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Three Essays on Microeconometrics analysis of development in Ethiopia

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Three Essays on Microeconometrics analysis of development in Ethiopia

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Contents

List of Figures

List of Tables

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Data Declaration

The data used in this thesis come from Young Lives, a 15-year study of the changing nature of childhood poverty in Ethiopia, India, Peru and Vietnam (www.younglives.org.uk). Young Lives is funded by UK aid from the Department for International Development (DFID). The views expressed here are those of the authors. They are not necessarily those of Young Lives, the University of Oxford, DFID or other funders.

Summary

This dissertation, composed of three essays, focuses on children's educational aspirations and attendances, and households access to credit applying microeconometric tools. All the three papers made use of the Young Lives data for Ethiopia. The first chapter presents a brief introduction to the Young Lives data and discusses the sampling strategies and attritions of the Ethiopian sample.

The second chapter assesses the impact of the Ethiopia's Productive Safety Net Program (PSNP) on children's educational aspirations. PSNP is a social protection program launched by the government of Ethiopia in 2005/06 with the aim of supporting food insecure rural households. Educational aspirations are important predictors of actual educational attainments and future success but in developing countries aspirations of individuals might be easily broken and led to poverty trap. This chapter explores the impacts of Ethiopia's PSNP on the educational aspirations of children. Using a longitudinal data from the Young Lives' survey in Ethiopia and applying a differences-in-differences methodology with fixed effect as a baseline regression, it was found that the program increases educational aspirations of children. Furthermore, aspirations are found to predict future educational attainments. The results indicate that safety-net programs might have important spillover effects on education. The third chapter explores the possible effects of mobile phones adoption on the credit uptakes of the rural poor who are mostly neglected from the formal credit markets but finance their credit demand from informal sources including relatives/friends. Mobile phones are one of the few ICT innovations that have found their way in to the hands of the poor residing in remote and rural areas. Empirical evidences generally document the positive role mobile phones play in facilitating the development efforts of poor households. The data are obtained from Young Lives Ethiopia, and a probit, tobit and special regressor estimator are employed. The econometric results suggest mobile phones are positively associated with the credit uptake of rural households specially credit uptake from informal sources. Thus, policy makers and financial providers working on providing credit in rural areas need to exploit the use of mobile phones in reaching out the rural poor. The last chapter, however, investigates the impacts of violent intra-state conflicts on the educational enrollments and aspirations of children. Using data from Young Lives and complemented with geo-referenced data from Armed Conflict Locations and Events Data (ACLED) on conflict events, a region-by-region analysis is conducted and the treatment and control groups are determined by the distance that household is located from the nearest conflict event. Heterogeneous results are found: null result is obtained for Oromia and Tigray regions but the conflict is found to have a neg-

ative effect on educational enrollments in Amhara region and on educational aspirations in SNNP region. Thus, the heterogeneous effect of the conflict in Ethiopia might be attributed to the different nature of the conflict in each region and to the unique mix of socioeconomic and demographic compositions of the regions under consideration.

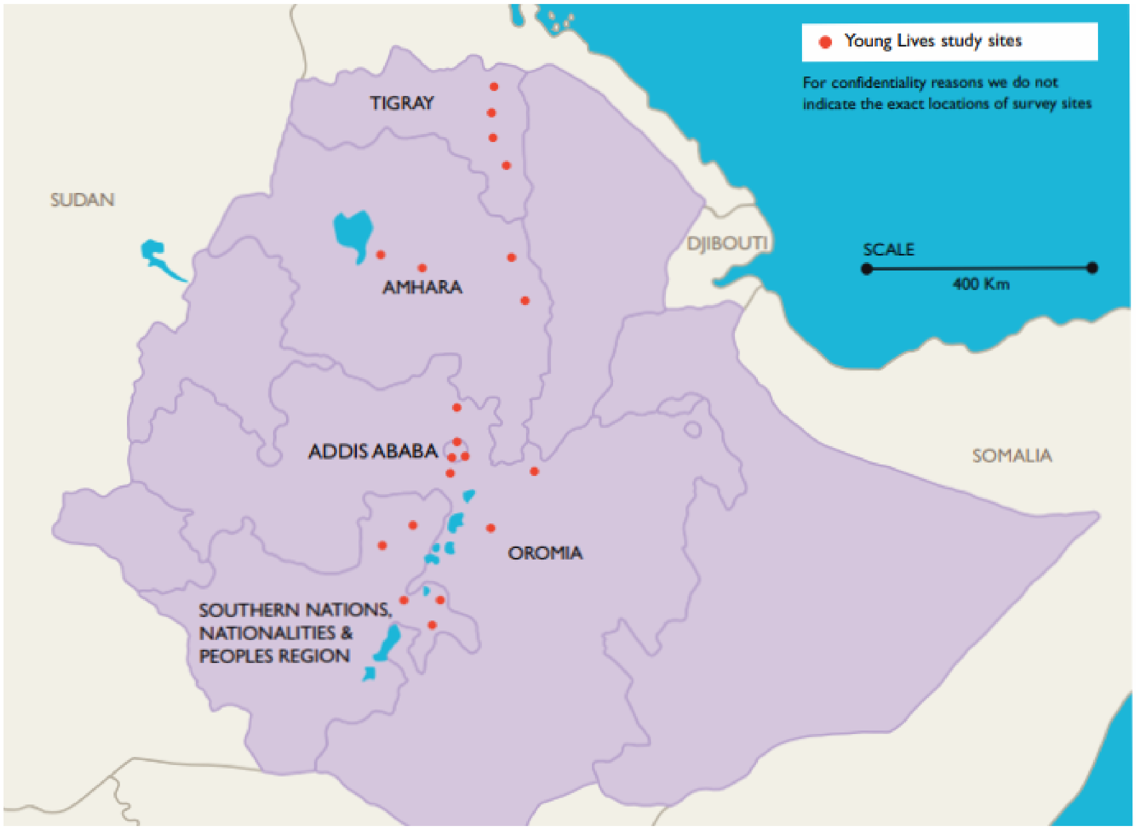
1. CHAPTER 1 INTRODUCTION

Yong Lives is a longitudinal cohort study tracking the lives of 12,000 children in four low- and middle-income countries including Ethiopia, India, Vietnam and Peru over 15 years. The sample in each country consists of two cohorts of children – a younger cohort and an older cohort. The younger cohort sample consists of children aged between 6 to 18 months while the older cohort sample consists of children aged 7.5 to 8.5 years when the survey started in 2002. Young lives is able to collect a wealth of information not only limited to the external constraints such as the material and resource circumstances of households where the children live but also includes internal constraints such as aspirations and subjective wellbeing which are obtained from the large-scale household level and child level surveys. The study tracks children starting from early infancy into adulthood and this helps to investigate the changing lives of children living in rural or urban areas, from poor or rich households, other backgrounds over time. Besides, the quantitative survey is supplemented with a qualitative study making the analysis of child poverty complete. Children were selected from 20 sentinel sites (clusters) in each of the study countries. The Young Lives survey started in 2002 when the younger cohort children were aged about 1 year and the older cohort children were aged about 8 years. The next surveys have been conducted in 2006 (round 2), 2009 (round 3), 2013 (round 4) and 2016 (round 5).

In Ethiopia the study sites are selected following a three-stage sampling process. Ethiopia is divided into nine regions and two administrative cities. In the first-stage, four regions including Oromia, Amhara, Tigray and SNNP, and an administrative city, Addis Ababa, are selected. The regions are selected based on the criterion that the they account for more than 90% of the populations of the country. In the second-stage, between 3 to 5 woredas (districts) are selected from the chosen regions, constituting a total of 20 woredas. Though the woredas with a pro-poor areas are oversampled, a balanced representation of poor and non-poor, urban and rural, and male and female compositions are also considered. In the third-stage, kebelle/s, which constitutes the study sites, (the lowest administrative unit) is/are selected. Then 100 households with a child aged between 6 to 18 months and 50 households with a child aged between 7.5 and 8.5 years are randomly selected from each study sites[1] (see figure 1 for the locations of the study sites) (Young-Lives, 2014).

[1] If a given household had both children with a specified age, the younger child was considered for the study.

Figure 1: Young Lives Ethiopia study sites



Source: Young Lives Ethiopia round 5 fact sheet

The Ethiopian Young Lives sample was compared with other nationally representative datasets. (Outes-Leon and Sanchez, 2008) compared the 2002 Young Lives sample for Ethiopia with the 2000 Ethiopian Demographic and Health Survey (EDHS) and the 2000 Welfare Monitoring Survey. And their analyses revealed that households in the Young Lives sample were slightly better-off and had better access to basic services than the average household in Ethiopia, but they held less land, owned less livestock, and were less likely to own a house. And they contended that though poorer sites were oversampled, the Young Lives sample was found to entertain diversity of the children in the country and cover a wide variety of attributes and experiences.

The main concerns with any longitudinal data are the problems associated with sample attrition rates. Regarding sample attrition, Young Lives is known to have lower attrition rate compared to other longitudinal studies in developing countries. Table 1 presents sample attrition for the last two waves of Young Lives data in Ethiopia. In 2013, after about 10 years, the sample attrition rates were about 2.2 percent and 8.4 percent for the younger cohort and older cohort sample children respectively. After 15 years, in the last wave of the survey, the sample attrition rate is still lower especially for the younger cohort sample, which stands at 5.3 percent and 17,7 percent for the younger cohort and the older cohort respectively. The sources of attrition, in respective order, comes from migrating out side the country, refusal and non traceability for the older cohorts, and non traceability, refusal and migrating outside of the country for the younger cohorts. But death rates are not included in the calculation of sample attrition rates.

Table 1: Young Lives Ethiopia sample attrition rates

	Younger cohort sample	Older cohort sample
Initial sample in Round 1 (2002)	1,999	1,000
Interviewed in Round 4 (2013)	1875	909
Attrition rate Round 1 - Round 4	2.20%	8.40%
Interviewed in Round 5 (2016)	1812	814
Attrition rate Round 1 - Round 5	5.30%	17.70%

Source: Own compilation based on Young Lives Ethiopia round 4 and 5 fact sheets
Notes: Attrition rates exclude death rates. For instance, in round 5, there were about 85 deaths (4.5%) associated with the younger cohorts and about 11 deaths (1.1%) associated with the older cohorts sample. But the attrition rates reported in this table do not include the death rates.

The rest of the chapters are organized as follows. The second chapter discusses the impact of the Ethiopian productive safety-net on the educational aspirations of children. While the next chapter explores the relationship between mobile phones and credit uptake in rural Ethiopia; the last chapter discusses the impact of intra-state conflicts on educational aspirations and enrollments in Ethiopia.

2. CHAPTER 2

The impact of Ethiopian Productive Safety-net Program on children's educational aspirations

With Elisabetta Lodigiani and Giacomo Pasini

Abstract

Children's educational aspirations are important predictors of educational attainment and of occupational success. However, aspirations can be affected by whether an individual is poor or rich. This paper evaluates the impacts of the Ethiopia's Productive Safety Net Program (PSNP), launched by the government of Ethiopia in 2005/06 to support food insecure rural households, on children's educational aspirations. Using a longitudinal data from the Young Lives' survey in Ethiopia and applying a differences-in-differences methodology and fixed effects as baseline regression, we find that the program increases educational aspirations of children. In our preferred specification, the immediate effect of the program is to increase by 0.87 years of education aspirations of children. Furthermore, we find that aspirations affect future actual educational attainments. The results point to broad and long lasting positive effects of a program designed to relieve chronically poor households from food insecurity.

JEL Classification: H43, I38, O12
Keywords: Educational aspirations; PSNP; differences-in-differences; food insecure

2.1. Introduction

Genicot and Ray (2017) define aspirations as reference points where individuals aim to achieve. Aspirations are important for decision making. Children's aspirations especially may shape their labour market outcomes, and may have long-term consequences on their later life. In particular, educational aspirations are important predictors of educational attainment and occupational success (Sewell et al. 1970). Using UK longitudinal data, Schoon and Parsons (2002) find that teenage aspirations play a major role in the occupational development of the youth and in mediating social background factors. Favara (2017) documents the relationships of early educational aspirations with years of schooling completed in Ethiopia. From a randomised control trial conducted in Uganda, Riley (2017) finds aspirations affect exam results of students in secondary school. Moreover, Serneels and Dercon (2014) document that aspirations raise educational attainment in India. However, aspirations can be affected by whether an individual is poor or rich. Dalton et al. (2016) show that though both the rich and the poor face the same behavioural bias (internal constraints such as myopia or lack of willpower), poverty may exacerbate the behavioural bias and may lead to aspirations failure and to behavioural poverty trap. They argue that poverty is the main cause for aspirations failure in developing countries and point out that raising aspirations can break the trap. Ray (2006) states that poverty stifles individual aspirations and may cause aspirations failure which in turn lead to a self sustaining poverty trap. Moreover, Duflo (2006) also argues that poverty affects the way people think and make decisions. Due to the prevalence of chronic poverty, children in developing countries mostly fail to aspire for higher educational attainment; they simply focus on quick fix solutions and forget the bigger picture. Thus, in this paper we investigate whether the introduction of anti-poverty programs such as a safety-net program influences children's educational aspirations in Ethiopia.

Households in developing countries not only face a labour market with excessive supply induced by the accelerating population growth, but also with limited or no social protections (Frölich and Haile, 2011). Households, therefore, become vulnerable to chronic food insecurity when they are exposed to different shocks. Safety-net programs in developing countries not only help households smooth consumption but also get households out of chronic poverty (Devereux, 2002). The change in households' poverty status, at least psychologically, may change aspirations of their children. Kao and Tienda (1998) argue that the socio-economic status of households plays a key role not only in favouring high education aspirations in earlier grades but also in maintaining the aspired levels in later grades. Laajaj (2017) also shows that economic prospects increase the planning horizon of the poor which again predicts asset accumulations. Ethiopian government launched a social protection program in 2005, the Productive Safety-Net Program (PSNP), to provide transfers to chronically food insecure households. It is designed to supply predictable support to defined households; it is a departure from previous social protection schemes of delivering emergency food when a specific catastrophe happens. The program is expected to reach more than 10 million beneficiaries in its current phase (PSNP Phase IV - 2014/15-2019/20) and the government together with the donor community is now planning to expand it to urban areas (the first phase of urban PSNP is planned to be run from 2016/17 to 2020/21). Given the program's magnitude and the important paradigm shift from temporary relief responses to long-term preventive asset building programs, several studies have already documented the impact of the PSNP on households in different respects. Gilligan et al. (2009) showed the public works program of the PSNP affects individual calorie acquisition. Studies also revealed that households' food security and consumption are impacted by PSNP (Berhane et al. 2011 and Berhane et al. 2014). Sabates-Wheeler and Devereux (2010) showed that food transfers are superior to cash transfers in affecting income growth, livestock accumulation and self-reported food security. Andersson et al. (2011) also evaluated the impacts of PSNP on livestock and tree holdings and find that the program increased households' tree holdings while livestock holdings are unaffected. However, studies investigating the impacts of PSNP on children are scant. Debela et al. (2015) and Porter and Goyal (2016) investigate the impacts of the program on children's health (mainly nutrition) and both studies document positive effects. Studies also investigated the impacts of PSNP on the trade-offs between education and work participation (Hoddinott et al. 2010; Woldehanna 2010). However, the program is extremely expensive (in 2009, PSNP had an annual budget of 360 million USD, roughly 1.2% of Ethiopian GDP), therefore it is important to understand whether the positive effects are limited to the immediate target of the program, namely chronic poverty and food insecurity of rural households, or it has long lasting effects on other dimensions of individual well-being, such as for example targeted children and human capital investments.

Few studies have explored how aspirations of the poor can be lifted. For instance, Bernard et al. (2015) studied how aspirations of poor people in remote rural Ethiopia improved after watching documentaries of people in the same status changing their life without outside intervention. Chiapa et al. (2012) explored the impacts of a social program and exposure to professionals on the aspirations of parents for their children in Mexico, and found a positive impact on the educational aspirations of parents for their children. They also checked the correlations of parental aspirations and educational attainment of children. The study mainly focused on households' aspirations for their children without involving children' s own educational aspirations. Ross (2017) studied whether the difference between occupational aspirations and initial conditions of the primary economic earner in the household has an effect on the human capital of a child at later ages. Besides, he studied the impact of India's National Rural Employment Guarantee Scheme (NREGS) on occupational aspirations and aspirations gaps of children using the Young Lives data for India. However, the paper's main focus is on occupational aspirations while ours is on educational aspirations, and the main flaw is that he assumed similar trends between urban and rural districts in the absence of the program. Beaman et al. (2012) also investigated the impact of female leadership on girls' aspirations and educational attainment exploiting a randomised natural experiment in India, and found a significant impact of female leadership on girls' career aspirations and educational attainment. However, it is appealing to see whether actual transfers targeted to the most disadvantaged households as in PSNP in Ethiopia, have an effect on children's own educational aspirations.

The paper is organised as follows. The next section discusses the Productive Safety-Net Program and its eligibility criteria in selecting beneficiaries. Section 3 describes the data we use in our study. Section 4 presents the methods used and the results obtained. Section 5 provides some robustness checks. Section 6 renders associations of aspirations and actual outcomes. The last section concludes.

2.2. The Productive Safety-Net Program (PSNP)

The Productive Safety-Net Program (PSNP) is a social protection program launched by the Ethiopian government in 2005 to provide transfers to chronically food insecure households. The PSNP aims to respond to food insecurity arising from shocks or natural calamities such as drought, flooding, pests, and so on, in addition to the chronic food needs of poor households. The PSNP consists of 80 per cent public work program that provides counter-cyclical employment mostly on rural infrastructure and land rehabilitation projects and 20 per cent direct support program that provides unconditional cash or food transfer to vulnerable households that have no able-bodied members to participate in public works. Once households have become food-sufficient, they will be graduated[2] from the program (Wiseman et al., 2010). The number of people supported by PSNP has increased from 4.5 million in 2005 to 7.6 million in 2009.

[2]The term 'graduation' refers to the movement of a household out of the PSNP. This occurs when a household has improved its food security status to a level that shifts it from being classified as chronically food insecure to food sufficient, and thus is no longer eligible for the PSNP.

The PSNP has been designed to respect the responsibilities of each level of the federal administrative structure of the Ethiopian Government, which is composed of nine regions and two administrative cities. Each region is then divided into woredas (districts), which are administered by locally elected councils.[3] Each woreda is subdivided into kebeles, the lowest administrative layers that can be understood as neighbourhood associations or wards. Finally, in the rural areas, each kebele includes a number of villages or communities (Wiseman et al., 2010). The selection process into PSNP proceeds as follows. The federal government first identifies chronically food insecure woredas, i.e. districts that have been recipients of food aid for at least 3 years. Using this criterion, the government identified 262 chronically food insecure woredas in 2005 and increased to 290 woredas in 2009. Then, woredas select chronically food insecure kebeles. Finally, households within these kebeles are selected to participate in the PSNP according to a process that takes place at the community, kebele and woreda levels. First, eligibility to PSNP depends on whether a household meets the criteria set by the local administration (kebele), and whether the household is selected by the Community Food Security Task Force (CFSTF). Then, the list of eligible households, finalised at the community level, should be approved at the kebele, woreda and regional levels (Wiseman et al., 2010). The CFSTF select households on the basis of basic PSNP criteria, and supplementary local criteria. The basic PSNP eligibility criteria are: Households that faced a continuous food shortage, for 3 months in the last 3 years; those that suddenly become more vulnerable and couldn't support themselves over the last 3 to 6 months; and those without family support and other social protections (Ministry of Agriculture, 2014).

2.3. The Data

This study uses a longitudinal data from the Young Lives (YL) survey. YL is an international research project, coordinated by the University of Oxford, which follows the lives of 12,000 children in four developing countries, namely Ethiopia, India, Peru and Vietnam over 15 years. The aim of the project is to identify the main drivers of child poverty, and assist local policy makers. The sample in each country consists of two cohorts of children: a Younger-Cohort of 2000 children born in 2001-2002, and an Older Cohort of 1,000 children, born in 1994-95. To date, there are four rounds of the surveys which have been conducted in 2002, 2006, 2009 and 2013, respectively. Focusing on Ethiopia, YL samples were selected from 20 sentinel sites following a three-stage sampling process. In the first stage, 5 regions,

[3] There are a total of 710 woredas.

including Oromia, Amhara, SNNP, Tigray, and Addis Ababa, an administrative city, were selected. The main criterion was national coverage, and the selected regions account for 96 per cent of the national population. Then from these regions, 20 woredas (districts) were chosen with a pro-poor bias: the food deficit woredas were oversampled as the major goals of YL is investigating childhood poverty and its dynamics. In the last stage, at least one kebele (the smallest administrative unit) in each woreda was chosen, in order to constitute the sentinel sites. Finally, households containing children were randomly selected within the sites[4] (Outes-Leon and Sanchez, 2008). Sample attrition rate is low; the attrition rate is about 5% for all cohorts and is about 8% for the older cohorts in round 4 (Young-Lives, 2014).

The YL data include questions on educational aspirations and other related issues, which were asked to the older cohort from the second round onwards (the children of the younger cohort were too young to be asked about their aspirations in the second (then aged 4 to 5 years) and third (aged 7 to 8 years) rounds of the survey). The question on educational aspirations was framed as: "Imagine you had no constraints and could study for as long as you liked, or go back to school if you have already left. What level of formal education would you like to complete?". The answer to this question is coded according to the highest grade the child aspires to achieve, 1 to 12 indicating grades 1 to 12; 13 for technical and vocational school and 14 for college degree and above. We recoded 14 to 15 (12 years of school plus 3 years of higher institution) to interpret educational aspirations in terms of years of education.

From the third round (2009) onwards households have been interviewed about their participation in PSNP as follows: (i) Was any member of household registered as a beneficiary of the PSNP – Public Works program? (ii) Was any member of household registered as beneficiary of Direct Support program (transfers of cash, food or other goods without requiring individuals to work)? If households response is "Yes" to either one or both of the questions, then the household would be regarded as a beneficiary of the PSNP program and belongs to a "treatment group". Whereas if the response to both questions is "No", then the household is considered as a "control" or "comparison" group.

In order to evaluate the effect of the PSNP on children' s educational aspirations, we follow Porter and Goyal (2016) who estimate the impact of the PSNP on child nutrition using a differences-in-differences estimator (DID) at the child level. As in Porter and Goyal (2016), the second round of the YL survey (conducted in 2006) is considered as a baseline since the

[4]Note one child per household is selected.

payment was delayed during the first year of the implementation of the program (2005/06) (Gilligan et al., 2009) and no impacts of the program were experienced in 2006 (Woldehanna, 2010).

The PSNP was conducted in rural areas and therefore we restrict the sample excluding the urban population. To improve the comparability of the groups of our analysis, two sites where no households participated in the program were dropped from the sample.[5]

Our analysis is, therefore, based on the older cohort of children, living in 11 rural sites, and interviewed at the ages of 12, 15 and 19 in 2006, 2009 and 2013 respectively. The rural sample consists of about 60% of the total sample observations. Besides, we excluded two rural sites where PSNP was not operational and this leaves us with 497 sample observations in 2006.

Table 2 depicts the descriptive statistics of observable characteristics for the individuals in the sample receiving the PSNP transfer (the treated group), and those living in the same areas but not enrolled in the program (the control group). No statistical difference between the mean of the treated and control groups is observed with respect to educational aspirations, future plan for education and work, gender, travel time to school, and wealth. However, the mean difference between the two groups seem to be significant with regard to aid history (90% of the treatment group reported to have been receiving food aid prior to PSNP while 36% of the control group reported to have received aid before PSNP), caregiver's aspirations (measured as children's aspirations), cognitive outcome (based on the score obtained on a mathematical test) and climatic shocks (a dummy that takes the value of 1 if the household has experienced any natural disasters since the previous wave).

[5]The reason why there was no PSNP participation in these two sites is that the first site is a relatively richer rural area in the outskirts of Debrezeit town in the Oromia region and the second site is a densely populated rural area growing "enset" (false banana) in the SNNP region. Hence, we can see the profiles of the two sites that they are relatively well off and we excluded them to have better comparison groups.

Table 2: Descriptive statistics by treatment status at the baseline (2006)

	N_control	Control	N_treated	Treated	Difference	P-value
Years of Educational Aspirations	165	13.7030	210	13.4571	-0.2459	.2684635
Future plan for education and work	164	0.0310	210	-0.0912	-0.1221	.2337389
Household and Child characteristics						
Male - Child's sex	165	0.4848	210	0.5571	0.0723	.1648949
Travel time to school (in minutes)	165	27.6061	210	29.4333	1.8273	.3973367
Wealth index	165	0.1999	210	0.2093	0.0094	.3896147
Male - Household head sex	165	0.8970	210	0.7381	-0.1589	.0000946
Mother's education-Adult literacy*	165	0.1152	210	0.1286	0.0134	.6950939
Mother's education-Grade 1 and above	165	0.3152	210	0.1381	-0.1771	.0000304
Household composition						
Number of males aged 0-5	165	0.3879	210	0.3667	-0.0212	.7375919
Number of males aged 6-12	165	0.7636	210	0.6476	-0.1160	.1245026
Number of males aged 13-17	165	0.6182	210	0.4571	-0.1610	.0147956
Number of males aged 18-60	165	1.6848	210	1.3952	-0.2896	.0085626
Number of males aged 61+	165	0.0970	210	0.1667	0.0697	.056155
Number of females aged 0-5	165	0.3939	210	0.4381	0.0442	.4777944
Number of females aged 6-12	165	0.6364	210	0.6381	0.0017	.9810371
Number of females aged 13-17	165	0.6909	210	0.6143	-0.0766	.3163333
Number of females aged 18-60	165	1.6364	210	1.5714	-0.0649	.4649514
Number of females aged 61+	165	0.0606	210	0.0810	0.0203	.4678691
Parent's years of education aspirations						
Years of aspirations by caregiver	165	14.0061	210	13.8095	-0.1965	.2837732
Aid history						
Ever_aid	165	0.3333	210	0.8952	0.5619	1.15e-35
Cognitive outcome score						
Z_raw_math	165	-0.2989	210	-0.1368	0.1622	.1133337
Shocks						
shock-drought	165	0.5515	210	0.5810	0.0294	.5690477
shock-flooding	165	0.3333	210	0.1190	-0.2143	3.41e-07
shock-erosion	165	0.1879	210	0.0619	-0.1260	.0001529
shock-frost	165	0.2061	210	0.0905	-0.1156	.0013715
shock-pests on crops	165	0.2242	210	0.0524	-0.1719	5.40e-07
shock-crop failure	165	0.3758	210	0.4000	0.0242	.6337963
shock-pests on storage	165	0.0848	210	0.0381	-0.0468	.0560437
shock-pests on livestock	165	0.1212	210	0.0476	-0.0736	.0090343

Notes: *Mother's level of education has three categories: No education (66%), Grade one and above (22%) and Adult literacy (12%).The first and the second columns describe the number of observation and the mean of the variables for the control group; the third and the fourth column presents the number of observations and the mean for the treatment group; while the last two columns are the difference between the mean values of the treatment and the control groups and the corresponding p-values respectively.

One concern of our analysis is that households receiving transfers from PSNP are different from those not enrolled in PSNP for reasons that could affect our outcome of interest. However, our econometric analysis will account for observable differences of the treatment and the control groups by directly controlling for several covariates and by applying matching techniques.

2.4. Econometric strategy and results

This section describes the methodology used and the main results of our analysis. The effect of PSNP on educational aspirations of children is analyzed using the differences-in-differences (DID) estimator. Our objective of interest is to measure the average treatment effect on the treated (ATT). The ATT is given by:

$$ATT = E[A_1 - A_0|P = 1] = E[A_1|P = 1] - E[A_0|P = 1] \quad (1)$$

Where A_1 is the outcome, i.e. educational aspirations, of the treated, A_0 is the outcome of the untreated, and P indicates the treatment status which is equal to 1 if the individual participates in PSNP and 0 otherwise. However, the problem is that we cannot observe the untreated outcome for the treated, $E[A_0|P = 1]$. We use the counter-factual outcome, $E[A_0|P = 0]$, as an estimate for the unobserved outcome, $E[A_0|P = 1]$. This might give rise to the problem of selection bias, and to the concern that changes in the outcome of interest would have been systematically different in the treatment and control groups even in the absence of the program. In our context, the PSNP was introduced to help chronically and transitory food insecure rural households and to enable them withstand shocks like droughts which are frequent in Ethiopia. Table 2 confirms that selection of households is done in a non-random way and makes it difficult to select comparison groups. In addition, we cannot test the assumption that trends in educational aspirations would be the same for the treatment and control groups in the absence of the program, the so-called common trends assumption, as children were not asked about their educational aspirations in the first round of the survey.

In order to address these concerns, we follow a similar approach to the one carried out by Porter and Goyal (2016) that analyze the impact of PSNP on child nutritional outcomes. First, we add a large set of child and household control variables to control for observable characteristics, including access to aid in previous rounds, climatic shocks, parental educational aspirations and sentinel site fixed effects. Second, by means of a propensity score matching procedure, we restrict the sample in order to improve the comparability of the treatment and control groups. Then, we compare results based on the "full sample" and the "matched sample".[6]

[6] For robustness, Porter and Goyal (2016) also restrict the comparison group using a propensity score matching technique based on pre-program observable household characteristics. In addition, they also consider a sample restriction based on households who were shortlisted for the program but were not able

We estimate the following model:

$$A_{ihvt} = \beta_0 + \beta_1 P_{hv} + \beta_2 Y_t + \beta_3 (P_{hv} * Y_t) + \mathbf{X}_{ihvt}\beta_4 + \lambda_v + u_{it} \tag{2}$$

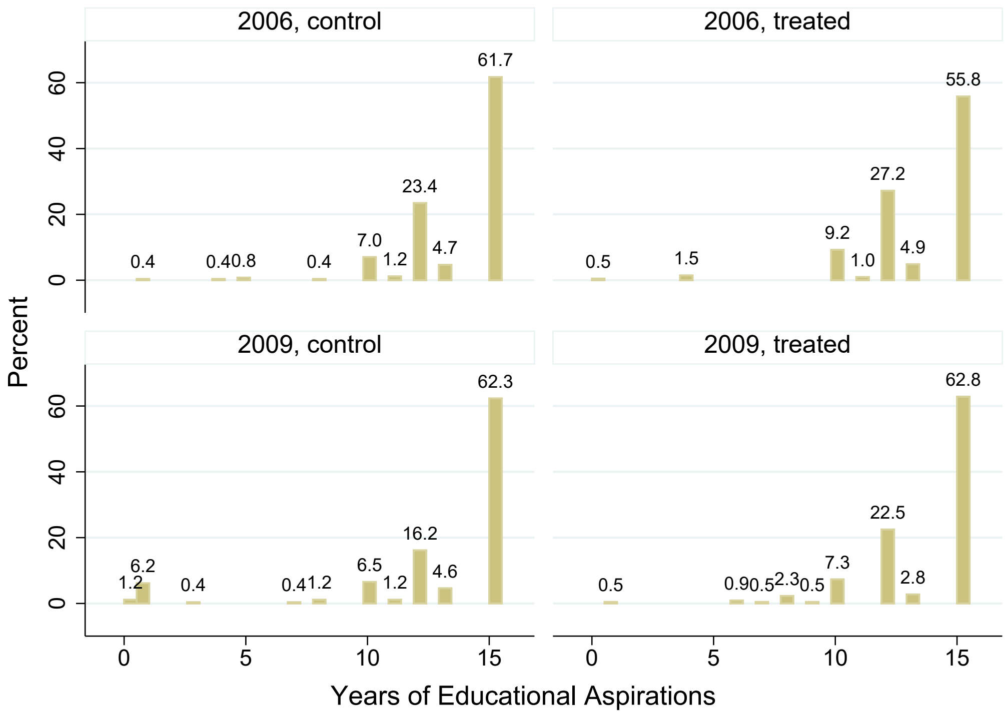
Where the outcome variable A_{ihvt} denotes educational aspirations of child i, in household h, living in site v at time t; P_{hv} is a treatment dummy that equals 1 for households participating in PSNP at baseline and 0 for non-participants; Y_t is a time dummy that equals one if year is 2009 or beyond and zero if year is 2006; and $\mathbf{X}_{ihvt}$ is a set of child and household characteristics living in site v at time t,[7] λ_v are sentinel site fixed effects. In our case, β_3 can be interpreted as the effect of PSNP on educational aspirations after controlling for household and child characteristics, and it can be estimated using ordinary least square method (Meyer, 1995). Moreover, β_1 is the estimated mean difference in educational aspirations of children between the treatment and control groups before the intervention; while β_2 is the expected mean change in educational aspirations from before to after the intervention period in the control group and indicates the effect of time in the absence of the program.

Figure 2 shows aspirations of the participants and the non-participants both before and after the intervention. The descriptive evidence suggests that aspirations for college increase after the program for the participants while they are pretty stable for the non-participants. This might indicate that the program raises aspirations of children.

to participate due to budget constraints. Unfortunately, we cannot use the shortlisted comparison group because we will retain very few observations as our sample includes only the older cohort of children.

[7] Control variables include: a dummy for the sex of the child, travel time to school (in minutes) for children enrolled in school, a wealth index of the household, a dummy that takes the value of 1 if the household head is a male, dummies for household composition, dummies to control for the level of education of the mother, a dummy that takes the value of 1 if the household had access to aid in previous rounds, a dummy if the household had experienced climatic shocks during the period of interest, a variable indicating the cognitive outcome of the child, educational aspirations of the caregiver.

Figure 2: Years of educational aspirations by treatment status



Notes: The figure depicts the percentage distribution of years of educational aspirations for the control group at the baseline (top left), for the treatment group at the baseline (top right), for the control group in 2009 (bottom left), and for the treatment group in 2009 (bottom right).

Table 3 presents the DID estimation results of the impact of PSNP on educational aspirations of children on the "full sample" (Panel A) and on the "matched sample" (Panel B) for the 2009 survey round, three years after the program's commencement. we employed fixed effects estimations to control for the time-invariant unobservables. Table 3 depicts the fixed effects estimation results. The treatment indicator is dropped as there is no within individual variation but both year dummy and the interaction (the diff-in-diff indicator) are reported. Column 1 presents the results controlling for child characteristic including time taken to the nearest school; household characteristics including wealth, livestock and land ownership, composition and mother's education. Households' experiences of different natural calamities such as drought, flooding, pests, etc. are significant contributors for their vulnerability and food insecurity, and this may also affect educational aspirations. Then, in column 2 we control for climatic shocks. Finally, in column 3 and column 4 we additionally control for cognitive outcome of children and care-giver's aspirations for the child in question, respectively.

Panel A of Table 3 presents the estimation results for the full sample. PSNP has a positive and statistically significant effect on educational aspirations across all the estimated specifications. Column (1) shows that PSNP increases educational aspirations by 0.71 school years after controlling for child and household characteristics. Furthermore, the impact of PSNP on educational aspirations of children increases to 0.96 school years and 1.00 school years when we control for shocks and cognitive outcome, respectively. The magnitude, however, decreases to 0.87 school years when we include parental educational aspirations for the child in question.[8]

Panel B of Table 3 depicts the DID estimation results on the matched sample. As the program is non-random, households that should have been targeted might be excluded or vice versa. Besides, woreda coverage has been increasing over time indicating for incomplete coverage of all areas. To this end, we match the treatment and control groups based on observable pre-program characteristics. More specifically, we construct a comparison group based on a Kernel matching with bandwidth of 0.09 on the pre-program child and household characteristics, including indicators for household wealth and vulnerability which includes livestock and land ownership, the number of male and female adult members, gender and age of the household head, household's aid history, housing quality, shocks, parental aspirations and cognitive outcome. We choose the Kernel matching because it satisfies the balancing characteristics. To check for balance, a "pstest" is used after matching. The "pstest" indicates that the mean and median per cent bias has reduced significantly[9]. The regressions are then conducted on observations which are on the common support. Similar to the results in Panel A, we find that the PSNP has a positive and statistically significant impact on educational aspirations. The estimation results provide very similar coefficients with respect to the full sample when all the covariates are included.

[8]Table 3 shows only the coefficients of interest. Estimation results with the full covariates are reported in Appendix A.

[9]See the figure in Appendix B for the balance before and after matching.

Table 3: Impacts of PSNP on Children's Educational Aspirations - Fixed effects (2009)

	(1)	(2)	(3)	(4)
Panel A: Full sample				
Year dummy (2009)	-0.112	-0.208	-0.255	-0.254
	(0.423)	(0.397)	(0.387)	(0.366)
DID	0.708*	0.956***	1.003***	0.872**
	(0.369)	(0.363)	(0.357)	(0.341)
N	737	736	728	721
Panel B: Matched sample				
Year dummy (2009)	-0.268	-0.354	-0.275	-0.224
	(0.428)	(0.403)	(0.391)	(0.367)
DID	0.801**	1.031***	0.995***	0.844**
	(0.381)	(0.375)	(0.366)	(0.345)
N	683	683	683	682
Household controls	YES	YES	YES	YES
Shocks	NO	YES	YES	YES
Cognitive outcome	NO	NO	YES	YES
Caregiver's aspirations	NO	NO	NO	YES

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors in parentheses, clustered at child level. Fixed effects is adopted as a baseline regression in all the specifications. DID refers to the differences-in-differences coefficient which is the interaction of time and treatment indicators. The dependent variable in all columns is years of educational aspirations. The first column controls for covariates including time taken to school as child control; household controls consisting of wealth index, household head sex, mother's education and household composition based on age and sex. The second column adds shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock. While the third column includes z-score of maths test scores of children as proxy for cognitive outcome, the last column controls for the years of educational aspirations that parents are aspiring for their child to complete.

As we have information on the children's educational aspirations for three periods (the baseline, 2006, and two periods after the implementation of the program), we can estimate not only the impact of the program in the short-run (after 3 years), but also in the long-run (after 6 years). Table 4 presents the DID estimates after combining both the 2009 and 2013 sample, and we used fixed effects as for the baseline regression. We included a time indicator of before and after the program, i.e. a time indicator taking value 1 if 2009 or 2013 and 0 otherwise. The results in Table 4 reveal that the impact of the program is significant once we control for shocks indicating that since the post-intervention period is longer now, it is important to control for exogenous shocks to family resources, as they may confound the effect of the policy intervention. If the model is correctly specified then, the effect of the program after combining 2009 and 2013 waves approaches the results from 2009 alone. An alternative explanation is that panel A estimates might be biased due to graduation from PSNP. YL asks households whether they graduated, i.e. whether they are not receiving the transfer because they are not considered poor anymore. About 17 per cent of the respondents who were treated in the 2006 wave reported that they are no more eligible. These PSNP graduates are in the treatment group but they did not receive any benefit in 2013, as those in the control group. To this end, we explored whether the effect on aspirations is different for the PSNP graduates. Panel C of table 4 presents whether the effect of the program is different for the graduated households, and included an interaction of the graduted dummy and the diff-in-diff indicator. We find that the interaction is insignificant indicating that the effect of the program is not different for graduated households.

Table 4: Impacts of PSNP on Children's Educational Aspirations - FE (combining 2009 and 2013)

	(1)	(2)	(3)
Panel A: Full sample			
Year dummy (2009 and 2013 combined)	0.159	0.000503	-0.135
	(0.336)	(0.336)	(0.334)
DID	0.536	0.714**	0.857**
	(0.348)	(0.350)	(0.342)
N	808	807	794
Panel B: Matched sample			
Year dummy (2009 and 2013 combined)	0.127	-0.0265	-0.178
	(0.331)	(0.334)	(0.331)
DID	0.479	0.651*	0.830**
	(0.354)	(0.354)	(0.349)
N	749	749	737
Panel C: PSNP graduate			
Time dummy (2009 and 2013)	0.166	0.00361	-0.133
	(0.336)	(0.337)	(0.335)
[1em] DID	0.474	0.687**	0.842**
	(0.344)	(0.344)	(0.339)
DID_grad	0.234	0.102	0.0555
	(0.623)	(0.582)	(0.559)
N	808	807	794
Household controls	YES	YES	YES
Shocks	NO	YES	YES
Cognitive outcome	NO	NO	YES

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors in parentheses, clustered at child level. Fixed effects is adopted as a baseline regression in all the specifications. DID refers to the differences-in-differences coefficient which is the interaction of time and treatment indicators. While DID_grad refers to the interaction of the differences-in-differences indicator (DID) and graduation dummy. The dependent variable in all columns is years of educational aspirations. The first column controls for covariates including time taken to school as child control; household controls consisting of wealth index, household head sex, mother's education and household composition based on age and sex. The second column adds shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock. The last column, however, includes z-score of maths test scores of children as proxy for cognitive outcome.

In general, our results suggest that the safety-net program in Ethiopia, designed to lift out the food insecure households out of the chronic poverty, also affects the educational aspirations of children. In 2009 (three years after the program intervention), an impact on aspirations is confirmed for both the full sample and the matched sample. Combining 2009 and 2013 sample, however, the effect on aspirations is positive and statistically significant once we control for shocks. Though the immediate effect is found to be more strong and precise, there seems to be an evidence of the long-run effect of the program on aspirations.

2.5. Robustness checks

PSNP transfers are delivered in two variants: the public works program and the direct support program. Participants of the public works program (PWP) are required to provide labour to pre-designed public works so as to get the transfers. The direct support program, instead, is unconditional cash or food transfers to households without able-bodied members who can contribute labour to public works. The effects of the two variants on our outcome of interest might be different. From one side, studies documented that unconditional transfers have a positive impact on the livelihoods of poor households. For instance, Haushofer and Shapiro (2016) documented a significant impact of unconditional cash transfers on households' economic and psychological well-being in Kenya. Baird et al. (2014) find that both conditional and unconditional cash transfers have an impact on schooling, but conditional transfers have a higher impact provided that the conditions are school related. Therefore, we expect a positive impact of the PSNP direct support program component on aspirations of the children. On the other hand, children from households involved in the PWP may substitute working adult members either in household chores or other household tasks. This might negatively interfere with their education and their desire for education. Haile and Haile (2012) find that child labour, which could include domestic chores and paid works, is associated with lower educational attainment. In our sample, only 7 per cent of the households are part of the direct support program, however we run our DID estimation only on the sample of PWP. Table 5 presents the estimation results for the full sample and the matched sample of PWP, and we employed fixed effect as the baseline regression. The results are similar to the findings in Table 3.

Table 5: Impacts of PSNP on educational aspirations (2009 - only PWP)

	(1)	(2)	(3)	(4)
Full sample				
Time dummy (2009)	-0.105	-0.224	-0.243	-0.158
	(0.450)	(0.425)	(0.415)	(0.385)
DID	0.785**	1.077***	1.098***	0.922**
	(0.387)	(0.383)	(0.377)	(0.361)
N	717	716	708	701
Matched sample				
Time dummy (2009)	-0.212	-0.314	-0.203	-0.119
	(0.451)	(0.428)	(0.416)	(0.387)
DID	0.865**	1.129***	1.068***	0.893**
	(0.399)	(0.396)	(0.386)	(0.366)
N	667	667	667	666
Household controls	YES	YES	YES	YES
Shocks	NO	YES	YES	YES
Cognitive outcome	NO	NO	YES	YES
Caregiver's aspirations	NO	NO	NO	YES

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors in parentheses, clustered at child level. Fixed effects is adopted as a baseline regression in all the specifications. DID refers to the differences-in-differences coefficient which is the interaction of time and treatment indicators. The dependent variable in all columns is years of educational aspirations. The first column controls for covariates including time taken to school as child control; household controls consisting of wealth index, household head sex, mother's education and household composition based on age and sex. The second column adds shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock. While the third column includes z-score of maths test scores of children as proxy for cognitive outcome, the last column controls for the years of educational aspirations that parents are aspiring for their child to complete.

In our main analysis, we consider only children currently enrolled in education, because the control variable distance to school (minutes) is available only for children currently attending school. This is an important covariate to be included in our analysis, since transportation costs may discourage educational aspirations of children. Education enrollment may have an influence on the educational aspirations of children and our results might be driven by sample selection. For robustness, we include in our sample out of school children (without controlling for distance to school) and conduct the DID estimation. Table 6 depicts the impacts on aspirations for the full sample and the matched sample. The results confirm that PSNP has a positive and significant impact at the 1 per cent level on the years of educational aspirations. This suggests that the results in our main analysis are not driven by sample selection.

Table 6: Impacts of PSNP on educational aspirations (2009 - Including non-enrolled children)

	(1)	(2)	(3)	(4)
Full sample				
Time dummy_2009	-0.0291	-0.127	-0.218	-0.281
	(0.437)	(0.421)	(0.420)	(0.402)
DID	0.891**	1.088***	1.159***	0.922**
	(0.384)	(0.378)	(0.375)	(0.358)
N	809	807	794	782
Matched sample				
Time dummy_2009	-0.204	-0.288	-0.241	-0.257
	(0.455)	(0.433)	(0.427)	(0.404)
DID	1.004**	1.191***	1.167***	0.907**
	(0.397)	(0.389)	(0.383)	(0.360)
N	735	735	735	730
Household controls & village dummies	YES	YES	YES	YES
Shocks	NO	YES	YES	YES
Cognitive outcome	NO	NO	YES	YES
Caregiver's aspirations	NO	NO	NO	YES

Robust standard errors in parentheses, clustered at child level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors in parentheses, clustered at child level. Fixed effects is adopted as a baseline regression in all the specifications. DID refers to the differences-in-differences coefficient which is the interaction of time and treatment indicators. The dependent variable in all columns is years of educational aspirations. The first column controls for covariates including time taken to school as child control; household controls consisting of wealth index, household head sex, mother's education and household composition based on age and sex. The second column adds shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock. While the third column includes z-score of maths test scores of children as proxy for cognitive outcome, the last column controls for the years of educational aspirations that parents are aspiring for their child to complete.

As an additional robustness check, we consider an alternative outcome variable, whether children would like to make plans for their future education and work, which is future oriented and related to future investments. This outcome variable is an indicator of forward-looking behaviour and shown to be correlated with future investments (Dercon and Singh, 2013). Bernard and Taffesse (2014) also stated three distinctive features of aspirations: aspirations are future oriented, aspirations are goals in which people invest their time and effort to realise them, and aspirations are perceived as ambitions to reach multidimensional life outcomes that affect the individual's future behaviour. To this end, we examine whether children's desire to plan about their future work and education is also affected by PSNP. We run the DID estimation using the same sample of households as in our main analysis. In the survey, children were asked whether they wanted to make plans for future education and work as follows: "I like to make plans for my future studies and work" and the response is categorical running from 1, indicating strongly disagree, to 5, strongly agree in round three while 1 to 4 in the second round. To normalise the question, a z-score[10] of each observation is computed.

Table 7 presents the results of plan for future education and work and we used fixed effects as baseline regression. They convey that PSNP positively impacts children's desire to plan for future education and work which is in line with our results above. This indicates that the program affects children's educational aspirations which might also be reflected somewhat on their desire to plan for future education.

[10]The z-score is computed by subtracting mean from each observations and dividing it by the standard deviation.

Table 7: Impacts of PSNP on Children's desire to plan for the future

	(1)	(2)	(3)	(4)
Full sample				
Time dummy (2009)	-0.106	-0.170	-0.154	-0.124
	(0.154)	(0.164)	(0.169)	(0.156)
DID	0.331**	0.361**	0.336**	0.268*
	(0.154)	(0.156)	(0.158)	(0.147)
N	735	734	727	791
Matched				
Time dummy (2009)	-0.0526	-0.118	-0.117	-0.119
	(0.158)	(0.168)	(0.172)	(0.171)
DID	0.290*	0.324**	0.324**	0.316**
	(0.154)	(0.155)	(0.156)	(0.156)
N	681	681	681	680
Household controls	YES	YES	YES	YES
Shocks	NO	YES	YES	YES
Cognitive outcome	NO	NO	YES	YES
Caregiver's aspirations	NO	NO	NO	YES

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors in parentheses, clustered at child level. Fixed effects is adopted as a baseline regression in all the specifications. DID refers to the differences-in-differences coefficient which is the interaction of time and treatment indicators. The dependent variable in all columns is children's desire to plan about their future work and education. The first column controls for covariates including time taken to school as child control; household controls consisting of wealth index, household head sex, mother's education and household composition based on age and sex. The second column adds shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock. While the third column includes z-score of maths test scores of children as proxy for cognitive outcome, the last column controls for the years of educational aspirations that parents are aspiring for their child to complete.

2.6. Aspirations and years of education

The aim of our paper is to explore whether educational aspirations are affected by an anti-poverty program. We claim that educational aspirations are very important for future education and work. A few studies have documented the effects of aspirations on future education (see for instance Favara (2017) for Ethiopia). In this section, we provide evidence on the correlation between aspirations and actual educational attainment in rural Ethiopia.

In Ethiopia, primary education consists of two cycles: the first cycle includes grade 1 to 4, and the second cycle includes grade 5 to 8. Even if primary education is compulsory by law (children should start going to school at age 7), late enrollment is a common phenomenon, especially in rural areas. In addition, it is quite common that children drop out of school and come back after a certain period. These behaviours lead children to reach compulsory educational targets at later age and are a barrier for further education. At the end of second cycle primary education, students are required to sit for 8^{th} grade regional examination so as to enter high school. Secondary education consists of two cycles: the first cycle is the general secondary education including grade 9 to 10 and the second cycle is preparatory school including grade 11 to 12. Given the system, completed primary education can be already seen as a success in rural Ethiopia. Table 8 shows that on average, at age 15 and 19, children have completed about 4.8 and 7.1 years of education, respectively. Data suggest that it is crucial to increase educational attainment of young people. In this respect, educational aspirations may be of primary importance.

Table 8: Years of education by survey rounds

Survey rounds	Average years of education	Std. Dev	N
2006 (Age 12)	2.488	1.567	400
2009 (Age 15)	4.716	2.108	402
2013 (Age 19)	7.089	2.823	372

Notes: Years of education refers to the highest education level the child has completed. The first column is the average years of education, the second column is the standard deviations and the third column is the number of observations for each survey rounds.

Table 9 presents the difference in the mean proportion of average years of schooling between those aspiring for college and those aspiring lower than college in the previous wave. Unconditional correlations show that higher aspirations in the previous wave are positively associated with the number of years of education completed at the ages of 15 (round 3) and 19 (round 4). In particular the difference in the years of education between those aspiring for college and those aspiring lower than college in the previous wave are 0.62 and 1.92 years in 2009 and 2013 respectively, and the differences are statistically significant.

Table 9: Education completion by lag of aspirations

Aspirations in the previous wave	2009 (R3)		2013 (R4)	
	N	Mean	N	Mean
<College	153	4.549	135	5.948
College	220	5.191	234	7.782
Difference (College - <College)		0.642		1.834
P-value		0.0017		0.000

Notes: Aspirations lag refers to the educational aspirations in the previous wave. Since aspiration questions are included starting from the 2006 (second) wave, we have aspiration gap for the 2009 (third) and 2013(fourth) waves. The first and the second columns refers to the number of observations and the proportions for the 2009 sample respectively. While the third and the fourth columns denote the number of observations and the mean respectively for the 2013 sample. College refers to educational aspirations of college and above, while <college refers to aspirations for less than college.

Pooling the data, Table 10 tests whether the positive correlation between aspirations (lagged) and actual years of education holds after controlling for characteristics at individual and household level. More specifically, Column (1) includes individual controls (child's sex and travel time to school in minutes) and household controls (sex of household head, wealth index, mother education dummies, household composition dummies), wave dummies and village dummies and shows a positive and statistically significant effect at 1 per cent level of (lagged) aspirations on years of education. The results are robust to the inclusion of additional covariates, such as climatic shocks, cognitive outcome, and whether the household has ever received any aid before the program (column (2)). As we want to link aspirations to actual educational outcomes, for robustness, in column (3) and (4), we include estimations only on the non-participants of the PSNP so as to partly avoid the program's intervention. The results convey a positive association of aspirations with actual educational outcomes even when considering only the control group. This implies that aspirations are a good predictors of future actual educational attainment as it also has been confirmed by Favara (2017) for Ethiopia and Chiapa et al. (2012) for Mexico.

Table 10: Lag of Aspirations and actual years of education

	All Sample		Non-participants of PSNP	
	(1)	(2)	(3)	(4)
Lag of years of Aspirations	0.151***	0.101***	0.136**	0.102**
	(0.0404)	(0.0332)	(0.0543)	(0.0443)
Constant	3.668***	4.465***	4.114***	3.567***
	(0.751)	(0.687)	(1.109)	(1.023)
N	471	466	225	222

Robust standard errors in parentheses, clustered at child level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable in all columns is actual years of education. Covariates include child and household controls. Columns 2 and 4 also include additional controls consisting of climatic shocks, cognitive outcome, and whether households received any aid before the program. Village (site) level dummies and year dummies are included in all columns. The first two columns contain the estimations on all sample observations while the third and fourth columns are estimation results conducted on the non-participants of the program.

2.7. Conclusions

Aspirations play a key role in the investment decisions of individuals towards their future endeavors. Children's educational aspirations especially enhances later educational attainment. However, in developing countries, aspirations might be muffled by the extreme poverty level of individuals. In understanding how to break the cycle of poverty, it is important to examine how aspirations of the poor can be encouraged. Using Young Lives' longitudinal data in Ethiopia, we investigate the impacts of the Ethiopian PSNP on educational aspirations of children.

We consider differences-in-differences approach with fixed effects as baseline regression on the "full sample" and we control for several covariates. We also use matching techniques to further curb the comparison groups. The results convey significant and positive impacts of PSNP on aspirations and suggest that the program lifts up children' s educational aspirations. As the vast majority of the population of Ethiopia depends on a small agricultural livelihood, food insecurity, caused mostly by natural calamities, is a threat to the rural households who mostly depend on rain-fed agriculture. Our results imply that small transfers may mean a lot for the food insecure rural households; they could sustain their life and affect their livelihoods in different directions: in this case we show that a financial safety-net can have important spillover effects on education.

We also look at the impacts of PSNP combining the 2009 and 2013 sample and whether it is different for the graduated households, in order to assess whether the program has a long-run effect on aspirations. In a longer spell between the transfers and the observed outcome, individuals may change their aspirations for reasons that remain unknown to the econometrician. Results are therefore less robust, but still point towards a positive effect of PSNP on educational aspirations of children once we control for household's exposure to shocks.

All in all, we find that PSNP affects educational aspirations, which are an important determinant of actual educational attainment.

Appendices

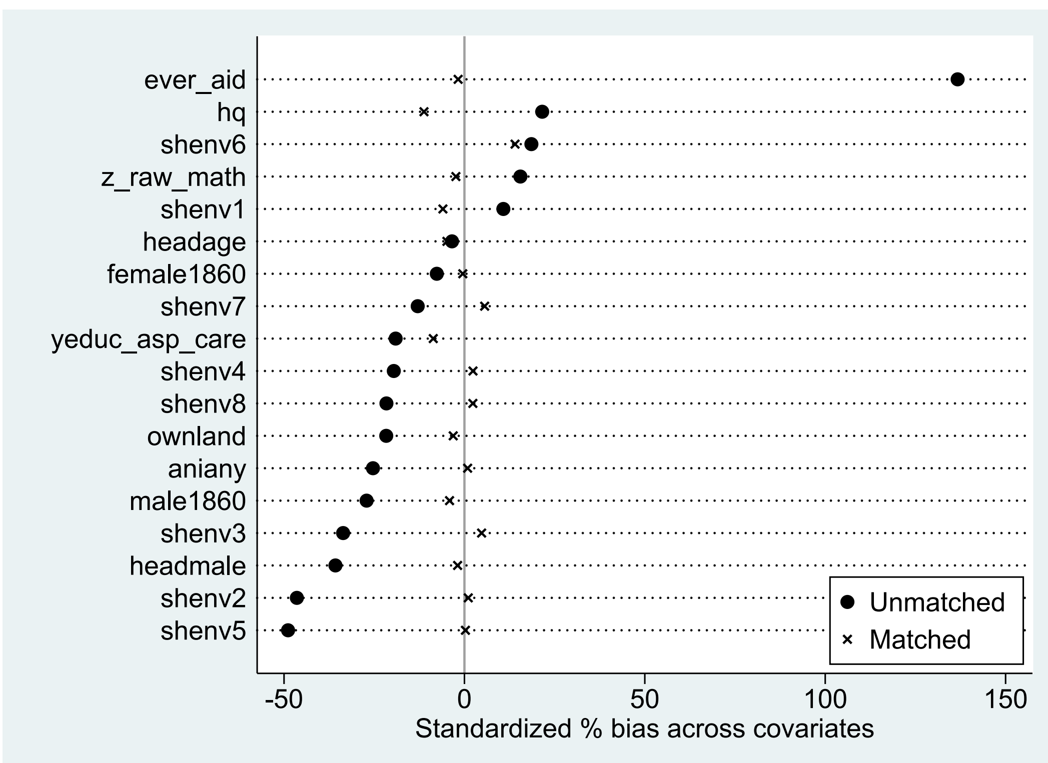
Appendix A Impact of PSNP on educational aspirations (full covariates)

	(1)	(2)	(3)	(4)
Time dummy_2009	-0.112	-0.208	-0.255	-0.254
	(0.423)	(0.397)	(0.387)	(0.366)
DID	0.708*	0.956***	1.003***	0.872**
	(0.369)	(0.363)	(0.357)	(0.341)
Travel time to school (in minutes)	-0.0150*	-0.0164**	-0.0114*	-0.00945
	(0.00788)	(0.00758)	(0.00684)	(0.00585)
Wealth index	-0.566	-0.0742	0.647	-0.435
	(1.995)	(1.961)	(1.858)	(1.796)
Household head-male	0.0472	-0.590	0.0240	0.220
	(0.946)	(0.863)	(0.788)	(0.800)
Mother education-Adult literacy	0.541	1.031*	1.141**	0.657
	(0.559)	(0.581)	(0.575)	(0.483)
Mother education-primary and above	0.167	0.291	0.0582	-0.110
	(1.310)	(1.201)	(1.254)	(1.133)
Livestock ownership in the past 12 months	-0.200	-0.0616	-0.395	-0.393
	(0.532)	(0.540)	(0.498)	(0.384)
Total area of land owned by the hh	0.00258	-0.0108	-0.0225	-0.0412
	(0.0195)	(0.0224)	(0.0364)	(0.0387)
Number of males aged 0-5	0.794*	0.748*	0.748*	0.545
	(0.421)	(0.436)	(0.428)	(0.435)
Number of males aged 6-12	0.863**	0.743*	0.492	0.370
	(0.426)	(0.420)	(0.407)	(0.398)
Number of males aged 13-17	-0.172	-0.306	-0.384	-0.445
	(0.439)	(0.458)	(0.500)	(0.488)
Number of males aged 18-60	-0.277	-0.397	-0.458	-0.261
	(0.453)	(0.457)	(0.486)	(0.480)
Number of males aged 61+	-1.018	-0.920	-0.892	-0.602
	(0.940)	(0.849)	(0.886)	(0.747)
Number of females aged 0-5	-0.448	-0.547	-0.541	-0.576*
	(0.348)	(0.346)	(0.350)	(0.337)
Number of females aged 6-12	-0.835*	-1.136***	-1.015**	-1.037**
	(0.436)	(0.430)	(0.452)	(0.431)
Number of females aged 13-17	-1.058*	-1.236**	-1.090*	-1.136*
	(0.609)	(0.598)	(0.597)	(0.612)
Number of females aged 18-60	-0.285	-0.524	-0.509	-0.436
	(0.620)	(0.602)	(0.627)	(0.647)
Number of females aged 61+	0.362	0.428	0.637	-0.598
	(0.870)	(0.830)	(0.928)	(1.464)
shock-drought		-0.566*	-0.639**	-0.631**
		(0.291)	(0.282)	(0.272)
shock-flooding		-0.912**	-0.915**	-0.804**
		(0.394)	(0.399)	(0.370)
shock-erosion		-0.822	-0.574	-0.277

		(0.539)	(0.555)	(0.540)
shock-frost		-0.536	-0.531	-0.483
		(0.429)	(0.434)	(0.412)
shock-pests on crops		-0.510	-0.612	-0.579
		(0.548)	(0.543)	(0.520)
shock-crop failure		-0.270	-0.225	0.00146
		(0.292)	(0.285)	(0.264)
shock-pests on storage		1.911**	1.841**	1.129*
		(0.811)	(0.827)	(0.664)
shock-pests on livestock		0.959***	1.000***	0.751***
		(0.280)	(0.281)	(0.287)
z_raw_math			0.521**	0.525***
			(0.205)	(0.199)
Years of education aspiration by caregiver				0.339***
				(0.0857)
Constant	15.66***	17.67***	17.50***	12.71***
	(1.988)	(1.982)	(2.041)	(2.338)
Observations	737	737	729	722

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Checking for balance after matching



Notes: The figure indicates the standardized percentage bias across the covariates for the matched and unmatched samples. Zero indicates for absence of bias for each of the covariates listed on the Y-axis and can be seen that the percentage bias for the matched sample is closer to zero.

3. CHAPTER 3

Hello, I am calling to ask for some money: Mobile phones and credit uptake in rural Ethiopia

Abstract

It is widely believed that ICT has a significant influence in the daily life of the poor and has positive spillover effects in their livelihoods. Mobile phones are one of the few ICT innovations that have found their way in to the hands of the poor residing in remote and rural areas. In Ethiopia, mobile phones are recently introduced but got an acceptance from everyone including the rural poor; in five years time, mobile phones subscription has increased from less than 4% to more than 40%. Empirical evidences generally document the positive role mobile phones play in facilitating the development efforts of poor households. However, using panel data from Ethiopia, the current paper explores a less investigated issue of the possible effects of mobile phones adoption on the credit uptakes of the rural poor who are mostly neglected from the formal credit markets but finance their credit demand from informal sources including relatives/friends. The econometric results suggest mobile phones are positively associated with the credit uptake of rural households specially credit uptake from informal sources. Households with mobile phones are found to have 4% to 14% higher probabilities of credit uptake and about 6% to 17% in the case of credit from informal sources. Besides, households with mobile phones are found to have about ETB 65 (USD 3.42) higher loan size and about ETB 78 (USD 4.11) higher amount of loan in the case of loan from the informal sources. Thus, policy makers and financial providers working on providing credit in rural areas need to exploit the use of mobile phones in reaching out the rural poor.

JEL Classification: D14, O33, O17

Keywords: Mobile phones; Ethiopia; credit uptake; probit; special regrossor

3.1. Introduction

The last few decades has been characterized by a boom in the Information and Communication Technologies (ICT) that has influenced lives of both the rich and the poor in many aspects. Particularly, mobile phones have found their way into the houses of even the poorest of the poor playing an important role in the development process of poor countries by reducing the costs and time associated with transportation (Duncombe, 2014). Aker and Mbiti (2010) argued mobile phones play a significant role in lowering communication costs which helps the rural households to access information quickly and cheaply. However, the possible effects of mobile phone adoption on the credit uptakes of the rural poor has not thoroughly investigated. The issue is especially pertinent to the rural poor that are mostly neglected from the formal credit markets and finance their credit demand from informal sources including relatives/friends.

Individuals usually use saving instruments to finance their consumption in times of unprecedented income shocks. However, savings are very limited in low income countries and households go for credit from non-market institutions including informal credit arrangements, cooperatives, saving and credit associations, and other arrangements (Besley, 1995). The development of microfinance institutions and cooperatives have contributed in relieving credit constraint of poor households. These institutions serve the poor who are excluded from the formal banking credits and these institutions are established with the aim of reducing poverty by unleashing the financial constraints of the low-income households (Morduch 1999; Khandker 2005). However, rural financial system has remained a bottle neck of development in many developing countries (Tenaw and Islam, 2009). Thus, poor households smooth their consumption by borrowing mostly from informal sources such as friends and relatives. Having access to credit relieves rural households from the input requirement and consumption constraints. Access to credit also plays a key role in coping with shocks, enhancing education and labour supply outcomes and asset holdings (Pitt and Khandker 1998; Okten and Osili 2004).

Empirical evidences so far signpost positive effects of mobile phones on different social and development indicators. Mobile phones are found to have positive impact in empowering women (Chew et al., 2015) as well as mass mobilization and protests in Africa (Manacorda and Tesei, 2016). Going beyond the social benefits, mobile phones accrue economic benefits by playing a facilitating role in agricultural technology adoption and extension service (Aker, 2011). The effects of mobile phones are not observed for all commodities, but in cases where it is observed, the impact is high in markets with high transport costs for both producers and consumers (Aker, 2010; Aker and Fafchamps, 2014). Mobile phones are also found to have a weak positive effect in influencing farmers marketing decision in Ethiopia (Tadesse and Bahiigwa, 2015). On the other hand, Abraham (2007) show mobile phones help fishermen in India respond quickly to markets by coordinating demand for and supply of markets. They further argue that mobile phones reduce the information asymmetries in rural and under developed markets. Using development indicators, Beuermann et al. (2012) show mobile phone ownership is associated with an increase in consumption and decrease in poverty indicators. Aker and Blumenstock (2014) contended that ICTs provide unique opportunities to development and play a great role in alleviating market failures and development constraints which are prevalent in most developing countries. Blumenstock et al. (2016) also analyzed whether mobile phones networks are used to transfer resources to individuals affected by covariate shocks and find a significant increase in air time transfers to these individuals. They argue that mobile phones can facilitate communication and thus serve as a new method of coping with unexpected disasters.

In order to understand the effects of mobile phones on the access to credit of the rural poor, exploring the scene and determinants of credit in rural areas would be helpful. Rural credit is mainly characterized by the absence of formal credit institutions due to high risks of default and very weak enforcement mechanisms. In Ethiopia, where the majority of the population live in poor rural areas with very poor infrastructural development, access to formal credit is almost inexistent. Most of the formal banking services are concentrated in urban areas leaving the rural people under-served. But rural households in Ethiopia has had long standing tradition of financing through informal ways such as 'Ikub' and 'Iddir'[11], and from neighbours, relatives and friends. Access to credit is, therefore, determined by the social networks and the level of information households have on where and how to get credit. In our case, let's assume that a household wants to borrow so as to satisfy his consumption or agricultural input requirements. The household either has access to formal sources or informal sources. The role of information comes in here. Households need a mechanism to exploit their social and community networks to either look for credit institutions or get credit from these networks themselves. However, since I am dealing with very poor rural households, most of the credit demands are pity amounts of credit intended to satisfy the immediate needs. Mobile phones, therefore, help these households in relieving the information constraints.

[11] Iquib is a traditional means of saving where by a group of voluntary people make a mandatory contributions and get rotating funds for members, while Iddir is a burial association established among neighbors or workers. Though formal financial institutions are underdeveloped, these traditional systems have been playing a vital role in the credit, saving and insurance markets of the Ethiopian people.

The results in this study reveal that mobile phones play a role in the credit uptake of rural households accruing to the fact that mobile phones may play a significant role in easing informational constraints especially in the face of high credit constraints. Okten and Osili (2004) examine the impact of networks on individual's access to credit by lowering the costs of borrowing through information provision and lower search costs. Information is very costly in rural areas; households may be required to travel long distances to ask for credit either from formal sources or from relatives or friends living in distant villages; and then to follow the advancement of the credit. To investigate whether mobile phones have a role in the credit uptake of the rural poor, I use rural households in Ethiopia. In Ethiopia, mobile phone penetration is quite recent, but it has shown a staggering change most recently, mobile cellular subscriptions has increased from 0.539 in 2005 to 42.764 per 100 people in 2015.

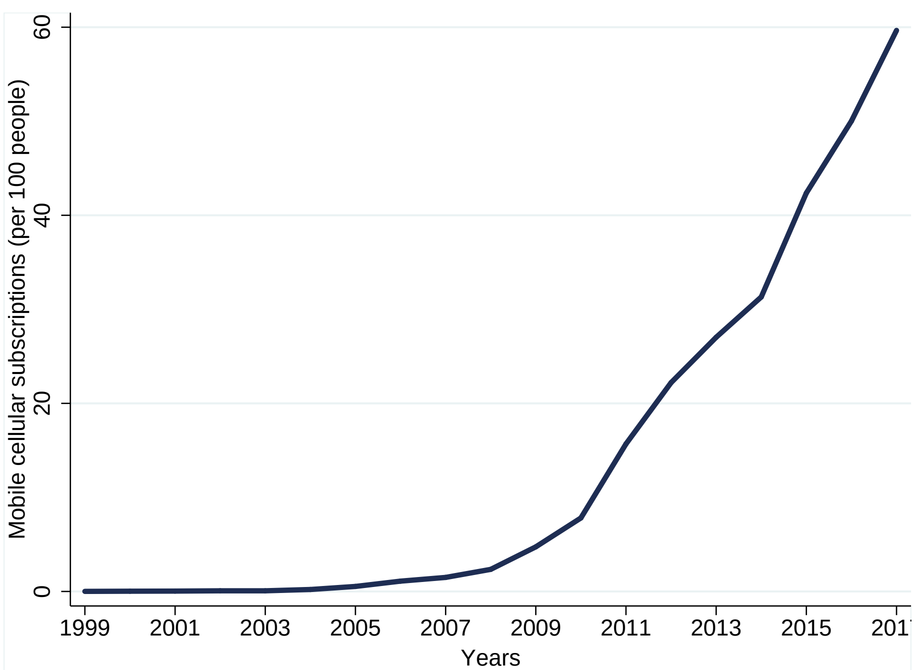
In this paper, I investigate whether households mobile phone adoption is linked with their credit uptake. The main contributions of the paper are the following. First, the determinants of credit have been studied but as far as to the knowledge of the author this paper is the pioneer to link credit with mobile phones adoption. Looking at the history of mobile phone penetration in Africa, one can unveil the dramatic intrusion of the services in the past decade. This high penetration of mobile phones is expected to affect individual decisions including the decision to take credit. Second, it opens up a discussion on the importance of applying mobile phone technology to improve the financial need of the poor through information-problem alleviation.

The paper is organized as follows. The second section discusses the developments of mobile phones in Ethiopia. Section 3 describes the data used in this paper. Section 4 presents the methods used and the results obtained. The last section concludes.

3.2. Mobile phones in Ethiopia

Ethiopian telecommunication services are provided by the government owned corporation, Ethio telecom, which is the sole telecommunications service provider in the country. It monopolizes all the telecom services in the country including mobile, fixed and internet and data service provisions. Albeit high government regulations and control of the sector, it has recently shown a dramatic growth especially with respect to mobile phones penetration. In Ethiopia, mobile phone penetration is quite recent but have shown a staggering change most recently. According to the World Bank data, mobile cellular subscriptions has increased from 0.539 in 2005 to 42.764 subscriptions per 100 people in 2015 (see figure 3). There was a sharp increase in the number of mobile phone subscribers starting from 2009/10. This sharp increase in the subscription rates might be attributed to different factors. One of the reasons could be the reduction in the sim card prices and lowering the per minute fees at the end of 2009. One of the barriers for mobile phone subscription was the high costs of sim cards. In a motive to attract more customers and expand its service, the corporation, Ethio telecom now, reduced the cost of sim cards by about 54% in 2009 (from ETB 367(USD 33) to about ETB 169 (USD 15)). Another reason could be that Ethio telecom outsourced its management, on a managerial contract arrangement, from 2010 to 2013 to France Télécom. The outsourcing was made in anticipation to boost coverage and improve services. Soon after the management takeover, they not only drove down the calling costs and sim card prices but also removed the regional tariff zones which used to charge a more than double fees for calling to another tariff zones. Due to these and other reasons, mobile phone subscription has increased dramatically and is expected to broaden the windows of information access and might relieve the acute information constraints. It might also improve the livelihoods of households in many ways. To investigate whether mobile phones have a role in the credit uptake of the rural poor, I use rural households in Ethiopia.

Figure 3: Mobile phone subscription in Ethiopia



Source World Bank data.

3.3. The Data

To investigate the effects of mobile phones on credit, I use a longitudinal data obtained from Young Lives Ethiopia. Young Lives is a research project working in four countries including Ethiopia, India, Vietnam and Peru. The Department of International Development at the University of Oxford coordinates it. It follows two cohorts of children totally make up to 3000, the younger cohort and the older cohort, about 7 years apart. The sampling units were selected following a four-stage sampling process based on the administrative structure of the country. In the first stage four regions including Tigray, Amhara, Oromia and SNNP, and one administrative city, Addis Ababa, were selected out of 9 regional states and 2 city administrations. In the second stage, woredas (districts) were selected from each region which make up to a total of 20 woredas[12]. Then, kebeles (the last administrative layer) were chosen from each woredas where the study sites are located. The study sites were selected to ensure a balanced representation of the country's diversity in terms of regional or urban-rural differences, and with a pro-poor bias to accommodate Young Lives objectives. To this end, poorer sites were oversampled though better-off sites were also considered for comparison and for better representation. In the final stage, 100 households with a child born in 2001-02 and 50 households with a child born in 1994-95 were randomly chosen from the selected study sites. The study include four rounds of quantitative survey of children, households and communities where they live in. In this paper, since I am dealing with rural households, the urban sites are excluded. A total of 12 sites (villages), 3 from each region, are included in this paper.

Beside to the child questions, the household questionnaire constitutes questions about the general socio-economic characteristics, access to services and exposure to different shocks of the households. In the current paper, since I am interested in the households access to credit related to their mobile phones adoption, I use the household questionnaire part. But to make sure that the same household is being tracked, I use the child questionnaire to identify whether the child lives in the same household as in the previous wave. So far, four waves of data have been collected, the 1st, 2nd, 3rd and 4th waves in 2002, 2006, 2009 and 2013 respectively. But I consider the last two waves as mobile phone adoption was negligible in the 1st and 2nd waves. As one can see from section 2, mobile phones start to have expanded starting from 2008/09 and hence it is natural to filter out the previous waves where mobile phones were not popularly used. Moreover, this study considers only the rural sample, which makes up about 60% of the total sample, because service provision in urban areas is different

[12] Three rural sites and one urban site were selected from each region except in SNNP where two out of the 5 sites are urban sites

and more developed than the rural counterparts.

Households were asked whether they accessed credit, the source of credit and the amount of loan taken. We construct a dummy variable of whether households took credit or not; the amount of credit is, however, a continuous variable put in terms of the total Ethiopian currency (known as 'Birr'). Moreover, households were asked about the sources of credit they took; a given household may took credit from more than one sources. And they are categorized into formal and informal credit sources. The classification is based on whether the institutions are supervised and regulated by the central bank of Ethiopia named National Bank of Ethiopia (NBE). Accordingly, while banks and micro-finance institutions are classified as formal sources, the rest are identified as informal ones [13]. On the other front, households were also asked whether they own mobile phones and a dummy variable of mobile phone ownership is constructed taking a value of 1 for households who own mobile phones and zero otherwise. Table 12 reveals that the proportions of mobile phone ownership has increased from 12% in 2009 to 56% in 2013 which confirms that mobile phone adoption has shown a tremendous change even in three years time. Though the credit uptake has shown a small change from 2009 to 2013, the sources of credit have changed significantly. As can be seen from table 12, of those households who took credit in 2009 about half of them reported that they took credit from informal sources only while about 35% from formal sources only and the rest 15% from both formal and informal sources. While in 2013, of those who took credit, the proportions of households who got credit solely from the formal sources has decreased by 15 percentage points. And the 15% decrease from the formal sources is shared by a 10% increase in the access from the informal sources and a 5% increase in both the formal and informal sources. This implies that albeit a flat increase in the general access to credit, the proportions of access from the informal sources has broaden. Besides, the amount of loan that households took from all sources, including from the formal and the informal ones, has increased.

[13] In this paper the formal sources include: micro-finance institutions (MFIs) and loans from micro and small enterprise (MSE) agency. While the informal sources include: cooperatives, associations, NGOs, friends/neighbours, relatives, money lenders, and other informal memberships

Table 12: Descriptive summary of mobile phones, credit and loan size

		2009		2013	
		Proportions (Mean)	N	Proportions (Mean)	N
	Mobile phone ownership	0.112	1,576	0.558	1,488
Access to credit					
	Total	76.71	1,209	79.30	1,180
	Formal	34.60	418	20.17	238
	Informal	50.33	608	59.58	703
	Both	15.07	182	20.25	239
Amount of loan (in ETB)					
	Total	2743.22	1,209	3689.41	1,180
	Total from formal	3213.21	600	4586.21	477
	Total from informal	1757.75	790	2318.94	934

Notes: The third and the fourth columns describe the proportion and the number of observations in 2009; the last two columns present the proportion and the number of observations in 2013. The means (proportions) are computed for the following variables: mobile phones ownership, access to credit, and amount of loan taken.

Households took credit from many different sources including formal or informal ones. Table D in the appendix presents that more than half of the households reported that they took credit more than once which indicates that a given household may access credit from several sources for different reasons. Households were asked to report the reasons for the loans they mentioned. Accordingly, I have seen the reasons behind taking credit for the first loan that households mentioned for both 2009 and 2013. Table 13 lists out the reasons for taking credit from formal, informal, and both. Looking at the formal sources, households mainly took credit for agricultural investment purposes. In 2009, more than 60% of the households reported that they took credit from formal sources mainly for agricultural purposes including fattening, bee keeping, horticulture, poultry, goat and sheep rearing, dairy, purchase of agricultural equipment and variable inputs, etc; about 14% of them reported for buying oxen; and about 5% for consumption purposes. Similarly, households took credit from formal sources mainly for agricultural and related investment purposes in 2013. On the other hand, the main reason for taking credit from informal sources is still for agricultural purposes but the shares of households taking credit for consumption purposes are much higher than those households who took credit from formal sources. So while the main motive behind taking credit from formal or informal sources is agricultural investment, but consumption motive is still high in the case of informal sources.

Table 13: Reasons for taking the 1st loan households mentioned

Reasons for taking the first loan households mentioned	2009 (R3)			2013 (R4)		
	Formal	Informal	Both	Formal	Informal	Both
Agriculture	62.92	37.01	61.54	54.20	46.72	64.85
Consumption	5.50	22.20	5.49	8.82	21.23	9.62
Financial/business	1.67	1.48	1.65	4.20	1.85	2.51
Food processing	4.55	3.29	3.85	2.94	0.71	0.84
Healthcare for children	0.00	5.92	1.65	0.00	3.56	1.26
Healthcare for adults	0.48	9.38	2.20	1.26	8.26	3.35
House construction an	3.11	5.76	4.95	4.62	2.14	3.35
Jewelery	0.00	0.33	0.00	0.00	0.00	0.00
Other	0.48	3.13	6.04	5.04	3.56	2.09
Paying taxes	0.00	0.16	0.00	0.00	0.28	0.00
Purchase of transport	1.67	1.15	1.10	2.94	0.43	0.00
Purchase of household	0.24	0.82	1.65	0.42	1.14	2.09
Purchase of oxen	14.11	2.63	7.14	7.14	0.57	5.44
Schooling for children	0.48	0.82	0.00	0.84	1.85	0.00
Schooling for adults	0.00	1.64	0.00	1.68	1.28	0.00
Paying for services	0.00	0.16	0.00	0.00	1.57	0.00
Settling other debts	0.48	0.49	0.55	0.84	0.85	0.84
Trade	4.31	3.62	2.20	3.78	2.99	3.35
Purchase equipment & machine-new firm	0.00	0.00	0.00	0.42	0.43	0.00
Purchase of equipments & machine-established firm	0.00	0.00	0.00	0.84	0.57	0.42

Notes: Households can mention as many as they take loans. In this table the reasons associated with the first loan that households mentioned are presented. The first three columns include the reasons for taking credit from formal, informal and both sources in 2009. While the last three columns include the reasons for taking credit from formal, informal and both sources in 2013.

The general characteristics of households is presented in table C. The general household characteristics in 2013 include: the household age is about 48 years, about 43% attended some primary education and above (albeit some secondary education and above is below 6%), about 80% are male headed households, the monthly total expenditure is about ETB 605, and the average size of land households own is about 1.4 hectares. Besides, the summary statistics of variables is presented in table C in the appendix for both 2009 and 2013. Moreover, table 14 depicts the difference in the exposure to shocks of households with and without mobile phones. Households with mobile phones are found to report lower exposure to drought, frost and crop failure but no significant difference is found comparing households with and without mobile phones.

Table 14: Households report of exposure to shocks by mobile phones ownership

	Without mobile phones		With mobile phones		Difference	P-value
	N	Mean(Proportion)	N	Mean(Proportion)		
Households access to credit	1210	0.7719	151	0.8146	0.0427	0.2355
shock-drought	1211	0.5615	151	0.2848	-0.2768	0.0000
shock-flooding	1211	0.2271	151	0.2053	-0.0218	0.5456
shock-erosion	1211	0.0966	151	0.0662	-0.0304	0.2262
shock-frost	1211	0.2081	151	0.0530	-0.1551	0.0000
shock-pests on crops	1211	0.1082	151	0.1126	0.0044	0.8698
shock-crop failure	1211	0.4377	151	0.3113	-0.1264	0.0030
shock-pests on storage	1211	0.0438	151	0.0464	0.0026	0.8837
shock-pests on livestock	1211	0.1742	151	0.1391	-0.0352	0.2788

Notes: The table reports the t-tests of the households exposure to shocks based on their mobile phone ownership IN 2009. The first column lists the type of shocks that households exposed.The second and the third column presents the number of observations and the mean of each shock respectively for households without mobile phones. The fourth and the fifth columns are the number of observations and the mean of exposure to shocks of households with mobile phones. While the last two columns are the difference between the mean values of households with mobile phones and without mobile phones, and the p-values corresponding to the t-tests with different variances respectively.

3.4. Econometric strategy and results

In this section, the econometric frameworks and the results obtained are discussed in detail. In the first part, the econometric strategy is presented while in the second -part, the results on the relationships of mobile phones with credit uptake are examined.

3.4.1. Econometric strategy

To investigate the relationship between mobile phones and credit uptake and/or loan size, one can use different empirical strategies. The general regression equation is specified as follows:

$$Y_{it} = \beta_0 + \beta_1 M_{it} + \mathbf{X}\beta_2 + \tau_t + \delta_i + \upsilon_{it} \tag{3}$$

Where Y_{it} refers to credit uptake or amount of loan taken by household i at time t; M_{it} is household i's mobile phone ownership at time t; $\mathbf{X}$ includes a set of household characteristics including household age, sex, education, total expenditure, land ownership, owning livestock, housing quality, indebtedness, household composition and exposure to climatic and other shocks; τ_t refers to a time dummy which equals 1 if year is 2013 and zero if 2009, δ_i is individual fixed effects and υ_{it} is the error component.

The model adopted depends on the nature of the dependent variable. In the first case, the dependent variable is a dummy variable taking a value 1 for households who accessed credit and zero otherwise, and a binary choice models or Linear probability models (LPM) could be adopted to analyze it. But in cases where the outcomes are binary, it is common to adopt probit or logit models. To this end, the probit model is used to estimate the relationship between mobile phones and credit uptake of households. Moreover, a fixed effect might be helpful to avoid the time invariant individual unobservables (δ_i) and I run estimations using logit fixed effects but the results reveal that many of my observations are omitted due to little within individual variations across time (see appendix F). Though using fixed effects might have helped in dealing with the individual time invariant unobservables, it is, however, very demanding to perform the fixed effects with little within individual variations. To this end, a random effect model, which considers the unobservables as part of the error component is considered in this paper.

Nonetheless, there might be an endogeneity problem emanating mainly from two sources. First, there might be omitted variables bias coming from common unobservables to mobile phones ownership and credit uptake; second reverse causality issues whereby individuals might access credit so as to buy mobile phones. Thus, to partly unleash the endogeneity problem, an instrumental variable estimation approach is adopted in this paper. Village (site) average mobile phone adoption[14] is used as an instrument based on the expectation that people adopt/imitate technologies from individuals around them. Peer effects play a significant role in individual's technology adoption decision. Bertrand et al. (2000) finds being surrounded by high welfare language groups increases the welfare of individuals which implies a sort of peer effect on individuals. Other studies investigate the role of peer effects on technology adoption. For instance, Oster and Thornton (2012) finds a strong evidence of peer effects in technology adoption in Nepal; Palm (2017) also find a suggestive evidence that neighborhood peer effects play a role in the adoption of solar PV technology. Hence, peer effects are one of the many factors contributing to technology adoption. To this end, I use village (site) level average adoption as an instrument to mobile phone adoption of households. This is even true when the practical case of rural Ethiopia is considered, where

[14] The average mobile phone adoption is calculated by excluding the individual for whom the average is computed.

social and neighborhood bonds are very intertwined and when one adopts new technology, others follow him/her. But the village average adoption might also capture the wealth of the villages under consideration and might weaken the exogeneity of the instrument. To resolve this, village level average monthly per capita expenditure is included as an additional control. Average adoption is not capturing the villages average wealth rather capturing the peer effect that I sought to control for and hence claim it is exogenous. However, one may argue peer effects may also be associated with the credit uptake of households such that households may take credit following their neighbours. But the peer effect considered here is specific to mobile adoption and this kind of peer effect affects credit uptake only through mobile phone adoption. Because people follows the footsteps of their neighbours in mobile phones adoption not in the anticipation of credit uptake facilitation rather for the ease communications that mobile phones render. So, I expect that the average mobile phone adoption in a village accelerates the mobile adoption of individuals and hence affect the credit uptake through mobile phones adoption but not directly. However, it is still not without pitfalls especially having only one instrumental variable as I cannot test the over-identification test.

To deal with the endogeneity problem, one may consider using the linear IV approach or the control function. But the outcome variable and the endogenous variable are binary in nature and the usual trend is to use the linear IV models or control functions, which do not consider these binary natures of the variables. To this end, I adopt the special regressors estimator, mostly used when both the dependent and the endogenous variables are binary in nature. The special regressors estimator is a newly developed model where the details and its implementations are described in Lewbel et al. (2012a) and Dong and Lewbel (2015) but its initial developments are based on Lewbel (2000). To identify the estimate of a binary choice model with an endogenous regressor, one need to have a special regressor, V, additively entered in the model with a unit coefficient. The special regressor should be exogenous, continuous and have a large support. The binary choice special regressor model is specified as:

$$D = I(X_e\beta_e + X_0\beta_0 + V + \epsilon \geq 0) \tag{4}$$

Where D is an observed binary outcome variable, X_e is an endogenous regressor(s) and X_0 includes a set of exogenous characteristics. To identify β_e, I need the usual instruments for the endogenous variable satisfying the usual requirements and a special regressor, V. The special regressor approach is based on the following assumptions: (i) the special regressor, V, and the error, ϵ, should appear additively as in equation (1); (ii) the special regressor needs to be conditionally (conditioned on the other covariates) independent of the error, ϵ; (iii) the special regressor is required to be continuously distributed with large support, so as to identify the estimates.

Special regressor model can be applied in a wide range of issues involving binary outcomes and endogenous binary regressors. Dong and Lewbel (2015) applied special regressor model to assess the migration decision of individuals from one state to another in the US where homeownership and income are the endogenous regressors. In this case, a special regressor method is used as homeownership is a dummy variable with age as a special regressor, V. Bontemps and Nauges (2015) applied the special regressor approach when examining the impact of water quality perceptions on the choices of drinking water. They claim that perceptions are endogenous to averting decisions and used average price of tap water as a special regressor. In the current paper, the dependent variable is a dummy for credit uptake, the endogenous variable is also a dummy for mobile phones ownership and the instrument is village level mean of mobile phone ownership. A special regressor with the mentioned properties is difficult to find. Nonetheless, in this paper, I use total land size in hectares the household has owned, sharecropped or rented as a special regressor. It is continuous and assumed to be exogenous based on the fact individuals have no rights to sale their land but only use and transfer (to family members) rights and this makes land less liquid which implies very low probability of association with mobile phones ownership. But owning land by it self is a collateral and affects the borrowing ability of households since land ownership might increase the credit trustworthiness of households and reduce the default rates. Land cannot be used as formal collateral to take loan specifically in the case of formal sources. But in the case where the formal sources of credit is dominated by MFIs, land may indirectly serve as a screening mechanism to form groups. It is known that MFIs provide credit based on a group-lending basis which helps the institutions in the screening and repayment, and enforcement (in case of default) processes (Ghatak and Guinnane, 1999). In this paper, all the formal sources of credit are from MFIs and therefore land ownership may implicitly increase the trustworthiness of households in forming groups for formal loan from MFIs. To this end, total land size is used as a special regressor in both the formal and the informal credit sources.

While in the second case, the dependent variable is the amount of loan that households took from different sources and is a continuous variable. The issue is to examine whether mobile phones ownership affects the amount of credit that households took conditional on their credit uptake either from formal, informal or both. While OLS does not consider the sample is censored, the Tobit model does. McDonald and Moffitt (1980) discuss that Tobit model is preferred to other models such as the OLS which consider sample observations above or below the limit only. However, the endogeneity problem of mobile phones ownership might still be a worrying issue. As usual, the alternative is to use IV estimation. Similar to the credit uptake, I use the mean of mobile phone adoption by village as an instrument for mobile phone ownership.

3.4.2. Results

(i) Mobile phones and credit

To analyze the relationship between mobile phones and credit uptake, both pooled and panel dimension of the data are considered ignoring the endogeneity problem. In the first instance, I use pooled probit model clustering at the individual level, which allows for individual heterogeneity albeit not considering the panel nature of the data. To account for this, I include a random effect probit model with robust standard errors. The dependent variables include the following dummies: a dummy that takes value 1 if households took credit of any form (could be formal or informal) and zero otherwise, a dummy taking value 1 if households took credit from informal sources and zero otherwise, and a dummy which equal to 1 if households accessed credit from formal sources and zero otherwise. Table 15 presents the marginal effects of mobile ownership after probit, considering both the pooled and the panel cases. The first three columns are based on the pooled probit model whereas columns 4 to 6 are based on the random effect panel probit model. All the columns include household characteristics along with year dummy and village average monthly per capita expenditure; exposure to different shocks such as illness or death of family members and other climatic shocks; and proxies for social capital and networks. The results from the pooled probit and the random effect probit yield that mobile phones are positively associated with credit uptake of households generally and informal sources particularly. The marginal effects after probit convey that the probability of credit uptake from any source is about 4% higher for mobile phone owners. I also estimated whether mobile phones are associated with any credit uptake from informal sources. Households have accessed credit from many sources but I define the dummy for informal here if households reported they took credit from at least one informal source. The results portray that mobile phones are found to have a positive and significant association with the credit uptake from the informal sources. Both the pooled probit and the RE probit indicate that owning mobile phones is associated with about 6% higher likelihood of taking credit from the informal sources. I further conducted regressions to elicit the associations of mobile phones with formal credit uptake of households. Columns 3 and 6 of table 15 indicate that there is no significant association of mobile phones with the formal credit uptake.

Table 15: Mobile phone and credit - Probit

	Pooled Probit			RE Probit		
	All sources dy/dx	Any informal dy/dx	Any formal dy/dx	All sources dy/dx	Any informal dy/dx	Any formal dy/dx
Own mobile phone	0.0443**	0.0560*	0.00626	0.0421**	0.0560*	0.00487
	(0.0204)	(0.0293)	(0.0285)	(0.0205)	(0.0293)	(0.0301)
Total real monthly expenditure	-0.0000736***	-0.000115***	0.0000348	-0.0000741***	-0.000115***	0.0000356
	(0.0000271)	(0.0000381)	(0.0000362)	(0.0000275)	(0.0000382)	(0.0000384)
Household head age	-0.00160	-0.000285	-0.00145	-0.00161	-0.000285	-0.00151
	(0.00113)	(0.00147)	(0.00142)	(0.00115)	(0.00147)	(0.00150)
Household head - male	0.0612*	0.0783**	0.0571	0.0659*	0.0783**	0.0607
	(0.0324)	(0.0378)	(0.0356)	(0.0338)	(0.0381)	(0.0373)
Adult and/or religious education	-0.0136	-0.00598	-0.00135	-0.0135	-0.00598	-0.0000355
	(0.0242)	(0.0291)	(0.0293)	(0.0245)	(0.0291)	(0.0310)
Some lower primary education	0.0165	0.0376	-0.0212	0.0160	0.0376	-0.0237
	(0.0265)	(0.0327)	(0.0323)	(0.0268)	(0.0327)	(0.0341)
Some higher primary education	-0.0960***	-0.0776**	-0.0716**	-0.102***	-0.0776**	-0.0777**
	(0.0324)	(0.0371)	(0.0337)	(0.0340)	(0.0371)	(0.0353)
Some secondary education	-0.0878*	-0.00192	-0.145***	-0.0961*	-0.00192	-0.154***
	(0.0495)	(0.0544)	(0.0469)	(0.0524)	(0.0544)	(0.0479)
Post secondary education	0.0136	-0.152	0.0969	0.0139	-0.152	0.0990
	(0.0882)	(0.124)	(0.123)	(0.0879)	(0.124)	(0.133)
Land ownership in hectares	0.0162	-0.00218**	0.00322*	0.0163	-0.00218**	0.00339*
	(0.0133)	(0.000909)	(0.00189)	(0.0133)	(0.000911)	(0.00197)
Own any livestock	0.103**	0.187***	0.0305	0.102*	0.187***	0.0349
	(0.0513)	(0.0565)	(0.0551)	(0.0536)	(0.0566)	(0.0576)
Housing quality index	-0.143***	-0.407***	0.222***	-0.141***	-0.407***	0.236***
	(0.0526)	(0.0665)	(0.0647)	(0.0532)	(0.0678)	(0.0689)
Lag of debt status - indebted	0.152***	0.0347	0.199***	0.139***	0.0347	0.196***
	(0.0185)	(0.0234)	(0.0208)	(0.0203)	(0.0237)	(0.0221)
N	2264	2264	2264	2264	2264	2264
N_groups				1338	1338	1338
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household and climatic shocks	Yes	Yes	Yes	Yes	Yes	Yes
Social network & capital	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors clustered at individual level in parentheses
Village mean per capita expenditure and time dummy are controlled in all regressions
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable in the first columns of each model is households credit uptake from any sources; the dependent variable in the second columns of both models is households credit access from any informal sources regardless of whether the household had access from formal source; whereas the dependent variable in last columns is credit uptake from formal sources regardless of access from informal sources. Other controls includes household compositions based on age and sex, year dummy and average village (site) level monthly per capita expenditure. Shocks include drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock; Household level shocks include Death or illness of household member, theft, increase in input prices, livestock death, increase in food prices, and dispute with neighbours. Social networks and capital includes the number of people household rely on, ability to raise money in times of need and having relatives in the community.

As explained in the methodology part, mobile phones ownership and credit uptake might be correlated with common unobservables and this could cause a bias on the (non-instrumented) estimates. Besides, there might also be reverse causality problem where individuals might take credit in order to buy mobile phones. To this effect, an IV estimation is adopted where village level mean of mobile phone adoption is used as an instrument. A special regressors estimator is adopted to take into consideration the binary nature of the endogenous and the outcome variables. But the Kleibergen-Paap Wald rk F statistic is obtained from the first stage estimations of the linear IV with clustered standard errors and it is equal to 125.2 which implies that the null of weak identification is rejected. Besides, the LM test statistic for underidentification is about 105.1 implying no underidentification problem (see table G in the Appendix). Table 16 presents the estimation results from the special regressors estimator using village level mean of mobile phone ownership as an IV, and total land size as a special regressor. Both the standard kernel density approach and the sorted data density are used in the density specifications and the estimated data are trimmed by 5% to ensure adequate support. The results yield positive and significant estimates for the general credit uptake and the informal credit uptake but insignificant for the formal credit uptake case. As in the case of logit or probit, the variable of interest is not of the estimated coefficients rather the marginal effects which are derived from the Average Index Function (AIF). The estimates of the AIF are derived in a similar fashion as in the case of marginal effects in the logit or probit models (Lewbel et al., 2012b). The marginal effects in this paper are computed from 250 bootstrapped replications. The estimates from the AIF indicate that the probability of general credit uptake is 11% to 14% higher for households with mobile phones when the sorted data density and Kernel density approaches are considered respectively. Whereas the informal credit uptake is about 15% to 18% higher for households. The point is, even after accounting the endogeneity and the binary nature of mobile phones, and controlling for social networks, mobile phones still play a significant role in the credit uptake of rural households, especially with respect to the credit uptake from the informal ones.

Table 16: Mobile phone and credit - Special Regressors Estimator

	Sorted data density approach			Kernel density approach		
	All sources AIF	Any informal AIF	Any formal AIF	All sources AIF	Any informal AIF	Any formal AIF
Own mobile phone	0.114***	0.177***	-0.0349	0.143***	0.148***	-0.0585
	(0.0264)	(0.0393)	(0.0754)	(0.0246)	(0.0404)	(0.0673)
Total real monthly expenditure	-0.0000483**	-0.0000779***	-0.0000158	-0.0000727***	-0.0000580**	-0.0000265
	(0.0000232)	(0.0000273)	(0.0000375)	(0.0000207)	(0.0000295)	(0.0000328)
Household head age	0.000117	0.000170	-0.000943	-0.000289	0.000271	-0.000592
	(0.000635)	(0.000643)	(0.00116)	(0.000590)	(0.000512)	(0.00103)
Household head - male	0.00488	0.00509	0.00628	-0.00151	-0.00178	0.0218
	(0.0185)	(0.0180)	(0.0380)	(0.0147)	(0.0166)	(0.0312)
Adult and/or religious education	-0.00541	-0.00315	0.000408	-0.00476	-0.00237	0.0164
	(0.0124)	(0.0121)	(0.0257)	(0.0105)	(0.00945)	(0.0207)
Some lower primary education	-0.0141	-0.00948	-0.00639	-0.0148	-0.0114	0.00431
	(0.0137)	(0.0130)	(0.0261)	(0.0105)	(0.0107)	(0.0215)
Some higher primary education	-0.0350*	-0.0289	-0.0323	-0.0497***	-0.0338**	-0.0321
	(0.0189)	(0.0189)	(0.0345)	(0.0154)	(0.0149)	(0.0292)
Some secondary education	-0.0269	-0.0188	-0.0521	-0.0378	-0.0221	-0.0387
	(0.0255)	(0.0298)	(0.0584)	(0.0250)	(0.0257)	(0.0515)
Post secondary education	-0.0259	-0.0595	0.0116	-0.0353	-0.0501	0.0866
	(0.0566)	(0.0441)	(0.116)	(0.0396)	(0.0390)	(0.0994)
Own any livestock	-0.00380	0.00989	-0.00602	-0.00756	0.00482	0.00564
	(0.0240)	(0.0212)	(0.0412)	(0.0208)	(0.0175)	(0.0300)
Housing quality index	-0.0315	-0.0723*	0.0828	-0.0412*	-0.0650*	0.106**
	(0.0293)	(0.0412)	(0.0551)	(0.0231)	(0.0348)	(0.0456)
Lag of debt status - indebted	0.0133	-0.00319	0.0506**	0.0222**	0.00155	0.0702***
	(0.0135)	(0.00971)	(0.0216)	(0.0112)	(0.00812)	(0.0211)
N	2044	2044	2044	2044	2044	2044
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Household and climatic shocks	Yes	Yes	Yes	Yes	Yes	Yes
Social network & capital	Yes	Yes	Yes	Yes	Yes	Yes

Bootstrapped standard errors in parentheses (250 replications)
Village mean per capita expenditure and time dummy are controlled in all regressions
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable in the first columns of each model is households credit uptake from any sources; the dependent variable in the second columns of both models is households credit access from any informal sources regardless of whether the household had access from formal source; whereas the dependent variable in last columns is credit uptake from formal sources regardless of access from informal sources. Other controls includes household compositions based on age and sex, year dummy and average village (site) level monthly per capita expenditure. Shocks include drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock; Household level shocks include Death or illness of household member, theft, increase in input prices, livestock death, increase in food prices, and dispute with neighbours. Social networks and capital includes the number of people household rely on, ability to raise money in times of need and having relatives in the community.

Another issue examined in this paper is whether mobile phones ownership affects the amount of credit that households took conditional on their credit uptake either from formal, informal or both. Households accessed credit from different sources; a given household may took credit from more than one source. Table D in the appendix indicates that more than half of the households in our sample had accessed credit from more than one source. In this paper, however, the total amount of loans that household accessed is aggregated regardless of the type of sources, for informal sources only, and for formal sources only. The dependent variables are the amount of loans from all, informal and formal sources expressed in terms of Ethiopian currency (Birr) but transformed using the inverse hyperbolic sine (ihs). A Tobit model is adopted to assess whether mobile phones affect the amount of loan that households mobilize. Moreover, I estimated the Tobit model considering the panel nature of the dataset. The marginal effects are computed from 300 bootstrap replications. Table 17 presents the estimation results from Tobit model where the first three columns are based on the pooled Tobit whereas the last three columns are based on the panel Tobit models. The results underline that mobile phones are positively and significantly associated with the amount of loan that households mobilized from all sources and the informal sources but insignificant in the case of loans from formal sources. The estimates from the Tobit model render mobile phones ownership is associated with about 65 Birr (USD 3.42 approximately[15]) increase in loan size when considering all sources. Whereas, it is associated with about 78 Birr (USD 4.11) higher amount of loan from informal sources of credit. The results portray that mobile phones increase the amount of loan that households mobilize and is mainly coming from the informal sources of credit. This can be attributed to the information problem alleviation that mobile phones play especially in facilitating and exploiting their social networks and other informal arrangements.

[15]The exchange rate is based on the average for October, 2013 that 1 USD $\approx$ 19 ETB

Table 17: Mobile phones and loan size - Tobit estimation

Dep.Var: Loan size	Pooled Tobit[a]			Panel Tobit[b]		
	(Total loan)	(Total form Informal)	(Total from Formal)	(Total loan)	(Total form Informal)	(Total form Formal)
Own mobile phone	0.646***	0.783**	0.172	0.616**	0.783**	0.118
	(0.231)	(0.342)	(0.598)	(0.247)	(0.367)	(0.599)
Total real monthly expenditure	-0.000622*	-0.00122**	0.000814	-0.000615	-0.00122**	0.000786
	(0.000373)	(0.000511)	(0.000764)	(0.000409)	(0.000540)	(0.000871)
Household head age	-0.0179	-0.00412	-0.0324	-0.0180	-0.00412	-0.0323
	(0.0127)	(0.0179)	(0.0302)	(0.0131)	(0.0196)	(0.0278)
Household head - male	0.867***	1.136**	1.347*	0.897***	1.136**	1.357*
	(0.335)	(0.472)	(0.810)	(0.323)	(0.457)	(0.813)
Adult and/or religious education	-0.225	-0.158	-0.0000918	-0.226	-0.158	0.0164
	(0.247)	(0.353)	(0.599)	(0.261)	(0.361)	(0.612)
Some lower primary education	0.0131	0.358	-0.451	0.00142	0.358	-0.494
	(0.267)	(0.373)	(0.688)	(0.272)	(0.382)	(0.701)
Some higher primary education	-1.197***	-0.936**	-1.586**	-1.237***	-0.936*	-1.640**
	(0.326)	(0.451)	(0.772)	(0.328)	(0.485)	(0.778)
Some secondary education	-1.301**	-0.148	-3.654***	-1.351**	-0.148	-3.748***
	(0.506)	(0.648)	(1.323)	(0.529)	(0.676)	(1.439)
Post secondary education	0.134	-2.417	2.359	0.132	-2.417	2.311
	(1.180)	(1.770)	(2.404)	(1.280)	(2.589)	(3.641)
Own any livestock	1.262**	2.429***	0.763	1.224**	2.429***	0.818
	(0.574)	(0.816)	(1.249)	(0.576)	(0.858)	(1.259)
Housing quality index	-1.006	-4.753***	4.910***	-0.990	-4.753***	4.952***
	(0.614)	(0.825)	(1.369)	(0.625)	(0.852)	(1.392)
Lag of debt status - indebted	2.041***	0.622**	4.484***	1.836***	0.622**	4.169***
	(0.200)	(0.283)	(0.471)	(0.232)	(0.285)	(0.477)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household and climatic shocks	Yes	Yes	Yes	Yes	Yes	Yes
Social network & capital	Yes	Yes	Yes	Yes	Yes	Yes
N	2264	2264	2264	2264	2264	2264
Uncensored	1775	1334	829	1775	1334	829
Censored	489	930	1435	489	930	1435

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a] Robust standard errors clustered at individual level in parentheses

[b] Bootstrapped standard errors in Parentheses (300 replications)

Notes: The dependent variable in the first columns of each model is the total amount of loan from all sources; the dependent variable in the second columns of both models is the total amount of loan informal sources only; whereas the dependent variable in last columns is the total amount of loan from formal sources only. All the dependent variables are transformed using an inverse hyperbolic sine (ihs) transformation. Other controls includes household compositions based on age and sex, year dummy and average village (site) level monthly per capita expenditure. Shocks include drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock; Household level shocks include Death or illness of household member, theft, increase in input prices, livestock death, increase in food prices, and dispute with neighbours. Social networks and capital includes the number of people household rely on, ability to raise money in times of need and having relatives in the community.

The results in this paper indicate that mobile phones are associated with the general credit uptakes and the informal credit uptakes but insignificant when the formal credit uptakes are considered. There might be several possible channels through which mobile phones influence credit uptakes. One possible mechanism could be the decrease in information costs associated with loan processing especially with those pity loans from the informal sources including friends/neighbors, relatives, cooperatives, money lenders, and other informal associations. The estimation results indicate that mobile phones are positively and significantly associated with credit uptake from the formal sources but insignificant with the credit uptakes from the formal ones. This implies that mobile phones are reducing the costs associated with the informal sources of credit but the formal sources of credit has its own bureaucracies and information might not be a pressing issue here. Information is costly to obtain in rural areas where the conventional information providers are rarely available. In the rural Ethiopian context, it is very difficult to get information even from news papers. As explained by Aker (2011) farmers in rural areas get information mainly from own trial and error means and their social networks but this way it is costly. Mobile phones can open the window for private information access or access form social networks which is expected to increase households information about the available sources of loans more easily. However, one may argue that social networks could be playing th role here. But I have already controlled for proxies of social networks and this helps explain the results are at least not due to social networks. Therefore, mobile phones help households exploit the available sources of credit more efficiently sitting in their home. And this substantially reduces the information costs of borrowing and thereby drive the credit uptake of rural households.

(ii) Robustness checks

(a) Mobile phones and credit using IV-Probit

As an alternative to the special regressor estimator model, we also use the IV-probit model, which ignores the binary nature of the endogenous variable, to check whether the results are sensitive to models. Table 18 presents the results from the IV-probit model with the same instrument, the village average mobile phone adoption, and reveal that mobile phones are positively and significantly associated with credit uptake of households from any source and from the informal sources but not from the formal sources as it is in the special regressor estimator. Though the sign and significance remained the same, the coefficients are unreasonably higher than the ones from the special regressor estimators. The inflated coefficient might be attributed to the fact that IV-probit is not considering the binary nature of the endogenous variable. But the results portray that households with mobile phones have higher likelihood of taking credit than those without mobile phones still indicating the positive associations of mobile phones ownership and credit uptakes specially from the informal ones.

Table 18: Mobile phone and credit - IV-Probit

	1 All sources	2 Any informal	3 Any formal
Own mobile phone	0.475***	0.639***	-0.0584
	(0.0361)	(0.0195)	(0.111)
Total real monthly expenditure	-0.000215***	-0.000266***	0.0000502
	(0.0000331)	(0.0000351)	(0.0000445)
Household head age	0.000332	0.00185	-0.00160
	(0.00124)	(0.00129)	(0.00144)
Household head - male	0.0198	0.0108	0.0593*
	(0.0312)	(0.0322)	(0.0359)
Adult and/or religious education	-0.0341	-0.0323	0.000825
	(0.0243)	(0.0247)	(0.0295)
Some lower primary education	-0.0480	-0.0533*	-0.0156
	(0.0293)	(0.0294)	(0.0338)
Some higher primary education	-0.189***	-0.178***	-0.0620
	(0.0332)	(0.0317)	(0.0380)
Some secondary education	-0.255***	-0.202***	-0.132**
	(0.0531)	(0.0491)	(0.0546)
Post secondary education	-0.155	-0.283***	0.113
	(0.114)	(0.0968)	(0.126)
Own any livestock	0.0371	0.0568	0.0348
	(0.0476)	(0.0466)	(0.0550)
Housing quality index	-0.245***	-0.414***	0.235***
	(0.0526)	(0.0590)	(0.0680)
Lag of debt status - indebted	0.113***	0.00501	0.200***
	(0.0199)	(0.0199)	(0.0208)
N	2264	2264	2264
Other Controls	Yes	Yes	Yes
Household and climatic shocks	Yes	Yes	Yes
Social network & capital	Yes	Yes	Yes

Robust standard errors clustered at individual level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable in the first column is households credit uptake from any sources; the dependent variable in the second column is households credit access from any informal sources regardless of whether the household had access from formal source; whereas the dependent variable in last column is credit uptake from formal sources regardless of access from informal sources. Other controls includes household compositions based on age and sex, year dummy and average village (site) level monthly per capita expenditure. Shocks include drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock; Household level shocks include Death or illness of household member, theft, increase in input prices, livestock death, increase in food prices, and dispute with neighbours. Social networks and capital includes the number of people household rely on, ability to raise money in times of need and having relatives in the community.

(b) Regressions on matched sample

As I have tried to indicate, ownership of mobile phones is also affected by common unobservable factors which makes it difficult to identify the effects on credit uptake. An instrumental variable estimation and several specifications and models are adopted to check whether the results are sensitive or not. However, the results should be scrutinized further. And in support of this, a robustness check based on the matched sample of observations is conducted.

To have a restricted matched sample, a matching technique is adopted to adjust for the observable differences between mobile phone owners and non-owners. I performed a kernel matching with a bandwidth of 0.001 on a set of household's socio-economic characteristics including households total expenditure, household head age, sex and education, household members age and sex composition, exposure to idiosyncratic and climatic shocks, and households social capital and networks. The extent of balancing is checked after running the matching and indicates that the mean bias after matching is below 5% and this is an indication for a good balancing (see figure E in the Appendix). Then, a set of estimations are conducted on the sample observations which are on the common support.

Table 19 presents the results from the set of estimations conducted on the sample of observations which are on the common support. The results in table 7 shows that the magnitude and significance of mobile phones yield very close results to the main estimations which confirm that mobile phones are positively associated with credit uptake of households specially with informal sources of credit.

Table 19: Mobile phones and credit - Matched sample

	Probit[a]			Special regressor[b]		
	Any source	informal	formal	Any source	informal	formal
Own mobile phone	0.0450**	0.0559*	-0.00591	0.129***	0.170***	-0.0475
	(0.0212)	(0.0305)	(0.0299)	(0.0304)	(0.0471)	(0.0935)
Total real monthly expenditure	-0.0000431	-0.000106**	0.0000793*	-0.0000593**	-0.0000596*	-0.0000337
	(0.0000335)	(0.0000444)	(0.0000445)	(0.0000256)	(0.0000347)	(0.0000475)
Household head age	-0.00195*	-0.000582	-0.00208	0.0000860	0.000280	-0.000916
	(0.00117)	(0.00153)	(0.00145)	(0.000729)	(0.000713)	(0.00141)
Household head - male	0.0579*	0.0788**	0.0504	0.00349	0.00210	0.00249
	(0.0330)	(0.0391)	(0.0369)	(0.0174)	(0.0228)	(0.0406)
Adult and/or religious education	-0.0141	-0.00631	-0.0000956	0.00118	-0.0105	0.0347
	(0.0247)	(0.0300)	(0.0299)	(0.0138)	(0.0143)	(0.0288)
Some lower primary education	0.0170	0.0436	-0.0145	-0.00775	-0.0107	0.0193
	(0.0271)	(0.0339)	(0.0335)	(0.0146)	(0.0154)	(0.0300)
Some higher primary education	-0.0957***	-0.0764**	-0.0870**	-0.0364*	-0.0344	0.0000101
	(0.0343)	(0.0390)	(0.0347)	(0.0187)	(0.0218)	(0.0377)
Some secondary education	-0.0504	0.0595	-0.155***	-0.0228	0.00241	-0.0390
	(0.0520)	(0.0600)	(0.0493)	(0.0323)	(0.0356)	(0.0598)
Post secondary education	0.0339	-0.113	0.155	-0.0416	-0.0433	0.0537
	(0.113)	(0.139)	(0.190)	(0.0602)	(0.0714)	(0.174)
Land ownership in hectares	0.00847	-0.00224**	0.00314*			
	(0.0118)	(0.000906)	(0.00178)			
Own any livestock	0.103**	0.195***	0.0219	-0.0200	0.00301	0.00189
	(0.0519)	(0.0585)	(0.0572)	(0.0289)	(0.0219)	(0.0428)
Housing quality index	-0.125**	-0.428***	0.290***	-0.0360	-0.0600	0.160**
	(0.0545)	(0.0698)	(0.0683)	(0.0318)	(0.0430)	(0.0718)
Lag of debt status - indebted	0.160***	0.0332	0.218***	0.0228	0.00237	0.0736***
	(0.0192)	(0.0242)	(0.0216)	(0.0140)	(0.0124)	(0.0267)
N	2097	2097	2097	1894	1894	1894

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a] Robust standard errors clustered at individual level in parentheses

[b] Bootstrapped standard errors in Parentheses (250 replications)

Notes: The dependent variable in the first columns of each model is households credit uptake from any sources; the dependent variable in the second columns of both models is households credit access from any informal sources regardless of whether the household had access from formal source; whereas the dependent variable in last columns is credit uptake from formal sources regardless of access from informal sources. Other controls includes household compositions based on age and sex, year dummy and average village (site) level monthly per capita expenditure. Shocks include drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, and pests on livestock; Household level shocks include Death or illness of household member, theft, increase in input prices, livestock death, increase in food prices, and dispute with neighbours. Social networks and capital includes the number of people households rely on, ability to raise money in times of need and having relatives in the community.

3.5. Conclusions

Mobile phones play a facilitating role in the development process of countries, especially in poor countries. Households access to credit might be explained by several factors. In poor countries, however, where households are credit constrained, information plays a key role in facilitating credit uptake of rural households. In Ethiopia, mobile phone adoption have shown a staggering change since 2008/09; mobile phone subscription has increased from 4% in 2009 to 42% in 2015. And it is worthwhile investigating the spillover effects of these mobile phone revolutions. The current paper tried to elicit whether mobile phones affects credit uptake of rural households in Ethiopia using data from Young Lives Ethiopia. Different models are adopted to investigate the relationship of mobile phones with credit uptakes and loan sizes of rural households. A probit model is used in the former case while a Tobit model is adopted in the second case. The results reveal that mobile phones are positively and significantly associated with credit uptake and loan size of households specially credit uptake from informal sources. However, the main challenge here is the endogeneity problem of mobile phones. To deal with this problem, an instrumental variable approach would be one solution. To this end, I use a special regressors estimator, which considers the binary nature of the endogenous and the outcome variables, where total land size is used as a special regressor and village level mean of mobile phone adoption as an instrument. The results still seems to suggest a positive role of mobile phones in the credit uptake of rural households in Ethiopia. Households with mobile phones are found to have 4% to 14% higher probabilities of credit uptake and about 6% to 17% in the case of informal sources. The results are further scrutinized using other models and a matching technique. The possible channel through which mobile phones ownership affect credit might be through lowering the costs of information. Therefore, stakeholders and policy makers might need to exploit the use of mobile phones in their interventions in rural Ethiopia.

Appendix C The general characteristics of households

	2009 – R3			2013 – R4		
	Mean	Std.Dev.	N	Mean	Std.Dev.	N
Total real monthly expenditure	621.421	346.8968	1362	602.5296	345.8147	1007
Household head age	46.0375	10.9129	1359	48.9614	10.7783	1373
Household head - male	0.867	0.3396	1362	0.814	0.3890	1373
Adult and/or religious education	0.319	0.4664	1325	0.326	0.4688	1302
Some lower primary education	0.198	0.3984	1325	0.205	0.4039	1302
Some higher primary education	0.165	0.3709	1325	0.167	0.3735	1302
Some secondary education	0.046	0.2096	1325	0.044	0.2047	1302
Post secondary education	0.006	0.0775	1325	0.008	0.0916	1302
Land ownership in hectares	1.794	13.5093	1359	1.274	27.7604	1382
Own any livestock	0.961	0.1935	1362	0.944	0.2309	1382
Housing quality index	0.2402	0.1709	1362	0.293	0.1746	1382
Lag of debt status - indebted	0.531	0.4992	1359	0.567	0.4957	1382
Number of males aged 0-5	0.523	0.6583	1362	0.355	0.5712	1382
Number of males aged 6-12	0.570	0.6759	1362	0.526	0.6539	1382
Number of males aged 13-17	0.532	0.6874	1362	0.570	0.6747	1382
Number of males aged 18-60	1.598	1.0476	1362	1.897	1.2283	1382
Number of males aged 61+	0.123	0.3334	1362	0.172	0.3834	1382
Number of females aged 0-5	0.535	0.6633	1362	0.365	0.5911	1382
Number of females aged 6-12	0.561	0.6779	1362	0.522	0.6361	1382
Number of females aged 13-17	0.528	0.6801	1362	0.556	0.6663	1382
Number of females aged 18-60	1.658	0.9454	1362	2.009	1.1457	1382
Number of females aged 61+	0.098	0.3124	1362	0.103	0.3177	1382
Death of father, mother or other family member of the hh	0.079	0.2692	1362	0.063	0.2429	1382
Illness of father, mother or other family member of the hh	0.475	0.4996	1362	0.253	0.4346	1382
shock-theft/destruction of cash, crops, livestock	0.115	0.3195	1362	0.108	0.3103	1382
shock-increase in input prices	0.556	0.4971	1362	0.238	0.4261	1382
shock-decrease in output prices	0.072	0.2585	1362	0.041	0.1972	1382
shock-death of livestock	0.456	0.4982	1362	0.278	0.4481	1382
shock-disputes with neighbours about assets	0.105	0.3067	1362	0.039	0.1938	1382
shock-increase in food prices	0.821	0.3836	1362	0.354	0.4783	1382
shock-divorce or separation	0.021	0.1444	1362	0.014	0.1165	1382
shock-birth of new hh member	0.188	0.3908	1362	0.022	0.1481	1382
shock-enrolment of child in school	0.135	0.3419	1362	0.022	0.1458	1382
shock-drought	0.531	0.4992	1362	0.213	0.4094	1382
shock-flooding	0.225	0.4175	1362	0.127	0.3327	1382
shock-erosion	0.093	0.2909	1362	0.064	0.244	1382
shock-frost	0.191	0.3932	1362	0.188	0.3909	1382
shock-pests on crops	0.109	0.3113	1362	0.095	0.2930	1382
shock-crop failure	0.424	0.4943	1362	0.295	0.4563	1382
shock-pests on storage	0.044	0.2053	1362	0.014	0.1195	1382
shock-pests on livestock	0.170	0.376	1362	0.033	0.1776	1382
Number of people households can rely on in times of need						
rely on 1 to 2 people	0.178	0.3829	1357	0.217	0.4124	1382
rely on 3 to 5 people	0.446	0.4972	1357	0.459	0.4985	1382
rely on 6 to 10 people	0.242	0.4283	1357	0.212	0.4089	1382
rely on 11 to 15 people	0.052	0.2228	1357	0.030	0.1697	1382
rely on 16 to 20 people	0.023	0.1495	1357	0.017	0.1307	1382
rely on 21 to 30 people	0.015	0.1235	1357	0.013	0.1134	1382

rely on Over 30 people	0.018	0.1345	1357	0.011	0.1037	1382
Able to raise money when needed	0.736	0.4411	1362	0.773	0.4193	1381
Have relatives living in this community	0.949	0.2194	1362	0.970	0.1717	1382
Village mean of per capita expenditure	118.789	26.270	1362	119.333	27.6705	1382

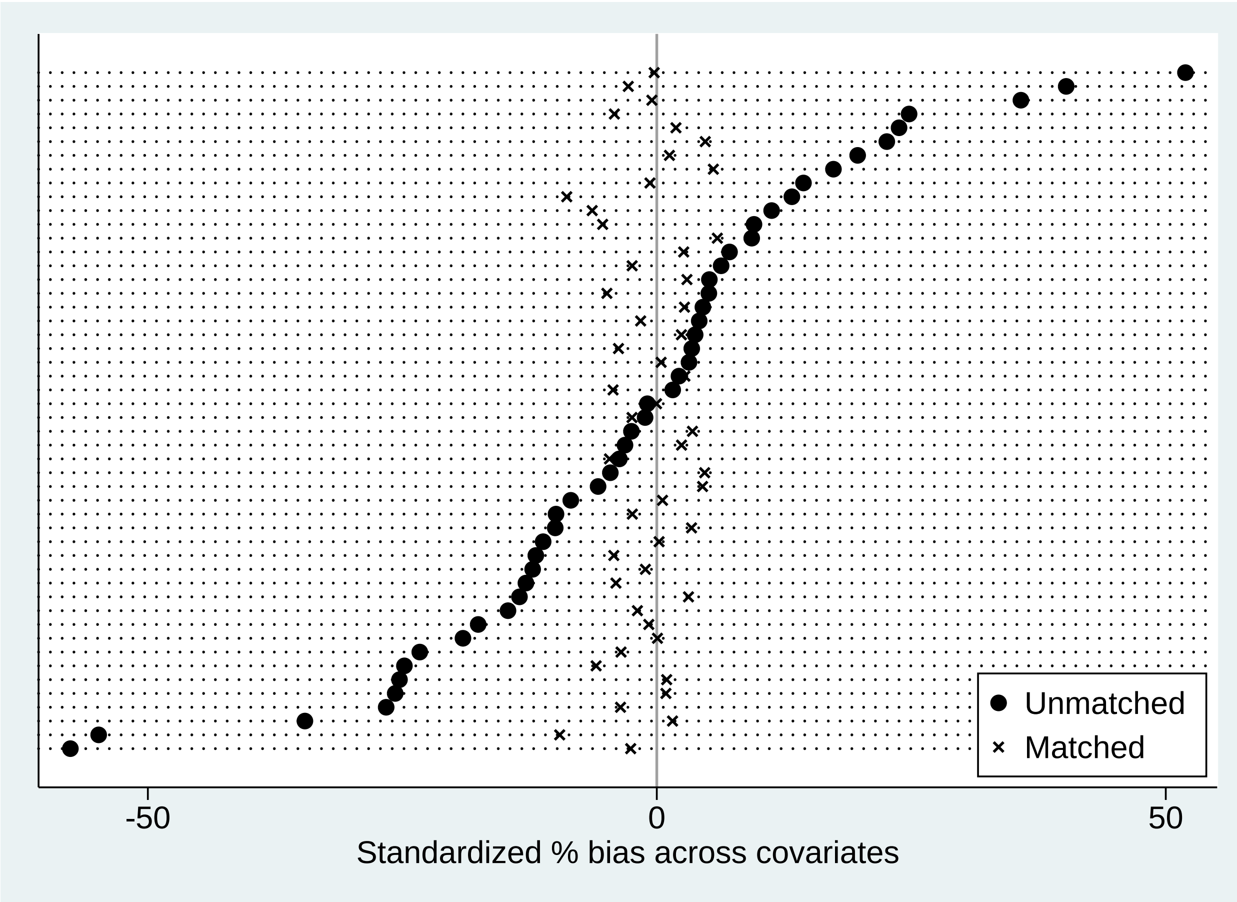
Notes: The table reports the general characteristics of households in both rounds (2009 and 2013). The first column includes the list of covariates. The next three columns include the mean, the standard deviation and the number of observations respectively associated with each covariates for the 2009 sample. While the last three columns depict the mean, the standard deviation and the number of observations for the 2013 sample.

Appendix D Number of loans taken in 2009 and 2013

Number of loans households took	2009 (R3)		2013 (R4)	
	N	Percent	N	Percent
1	603	49.92	579	49.07
2	271	22.43	179	15.17
3	119	9.85	139	11.78
4	91	7.53	129	10.93
5	61	5.05	88	7.46
6	33	2.73	38	3.22
7	11	0.91	11	0.93
8	3	0.25	8	0.68
9	4	0.33	5	0.42
10	6	0.50	2	0.17
12	3	0.25	0	0.00
13	3	0.25	1	0.08
15	0	0.00	1	0.08
Total	1,208	100.00	1180	100.00

Notes: The table reports the number of loans that households has reported to have taken. The first column is the number of loans taken. The next two columns present the frequencies and percentage of households for each number of loans respectively for the 2009 sample. While the last two columns include the frequencies and the percentage of households reported for each of the number of loans respectively for the 2013 sample.

Appendix E Checking for balance after matching



Notes: The figure indicates the standardized percentage bias across the covariates for the matched and unmatched samples. Zero indicates for absence of bias for each of the covariates and can be seen that the percentage bias for the matched sample is closer to zero indicating for a good balance.

Appendix F Mobile phones and credit - Logit FE

	(1) Any source	(2) informal	(3) formal
Own mobile phone	-0.475	0.0583	-0.286
	(0.413)	(0.245)	(0.266)
Total real monthly expenditure	-0.000557	-0.00101***	0.000335
	(0.000545)	(0.000364)	(0.000344)
Household head age	-0.0710	-0.0334	-0.0449
	(0.0555)	(0.0482)	(0.0480)
Household head - male	0.554	0.873	0.818
	(1.141)	(0.718)	(1.169)
Adult and/or religious education	1.701	0.649	0.211
	(2.483)	(1.186)	(1.609)
Some lower primary education	1.310	-0.998	-13.34
	(2.800)	(1.558)	(1696.6)
Some higher primary education	2.224	0.552	-13.94
	(3.718)	(2.066)	(1696.6)
Some secondary education	14.25	14.28	-28.02
	(2686.6)	(1170.1)	(2338.9)
Post secondary education	28.64	0	-13.52
	(2983.2)	(.)	(2940.9)
Land ownership in hectares	0.478	-0.0188	0.0172
	(0.341)	(0.0386)	(0.0730)
Own any livestock	0.232	1.322**	0.0552
	(1.133)	(0.642)	(0.707)
Housing quality index	-0.549	-0.743	1.652
	(1.573)	(0.998)	(1.176)
Lag of debt status - indebted	-2.256***	-1.016***	-0.530**
	(0.410)	(0.219)	(0.220)
N	446	844	674
N_g	223	422	337

Bootstrapped standard errors in parentheses with 250 replications
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable in the first column is households credit uptake from any sources; the dependent variable in the second column is households credit access from any informal sources regardless of whether the household had access from formal source; whereas the dependent variable in third column is credit uptake from formal sources regardless of access from informal sources. Covariates include household compositions based on age and sex, year dummy, average village (site) level monthly per capita expenditure, drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, pests on livestock, death or illness of household member, theft, increase in input prices, livestock death, increase in food prices, and dispute with neighbours, and proxies for social networks and capital including the number of people household rely on, ability to raise money in times of need and having relatives in the community.

Appendix G First stage regression results from LPM

	(1) Any source	(2) Informal	(3) Formal
Average mobile adoption by sites (excluding own adoption) - IV	0.896***	0.896***	0.896***
	(0.0801)	(0.0801)	(0.0801)
Constant	-0.305***	-0.305***	-0.305***
	(0.0875)	(0.0875)	(0.0875)
Observations	2,264	2,264	2,264
Kleibergen-Paap F statistic for weak identification	125.2	125.2	125.2
p-value of underidentification LM statistic	0.000	0.000	0.000
LM test statistic for underidentification	105.1	105.1	105.1
Controls	Yes	Yes	Yes
Household and climatic shocks	Yes	Yes	Yes
Social network & capital	Yes	Yes	Yes

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

Notes: The dependent variable in the first column is mobile phone adoption for households who took credit from any sources; the dependent variable in the second column is mobile phone adoption of households who took credit from any informal sources regardless of whether the household had access from formal source; whereas the dependent variable in third column is mobile phone adoption for households who took credit from formal sources regardless of access from informal sources. Covariates include household compositions based on age and sex, year dummy, average village (site) level monthly per capita expenditure, drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, pests on livestock, death or illness of household member, theft, increase in input prices, livestock death, increase in food prices, and dispute with neighbours, and proxies for social networks and capital including the number of people household rely on, ability to raise money in times of need and having relatives in the community. The table also reported the weak identification and underidentification tests for each model.

4. CHAPTER 4

Violent conflicts and adolescent's educational attendances and aspirations: Evidence from Ethiopia

With Elisabetta Lodigiani, Giacomo Pasini and Tassew Woldehanna

Abstract

Households in sub-Saharan African countries are vulnerable to a number of shocks but political conflicts further complicate the lives of these households. Studies have investigated the impacts of inter-state or civil wars on educational and health outcomes. However, the effects of intra-state violent political conflicts are less investigated and the current paper tries to explore whether these kinds of conflicts affect educational enrollments and aspirations of adolescents in Ethiopia. We used data obtained from Young Lives and complement the data on conflict events from Armed Conflict Location and Event Data (ACLED). A region-by-region analysis is conducted and the treatment and control groups are determined by the distance that household is located from the nearest conflict event. We found heterogeneous results: null result is obtained for Oromia and Tigray regions but the conflict is found to have a negative effect on educational enrollments in Amhara region and on educational aspirations in SNNP region. The results, therefore, seems to highlight intra-state conflicts have short-run effects (during the initial stage) but decays away in the long-run.

Keywords: Conflicts; Ethiopia; Educational enrollments; aspirations; Violence

4.1. Introduction

Households in developing countries are usually vulnerable to a number of adverse shocks and other exogenous events. In Africa, particularly in sub-Saharan Africa, political conflicts and insecurities add insult to injury and complicates the livelihoods of households further. Conflicts, inter or intra state, are very common in these countries (Gleditsch et al., 2002) and have unprecedented effects on the livelihood of the people especially the poor. Violent civil and political conflicts claim the lives of individuals and may have long-term consequences in educational and health outcomes of children. Studies have investigated the impacts of inter-state conflicts and civil wars on educational and health outcomes of children and the youth. However, intra-state violent political conflicts, which claims the lives of many people, haven't been explored. To this end, the current paper is intended to explore the possible impacts of violent political conflicts on the educational enrollments and educational aspirations which is less exploited but sensitive area, making use of geographic and temporal variations.

Micro-based studies spotlight evidences of the effects of conflicts on several dimensions of people's lives, mainly on the educational, health and related outcomes exploiting geographic and cohort level variations. A dozen of studies have investigated the impacts of conflicts on the health outcomes including mental health, nutrition, birth weights, and other complications during pregnancy and birth (e.g., Akresh et al., 2016,1,1; Bundervoet et al., 2009; Mansour and Rees, 2012; Miller and Rasmussen, 2010a,1; Minoiu and Shemyakina, 2014; Weldeegzie, 2017). While some studies exploit the impact of conflict exposure on educational and cognitive achievements (e.g., Akresh, 2008; Chamarbagwala and Morán, 2011; Pivovarova and Swee, 2015; Poirier, 2012; Shemyakina, 2011; Swee, 2015; Weldeegzie, 2017), studies, however, also investigated the effects of conflict on other issues such as social capital, physical destruction, stature, risk and time preferences (e.g., Akbulut-Yuksel, 2014; Akresh et al., 2012a; Bauer et al., 2016; De Luca and Verpoorten, 2015; Gilligan et al., 2014; Malasquez, 2016; Voors et al., 2012). However, Pivovarova and Swee (2015) argued that most of the studies in the areas of conflict use cross-section data and misses out individual heterogeneity as it is difficult to observe the same individuals before and after the conflict in conflict studies. But, the current paper will exploit a longitudinal data set from Young Lives collected before and after the conflicts in Ethiopia. Moreover, in conflict literature, beyond the physical destructions and the extended effects on health and education, which are highly studied areas, the impacts of internal conflicts on aspirations remained under investigated. Few studies have examined and described the traumatic and psychological effects of conflicts. For instance, studies came out from the Palestine's intifada assessed the mental health and psychological impacts of the war (Espié et al., 2009; Khamis, 2005; Mataria et al., 2009) but they are mainly based on simple descriptives and gave less attention to the identification problem. However, a recent paper by Moya (2018) explored the impacts of violence on psychological trauma and risk behaviours, and implication for poverty. He argued that the impacts of violence on poverty could be channeled through its effect on psychological trauma and behavioural changes.

The current paper is devoted to the effects of intra-state violent conflict on the educational enrollments and aspirations of children in Ethiopia. Since 2014, Ethiopia has faced a deadly violent protests in different places, especially in Oromia and Amhara regions. The immediate cause for the protest in Oromia, which erupted in April 2014, is the Addis Ababa 'Master Plan' (intended to connect the capital with the neighboring localities) for the reason that it would be at the cost of the farmers. Following this, numbers of protests evolved in different corners of Oromia region (but some also outside of the region by Oromo natives living in other regions, e.g. in universities located in SNNP and Addis Ababa) followed by government's crackdown of the protesters which further escalated the protests. The protest resumed in November 2015 and finally the government decided to suspend the 'Master Plan' in January 2016. However, the protest continues in Oromia region though the government suspended the 'Master Plan'. The protest again revived in May 2016 with a large coverage in Oromia region. Besides, a fresh protest also erupted in Amhara region in July 2016 followed by property destructions by protesters and heavy crackdowns by government security forces. In early October 2016, a stampede left dozens, celebrating the Ireecha Festival, killed and injured. This aggravated the ongoing protest and followed by mass destruction of businesses and flower farms owned by local and foreign investors. The government then declared a state of emergency to be extended for six months which included curfews, travel bans, and mass arrests estimated more than 21,000 people. Though the violent protest stopped temporarily and state of emergency declared, the violence already left more than 1000 people dead and mass property destructions and closure of different public and private services for long time in the conflict areas.

It is, therefore, appealing to explore the possible effect the violence would have on adolescents general educational enrollments and aspirations. But it is usually hard to find plausible control group and the before-after data. The main contribution of this paper are the following. First, the paper will use the geographic and temporal variations to identify the impacts of the violence. Previous studies mainly use cross sectional data and cohort variations to identify the impact but the current paper follows the same children before and after the conflict. This will help us control for individual heterogeneities which is absent in most of the conflict papers (Pivovarova and Swee, 2015). Besides, we use the distance of each household from the conflict areas to capture the exposure of each household to the violences. Second, the paper will extend the literature in economics of conflict to include aspirations which are important for future decision making. Few studies have tried to assess the impact of conflict on the psychological and mental health outcomes but they are more or less descriptive studies and much need to be done in the identification issues and this study will add to the short term effect of violent and deadly protests on children's aspirations which are expected to have long lasting effects. Third, the focuses of most conflict literatures is on inter-state wars, civil wars and other heavy armed conflicts. But intra-state violences, though restricted to some areas, may have effects on children's educational aspirations if not on actual outcomes. And the current paper explores the effects of intra-state conflicts in Ethiopia on educational aspirations and attendances.

4.2. The Data

This study uses a longitudinal data from the Young Lives (YL) survey. YL is an international research project, coordinated by the University of Oxford, which follows the lives of 12,000 children in four developing countries, namely Ethiopia, India, Peru and Vietnam over 15 years. The aim of the project is to identify the main drivers of child poverty, and assist local policy makers. The sample in each country consists of two cohorts of children: a Younger-Cohort of 2000 children born in 2001-2002, and an Older Cohort of 1,000 children, born in 1994-95. To date, there are five rounds of the surveys which have been conducted in 2002, 2006, 2009, 2013 and 2016/17, respectively. Focusing on Ethiopia, YL samples were selected from 20 sentinel sites following a three-stage sampling process. In the first stage, 5 regions, including Oromia, Amhara, SNNP, Tigray, and Addis Ababa, an administrative city, were selected. The main criterion was national coverage, and the selected regions account for 96% of the national population. Then from these regions, 20 woredas (districts), four from each[16], were chosen with a pro-poor bias: the food deficit woredas were oversampled as the major goals of YL is investigating childhood poverty and its dynamics. In the last stage, at least one kebele (the smallest administrative unit) in each woreda was chosen, in order to constitute the sentinel sites. Finally, households containing children of specified age were randomly selected within the sites and one child per household is selected.

In the current paper we use the younger cohorts Young Lives data in Ethiopia which renders

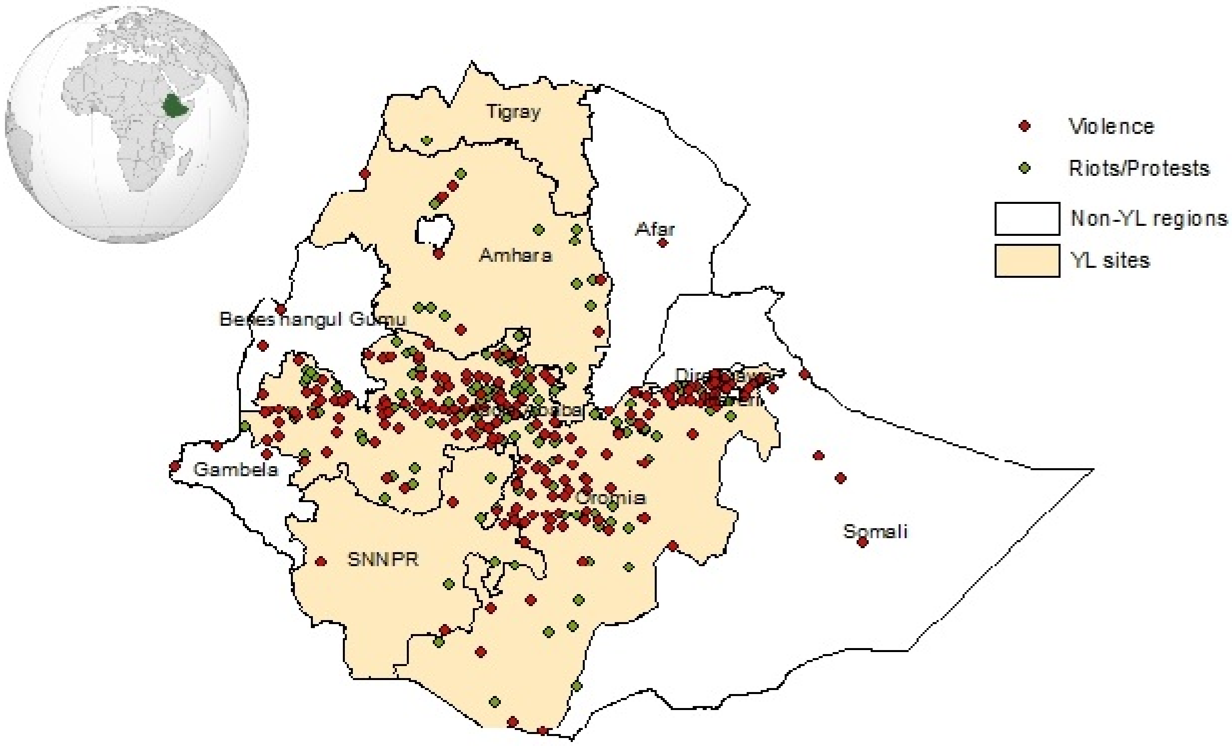
[16] Four woredas are selected from each region except in SNNP and Addis Ababa where five and three woredas are selected respectively.

data before the protest in 2013 and after the protest, especially after the declaration of state of emergency – at the end of 2016 (December) and beginning of 2017. Besides, YL also have information for both the highly affected regions and less affected regions. In this case we consider four regions (omitting Addis Ababa) including Oromia, Amhara, SNNP and Tigray of which Oromia and Amhara are the regions with high concentration of conflicts; Whereas SNNP and Tigray are regions with lower concentration of conflict events. We use the younger cohorts because the older cohorts were exposed to the Ethio-Eritrean war, which was between 1998 to 2000 (Weldeegzie, 2017). In addition to the YL data, we use a location and event data obtained from the Armed Conflict Location and Event Data (ACLED) which provides us with a specific geographic location, time and fatalities of conflicts. This will help us to geographically and temporally identify the treatment and control areas and to further exploit the distances of YL households from the conflict areas. The evolution of the protest and violence is put in the time line below. First, protest erupted in Oromia in April 2014 following the Addis Ababa master plan. The protest became violent later on and ended up in more than 1000 deaths, mass property destructions and joined by the Amhara protest (after July 2016) which finally lead to the declaration of state of emergency in October 2016.

YL R4 survey	Protest erupted – resumed	Master plan suspended	Fresh protest erupted in Amhara	Ireecha Festival stampede – State of emergency declared	YL R5 survey
Before Jan 14	Apr-14 – Nov-15	Jan-16	Jul-16	Oct-16	After Dec-16

Combining the data from YL and ACLED, we exploit geographic and temporal (before-after) variations to identify the impact of the deadly violence in Ethiopia. Figure 4 presents the geographic concentration of riots and deadly violences in Ethiopia starting from April 2014 to December 2016. We can see from the map that riots and violences were mainly concentrated in Oromia region followed by Amhara region. Despite the fact that SNNP and Tigray regions had encountered very small incidences of conflicts, SNNP region staged incidences of conflicts which left more than 40 people killed and Tigray region hosted few events especially clashes between insurgents from Eritrea and government forces.

Figure 4: Riots and violences in Ethiopia from April 2014 to Oct 2016



Source: Own computation based on Armed Conflict Location and Event Data (ACLED)

Table 21 presents the concentrations of two common types of conflicts, violence and protests, in the four regions starting from the beginning of 2014 to end of 2016. We can observe that more than 90% of the conflicts are concentrated in Oromia region. When we see the two popular types of conflicts in Ethiopia, riots/protests and violence against civilians, more than 94% of them were concentrated in Oromia region and then in Amhara region. The other regions also host some few events though not as vast as the two regions. According to ACLED, the number of fatalities due to violence against civilians surpass 1000 between the beginning of 2014 to the end of 2016.

Table 21: Types of conflict events by region from 2014 to end of 2016

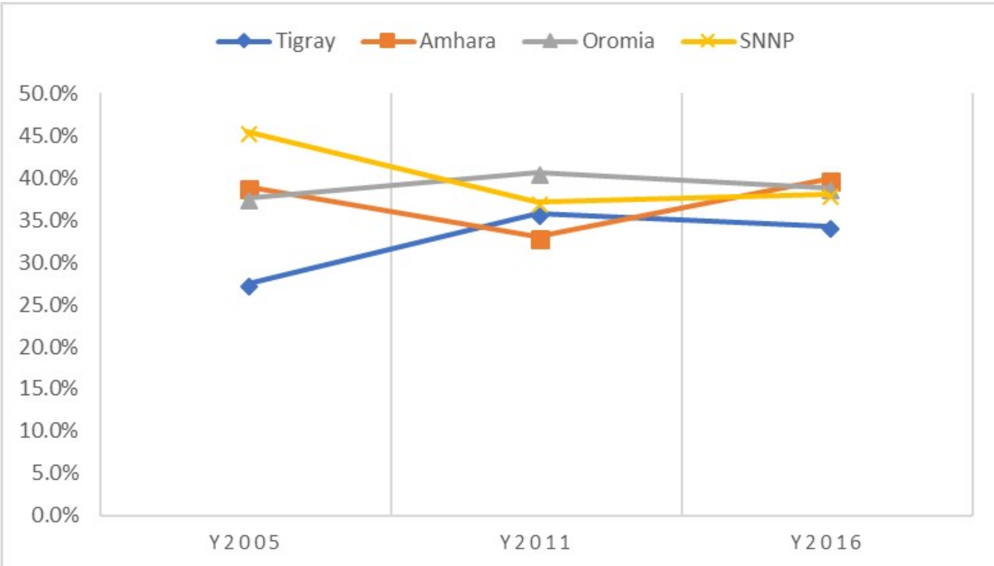
Types of conflict events		Amhara	Oromia	SNNP	Tigray	Total
Battle-No change of territories	N	35	103	10	12	160
	%	21.88	64.38	6.25	7.5	100
Battle-Non-state actor overtakes territory	N	2	0	0	0	2
	%	100	0	0	0	100
Remote violence	N	1	7	0	0	8
	%	12.5	87.5	0	0	100
Riots/Protests	N	31	792	12	6	841
	%	3.69	94.17	1.43	0.71	100
Strategic development	N	5	9	1	2	17
	%	29.41	52.94	5.88	11.76	100
Violence against civilians	N	21	472	9	0	502
	%	4.18	94.02	1.79	0	100
Total	N	95	1,383	32	20	1,530
	%	6.21	90.39	2.09	1.31	100

Source: Own computation based on Armed Conflict Location and Event Data (ACLED)

The outcome variables include indicators of educational enrollments and aspirations. Children were asked whether they were enrolled in school in the time of the survey and the response is binary, yes or no. Regarding educational aspirations, they were asked about the highest level of education they want to achieve. Specifically, the aspiration question is phrased as: "Imagine you had no constraints and could study for as long as you liked, or go back to school if you have already left. What level of formal education would you like to complete?". The response to this question runs from 1 to 15 indicating the years of education the child wants to attain, where 15 refers to university graduate.

But before we jump into the econometric discussion, we highlight the characteristics of households among the regions using the Ethiopian Demographic and Health Survey (DHS) for 2005, 2011 and 2016. The comparison of the four regions might help us see the differences and the patterns of change with respect to the selected indicators. Figure 5 depicts the percentage of households in the top two wealth quintiles for the four regions, Tigray, Amhara, Oromia, and SNNP. We can see that there are disparities among regions though the gap seems to be narrowing in the later years, which indicates that considering region-by-region analysis might be important.

Figure 5: Percentage of households in the highest & 2nd highest wealth quintile



Source: Own computation based on Demographic and Health Survey (DHS) statistical reports

Another concern is the proportion of ethnicity in the regions of interest as ethnicity is the major play ground in the Ethiopian violent conflicts. Ethiopia is divided into nine regions which are organized based on the ethnic backgrounds except the SNNP region (contains more than 50 ethnic groups). According to CIA World Fact-book the major ethnic groups in Ethiopia include: Oromo (34.4%), Amhara (27%), Somali (6.2%), Tigray (6.1%), Sidama (4%), Gurage (2.5%), Welaita (2.3%), Hadiya (1.7%), Afar (1.7%), Gamo (1.5%), Gedeo (1.3%), Silte (1.3%), Kefficho (1.2%), other (8.8%). We tried to see the proportion of ethnic groups of each region in our data for the sample under study. Table 22 presents the percentage of ethnic groups in the four regions in our study and indicates that the sample observations in Tigray and Amhara regions are homogeneous but in Oromia are less homogeneous and are heterogeneous in SNNP region. Our data reveal that about 98.1% of the sample observations in Amhara region are identified as ethnic Amhara; about 99.5% of the observations in Tigray region are identified as ethnic Tigray; whereas about 78.1% of the observations in Oromia region are ethnic Oromo; and the sample observations in SNNP region are identified as ethnic Gurage (20.1%), Hadiya (21%), Sidama (21.4%), Wolayta (24.9%), Amhara (8.7%), and others. This, hence, supports for the importance of considering a region-by-region analysis.

Table 22: Proportion of ethnic group compositions by region (%)

Ethnic groups	Regions			
	Amhara	Oromia	SNNP	Tigray
Oromo	0.55	78.06	1.73	0.00
Amhara	98.08	10.97	8.66	0.26
Tigrian	0.82	0.51	0.87	99.48
Agew	0.27	0.00	0.00	0.26
Gurage	0.27	1.02	20.13	0.00
HadiYa	0.00	0.51	21.00	0.00
Kambata	0.00	0.26	0.43	0.00
Sidama	0.00	1.02	21.43	0.00
WolaYta	0.00	0.26	24.89	0.00
Other	0.00	7.40	0.87	0.00
Total	100.00	100.00	100.00	100.00

The reason behind using a region-by-region analysis is not only due to the differences in the characteristics of the regions but mainly due to the different nature of the conflict in each of the regions. Studying the region-specific conflict events and its impact helps to explore the contextual regional factors associated with it. Therefore, in order to provide a detailed region specific explanations on the effect of conflict, a region-by-region analysis is followed.

4.3. Econometric strategy and results

This section elicits the methodology employed and the results obtained. The first part discusses the econometric strategy; the impacts of conflict on children's educational enrollments and aspirations is analyzed using the differences-in-differences (DID) estimation technique. The second part presents the main results and some robustness or sensitivity checks. The final part discusses the results obtained.

4.3.1. Econometric strategy

We use a DID method to examine the impacts of conflicts. The aim here is to measure the average treatment effects on the treated (ATT) and is given by:

$$\beta_{DID} = [E(Y_{t_1a_0}) - E(Y_{t_0a_0})] - [E(Y_{t_1a_1}) - E(Y_{t_0a_1})] \tag{5}$$

Where, β_{DID} is the parameter which captures the effect of the violence; t_0 and t_1 refer to the before and after the violence respectively; a_0 and a_1 refer to areas far from and near to the violence points respectively. We determine the distance of each household from the violence points using the coordinates of households obtained from YL and coordinates of conflict points obtained from ACLED. And the differences-in-differences (DID) regression equation is specified as follows:

$$Y_{itar} = \beta_0 + \beta_1 Year_t + \beta_2 Conflict_a + \beta_3(Year_t * Conflict_a) + X_{itar}\beta_4 + \lambda_s + \upsilon_{it} \tag{6}$$

Where, Y_{itar} refers to the outcome variable for individual i, at time t, living in area a and region r. Year t will be 1 for round 5 (after the conflict) and 0 otherwise. Area a is 1 if the child is living near to violence hit areas but 0 otherwise. X_{itar} includes a bunch of household characteristics. λ_s consists of site level fixed effects and υ_{it} includes the usual error term. So the parameter of interest, which shows the impact of the violence, is captured by β_3.

Rather than defining the treatments groups based on violence/riot happenings, we consider the distance of each household, where the child lives, from the conflict events. We define treatment based on proximities to the violence events. To do this, we measure the distance of children's residence to the nearest violence event. Then, our treatment is defined to take value 1 if the distance to the nearest violence event is with in certain km radius, and a value 0 otherwise. However, due to differences in the nature of conflicts, and the socio-economic characteristics and demographic compositions of the regions, we conduct region-by-region analysis. Oromia is the region with intense violence events in the three years time followed by Amhara region. SNNP and Tigray regions, however, experienced lighter conflict events and with different natures of conflicts. For instance, while most of the reported conflict events in Tigray were due to insurgencies of rebel groups (government opposition groups) from Eritrea, the conflicts in Oromia were due to mass protests/riots against the government with heavy government crackdowns. Thus, we conducted a region-by-region estimations to explore whether the conflicts in a region affects our outcome variables. We decide the distance of households from the violence points to be 12km for Oromia region (because it had concentrated conflict events and the average distance is about 13km for Oromia region) and 24km for the other regions (double of the Oromia region as they had less concentrated conflict events). Therefore, children are grouped as treatments in Oromia region if they live within the 12km radius of conflict events and to the control group if they live off the 12km radius of the conflict events. While children in other regions belong to the treatment group if they live within 24km radius of the conflict events and to the control group if otherwise.

But one of the concerns here is the arbitrary selection of distance cuts for the regions. To partly avoid the selection problem with regard to the distance cut, we tried to consider different distance cuts to see whether the results are sensitive to these cuts. Besides, we tried to include children's height-for-age and weight-for-age at age 5, and PPVT scores at age 8 to capture children's health and cognitive abilities prior to the conflict. Moreover, we controlled for household's education, expenditure, exposure to shocks, and other indicators.

4.3.2. Results

Table 28 depicts the characteristics of children and their households living within and off the 12km radius for Oromia region and 24km radius for the other regions from the violence points in 2013 (before the conflict). We can see that there is no significance difference between the control and treatment groups with respect to the outcome variables (educational enrollments and aspirations) for Oromia and Tigray regions but there was significant differences in the baseline for Amhara and SNNP regions. With respect to the covariates, a significance differences between the treatment and control groups is observed at the baseline for instance a significance difference is obtained with respect to ppvt test score at age 8, urban dummy, male household head, and total monthly expenditure.

Table 23 depicts whether exposure to violent conflicts affects the educational enrollments and aspirations of adolescents. We calculated the distance of each household's area to the nearest violence area using YL and ACLED locations[17]. One of the concerns here is that households who are at risk of being reached by the conflict could migrate and this might make the treatment variable endogenous. But our data contain information about the movement history and the associated reasons behind. And the highlighted that though about 14 percent of the children reported to have moved to a different kebelle for at least one month, only 1 child reported it was due to violence/crime/war. But to be on the safe side, we excluded those who moved outside of the region previously living (including them does not change the

[17]The distance is computed by YL team in Ethiopia after providing them the ACLED's conflict event locations

results). The results in table 5 revealed that the conflicts in Oromia and Tigray regions have no significant effect on both educational enrollment and educational aspirations. However, we find a negative and statistically significant effect on educational enrollment though null effect on educational aspirations in Amhara region. Opposite to the results in Amhara region, a negative and statistically significant effect is obtained on educational aspirations but no significant effect on educational enrollments is found in SNNP region. As we stated earlier, the differences in the impacts of the conflicts on the outcome variables might be attributed to the differences in the nature of the conflicts in each region and to the characteristics of the regions. Though we have tried to see the impacts of the conflicts in a region-by-region analysis to reduce the biases arising from the different nature of the conflicts and characteristics of the regions, there might be still concerns on the differences between the treatment and control groups within the regions with respect to the covariates. To partly resolve the concern, we tried to match the treatment and control groups using matching techniques, matched based on observable characteristics before the conflict.

Table 23: Impacts of conflicts by regions

	Oromo		Amhara		SNNP		Tigray	
	Enrollment	Aspiration	Enrollment	Aspiration	Enrollment	Aspiration	Enrollment	Aspiration
time dummy (2016)	-0.0583*	0.617***	0.0542*	0.710***	0.00530	0.682***	-0.0412	0.542***
	(0.0308)	(0.222)	(0.0286)	(0.266)	(0.0153)	(0.163)	(0.0299)	(0.175)
dist_12km	-0.000639	0.156						
	(0.0192)	(0.206)						
(dist_12km)*time	-0.0328	-0.240						
	(0.0387)	(0.264)						
dist_24km			0.0619	0.356	0.0354**	0.672***	-0.0496	0.0494
			(0.0626)	(0.454)	(0.0167)	(0.206)	(0.0531)	(0.406)
(dist_24km)*time			-0.105***	-0.441	-0.00172	-0.629***	0.0541	0.0375
			(0.0385)	(0.352)	(0.0150)	(0.161)	(0.0681)	(0.420)
N	703	703	666	669	822	823	678	691
Household and child covariates	YES	YES	YES	YES		YES	YES	YES
Site(Village) fixed effects	YES	YES	YES	YES		YES	YES	YES
Household and climatic shocks	YES	YES	YES	YES		YES	YES	YES

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

Notes: The dependent variables include educational enrollments and educational aspirations. Covariates includes child level characteristics including gender, height-for-age z-score at age 5, weight-for-age z-score at age 5, ppvt test score at age 8; household characteristics including household head age, household head education, and households total real monthly expenditure; and shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, pests on livestock, death of father and death of mother. Village (site) level dummies are included in all columns.
Notes: The distance cut is 12km for Oromia region and 24km for the rest of the regions.

Table 24 presents the estimation results on the matched subsamples. We match both the treated and control groups based on observable household characteristics and reports of climatic shocks before the conflict for each region. A kernel matching with a bandwidth of 0.005, 0.008, 0.07, and 0.04 for Oromia, Amhara, SNNP, and Tigray regions respectively are conducted. The matching algorithm satisfies the balancing checks after matching. Then, we run our estimations on the sample of observations which are on the common support for the respective regions. The results reconfirm that the conflict is found to have null effect on the outcome variables in Oromia and Tigray regions. But it has a significant effect on educational enrollments in Amhara region and educational aspirations in SNNP region.

Table 24: Impacts of conflicts by regions - matched sample

	Oromo		Amhara		SNNP		Tigray	
	Enrollment	Aspiration	Enrollment	Aspiration	Enrollment	Aspiration	Enrollment	Aspiration
time dummy (2016)	-0.0717**	0.592***	0.0270	0.786***	-0.00340	0.560***	-0.0383	0.526***
	(0.0331)	(0.226)	(0.0261)	(0.265)	(0.0172)	(0.181)	(0.0307)	(0.177)
dist_12km	0.00222	0.131						
	(0.0209)	(0.216)						
(dist_12km)*time	-0.0275	-0.124						
	(0.0428)	(0.292)						
dist_24km			0.0316	0.431	0.0370*	0.582***	-0.0480	0.0346
			(0.0698)	(0.516)	(0.0190)	(0.215)	(0.0547)	(0.413)
(dist_24km)*time			-0.0847*	-0.602	0.00448	-0.540***	0.0604	-0.0147
			(0.0456)	(0.475)	(0.0159)	(0.166)	(0.0734)	(0.438)
N	617	618	558	563	719	719	642	653
Household and child covariates	YES	YES	YES	YES		YES	YES	YES
Site(Village) fixed effects	YES	YES	YES	YES		YES	YES	YES
Household and climatic shocks	YES	YES	YES	YES		YES	YES	YES

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

Notes: The dependent variables include educational enrollments and educational aspirations. Covariates includes child level characteristics including gender, height-for-age z-score at age 5, weight-for-age z-score at age 5, ppvt test score at age 8; household characteristics including household head age, household head education, and households total real monthly expenditure; and shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, pests on livestock, death of father and death of mother. Village (site) level dummies are included in all columns.
Notes: The distance cut is 12km for Oromia region and 24km for the rest of the regions.

Another important issue, which usually given less attention in the conflict literature[18], is the individual heterogeneity as it is difficult to observe people before and after the conflicts. In this paper, we control for individual heterogeneities by exploiting the panel nature of the data and applying fixed effects estimation. So, we used the differences-in-differences model with fixed effect as baseline regression so as to control for time-invariant unobservables. Table 25

[18] Most conflict papers evaluate the impact of a conflict using cohort and geographic variations, and usually have two cohorts: one exposed to the conflict and the other not exposed to the conflict. But in this paper we are exploiting the fact that the same children are exposed to the conflict. And this helps us to control for time-invariant unobservables exploiting the panel nature of the data.

presents the results from the fixed effects regression. But the treatment variable is dropped because there is no within individual variation. The results indicate that significant impact of the conflict is found on educational enrollments in Amhara region and on educational aspirations in SNNP region. One can see that the results are similar to table 23 though lower precision and coefficients are obtained.

Table 25: Impacts of conflicts by regions - Fixed Effects regression

	Oromo		Amhara		SNNP		Tigray	
	Enrollment	Aspiration	Enrollment	Aspiration	Enrollment	Aspiration	Enrollment	Aspiration
time dummy (2016)	-0.0755**	0.519**	-0.0456*	0.700**	-0.0149	0.624***	-0.0868***	0.522***
	(0.0375)	(0.248)	(0.0274)	(0.305)	(0.0129)	(0.180)	(0.0327)	(0.168)
(dist_12km)*time	-0.0405	-0.0711						
	(0.0411)	(0.270)						
(dist_24km)*time			-0.0620*	-0.449	0.0142	-0.517***	0.0429	-0.0668
			(0.0346)	(0.378)	(0.0124)	(0.167)	(0.0703)	(0.465)
N	703	703	666	669	822	823	678	691
N_g	380	380	357	355	437	438	356	358
Household and child covariates	YES	YES	YES	YES		YES	YES	YES
Site(Village) fixed effects	YES	YES	YES	YES		YES	YES	YES
Household and climatic shocks	YES	YES	YES	YES		YES	YES	YES

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

Notes: The dependent variables include educational enrollments and educational aspirations. Covariates include: household head age, household head education, and households total real monthly expenditure; and shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, pests on livestock, death of father and death of mother. Village (site) level dummies are included in all columns.
Notes: The distance cut is 12km for Oromia region and 24km for the rest of the regions.

4.3.3. Sensitivity checks

As robustness check, we have tried to conduct our estimations on the matched sub-sample. Table 24 presented the differences-in-differences estimation on the set of matched subsample and the results are similar to the ones from the full sample. Another concern one would raise is the arbitrary selection of distance cuts as the differences-in-differences estimations is conducted based on these distance cuts. Therefore, we need to check whether our results are sensitive to changing the distance cuts. Accordingly, we considered 13km, 14km, 15km and 16km distance cuts for Oromia region, and the results are presented in table 26. For the rest of the regions, however, 25km, 26km, 27km and 28km distance cuts are considered and the regression results are put in 27. The results from both table 26 and 27 portray that there is no significant impact of conflict in Oromia and Tigray regions for all distance cuts but significant impact of conflict on educational enrollment in Amhara and on educational aspirations in SNNP regions, asserting the previous results. The results, hence, indicate that the selection bias from the distance cuts is limited.

Table 26: Impacts of conflicts by different distance cuts - Oromia region

	(13)		(14)		(15)		(16)	
	enrol	educ_asp	enrol	educ_asp	enrol	educ_asp	enrol	educ_asp
Oromia region								
Time*Distance()	-0.0519	-0.296	-0.0384	-0.215	-0.0326	-0.0860	-0.0520	0.274
	(0.0385)	(0.272)	(0.0415)	(0.310)	(0.0449)	(0.319)	(0.0552)	(0.368)
N	703	703	703	703	703	703	703	703

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

Notes: The dependent variables include educational enrollments and educational aspirations. Covariates includes child level characteristics including gender, height-for-age z-score at age 5, weight-for-age z-score at age 5, ppvt test score at age 8; household characteristics including household head age, household head education, and households total real monthly expenditure; and shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, pests on livestock, death of father and death of mother. Village (site) level dummies are included in all columns.

Table 27: Impacts of conflicts by different distance cuts - Other regions

	(25)		(26)		(27)		(28)	
	enrol	educ_asp	enrol	educ_asp	enrol	educ_asp	enrol	educ_asp
Amhara region								
Time*Distance()	-0.0886**	-0.432	-0.0893**	-0.477	-0.0900**	-0.488	-0.0917**	-0.509
	(0.0390)	(0.352)	(0.0388)	(0.353)	(0.0391)	(0.359)	(0.0395)	(0.363)
N	666	669	666	669	666	669	666	669
SNNP region								
Time*Distance()	0.0133	-0.573***	0.0135	-0.589***	0.0146	-0.592***	0.0133	-0.663***
	(0.0171)	(0.164)	(0.0171)	(0.173)	(0.0173)	(0.182)	(0.0173)	(0.183)
N	824	825	824	825	824	825	824	825
Tigray region								
Time*Distance()	0.0511	-0.0493	0.00961	-0.234	0.0332	-0.149	0.0163	-0.307
	(0.0691)	(0.458)	(0.0676)	(0.411)	(0.0616)	(0.365)	(0.0574)	(0.346)
N	678	691	678	691	678	691	678	691

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

Notes: The dependent variables include educational enrollments and educational aspirations. Covariates includes child level characteristics including gender, height-for-age z-score at age 5, weight-for-age z-score at age 5, ppvt test score at age 8; household characteristics including household head age, household head education, and households total real monthly expenditure; and shocks including drought, flooding, erosion, frost, pests on crops, crop failure, pests on storage, pests on livestock, death of father and death of mother. Village (site) level dummies are included in all columns.

4.4. Discussion of the results

Our results indicate that the conflict in Oromia and Tigray regions are found to have null effects on both educational enrollments and aspirations. For Tigray region, it is pretty intuitive to find the null effect of conflict because there were very few incidences of conflict events and most of them were between government forces and opposition forces surging from Eritrea with limited civilian fatalities. So the effect of conflict on the educational enrollments and aspirations is expected to be very weak. However, one would expect the conflict in Oromia region to have an effect on the educational enrollments and aspirations of children living in the region. But opposite to what was expected, we find insignificant impacts of the conflict on educational enrollments and aspirations. The null effect of conflict in Oromia might be attributed to the lengthy nature of the conflict in the region. The conflict in Oromia have been rampant throughout the region for more than three years since 2014, and people might get used to it and adjusted their way of life accordingly. Another reason could be that several measures were taken by the government to draw attention of the youth. Among these measures, the Oromia Economic Revolution is one which has gotten popular support. The Oromia Economic Revolution was initiated at the end of 2016 following the popular uprising and protest in Oromia with the objective of employment creation, cultural transformation, building Oromo nationalism, economic empowerment, utilization of regional resources, and enhancing agro-processing. Hence, the effects of conflict might be washed away by these and other factors. But the conflict in Amhara region erupted in July 2016 and continued in August and afterwards. In Ethiopia, students' registration is usually conducted during the month of August for the academic year starting in September. Therefore, families might get frightened to register and to send their children to school due to the fresh conflict in the Amhara region. And this might have a direct effect on student's educational enrollment as evidenced in the this paper. But no significant effect of the conflict on educational aspiration is found in Amhara region. Our results further indicate that the conflict in SNNP is found to have an effect on educational aspirations but not on educational enrollments. The result is not too intuitive but might be due to the region's unique mix of different ethnic groups which may imply that people are not directly threatened but indirectly which would be reflected in their educational aspirations. In a nut shell, the impacts of violent intra-state conflict in Ethiopia is found to be heterogeneous among the regions which might be attributed to the nature of the conflict and the unique mix of the specific region under consideration.

4.5. Conclusion

Households in developing countries faced a number of shocks; political conflicts are one of the number of shocks which complicate the socioeconomic lives of households in general and children in particular. The current paper tried to elicit the impacts of intra-state conflicts, such as riots and violences, on educational attendances and educational aspirations of children. We used data obtained from Young Lives and from Armed Conflicts Locations and Event Data (ACLED). We calculated the distance of households from the conflict events using the GPS coordinates of households and conflict events. The treatment is defined based on proximities to the violence events and is measured by the distance of children's residence to the nearest violence event. However, due to differences in the nature of conflicts, and the socio-economic characteristics and demographic compositions of the regions, we conduct region-by-region analysis. Thus, individuals are grouped to the treatment group in Oromia region if they live within the 12km radius of conflict events and to the control group if they live off the 12km radius of the conflict events. In the rest of the regions, however, individuals belong to the treatment group if they live within 24km radius of the conflict events and to the control group if otherwise. Applying the differences-in-differences methodology and also using fixed effects, we find null effects of conflicts in Oromia and Tigray regions but significant effect on educational enrollments in Amhara region and on educational aspirations in SNNP region are obtained indicating that intra-state conflicts might have higher effects at the initial stage as evidenced in Amhara region but vanish when time passes as is the case in Oromia region.

Table 28: Differences (T-C) between treatment and control groups with respect to outcome variables and covariates at baseline

	Oromia	Amhara	SNNP	Tigray
Outcome variables				
Educational enrollment	0.023	0.076**	0.050**	-0.047
Educational aspirations	0.147	0.836***	1.569***	-0.280
Covariates				
Male	0.044	-0.079	0.123**	0.001
zwfa_age5	0.208**	0.169*	0.467***	0.042
zhfa_age5	0.145	0.070	0.767***	-0.378 **
ppvt_age8	9.232***	29.942***	62.260***	8.593
Urban	0.205***	0.633***	0.522***	0.079
Age of household head	-0.983	-1.069	1.319	1.356
Male household head	-0.058	-0.142***	-0.188***	-0.022
HH head - some lower primary	0.051	-0.024	-0.108**	-0.040
Hh head - some upper primary	0.031	-0.033	-0.009	-0.058
Hh head - some secondary	-0.017	0.096***	0.090**	-0.002
Hh head- post secondary and college	0.060**	0.145***	0.169***	0.070***
Hh head- adult literacy and religious	-0.068	-0.314***	-0.041	-0.027
Total monthly real expenditure	305.141***	560.832***	363.341***	92.777
shock-drought	-0.038	-0.494***	-0.018	0.070
shock-flooding	-0.050**	-0.218***	-0.094***	-0.013
shock-erosion	-0.010	-0.224 ***	-0.012	-0.006
shock-frost	-0.005	-0.356***	-0.006	-0.000
shock-pests on crops	-0.017	-0.264***	-0.032*	0.022
shock-crop failure	-0.056	-0.354***	-0.065 ***	-0.035
shock-pests on storage	-0.005	-0.044*	0.009*	-0.000
shock-pests on livestock	0.006	-0.069**	-0.029	0.016 **
shock-death of father	-0.003	0.009	0.001	-0.010
shock-death of mother	0.006	-0.000	0.012	-0.003
N	386	363	449	378

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the results from the t-tests for each of the covariates listed in column one. The rest of the columns depict the difference between treatment and control groups and the associated p-values obtained from the t-tests with different variances for Oromia, Amhara, SNNP and Tigray respectively before the conflict (2013).

References

Abraham, R. (2007). Mobile phones and economic development: Evidence from the fishing industry in india. *Information Technologies and International Development*, 4(1):5–17.

Akbulut-Yuksel, M. (2014). Children of war the long-run effects of large-scale physical destruction and warfare on children. *Journal of Human resources*, 49(3):634–662.

Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in niger. *American Economic Journal: Applied Economics*, 2(3):46–59.

Aker, J. C. (2011). Dial "a" for agriculture: a review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics*, 42(6):631–647.

Aker, J. C. and Blumenstock, J. E. (2014). *The economic impacts of new technologies in Africa*. The Oxford Handbook of Africa and Economics: Policies and Practices.

Aker, J. C. and Fafchamps, M. (2014). Mobile phone coverage and producer markets: evidence from west africa. Policy Research Working Paper Series 6986, The World Bank.

Aker, J. C. and Mbiti, I. M. (2010). Mobile phones and economic development in africa. *Journal of Economic Perspectives*, 24(3):207–32.

Akresh, R. (2008). *Armed conflict and schooling: Evidence from the 1994 Rwandan genocide*, volume 3516. World Bank Publications.

Akresh, R., Bhalotra, S., Leone, M., and Osili, U. O. (2012a). War and stature: growing up during the nigerian civil war. *The American Economic Review*, 102(3):273–277.

Akresh, R., Caruso, G. D., and Thirumurthy, H. (2016). Detailed geographic information, conflict exposure, and health impacts. Technical report, IZA Discussion Papers.

Akresh, R., Lucchetti, L., and Thirumurthy, H. (2012b). Wars and child health: Evidence from the eritrean–ethiopian conflict. *Journal of development economics*, 99(2):330–340.

Akresh, R., Verwimp, P., and Bundervoet, T. (2011). Civil war, crop failure, and child stunting in rwanda. *Economic Development and Cultural Change*, 59(4):777–810.

Andersson, C., Mekonnen, A., and Stage, J. (2011). Impacts of the Productive Safety Net Program in Ethiopia on livestock and tree holdings of rural households. *Journal of Development Economics*, 94(1):119–126.

Baird, S., Ferreira, F. H., Özler, B., and Woolcock, M. (2014). Conditional, unconditional and everything in between: a systematic review of the effects of cash transfer programmes on schooling outcomes. *Journal of Development Effectiveness*, 6(1):1–43.

Bauer, M., Blattman, C., Chytilová, J., Henrich, J., Miguel, E., and Mitts, T. (2016). Can war foster cooperation? *The Journal of Economic Perspectives*, 30(3):249–274.

Beaman, L., Duflo, E., Pande, R., and Topalova, P. (2012). Female leadership raises aspirations and educational attainment for girls: A policy experiment in India. *Science*, 335(6068):582–586.

Berhane, G., Gilligan, D. O., Hoddinott, J., Kumar, N., and Taffesse, A. S. (2014). Can social protection work in Africa? The impact of Ethiopia's Productive Safety Net Programme. *Economic Development and Cultural Change*, 63(1):1–26.

Berhane, G., Hoddinott, J., Kumar, N., and Taffesse, A. S. (2011). The impact of Ethiopia's productive safety nets and household asset building programme: 2006–2010. Technical report, International Food Policy Research Institute, Washington, DC.

Bernard, T., Dercon, S., Orkin, K., and Seyoum Taffesse, A. (2015). Will Video Kill the Radio Star? Assessing the Potential of Targeted Exposure to Role Models through Video. *The World Bank Economic Review*, 29:226–237.

Bernard, T. and Taffesse, A. S. (2014). Aspirations: An approach to measurement with validation using Ethiopian data. *Journal of African Economies*, 23(2):189–224.

Bertrand, M., Luttmer, E. F., and Mullainathan, S. (2000). Network effects and welfare cultures. *The Quarterly Journal of Economics*, 115(3):1019–1055.

Besley, T. (1995). Nonmarket institutions for credit and risk sharing in low-income countries. *The Journal of Economic Perspectives*, 9(3):115–127.

Beuermann, D., McKelvey, C., and Vakis, R. (2012). Mobile phones and economic development in rural peru. *Journal of Development Studies*, 48(11):1617–1628.

Blumenstock, J. E., Eagle, N., and Fafchamps, M. (2016). Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters. *Journal of Development Economics*, 120:157–181.

Bontemps, C. and Nauges, C. (2015). The impact of perceptions in averting-decision models: An application of the special regressor method to drinking water choices. *American Journal of Agricultural Economics*, 98(1):297–313.

Bundervoet, T., Verwimp, P., and Akresh, R. (2009). Health and civil war in rural burundi. *Journal of Human Resources*, 44(2):536–563.

Chamarbagwala, R. and Morán, H. E. (2011). The human capital consequences of civil war: Evidence from guatemala. *Journal of Development Economics*, 94(1):41–61.

Chew, H. E., Ilavarasan, V. P., and Levy, M. R. (2015). Mattering matters: Agency, empowerment, and mobile phone use by female microentrepreneurs. *Information Technology for Development*, 21(4):523–542.

Chiapa, C., Garrido, J. L., and Prina, S. (2012). The effect of social programs and exposure to professionals on the educational aspirations of the poor. *Economics of Education Review*, 31(5):778–798.

Dalton, P. S., Ghosal, S., and Mani, A. (2016). Poverty and aspirations failure. *The Economic Journal*, 126(590):165–188.

De Luca, G. and Verpoorten, M. (2015). Civil war, social capital and resilience in uganda. *Oxford Economic Papers*, 67(3):661–686.

Debela, B. L., Shively, G., and Holden, S. T. (2015). Does Ethiopia's Productive Safety Net Program Improve Child Nutrition? *Food Security*, 7(6):1273–1289.

Dercon, S. and Singh, A. (2013). From nutrition to aspirations and self-efficacy: gender bias over time among children in four countries. *World Development*, 45:31–50.

Devereux, S. (2002). Can social safety nets reduce chronic poverty? *Development Policy Review*, 20(5):657–675.

Dong, Y. and Lewbel, A. (2015). A simple estimator for binary choice models with endogenous regressors. *Econometric Reviews*, 34(1-2):82–105.

Duflo, E. (2006). Poor but rational? In Banerjee, A., Benabou, R., and Mookherjee, D., editors, *Understanding poverty*, pages 367–378. Oxford University Press, Oxford.

Duncombe, R. A. (2014). Understanding the impact of mobile phones on livelihoods in developing countries. *Development Policy Review*, 32(5):567–588.

Espié, E., Gaboulaud, V., Baubet, T., Casas, G., Mouchenik, Y., Yun, O., Grais, R. F., and Moro, M. R. (2009). Trauma-related psychological disorders among palestinian children and adults in gaza and west bank, 2005-2008. *International journal of mental health systems*, 3(1):21.

Favara, M. (2017). Do dreams come true? Aspirations and educational attainments of Ethiopian boys and girls. *Journal of African Economies*, Forthcoming:1–23.

Frölich, M. and Haile, G. (2011). Labour markets in developing countries. *Labour Economics*, 18(Supplement 1):S2 – S6.

Genicot, G. and Ray, D. (2017). Aspirations and inequality. *Econometrica*, 85(2):489–519.

Ghatak, M. and Guinnane, T. W. (1999). The economics of lending with joint liability: theory and practice1. *Journal of development economics*, 60(1):195–228.

Gilligan, D. O., Hoddinott, J., and Taffesse, A. S. (2009). The impact of Ethiopia's Productive Safety Net Programme and its linkages. *The Journal of Development Studies*, 45(10):1684–1706.

Gilligan, M. J., Pasquale, B. J., and Samii, C. (2014). Civil war and social cohesion: Lab-in-the-field evidence from nepal. *American Journal of Political Science*, 58(3):604–619.

Gleditsch, N. P., Wallensteen, P., Eriksson, M., Sollenberg, M., and Strand, H. (2002). Armed conflict 1946-2001: A new dataset. *Journal of peace research*, 39(5):615–637.

Haile, G. and Haile, B. (2012). Child labour and child schooling in rural Ethiopia: nature and trade-off. *Education Economics*, 20(4):365–385.

Haushofer, J. and Shapiro, J. (2016). The Short-term Impact of Unconditional Cash Transfers to the Poor: Experimental Evidence from Kenya. *The Quarterly Journal of Economics*, 131(4):1973–2042.

Hoddinott, J., Gilligan, D. O., and Taffesse, A. S. (2010). The impact of Ethiopia's productive safety net program on schooling and child labor. In Handa, S., Devereux, S., and Webb, D. E., editors, *Social Protection for Africa's Children*, pages 71–96. Routledge.

Kao, G. and Tienda, M. (1998). Educational aspirations of minority youth. *American Journal of Education*, 106(3):349–384.

Khamis, V. (2005). Post-traumatic stress disorder among school age palestinian children. *Child abuse & neglect*, 29(1):81–95.

Khandker, S. R. (2005). Microfinance and poverty: Evidence using panel data from bangladesh. *The World Bank Economic Review*, 19(2):263–286.

Laajaj, R. (2017). Endogenous time horizon and behavioral poverty trap: Theory and Evidence from Mozambique. *Journal of Development Economics*, 127:187–208.

Lewbel, A. (2000). Semiparametric qualitative response model estimation with unknown heteroscedasticity or instrumental variables. *Journal of Econometrics*, 97(1):145–177.

Lewbel, A., Dong, Y., and Yang, T. T. (2012a). Comparing features of convenient estimators for binary choice models with endogenous regressors. *Canadian Journal of Economics/Revue canadienne d'économique*, 45(3):809–829.

Lewbel, A., Dong, Y., and Yang, T. T. (2012b). Comparing features of convenient estimators for binary choice models with endogenous regressors. *Canadian Journal of Economics/Revue canadienne d'économique*, 45(3):809–829.

Malasquez, E. A. (2016). Does conflict undermine social capital? long-run evidence from peru.

Manacorda, M. and Tesei, A. (2016). Liberation technology: Mobile phones and political mobilization in africa. Cep discussion papers, Centre for Economic Performance, LSE.

Mansour, H. and Rees, D. I. (2012). Armed conflict and birth weight: Evidence from the al-aqsa intifada. *Journal of Development Economics*, 99(1):190–199.

Mataria, A., Giacaman, R., Stefanini, A., Naidoo, N., Kowal, P., and Chatterji, S. (2009). The quality of life of palestinians living in chronic conflict: assessment and determinants. *The European Journal of Health Economics*, 10(1):93–101.

McDonald, J. F. and Moffitt, R. A. (1980). The uses of tobit analysis. *The review of economics and statistics*, pages 318–321.

Meyer, B. D. (1995). Natural and quasi-experiments in economics. *Journal of Business & Economic Statistics*, 13(2):151–161.

Miller, K. E. and Rasmussen, A. (2010a). Mental health and armed conflict: the importance of distinguishing between war exposure and other sources of adversity: a response to neuner. *Social Science & Medicine*, 71(8):1385–1389.

Miller, K. E. and Rasmussen, A. (2010b). War exposure, daily stressors, and mental health in conflict and post-conflict settings: bridging the divide between trauma-focused and psychosocial frameworks. *Social science & medicine*, 70(1):7–16.

Ministry of Agriculture, E. (2014). Productive Safety Net Programme Phase IV Programme Implementation Manual. *Addis Ababa: Ethiopia*.

Minoiu, C. and Shemyakina, O. N. (2014). Armed conflict, household victimization, and child health in côte d'ivoire. *Journal of Development Economics*, 108:237–255.

Morduch, J. (1999). The microfinance promise. *Journal of economic literature*, 37(4):1569–1614.

Moya, A. (2018). Violence, psychological trauma, and risk attitudes: Evidence from victims of violence in colombia. *Journal of Development Economics*, 131:15–27.

Okten, C. and Osili, U. O. (2004). Social networks and credit access in indonesia. *World Development*, 32(7):1225–1246.

Oster, E. and Thornton, R. (2012). Determinants of technology adoption: Peer effects in menstrual cup take-up. *Journal of the European Economic Association*, 10(6):1263–1293.

Outes-Leon, I. and Sanchez, A. (2008). An assessment of the young lives sampling approach in ethiopia.

Palm, A. (2017). Peer effects in residential solar photovoltaics adoption—a mixed methods study of swedish users. *Energy Research & Social Science*, 26:1–10.

Pitt, M. M. and Khandker, S. R. (1998). The impact of group-based credit programs on poor households in bangladesh: Does the gender of participants matter? *Journal of political economy*, 106(5):958–996.

Pivovarova, M. and Swee, E. L. (2015). Quantifying the microeconomic effects of war using panel data: Evidence from nepal. *World Development*, 66:308–321.

Poirier, T. (2012). The effects of armed conflict on schooling in sub-saharan africa. *International Journal of Educational Development*, 32(2):341–351.

Porter, C. and Goyal, R. (2016). Social protection for all ages? Impacts of Ethiopia's Productive Safety Net Program on child nutrition. *Social Science & Medicine*, 159:92–99.

Ray, D. (2006). Aspirations, poverty, and economic change. In Banerjee, A., Benabou, R., and Mookherjee, D., editors, *Understanding poverty*, pages 409–421. Oxford University Press, Oxford.

Riley, E. (2017). Increasing students' aspirations: the impact of Queen of Katwe on students' educational attainment (Working Paper WPS/2017-13). *Centre for the Study of African Economies, University of Oxford: Oxford.*

Ross, P. H. (2017). The Aspirations Gap and Human Capital Investment: Evidence from Indian Adolescents. *mimeo, Boston University.*

Sabates-Wheeler, R. and Devereux, S. (2010). Cash transfers and high food prices: explaining outcomes on Ethiopia's productive safety net programme. *Food Policy*, 35(4):274–285.

Schoon, I. and Parsons, S. (2002). Teenage aspirations for future careers and occupational outcomes. *Journal of Vocational Behavior*, 60(2):262–288.

Serneels, P. and Dercon, S. (2014). Aspirations, poverty and education: evidence from India (Young Lives Working Paper No. 125). *Young Lives: Oxford.*

Sewell, W. H., Haller, A. O., and Ohlendorf, G. W. (1970). The educational and early occupational status attainment process: Replication and revision. *American Sociological Review*, 35(6):1014–1027.

Shemyakina, O. (2011). The effect of armed conflict on accumulation of schooling: Results from tajikistan. *Journal of Development Economics*, 95(2):186–200.

Swee, E. L. (2015). On war intensity and schooling attainment: The case of Bosnia and Herzegovina. *European Journal of Political Economy*, 40(Part A):158 – 172.

Tadesse, G. and Bahiigwa, G. (2015). Mobile phones and farmers' marketing decisions in ethiopia. 2015 Conference, August 9-14, 2015, Milan, Italy 212685, International Association of Agricultural Economists.

Tenaw, S. and Islam, K. Z. (2009). Rural financial services and effects of microfinance on agricultural productivity and on poverty. *University of Helsinki Department of Economics and Management (Discussion Papers series)*, 1:28.

Voors, M. J., Nillesen, E. E., Verwimp, P., Bulte, E. H., Lensink, R., and Van Soest, D. P. (2012). Violent conflict and behavior: a field experiment in burundi. *The American Economic Review*, 102(2):941–964.

Weldeegzie, S. G. (2017). Growing-up unfortunate: War and human capital in ethiopia. *World Development*, 96:474–489.

Wiseman, W., Van Domelen, J., and Coll-Black, S. (2010). Designing and implementing a rural safety net in a low income setting: Lessons learned from Ethiopia's Productive Safety Net Program 2005-2009. Technical report, World Bank, Washington DC.

Woldehanna, T. (2010). Productive Safety Net Program and Children's Time Use Between Work and Schooling in Ethiopia. In Cockburn, J., Kabubo-Mariara, J., and SpringerLink, editors, *Child Welfare in Developing Countries*, pages 157–209. Springer, New York.

Young-Lives (2014). Young lives survey design and sampling in ethiopia. preliminary findings

from the 2013 young lives survey (round 4).