**	0.027**	0.005***	0.005***	0.005***

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Table B7 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.011)	(0.010)	(0.011)	(0.002)	(0.002)	(0.002)
Predicted lapsed IBLI/ TLUs insured						
prob(SWB=1)	0.048***	0.049***	0.048***	0.009***	0.009***	0.009***
	(0.015)	(0.016)	(0.016)	(0.002)	(0.002)	(0.002)
prob(SWB=2)	0.073***	0.074***	0.073***	0.014***	0.013***	0.013***
	(0.023)	(0.024)	(0.024)	(0.003)	(0.003)	(0.003)
prob(SWB=3)	0.003	0.002	0.003	0.0005	0.0004	0.0005
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
prob(SWB=4)	-0.094***	-0.094***	-0.093***	-0.017***	-0.017***	-0.017***
	(0.030)	(0.030)	(0.030)	(0.004)	(0.004)	(0.004)
prob(SWB=5)	-0.031***	-0.031***	-0.031***	-0.006***	-0.006***	-0.006***
	(0.010)	(0.010)	(0.010)	(0.002)	(0.002)	(0.002)
Number of TLUs owned						
prob(SWB=1)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
prob(SWB=2)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
prob(SWB=3)	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
prob(SWB=4)	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
prob(SWB=5)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Household composition	No	No	Yes	No	No	Yes
Round dummy	No	No	Yes	No	No	Yes
Observations	1,530	1,530	1,530	1,530	1,530	1,530
Number of households	550	550	550	550	550	550

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Panel (a) reports the effects of IBLI uptake and volume of TLUs insured on raw (unadjusted) SWB in log-odds units. Panel (b) reports the marginal effects for the main results in panel (a) – IBLI/ TLUs insured, lapsed IBLI/ TLUs insured and number of TLUs owned. The marginal effects estimates in panel (b) show the effects of these variables on the probability of reporting one of the five unique scales of SWB. In column 3 for example, IBLI uptake reduces the probability of reporting SWB=1 by 4.3% and increases the probability of reporting SWB=5 by 2.7%. In column 6, unit increase in the number of TLUs insured reduces the probability of reporting SWB=1 by 0.8% and increases the probability of reporting SWB=5 by 0.5%

Table B8: Ordered logit regression: Vignette adjusted SWB estimates using IBLI uptake and TLUs insured – panel households only

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: SWB	panel (a)					
Predicted IBLI/ TLUs insured	0.921***	0.799***	0.944***	0.143***	0.145***	0.154***
	(0.274)	(0.269)	(0.300)	(0.041)	(0.040)	(0.042)
Predicted lapsed IBLI/ TLUs insured	-0.486**	-0.449**	-0.452**	-0.074**	-0.066**	-0.068**
	(0.203)	(0.190)	(0.190)	(0.031)	(0.031)	(0.031)
Number of TLUs owned	0.013	0.010	0.009	0.014*	0.009	0.009
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Asset index		0.237*	0.186		0.315***	0.280***
		(0.129)	(0.135)		(0.110)	(0.106)
Annual income ('000 Birr)		0.004*	0.004*		0.004*	0.004*
		(0.003)	(0.003)		(0.003)	(0.003)
Household head gender (Male=1)			0.801**			0.663**
			(0.372)			(0.335)
Household head age			-0.049			-0.047
			(0.042)			(0.038)
Household head age squared			0.0005			0.0004
			(0.0004)			(0.0003)
Household size			-0.208**			-0.173**
			(0.093)			(0.086)
Household head schooling			0.034			0.034
			(0.059)			(0.062)
	panel (b)					
Predicted IBLI/ TLUs insured						
prob(SWB=1)	-0.045***	-0.039***	-0.046***	-0.007***	-0.007***	-0.007***
	(0.014)	(0.014)	(0.015)	(0.002)	(0.002)	(0.002)
prob(SWB=2)	-0.038***	-0.032***	-0.039***	-0.006***	-0.006***	-0.006***
	(0.011)	(0.011)	(0.012)	(0.002)	(0.002)	(0.002)
prob(SWB=3)	-0.030***	-0.026***	-0.031***	-0.005***	-0.005***	-0.005***
	(0.009)	(0.009)	(0.010)	(0.002)	(0.002)	(0.002)
prob(SWB=4)	0.006**	0.005*	0.007**	0.001*	0.001*	0.001*
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
prob(SWB=5)	0.060***	0.051***	0.062***	0.009***	0.009***	0.010***

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Table B8 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.018)	(0.018)	(0.019)	(0.003)	(0.003)	(0.003)
prob(SWB=6)	0.029***	0.025***	0.030***	0.005***	0.005***	0.005***
	(0.009)	(0.008)	(0.009)	(0.001)	(0.001)	(0.001)
prob(SWB=7)	0.018***	0.015***	0.018***	0.003***	0.003***	0.003***
	(0.005)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
Predicted lapsed IBLI/ TLUs insured						
prob(SWB=1)	0.024**	0.022**	0.022**	0.004**	0.003**	0.003**
	(0.009)	(0.009)	(0.009)	(0.002)	(0.002)	(0.002)
prob(SWB=2)	0.020***	0.018**	0.018**	0.003**	0.003**	0.003**
	(0.008)	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)
prob(SWB=3)	0.016**	0.014**	0.015**	0.002**	0.002*	0.002**
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
prob(SWB=4)	-0.003*	-0.003*	-0.003*	-0.0005	-0.0004	-0.0005
	(0.002)	(0.002)	(0.002)	(0.0003)	(0.0003)	(0.0003)
prob(SWB=5)	-0.032***	-0.029**	-0.029**	-0.005**	-0.004**	-0.004**
	(0.012)	(0.012)	(0.012)	(0.002)	(0.002)	(0.002)
prob(SWB=6)	-0.016***	-0.014**	-0.014**	-0.002**	-0.002**	-0.002**
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
prob(SWB=7)	-0.009***	-0.009**	-0.008**	-0.001**	-0.001**	-0.001**
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Number of TLUs owned						
prob(SWB=1)	-0.001	-0.0005	-0.0005	-0.001*	-0.0004	-0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
prob(SWB=2)	-0.001	-0.0004	-0.0004	-0.001*	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
prob(SWB=3)	-0.0004	-0.0003	-0.0003	-0.0004	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
prob(SWB=4)	0.00008	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.00007)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
prob(SWB=5)	0.001	0.001	0.001	0.001*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
prob(SWB=6)	0.0004	0.0003	0.0003	0.0004*	0.0003	0.0003
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
prob(SWB=7)	0.0002	0.0002	0.0002	0.0003*	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Household composition	No	No	Yes	No	No	Yes

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Table B8 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Round dummy	No	No	Yes	No	No	Yes
Observations	1,395	1,395	1,395	1,395	1,395	1,395
Number of households	465	465	465	465	465	465

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Panel (a) reports the effects of IBLI uptake and volume of TLUs insured on vignette adjusted SWB in log-odds units. Panel (b) reports the marginal effects for the main results in panel (a) – IBLI/ TLUs insured, lapsed IBLI/ TLUs insured and number of TLUs owned. The marginal effects estimates in panel (b) show the effects of these variables on the probability of reporting one of the seven unique scales of SWB. In column 3 for example, IBLI uptake reduces the probability of reporting SWB=1 by 4.6% and increases the probability of reporting SWB=7 by 1.8%. In column 6, a unit increase in the number of TLUs insured reduces the probability of reporting SWB=1 by 0.7% and increases the probability of reporting SWB=7 by 0.3%

Table B9: Ordered logit regression: Vignette adjusted SWB estimates using IBLI uptake and volume of TLUs insured with omitted lapsed IBLI

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: SWB	panel (a)					
Predicted IBLI/ TLUs insured	0.641***	0.552**	0.704**	0.105***	0.108***	0.115***
	(0.245)	(0.249)	(0.282)	(0.037)	(0.037)	(0.038)
Number of TLUs owned	0.014**	0.012*	0.012*	0.015**	0.011*	0.012*
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Asset index		0.286**	0.243**		0.329***	0.296***
		(0.116)	(0.123)		(0.103)	(0.102)
Annual income ('000 Birr)		0.004	0.004		0.004	0.004
		(0.002)	(0.002)		(0.002)	(0.002)
Household head gender (Male=1)			0.747**			0.635*
			(0.360)			(0.333)
Household head age			-0.046			-0.040
			(0.040)			(0.038)
Household head age squared			0.000			0.000
			(0.000)			(0.000)
Household size			-0.229**			-0.197**
			(0.090)			(0.085)
Household head schooling			0.049			0.051
			(0.051)			(0.052)
	panel (b)					
Predicted IBLI/ TLUs insured						
prob(SWB=1)	-0.033***	-0.029**	-0.036**	-0.005**	-0.006***	-0.006***
	(0.013)	(0.013)	(0.014)	(0.002)	(0.002)	(0.002)
prob(SWB=2)	-0.026**	-0.022**	-0.029**	-0.004**	-0.004**	-0.005***
	(0.010)	(0.010)	(0.011)	(0.002)	(0.002)	(0.002)
prob(SWB=3)	-0.019**	-0.016**	-0.021**	-0.003**	-0.003***	-0.003***
	(0.008)	(0.008)	(0.009)	(0.001)	(0.001)	(0.001)
prob(SWB=4)	0.004*	0.004	0.005*	0.001	0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.0005)	(0.0005)	(0.001)
prob(SWB=5)	0.041**	0.035**	0.045**	0.007**	0.007***	0.007***
	(0.016)	(0.016)	(0.018)	(0.003)	(0.003)	(0.003)
prob(SWB=6)	0.021***	0.018**	0.023***	0.003***	0.004***	0.004***

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Table B9 – *Continued from previous page*

	IBLI uptake			TLUs insured		
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.008)	(0.008)	(0.009)	(0.001)	(0.001)	(0.001)
prob(SWB=7)	0.012**	0.010**	0.013**	0.002**	0.002**	0.002**
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Number of TLUs owned						
prob(SWB=1)	-0.001**	-0.001*	-0.001*	-0.001**	-0.001*	-0.001*
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
prob(SWB=2)	-0.001**	-0.0005*	-0.000*	-0.001**	-0.0005*	-0.0005*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
prob(SWB=3)	-0.0004**	-0.0003	-0.0004	-0.0004**	-0.0003	-0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prob(SWB=4)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
prob(SWB=5)	0.001**	0.001*	0.001*	0.001**	0.001*	0.001*
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
prob(SWB=6)	0.0005**	0.0004*	0.0004*	0.0005**	0.0004*	0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prob(SWB=7)	0.0003**	0.0002*	0.0002	0.0003**	0.0002*	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Household composition	No	No	Yes	No	No	Yes
Round dummy	No	No	Yes	No	No	Yes
Observations	1,530	1,530	1,530	1,530	1,530	1,530
Number of households	550	550	550	550	550	550

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Note: Panel (a) reports the effects of IBLI uptake and volume of TLUs insured on vignette adjusted SWB when lagged IBLI/ TLUs insured is omitted, in log-odds units. Panel (b) reports the marginal effects for the main results in panel (a) – IBLI/ TLUs insured and number of TLUs owned. The marginal effects estimates in panel (b) show the effects of these variables on the probability of reporting one of the seven unique scales of SWB. In column 3, IBLI uptake reduces the probability of reporting SWB=1 by 3.6% and increases the probability of reporting SWB=7 by 1.3%. In column 6, a unit increase in the number of TLUs insured reduces the probability of reporting SWB=1 by 0.6% and increases the probability of reporting SWB=7 by 0.2%

B.2 Attrition Correction

There was attrition of some sample households in the follow up rounds of the survey used in this paper. If the sample households who dropped out differ systematically from those who remained in the sample, inference becomes difficult due to attrition bias. In this section, we test whether households who dropped out of the sample introduce attrition bias into our estimates. We find that they do not.

Between the baseline and second round survey 40 (about 8% of the sample) households dropped out, and in round three an additional 10 households (2% of sample) dropped out. Yet in round three, 10 of the 40 households who dropped out in round two returned and were re-interviewed. Following [90], we first check if attrition is random by estimating attrition probit equations for our outcome variables: IBLI uptake and SWB. Then, if attrition is found to be non-random, we make attrition bias correction to our estimates in Tables 4 and 5.

We estimate the equations:

$$pr(A_{ivt} = 1) = \tau_0 + \tau_1 IBLI_{ivt-1} + \tau_2 X_{ivt} + \tau_3 Z_{ivt} + \psi_i + e_{ivt} \tag{B1}$$

and

$$pr(A_{ivt} = 1) = \tau'_0 + \tau'_1 SWB_{ivt-1} + \tau'_2 X_{ivt} + \tau'_3 Z_{ivt} + \psi'_i + e'_{ivt} \tag{B2}$$

where, A is an attrition dummy variable that takes value one if a households attrites in any survey rounds or zero otherwise; X is a vector of household de-

mographic characteristics, household composition, household income and wealth variables, Z is a vector of auxiliary variables that may affect attrition including discount and information treatments, group membership dummies, and exposure to various shocks. The right hand side variables also include lagged IBLI uptake and SWB.

Appendix Table A10 presents probit estimates of the probability of attrition with lagged IBLI and SWB equations. Column 1 shows that all of the coefficients are individually insignificant, suggesting that attrition is random. Wald joint test of the group (auxiliary) variables (Chi-squared statistic of 26.08 with 23 degrees of freedom and p-value of 0.297) indicates that these variables are not jointly statistically significantly different from zero. Similarly, column two shows that all of the explanatory variables are statistically insignificant, except for the discount coupon in sales period one, which is significant only at the 10% level. These results also suggest attrition is random. The resulting Chi-squared statistic of a joint Wald test of the group variables and discount coupon in sales period one of 26.37 with 24 degrees of freedom and p-value of 0.335 indicates attrition is random. This leads us to conclude that our estimates of IBLI participation and the effect of IBLI on SWB are likely free of attrition bias, and that no attrition correction is required.

Table B10: Attrition probit estimates

Dependent variable: Attrition dummy	(1) Attrition on IBLI status	(2) Attrition on SWB
$IBLI_{t-1}$	-0.219	
	(0.289)	
SWB_{t-1}		0.086
		(0.126)
Discount: SP1 only	-0.868	-0.898*
	(0.456)	(0.545)
Discount: SP2 only	-0.673	-0.670
	(0.695)	(0.730)
Value of discount (%) SP1	-0.650	-0.692
	(0.786)	(0.959)
Value of discount (%) SP2	-0.128	-0.220
	(0.992)	(1.416)
Comic book: SP1 only	0.430	0.482
	(0.409)	(0.416)
Household head gender (Male=1)	-0.317	-0.352
	(0.282)	(0.325)
Household head age	-0.011	-0.014
	(0.041)	(0.048)
Household age squared	0.00002	0.00005
	(0.0004)	(0.0005)
Household size	-0.306	-0.321
	(0.380)	(0.472)
Household head highest grade	-0.053	-0.055
	(0.115)	(0.098)
Number of female household members	-0.041	-0.050
	(0.104)	(0.122)
Number of household members under 5	0.266	0.292
	(0.389)	(0.472)
Number of household members between 5 and 15	0.282	0.297
	(0.377)	(0.475)
Number of household members between 15 and 64	0.278	0.297

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Table B10 – *Continued from previous page*

Dependent variable: Attrition dummy	Attrition on IBLI status	Attrition on SWB
	(0.362)	(0.442)
Number of TLUs owned	0.002	0.001
	(0.007)	(0.007)
Asset index	-0.027	-0.030
	(0.217)	(0.250)
Annual income ('000 Birr)	0.001	0.0003
	(0.007)	(0.009)
Net transfers ('000 Birr)	-0.041	-0.036
	(0.038)	(0.036)
If household head is village water point group	-0.157	-0.189
	(0.464)	(0.604)
If household head is village pasture group	0.006	0.016
	(0.401)	(0.465)
If household head is a member of Iqub	0.726	0.701
	(0.534)	(0.624)
Animal sickness or death	0.016	0.014
	(0.259)	(0.274)
Animal loss or theft	0.083	0.077
	(0.277)	(0.326)
Insecurity/Violence/Fights	0.218	0.223
	(0.256)	(0.314)
Human sickness	-0.068	-0.070
	(0.261)	(0.304)
Low prices for animals one wishes to sell	0.134	0.119
	(0.214)	(0.243)
Crop disease	-0.137	-0.148
	(0.206)	(0.258)
Lack of food	-0.079	-0.063
	(0.417)	(0.465)
High food prices	0.050	0.076
	(0.392)	(0.524)
Land scarcity/disputes	0.063	0.089
	(0.283)	(0.317)
Lack of employment opportunities	-0.442	-0.474

Continued on next page

Table B10 – *Continued from previous page*

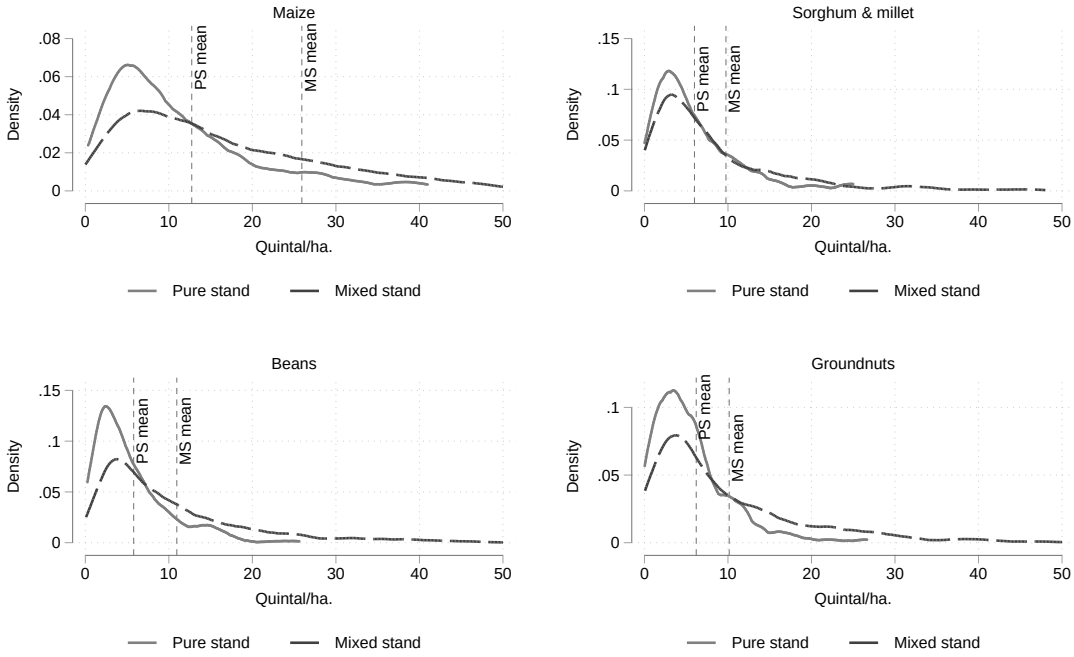
Dependent variable: Attrition dummy	Attrition on IBLI status	Attrition on SWB
	(0.320)	(0.407)
Flood damage	0.013	-0.007
	(0.285)	(0.329)
Constant	-0.113	-0.299
	(1.051)	(1.306)
Observations	1,012	1,012
Number of groups (households)	538	538

Cluster bootstrap standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX C

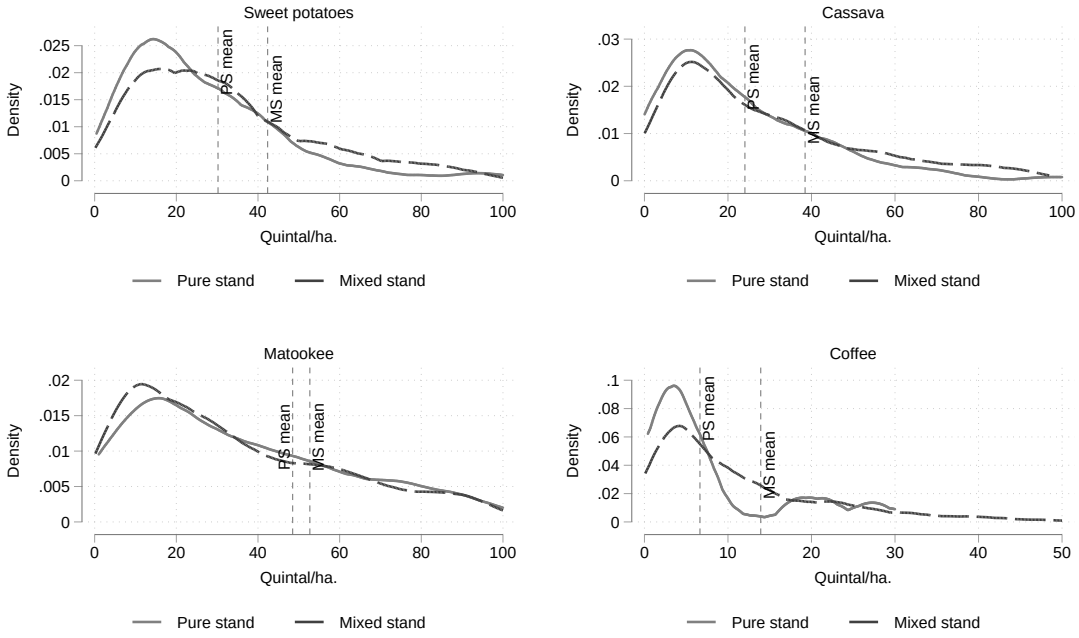
CHAPTER 3 OF APPENDIX

C.1 Figures



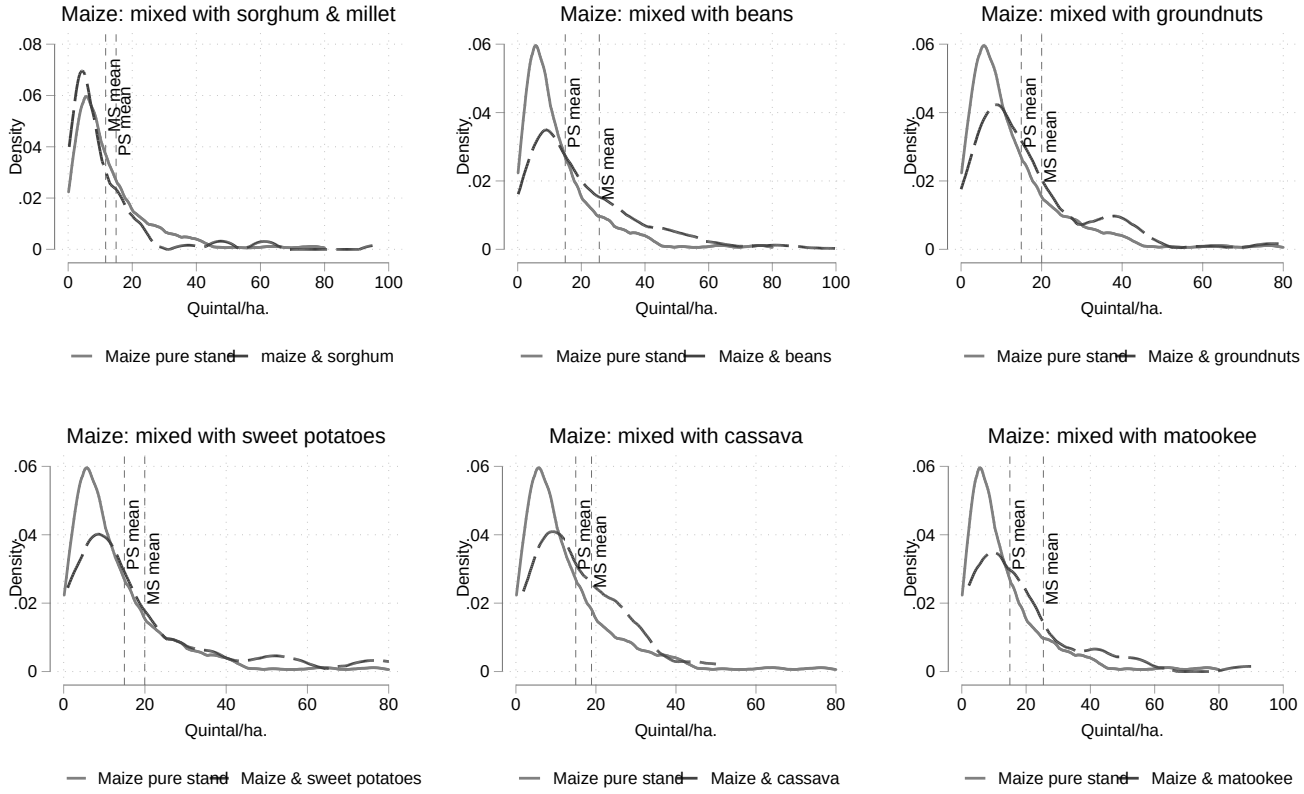
Note: For presentation purposes, output per hectare is trimmed at 50Q/ha in each plane.

Figure C1: Distribution of yield by cropping system



Note: For presentation purposes, output per hectare is trimmed at 50Q/ha in each plane.
The distribution of 'Mixed stand' has fatter and longer tail in all four panels.

Figure C2: Distribution of yield by cropping system



Note: For presentation purposes, yield in all panels is trimmed at 100Q/ha

Figure C3: Distribution of pure-stand maize yield vs. mixed-stand maize yield with various crops

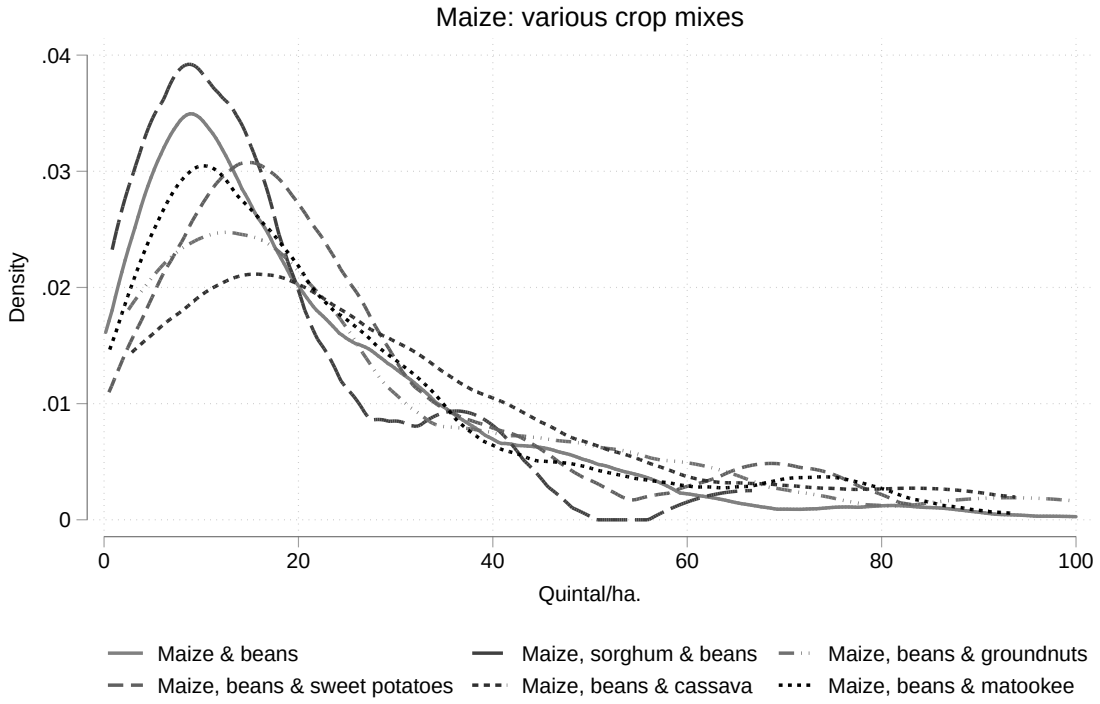


Figure C4: Distribution of maize yield under various crop-mix conditions

C.2 Tables

Table C1: GMM estimates of mean elasticities using translog production technology - marginal effects

Dependent variable: log crop yield	(1) Maize	(2) Sorghum	(3) Beans	(4) Groundnuts	(5) Sweet potatoes	(6) Cassava	(7) Matoke
Log labor (days)	1.303***	1.430***	0.932***	1.289***	1.955***	1.992***	1.609***
	(0.009)	(0.016)	(0.009)	(0.015)	(0.013)	(0.012)	(0.012)
Log fertilizer (kg)	0.118***	-0.019	0.128***	0.165*	0.160**	0.501***	0.066***
	(0.033)	(0.053)	(0.020)	(0.094)	(0.065)	(0.054)	(0.016)
Log seed value (USh)	0.122***	0.126***	0.080***	0.121***	0.076***	0.070***	0.046
	(0.004)	(0.006)	(0.003)	(0.004)	(0.013)	(0.016)	(0.030)
Log pesticides (kg)	-0.292	17.686**	-0.446	-2.779***	1.086**	1.355***	1.087
	(0.231)	(7.222)	(0.345)	(0.777)	(0.488)	(0.435)	(0.756)
Log maize plot (ht)	-1.674***	0.014	0.232***	0.107**	0.029	0.093	0.098
	(0.149)	(0.032)	(0.080)	(0.048)	(0.073)	(0.068)	(0.094)
Log sorghum plot (ht)	-0.478**	-1.538***	-0.352*	-0.083	0.066	0.025	0.185
	(0.223)	(0.190)	(0.196)	(0.098)	(0.163)	(0.140)	(0.391)
Log beans plot (ht)	0.621***	0.034	-2.139***	0.004	0.116	0.155**	0.076
	(0.098)	(0.038)	(0.165)	(0.052)	(0.080)	(0.073)	(0.100)
Log groundnuts plot (ht)	0.504***	-0.016	0.856***	0.502***	0.090	0.270**	0.267
	(0.154)	(0.053)	(0.138)	(0.162)	(0.123)	(0.116)	(0.163)
Log sweet potatoes plot (ht)	0.565***	-0.027	0.467***	0.017	1.997***	0.181**	-0.019
	(0.111)	(0.038)	(0.102)	(0.058)	(0.198)	(0.082)	(0.113)
Log cassava plot (ht)	0.031	-0.066*	0.273***	0.077	-0.109	1.040***	0.062
	(0.111)	(0.038)	(0.101)	(0.058)	(0.087)	(0.150)	(0.115)
Log matoke plot (ht)	0.444***	-0.061**	0.273***	0.046	0.016	0.111*	0.510***

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Table C1 – *Continued from previous page*

Dependent variable: squared residual (u^2)	Maize	Sorghum	Beans	Groundnuts	Sweet potatoes	Cassava	Matoke
	(0.084)	(0.030)	(0.073)	(0.044)	(0.066)	(0.062)	(0.130)
Log total land area (ht)	-0.068***	0.007	-0.068***	-0.019***	0.002	-0.067***	-0.052***
	(0.014)	(0.005)	(0.013)	(0.007)	(0.011)	(0.011)	(0.014)
Parcel slope (%)	-0.0005	-0.00001	0.001	0.001	-0.001	-0.002***	-0.003***
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parcel elevation (m)	-0.0001***	0.000005	-0.0002***	-0.00005**	-0.00002	-0.00002	0.0003***
	(0.00004)	(0.00002)	(0.00004)	(0.00002)	(0.00004)	(0.00003)	(0.00004)
Rainfall ('000 mm)	0.048	-0.002	0.121***	0.085***	0.160***	0.002	0.182***
	(0.045)	(0.016)	(0.040)	(0.024)	(0.036)	(0.034)	(0.045)
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18,774	18,774	18,774	18,774	18,774	18,774	18,774
R^2	0.783	0.846	0.758	0.790	0.858	0.854	0.845

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents the elasticity estimates of yield (mean) equation. Due to interaction terms in the translog specification, marginal effects evaluated at the mean value of covariates are reported. The dependent variables are log crop yields in quintals. All regressors listed above are in logs and the units in which each regressor is measured is given in parenthesis. The amount of fertilizer used includes both organic and inorganic fertilizer. *kg*, *ht*, *m* and *mm* stand for kilogram, hectare, meter and millimeter, respectively. Household characteristics include household (hh) head gender, age, marital status, years of schooling, household size, hh average years of schooling, spouse years of schooling, hh average age, distance to major road, population center of 20,000, and nearest market. Parcel characteristics include agro-ecology, soil type, soil quality, water source (irrigation=1) and topography.

Table C2: GMM estimates of variance elasticities using translog production technology - marginal effects

Dependent variable: squared residual (u^2)	(1) Maize	(2) Sorghum	(3) Beans	(4) Groundnuts	(5) Sweet potatoes	(6) Cassava	(7) Matoke
Log labor (days)	0.392***	0.506***	0.188***	0.618***	0.344***	0.398***	0.304***
	(0.024)	(0.031)	(0.019)	(0.031)	(0.036)	(0.032)	(0.033)
Log fertilizer (kg)	-0.140*	-0.130	0.120***	-1.298***	0.152	0.136	0.189***
	(0.083)	(0.101)	(0.044)	(0.192)	(0.178)	(0.139)	(0.044)
Log seed value (USh)	0.052***	0.127***	0.025***	0.085***	-0.089***	-0.076*	-0.202**
	(0.011)	(0.011)	(0.006)	(0.009)	(0.035)	(0.042)	(0.083)
Log pesticides (kg)	-1.224**	-13.585	-0.808	1.393	1.106	1.753	-2.233
	(0.586)	(13.606)	(0.753)	(1.589)	(1.337)	(1.120)	(2.101)
Log maize plot (ht)	1.664***	0.021	0.477***	0.163	-0.384*	-0.120	-0.252
	(0.379)	(0.060)	(0.175)	(0.099)	(0.199)	(0.176)	(0.263)
Log sorghum plot (ht)	-0.282	0.479	-0.914**	-0.350*	-0.893**	-0.102	-1.185
	(0.568)	(0.357)	(0.428)	(0.201)	(0.446)	(0.360)	(1.089)
Log beans plot (ht)	0.269	0.006	2.554***	0.086	0.280	0.047	-0.135
	(0.248)	(0.071)	(0.361)	(0.106)	(0.220)	(0.188)	(0.279)
Log groundnuts plot (ht)	0.640	0.192*	0.421	1.508***	0.073	0.001	-0.971**
	(0.392)	(0.101)	(0.300)	(0.332)	(0.338)	(0.298)	(0.454)
Log sweet potatoes plot (ht)	0.360	-0.106	-0.132	0.108	7.564***	0.258	-0.345
	(0.281)	(0.071)	(0.222)	(0.120)	(0.543)	(0.212)	(0.316)
Log cassava plot (ht)	-0.599**	-0.051	-0.291	-0.098	-0.329	6.948***	-0.420
	(0.283)	(0.071)	(0.220)	(0.119)	(0.237)	(0.387)	(0.322)
Log matoke plot (ht)	0.497**	0.044	0.262	0.009	0.224	0.164	4.923***

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Table C2 – *Continued from previous page*

Dependent variable: squared residual (u^2)	Maize	Sorghum	Beans	Groundnuts	Sweet potatoes	Cassava	Matoke
	(0.213)	(0.057)	(0.160)	(0.090)	(0.181)	(0.159)	(0.363)
Log total land area (ht)	-0.109***	0.008	-0.135***	-0.023	0.003	-0.068**	0.036
	(0.036)	(0.009)	(0.027)	(0.015)	(0.031)	(0.027)	(0.039)
Parcel slope (%)	-0.0003	-0.001	0.0004	0.002*	-0.004*	-0.005**	0.007**
	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
Parcel elevation (m)	-0.0003**	0.00002	-0.00002	-0.0001	-0.0001	-0.0001	-0.0003**
	(0.0001)	(0.00003)	(0.0001)	(0.00005)	(0.0001)	(0.0001)	(0.0001)
Rainfall ('000 mm)	0.363***	0.036	0.369***	0.249***	0.351***	0.027	0.609***
	(0.115)	(0.029)	(0.087)	(0.049)	(0.099)	(0.087)	(0.125)
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18,774	18,774	18,774	18,774	18,774	18,774	18,774
R^2	0.086	0.146	0.073	0.168	0.079	0.088	0.082

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents the elasticity estimates of yield (mean) equation. Due to interaction terms in the translog specification, marginal effects evaluated at the mean value of covariates are reported. The dependent variables are squared residuals from the mean equation. All regressors listed above are in logs and the units in which each regressor is measured is given in parenthesis. The amount of fertilizer used includes both organic and inorganic fertilizer. *kg*, *ht*, *m* and *mm* stand for kilogram, hectare, meter and millimeter, respectively. Household characteristics include household (hh) head gender, age, marital status, years of schooling, household size, hh average years of schooling, spouse years of schooling, hh average age, distance to major road, population center of 20,000, and nearest market. Parcel characteristics include agro-ecology, soil type, soil quality, water source (irrigation=1) and topography.

Table C3: GMM estimates of skewness elasticities using translog production technology - marginal effects

Dependent variable: cubic residual (u^3)	(1) Maize	(2) Sorghum	(3) Beans	(4) Groundnuts	(5) Sweet potatoes	(6) Cassava	(7) Matoke
Log labor (days)	-0.154	-0.174	-0.265***	-0.063	-0.494***	-0.854***	-1.069***
	(0.115)	(0.117)	(0.079)	(0.110)	(0.157)	(0.139)	(0.161)
Log fertilizer (kg)	-0.346	-0.324	0.223	-1.354**	0.875	0.538	1.055***
	(0.402)	(0.378)	(0.186)	(0.681)	(0.787)	(0.612)	(0.212)
Log seed value (USh)	0.028	0.338***	-0.060**	0.284***	-0.188	-0.111	-0.535
	(0.053)	(0.041)	(0.027)	(0.031)	(0.153)	(0.183)	(0.405)
Log pesticides (kg)	1.718	-8.357	-2.642	4.662	-7.992	3.635	-4.221
	(2.834)	(51.174)	(3.177)	(5.618)	(5.912)	(4.923)	(10.207)
Log maize plot (ht)	4.387**	0.051	1.600**	1.011***	-0.947	0.362	-0.452
	(1.834)	(0.225)	(0.748)	(0.351)	(0.885)	(0.774)	(1.296)
Log sorghum plot (ht)	-0.257	3.469***	-1.615	-0.212	-2.768	1.251	-4.519
	(2.751)	(1.345)	(1.821)	(0.709)	(1.982)	(1.587)	(5.308)
Log beans plot (ht)	1.934	0.099	7.196***	0.183	0.816	0.804	-0.761
	(1.205)	(0.267)	(1.530)	(0.376)	(0.978)	(0.830)	(1.374)
Log groundnuts plot (ht)	0.450	1.238***	1.042	0.742	1.268	0.563	-1.585
	(1.902)	(0.380)	(1.282)	(1.173)	(1.504)	(1.311)	(2.233)
Log sweet potatoes plot (ht)	1.987	-0.225	0.362	0.212	10.834***	1.390	-0.160
	(1.363)	(0.269)	(0.947)	(0.424)	(2.404)	(0.933)	(1.557)
Log cassava plot (ht)	-2.117	-0.151	-0.490	-0.010	-0.961	17.848***	-0.716
	(1.374)	(0.269)	(0.938)	(0.421)	(1.055)	(1.701)	(1.584)
Log matoke plot (ht)	1.719*	0.307	0.496	-0.080	0.983	1.494**	7.505***

Continued on next page

Table C3 – *Continued from previous page*

Dependent variable: squared residual (u^2)	Maize	Sorghum	Beans	Groundnuts	Sweet potatoes	Cassava	Matoke
	(1.031)	(0.214)	(0.684)	(0.318)	(0.803)	(0.702)	(1.774)
Log total land area (ht)	-0.602***	0.042	-0.401***	-0.090*	0.029	-0.392***	-0.005
	(0.175)	(0.034)	(0.117)	(0.054)	(0.137)	(0.120)	(0.193)
Parcel slope (%)	0.006	-0.003	-0.002	0.010**	-0.015	-0.007	0.011
	(0.014)	(0.003)	(0.009)	(0.004)	(0.011)	(0.010)	(0.016)
Parcel elevation (m)	-0.002***	0.0001	0.0004	-0.0003	0.0002	-0.001	0.001
	(0.001)	(0.0001)	(0.0004)	(0.0002)	(0.0004)	(0.0004)	(0.001)
Rainfall ('000 mm)	1.765***	0.191*	1.799***	0.714***	1.638***	0.288	3.435***
	(0.556)	(0.111)	(0.372)	(0.174)	(0.439)	(0.384)	(0.618)
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18,774	18,774	18,774	18,774	18,774	18,774	18,774
R^2	0.015	0.015	0.013	0.017	0.019	0.020	0.021

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table presents the elasticity estimates of yield (mean) equation. Due to interaction terms in the translog specification, marginal effects evaluated at the mean value of covariates are reported. The dependent variables are cubed residuals from the mean equation. All regressors listed above are in logs and the units in which each regressor is measured is given in parenthesis. The amount of fertilizer used includes both organic and inorganic fertilizer. *kg*, *ht*, *m* and *mm* stand for kilogram, hectare, meter and millimeter, respectively. Household characteristics include household (hh) head gender, age, marital status, years of schooling, household size, hh average years of schooling, spouse years of schooling, hh average age, distance to major road, population center of 20,000, and nearest market. Parcel characteristics include agro-ecology, soil type, soil quality, water source (irrigation=1) and topography.

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