Access to credit and heterogeneous effects on agricultural technology adoption: Evidence from large rural surveys in Ethiopia

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Abstract: Modern agricultural technologies hold great potential for increasing productivity and rapid poverty reduction in developing countries. However, adoption levels of these technologies have remained disappointingly low in Africa. This paper analyzes the effect of access to credit on adoption and use intensity of modern agricultural technologies using data from large rural surveys in Ethiopia. Using an instrumental variables (IV) approach to address the potential endogeneity concern due to possible reverse-causality and non-random access to credit, we find evidence that access to credit has a positive and significant effect on adoption and intensity of use of different agricultural technologies. However, important heterogeneities are observed. Strong and consistent effect is reported for chemical fertilizer. Credit accessed from formal sources is more important for the intensity of use than for the decision to adopt modern inputs. Credit taken with the primary purpose of financing agricultural inputs is more likely to promote technology adoption than credit taken *per se*. Also, it is important to distinguish between credit-constrained and non-constrained households in credit effect analysis—reported credit effects are larger when estimated against credit-constrained non-users as compared with the pool of credit non-users. The results remain robust to several sensitivity analyses. The policy implication of our results is that targeting and design of credit are important to leverage the effect of credit on adoption of modern agricultural technologies.

JEL Classification: G21, O12, O16, O23, Q14, Q16

Key words: Access to credit, technology adoption, impact heterogeneity, IV approach, Ethiopia

1. Introduction

Modern agricultural technologies hold huge potential for increasing farm level productivity and rapid poverty reduction in developing countries, particularly sub-Saharan Africa where the gap between potential and actual agricultural yield is substantial (World Bank, 2008; Licker et al., 2010). However, despite their potential to increase productivity and considerable efforts made in promoting adoption, many modern agricultural technologies have not been adopted as widely as hoped. Evidently, aggregate adoption rates remain disappointingly low in many sub-Saharan African countries (Feder et al., 1985; Duflo et al., 2011; Rashid et al., 2013; Sheahan and Barrett, 2014).

Explaining low adoption rates of potentially productive but risky agricultural technologies remains an important empirical challenge. A large literature has pointed to the role of credit constraints as a key deterrent to technology adoption and development in Africa (Giné and Klonner, 2005; Moser and Barrett, 2006; Zerfu and Larsen, 2010; Lambrecht et al., 2014; Abate et al., 2016).[1] In rural Africa, cash inflows do not arrive when inputs need to be purchased because of high seasonality of economic activities (Fink et al., 2014; Christiaensen, 2017). Thus, household cash resources are inadequate to finance investments in agricultural technologies, particularly those that require substantial investment (Croppenstedt et al., 2003).

Under these conditions, relaxing credit constraints is expected to improve technology adoption and aggregate agricultural productivity. Theoretically, access to credit can contribute to improved technology adoption through two main ways. More directly, access to credit can be

[1]The literature put forward other diverse but complementary reasons for low adoption, including profitability (Duflo et al., 2011; Minten et al., 2013; Christiaensen, 2017), imperfections in insurance markets (Cole et al., 2013; Karlan et al., 2015), poor land rights (Goldstein and Udry, 2008; Ali et al., 2014a), risk preferences (Liu, 2013; Barham et al., 2014), consumption risk (Dercon and Christiaensen,2011), and motivation and locus of control (Duflo et al, 2011; Abay et al., 2017). A practically obvious reason might be that modern agricultural technologies simply would not always yield expected returns, perhaps because of limited knowledge and education leading to inappropriate applications and poor management, or input complementarities (Feder et al., 1985; Spielman et al., 2011; Krishnan and Patnam, 2014).

used to finance more productive agricultural technologies, such as improved seeds and fertilizer, which farmers might not otherwise be able to afford (Diagne, 2002, Clark et al., 2015). Indirectly, access to credit can help poor farmers to cope with *ex post* risks associated with adopting potentially more productive but also riskier agricultural technologies. The fear of low consumption due to production risk pushes rural households to engage in low-risk but low-return agriculture activities that subsequently lock them into risk-induced poverty traps (Giné and Yang, 2009; Dercon and Christiaensen, 2011). This problem is compounded by complete absence of formal insurance markets in rural Africa (Karlan et al., 2015). In such settings, access to credit—as it relates to smoothing consumption variabilities—is expected to allow poor households to avoid risk-reducing diversification strategies and precautionary savings to instead invest in high-return agricultural activities (Eswaran and Kotwal, 1990; Udry, 1991; Ali, et al., 2014a). In line with these arguments, many studies have documented positive effects of access to credit on technology adoption using various empirical strategies (Croppenstedt et al., 2003; Giné and Klonner, 2005; Moser and Barrett, 2006; Duflo et al., 2011; Lambrecht et al., 2014; Abate et al., 2016).

In this study, we contribute to the literature in two important ways. First, we carry out a series of heterogenous analyses to identify relevant sources of variations in effects of credit.[2] Reporting average effects may mask substantial heterogeneity and bias true effects of access to credit (Suri, 2011). Heterogeneous impacts related to borrower characteristics, such as farm size and education, have been a common theme in evaluations of credit and microfinance programs (Feder and O'Mara, 1981; Just & Zilberman, 1983; Feder et al., 1985; Suri, 2011; Banerjee et al., 2015; Crépon et al., 2015). However, impact heterogeneities due to the nature and purpose of credit are less explored. Abate et al. (2016) is a notable exception, which showed

[2] 'Access to credit' refers to those who actually managed to take certain amount of credit and used it for different purposes over the previous 12 months prior to the survey.

that the institutional design of relatively formal lending institutions induced impact variations—credit accessed through cooperatives had a greater impact on technology adoption than through microfinances in Ethiopia. In this study, we examine heterogeneous effects of credit due to the nature of credit sources (informal vs. formal) and purpose to which credit is committed (agricultural vs. non-agricultural). Such analysis can provide policy-relevant insights to leverage effects of credit on agricultural technology adoption.

Second, we distinguish between credit-constrained and non-constrained households to study the full burden of liquidity constraint on agricultural technology adoption. Poor farm households could be credit constrained for several reasons, including cost of borrowing, transaction costs, and risk aversion (Ali and Deininger, 2012; Mukasa et al., 2017). Access to credit is expected to greatly promote adoption only if it targets households that face binding liquidity constraints. The difficulty to distinguish whether farm households are credit constrained or not has posed a serious challenge to estimating the effect of credit on those who actually take it up (Crépon et al., 2015).[3] Particularly, estimating effect without differentiating between credit-constrained and non-constrained households is likely to underestimate the true effect of access to credit for those who want credit the most (both in credit user and non-user groups).[4] This paper seeks to provide evidence on the full burden of credit constraint on technology adoption by the poor.

The analysis of this paper relies on rich and detailed data collected in a large survey of households from the four main regions in Ethiopia—Tigray, Amhara, Oromia, and Southern Nations, Nationalities and Peoples Region (SNNP). The survey included comprehensive modules on the use of agricultural technologies, household sociodemographic and community

[3] Note that this challenge is not related to the so-called counterfactual problem of the impact evaluation literature.
[4] Perhaps, this might partially explain routinely reported positive but statistically insignificant results on welfare impacts of microcredit (Rooyen et al., 2012; Banerjee et al., 2015; Crépon et al., 2015; Tarozzi et al., 2015).

characteristics. The dataset uniquely contains detailed information on credit access, and its sources and purposes. The survey also asked credit non-users for main reasons for not using credit, thereby allowing us to identify credit-constrained and unconstrained non-users. The measurement of outcome variables is comprehensive and includes four important agricultural technologies: (i) chemical fertilizer (DAP, Urea and NPS), (ii) improved seeds, (iii) agricultural chemicals (pesticides, herbicides, fungicides), and (iv) other technologies (use of manure, compost and irrigation).

Another contribution of this paper follows Feder (1982) which allows us to define technology adoption as a two-stage decision-making process. The first-stage decision is the propensity of a farmer to adopt a modern technology ('adoption'), and once the decision to adopt is settled, the second-stage decision is how much of the technology to use ('intensity'). Conceptualizing technology adoption this way is especially useful for divisible inputs such as fertilizer, improved seed and agricultural chemicals, as the ultimate effect of these technologies essentially depends on the intensity of their use (Feder et al., 1985; Abate et al., 2016).

An obvious empirical challenge for this type of work is that access to credit may be endogenous due to potential reverse causality and omitted variables, such as entrepreneurial behavior, that may drive the affinity of households to use credit. To address this challenge, we rely on instrumental variables (IV) strategy for credible identification. We employ distance to the nearest formal credit source and the average credit amount in the community excluding the household of interest as instruments. To establish the validity of the instruments, we subject them to a battery of tests. Despite this, we realize that some reservations may remain with unobserved heterogeneities to the extent that they contaminate the exclusion restriction requirement for instruments. To further minimize this concern, we carry out formal analyses on the sensitivity of our results to unobserved heterogeneity using panel fixed effect estimators.

Our main finding is that access to credit significantly enhances adoption and intensity of use of improved agricultural technologies. However, there is considerable variation across different technologies. The strongest and consistent effect is observed for chemical fertilizer. We also find that the nature of the source of credit matters—credit from formal and informal sources appears to play different roles in the technology adoption process. Specifically, credit accessed from formal sources is strongly correlated with the intensity of technology adoption rather than with the decision to adopt. Credit taken with the primary purpose of financing agricultural inputs tends to be more important for promoting technology adoption compared to credit taken *per se*. The effect of credit on those who used credit is significantly higher when it is estimated against credit-constrained non-users as compared with the pool of credit non-users (both constrained and unconstrained). This suggests that credit constrained non-users are greatly disadvantaged in terms of technology adoption. Overall, our findings underlie the importance of accounting for heterogeneous impacts in assessing the effects of credit on technology adoption. The results provide useful insights into targeting and design of credit that are relevant for policymaking geared towards promoting increased adoption.

The rest of the paper is organized as follows. Section 2 outlines the data and the econometric approach of the study. Section 3 presents and discusses the results. Section 4 provides some robustness checks and sensitivity analyses, while Section 5 concludes the paper.

2. Data and econometric approach

2.1. Data and descriptive analysis

We use a two-wave panel data collected by the Central Statistical Agency (CSA) of Ethiopia in collaboration with the International Food Policy Research Institute (IFPRI) for the evaluation of the Feed the Future (FtF) program in Ethiopia. FtF is part of a program supported by the U.S. government to address global hunger by sustainably increasing agricultural productivity, access to markets and incomes for the rural poor[5]. The main strategy is to focus attention on defined area of coverage—Zone of influence (ZOI)—in order to measure impact. In Ethiopia, the ZOI covers 149 districts where the FtF projects were implemented over the five year period of 2013-2017 (Bachewe et al., 2014).

The survey design followed stratified random sampling of program districts, Enumeration Areas (EAs) and households from major regions of the country—Tigray, Amhara, Oromia, and SNNP.[6] First, 56 districts from among the 149 FtF districts and 28 comparable districts outside the FtF area were randomly selected from the five major regions. Then, from each selected district, three EAs were randomly selected. Finally, 28 households from each EA were randomly selected based on a list of households in each sampled EA.

This sampling framework produced a total of 6,977 households in 84 districts from whom the baseline data were collected in June 2013. The follow up survey, conducted in 2015, resurveyed 6,696 households that continued to live in the same districts[7]. While the sample was not nationally representative, it was designed to represent 6.16 million rural households (roughly 31 million individuals) in the regions. It included detailed modules on adoption and intensity of use of agricultural technologies, credit use and relevant household and community characteristics. Since the dataset contained detailed information on the type, size and sources of credit, it is suitable to conduct extensive heterogonous analysis. Community-level information on credit sources and other factors that might influence technology adoption, such as infrastructure and institutions, were also collected. Table A1 in the appendix presents the description of all variables and their summary by splitting the sample over the two survey years.

[5] More on feed the future program at https://www.feedthefuture.gov/

[6] The survey included Somalia region, but we dropped it from our analysis, as overall input use in the region is almost none. This is not surprising given the region is largely dryland and dominated by pastoralists.

[7] The resulting attrition rate is only 4%. This attrition rate is low compared to similar sized surveys. We failed to reject the null hypothesis that attrited households are not systematically different from the rest of the sampled households in key covariates.

We systematically aggregated individual inputs in the analysis. Specifically, we sum up the quantity of different types of chemical fertilizers (Dap, Urea, and NPS) to define chemical fertilizer. The same is true for agricultural chemicals (pesticides, fungicides, and herbicides). However, we also replicated the basic analysis using individual inputs. These results are presented in Tables A2 and A3 in the appendix.

The access to credit indicator is generated based on the survey question posed to each respondent as: “over the last 12 months, did you or anyone in this household borrow credit from someone outside the household or an institution?”. Overall, about 12% of the surveyed households had borrowed. The average volume of credit among those who took credit is 3,679 Eth. Birr (approximately $193 based on the average exchange rate of the survey years). There is a slight growth in both the propensity of credit use and intensity over the two rounds though it still remains very low compared to other developing countries (Mukasa et al., 2017; World Bank, 2014).

For Ethiopia, studies suggest that limited access to credit has negative implications for households’ income generating activities and consumption smoothing ability (Croppenstedt et al., 2003; Dercon and Christiaensen, 2011; Setargie, 2013). This is attributed to lack of adequate credit supply, high cost of borrowing, inadequate collateral and risk averseness of borrowers (Ali et al., 2014b; Mukasa et al., 2017). Alternatively, the low prevalence of credit use could partially be consistent with lack of demand for credit. Indeed, 10% of credit non-users mentioned availability of own capital as their main reason for not using credit.

Table 1 presents descriptive statistics and simple mean difference tests for variables by credit use status of households. Panel A of Table 1 shows that distributions of several covariates are significantly different between credit users and non-users. This points to the need to control for a set of household and community level variables in the analysis to attenuate many potential sources of selection biases (see below). The last two rows of panel A present the descriptive of the two instruments by access to credit. The average difference in magnitudes of both variables between the two groups are statistically significant with the theoretically expected sign.

Panel B of Table 1 provides information on outcome variables. Outcome variables include adoption of several important agricultural technologies. Four groups of technologies were identified: i) chemical fertilizers (DAP, Urea and NPS), (ii) improved seeds, (iii) agricultural chemicals (pesticides, herbicides, fungicides), and (iv) other technologies (use of manure, compost and irrigation). This schema could reflect the level of required investment capital and extent of risk involved thereof related to the different categories of technology. Furthermore, we consider adoption as a two-stage decision, and distinguish between the propensity to adopt and the intensity of adoption.

Generally, the descriptive results show that households adopted all agricultural technologies in some degree. Chemical fertilizer is the most adopted technology (used by about 62% of the households), while improved seeds are the least adopted technologies (21%). Overall, propensities to adopt agricultural inputs are significantly different between credit users and non-users. On average, households that have accessed credit tend to have higher rates of adoption. About 80% of the households with access to credit used chemical fertilizer, while only 60% of those without access to credit used the technology. Adoption rates of other technologies show similar patterns (Table 1). However, when we look at the intensity of use, credit appears to be significantly correlated only with the application of chemical fertilizer and improved seed. Credit users applied 80.8 kg per hectare of chemical fertilizer as compared with 60.3 kg per hectare applied by credit non-users. However, these results cannot be used to make causal inferences regarding the effect of credit on technology adoption, since they do not account for potential confounding factors. We employ instrumental variables (IV) approach for identification.

Table 1: Descriptive statistics of the study sample by credit use status

Variable	**Overall sample (N=12,137)**	**Credit users (N=1,451)**	**Credit non-users (N=10,686)**	**Mean difference test (p-value)**
Panel A: Covariates				
Head is female, yes=1	0.27	0.23	0.28	0.00
Age of household head	44(14.9)	42(13)	44(15.1)	0.00
Household size	4.9(2.1)	5.2(2.1)	4.9(2.1)	0.00
Formal completed years of education level of head	1.5(2.8)	1.6(2.8)	1.4(2.8)	0.03
Land size in hectares	1.6(2.6)	1.8(1.6)	1.6(2.7)	0.01
Livestock owned in TLU[ɸ]	3.3(3.9)	3.1(3.2)	3.3(4)	0.15
Durable assets owned[¶]	0.05(1.4)	0.22(1.3)	0.02(1.4)	0.00
Household has good floor, yes=1	0.09	0.1	0.09	0.81
Household has good roof, yes=1	0.43	0.52	0.41	0.00
Access to electricity, yes=1	0.06	0.06	0.06	0.26
Religion-Orthodox, yes=1	0.53	0.64	0.51	0.00
Religion-other Christian, yes=1	0.25	0.24	0.25	0.22
Religion-others, yes=1	0.02	0.01	0.03	0.00
Plot distance from residence in km	14.7(26.6)	17.4(36.1)	14.3(25)	0.00
Share of plots with fertile soil	0.71(0.4)	0.66(0.4)	0.72(0.4)	0.00
Share of plots with plain slope	0.73(0.4)	0.74(0.4)	0.73(0.4)	0.26
Average size of credit in village in Birr	440 (895)	1202(1503)	336 (717)	0.00
Distance to credit sources in km	4.11 (12.8)	2.11 (7.3)	4.38 (13.3)	0.00
Panel B: Outcome variables				
Propensity of input adoption (% HHs)				
Chemical Fertilizer	62.4	80	60	0.00
Improved seeds	20.8	35.1	18.9	0.00
Agricultural chemicals	28.1	35.3	27.1	0.00
Other technologies	48	58.6	46.5	0.00
Quantity of inputs used				
Chemical Fertilizer (kg per hectare)	62.8(98.9)	80.8(97.4)	60.3(98.9)	0.00
Improved seeds (kg per hectare)	5.14(22.9)	6.6(24.1)	4.9(22.8)	0.01
Agricultural chemicals (liters per hectare)	1.4(9.9)	1.31(8.7)	1.4(10.2)	0.83

Source: Ethiopian FtF survey (2013, 2015)

Note: Standard deviations are presented in parentheses. [ɸ] Livestock was measured using tropical livestock units (TLU), which is a common unit used to quantify a wide range of various livestock species to a single figure to get the total amount of livestock owned by a household. We employed a tropical livestock unit applicable for SSA. [¶] Durable assets owned is an index generated using principal component analysis from individual asset items owned by households.

Farmers financed input purchases in several ways. They primarily finance modern input purchases with cash from crop and livestock sales and nonfarm activities. Cash financing accounts for 84% of chemical fertilizer, 50% of improved seed and 93% of agricultural chemical purchases of survey households. Only small proportion of households used credit to finance purchase of modern inputs. Relatively, credit appears to be more important for financing chemical fertilizer purchases. Of the total farmers who applied chemical fertilizer, 16% used credit to finance its purchases. But credit use is very low for improved seed (4%) and agricultural chemical purchases (1%), perhaps because these inputs are usually required in small volumes and hence primarily financed by households' own resources. Relatedly, households purchase inputs from four major sources of input purchases; in order of their importance, these sources are service cooperatives, government extension agents, producer cooperatives and local markets. Farmers also sparsely purchase inputs from other sources, including private traders, other farmers, NGOs and agro-dealers. About 10% of the farmers reported accessing improved seeds from own production (recycling their own-saved seed).

2.2. Econometric approach

We model adoption and intensity of use of agricultural technologies ($\mathrm{T_{it}}$) reported by household i at time t as a function of use of credit ($\mathrm{C_{it}}$), and specify the basic econometric model as:

$$T_{it} = \beta_0 + \beta_1 C_{it} + \beta_2 X_{it} + \varepsilon_{it} \quad \text{………………………………………………………} (1)$$

where X_{it} is a vector of plot, household and community level characteristics. Plot level characteristics include slope of the plot, fertility of the soil and distance of the plot from residence. Household characteristics cover household size, religion and education level of the household head, log (value of durable assets), log (size of livestock owned, in TLU), log (land size) and other wealth indicators (e.g., housing quality). Woreda (district) level dummies are included to control for observed and unobserved agro-ecological and other characteristics associated with each district. The last term in the equation, ε_{it}, is the random error term. Standard errors are clustered at the village (kebele) level.

In equation 1, β_1 captures the main relationship of interest: the effect of credit use on technology adoption. Our central hypothesis is that credit relaxes households' liquidity constraint to finance agricultural technology adoption and, hence, β_1 is positive. However, as indicated before, credit use might be endogenous, rendering the consistency of β_1 estimated using ordinary least squares (OLS) questionable. β_1 could be biased due to at least two main reasons. First, despite the sufficiently large set of variables controlled for in our specification, omitted variables could still be a problem. For instance, credit users might have distinct risk profile or entrepreneurship quality. This might lead to biased estimate of the effect of credit use on technology adoption. Second, reverse causality might also be a problem. For example, good harvest resulting from technology use could be used to finance and/or serve as collateral to obtain credit.

When credit use is endogenous, $corr(C_{it}, \varepsilon_{it}) \neq 0$ and β_1 would be biased. We adopt instrumental variables (IV) approach to address this endogeneity concern. The identification of instrumental variables is guided by previous literature and insights from recent efforts to increase availability of agricultural credit to smallholder farmers in Ethiopia. Over the last few years, Ethiopia has adopted a more market-oriented financial system to increase agricultural credit availability for smallholder farmers, and specialized microfinance institutions and financial cooperatives have become important sources of credit for farmers (Amha and Peck, 2010; Abate et al., 2016). Simultaneously, a large majority of smallholders in the country continue to heavily draw on informal credit sources (Setargie, 2013). Based on these insights, we use distance to the nearest formal source of credit and the average credit amount in the community excluding the household of interest as instruments. Distance to formal credit sources is a key factor affecting the physical approach and transaction costs of accessing credit by the poor. On the other hand, the average credit amount in the community excluding the household of interest is considered to reflect the overall availability of credit from both formal and informal sources in communities. It may also account for community level differences in costs and norms related to accessing credit from informal sources.

The validity of IV strategy rests on two criteria. The first criterion is the relevance criterion that instruments should be good predictors of credit use. To formally test for this criterion, we estimated credit use as a function of our instruments and other relevant household and community characteristics. Table 2 shows the first stage regression results, with more covariates are gradually included starting from a parsimonious model. The coefficients on the instruments are statistically significant and appear with expected signs.

The second criterion for good instruments is the exclusion restriction that requires instruments not to affect the outcome variable (i.e. technology adoption), other than through the credit use channel. This criterion is more difficult to satisfy and even more so to prove. The average credit amount in the community excluding the household of interest is primarily an outcome of a combination of policy, institutions and other community level factors and can be reasonably considered exogenous to production choices of individual households. Regarding our distance instrument, one potential concern is that households concerned about their financial access may relocate to areas characterized by better credit access. If so, this would violate the exclusion restriction. However, we think that this does not pose a serious threat given the structure of the Ethiopian land system. In Ethiopia, all land is owned by the state (Deininger et al., 2008). Individual farmers enjoy only user rights and cannot officially sell the land. Moreover, the Ethiopian land proclamation has made enjoying secure and continuous land use rights contingent on permanent physical residence in the community (Deininger and Jin, 2006). The absence of land markets means that households seeking better access to credit, and hence production outcomes, would have considerable difficulties doing so by relocating their farms.

Table 2: First stage regression results—determinants of households' access to credit

Explanatory variable	**Credit use**	**Credit use**
Log (credit size in village)	0.033***	0.017***
	(0.001)	(0.001)
Log (distance to credit source in km)	-0.005**	-0.006**
	(0.002)	(0.003)
Plot and household characteristics	No	Yes
Woreda fixed effects	No	Yes
Constant	-0.006	0.204***
	(0.004)	(0.053)
Adjusted R^2	0.089	0.136
F test of excluded instruments:		
F (2, 236)	474.9	28.4
Prob > f	0.00	0.00
Weak-identification tests		
Cragg-Donald f-statistic		69.11
Kleibergen-Paap rk Wald f-statistic		28.35
Kleibergen-Paap p-value		0.000***
Number of observations	12,137	11,871

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

Another specific concern with the distance instrument is that formal credit sources, like microfinance institutions, are mostly located in district towns, which are usually considered as centers for the respective districts with broader social interactions. As such, our distance instrument may also pick effects of other factors on technology adoption. However, this is less likely to be the case as major markets are also located in district towns, and credit non-users would also be randomly exposed to similar social networks and interactions as they travel to market for shopping or other reasons. We turn to this issue in our sensitivity analysis.

3. Results

3.1. Basic results

We set out the analysis by establishing the causal effect of credit use on the propensity to adopt and intensity of agricultural technology adoption. To set the stage, we first estimate the association between credit use and the propensity to adopt different improved technologies through estimating a simple linear probability model (LPM).[8] Results presented in Table 3 show that credit use is positively associated with adoption of different modern agricultural technologies. These results suggest that farmers who used credit are more likely to adopt the different agricultural technologies by 4% to 10% points compared to those who did not take credit.

Next, rather than using adoption dummies, we use quantity of inputs that measures intensity of adoption. In the dataset, intensity of use of 'other technologies' was not asked. Therefore, estimates are presented only for chemical fertilizer, improved seed and agricultural chemicals. OLS regression results are presented in Table 4. The results show that the use of credit is positively correlated with the quantities of chemical fertilizer and improved seed. Specifically, compared to credit non-users, households with access to credit are likely to apply 35.3% more chemical fertilizer per hectare and about 9.4% more improved seed per hectare.

Tables 3 and 4 also reveal that adoption decision and intensity of use of different agricultural technologies are significantly correlated with many other covariates. Of course, some of these estimates should not be interpreted causally as they are likely to be endogenous. Consistent with other empirical studies, results in Table 3 show that standard wealth indicators—type of roof, ownership of livestock, and ownership of durable assets—appear to be important covariates of technology adoption. Household size and demographic characteristics of the household head are also found to have significant association with adoption of agricultural technologies. Similarly, many of these covariates are significantly associated with the intensity of use of different inputs (Table 4).

[8] Here we report regression results based on the identified four groups of modern technologies but results using individual inputs as outcome variables are reported in appendix A2, and they remain on balance qualitatively similar.

Table 3: Association between credit use and propensity of adoption of agricultural technologies

Outcome variables	**Chemical Fertilizer**	**Improved seed**	**Agricultural Chemicals**	**Other technologies**
Access to credit	0.088***	0.043***	0.045***	0.062***
	(0.012)	(0.013)	(0.015)	(0.015)
Survey round 2015	0.060***	0.105***	0.041***	0.063***
	(0.012)	(0.012)	(0.015)	(0.019)
Head is female	-0.029***	-0.004	-0.020**	-0.013
	(0.009)	(0.008)	(0.008)	(0.009)
Log (age of household head)	-0.031***	-0.025**	-0.031***	0.023*
	(0.012)	(0.010)	(0.012)	(0.013)
Log (household size)	0.051***	0.021*	-0.015	0.019
	(0.012)	(0.011)	(0.011)	(0.013)
Log (education level of head)	0.000	0.004	0.004	0.006
	(0.005)	(0.005)	(0.005)	(0.006)
Log (land size in hectares)	0.080***	0.056***	0.092***	0.053***
	(0.013)	(0.011)	(0.013)	(0.015)
Log (livestock owned in TLU) ɸ	0.043***	0.017**	0.058***	0.072***
	(0.008)	(0.007)	(0.008)	(0.009)
Log (durable assets owned) ¶	0.066***	0.025***	0.019*	0.067***
	(0.009)	(0.009)	(0.010)	(0.012)
Household has good floor	0.000	0.014	0.013	-0.014
	(0.014)	(0.017)	(0.015)	(0.022)
Household has good roof	0.059***	0.026**	-0.001	-0.017
	(0.013)	(0.010)	(0.010)	(0.013)
Access to electricity	-0.058*	0.009	-0.069***	-0.051**
	(0.034)	(0.025)	(0.027)	(0.024)
Religion (reference=Muslim)				
Religion-Orthodox	0.052*	0.019	0.027	-0.006
	(0.031)	(0.017)	(0.025)	(0.026)
Religion-other Christian	0.038	0.015	-0.010	-0.028
	(0.029)	(0.022)	(0.025)	(0.027)
Religion-others	-0.013	0.024	0.009	0.014
	(0.040)	(0.030)	(0.032)	(0.047)
Log (plot distance from residence in km)	0.032***	0.013***	0.016***	-0.022***
	(0.005)	(0.004)	(0.005)	(0.005)
Share of plots with fertile soil	-0.020	-0.026**	-0.032**	-0.019
	(0.014)	(0.013)	(0.014)	(0.018)
Share of plots with plain slope	0.042**	0.008	0.017	0.004
	(0.017)	(0.012)	(0.016)	(0.019)
Woreda fixed effects	Yes	Yes	Yes	Yes
Constant	0.136	-0.188***	0.363***	0.060
	(0.214)	(0.045)	(0.121)	(0.080)
Adjusted R^2	0.414	0.306	0.344	0.207
Number of observations	11,871	11,871	11,871	11,871

Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. ɸ Livestock is measured using tropical livestock units (TLU), which is a common unit used to quantify a wide range of various livestock species to a single figure to get the total amount of livestock owned by a household. We employed a tropical livestock unit applicable for SSA. ¶ Durable assets owned is an index generated using principal component analysis from individual asset items owned by households.

Table 4: Association between credit use and intensity of agricultural technology use

Outcome variables	**Chemical Fertilizer (kg per ha)**	**Improved seed (kg per ha)**	**Agricultural Chemicals (liter per ha)**
Access to credit	0.353***	0.094**	0.007
	(0.053)	(0.039)	(0.024)
Survey round 2015	0.215***	0.236***	-0.017
	(0.054)	(0.036)	(0.025)
Head is female	-0.180***	-0.018	-0.040***
	(0.041)	(0.021)	(0.015)
Log (age of household head)	-0.185***	-0.049	-0.021
	(0.053)	(0.030)	(0.018)
Log (household size)	0.245***	0.058*	-0.055**
	(0.054)	(0.032)	(0.022)
Log (education level of head)	0.009	0.013	-0.002
	(0.022)	(0.017)	(0.009)
Log (land size in hectares)	-0.271***	-0.082***	-0.099***
	(0.059)	(0.030)	(0.021)
Log (livestock owned in TLU) [ɸ]	0.276***	0.058***	0.066***
	(0.036)	(0.021)	(0.013)
Log (durable assets owned) [¶]	0.258***	0.067**	0.012
	(0.043)	(0.028)	(0.016)
Household has good floor	-0.032	-0.008	-0.035
	(0.057)	(0.047)	(0.029)
Household has good roof	0.300***	0.067**	-0.012
	(0.057)	(0.028)	(0.015)
Access to electricity	-0.216	-0.010	-0.034
	(0.146)	(0.064)	(0.032)
Religion (reference=Muslim)			
Religion-Orthodox	0.273*	0.119**	0.062*
	(0.139)	(0.050)	(0.036)
Religion-other Christian	0.236*	0.069	0.045
	(0.127)	(0.065)	(0.042)
Religion-others	0.103	0.039	0.011
	(0.159)	(0.071)	(0.044)
Log (plot distance from residence in km)	0.179***	0.043***	0.028***
	(0.023)	(0.011)	(0.007)
Share of plots with fertile soil	-0.070	-0.060	-0.050*
	(0.063)	(0.041)	(0.030)
Share of plots with plain slope	0.201**	0.024	0.024
	(0.078)	(0.031)	(0.027)
Woreda fixed effects	Yes	Yes	Yes
Constant	0.755	-0.359**	0.268***
	(0.731)	(0.147)	(0.091)
Adjusted R^2	0.463	0.245	0.122
Number of observations	11,869	11,869	11,869

Note: *** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. [ɸ] Livestock is measured using tropical livestock units (TLU), which is a common unit used to quantify a wide range of various livestock species to a single figure to get the total amount of livestock owned by a household. We employed a tropical livestock unit applicable for SSA. [¶] Durable assets owned is an index generated using principal component analysis from individual asset items owned by households

An interesting result is that both adoption and intensity of use of fertilizer, improved seed and agricultural chemicals are positively and significantly associated with plot distance from residence. At glance, this correlation appears counter intuitive. However, the positive correlation between technology adoption and plot distance from residence is plausible, as organic and inorganic inputs can be substitutable. Mixed crop-livestock farming is predominant in a large part of rural Ethiopia, and the use of organic fertilizers (crop and animal residues) is very common. When used, organic fertilizer is likely to be used on plots that are closer to residence, as it is heavy to transport to distant plots. This is also confirmed by the significant negative association between this variable and adoption of other technologies i.e. use of manure, compost and irrigation (Table 3).

Lastly, the survey round dummy appears with positive and significant coefficient in all regressions in Table 3, and in the chemical fertilizer and improved seed models in Table 4. This indicates that the propensity and intensity of agricultural technology adoption generally improved between 2013 and 2015. This is also corroborated by the clear time trend for credit use between the survey periods. The share of households who used credit was smaller in 2013 than in 2015, increasing from 8% to 16%.

However, as discussed earlier, credit use may be endogenous in models explaining technology adoption and intensity of use. To attenuate this concern, we employ an IV strategy. We use distance to the nearest formal source of credit and average credit size in the community excluding the household of interest as instruments. The results for adoption and intensity of use of different technologies based on the IV estimations are presented in Tables 5 and 6, respectively. While we control for plot and household characteristics in all regressions that follow, in the interest of preserving space, hereafter we only report coefficients associated with our key variables of interest, access to credit, in all tables. The results in Table 5 show that credit use has causally contributed to increasing adoption propensity of different agricultural technologies. Similarly, Table 6 indicates that credit use has a causally positive effect on the intensity of application of chemical fertilizers and agricultural chemicals. However, the effect of credit use on the quantity of improved seed is insignificant. Further, while the results of the simple regressions and IV estimations are largely consistent, the coefficients of the credit variable are generally higher for the IV estimates than their corresponding values from the simple regressions. Such differences are consistent with measurement error, as expected in retrospective data measurements from rural household surveys. While measurement errors can lead to an attenuation bias towards zero in the LPM and OLS coefficients (Theil, 1971: p. 608), instrumental variable approaches often mitigate such problems (Gujarati, 2003: p. 527).

Table 5: Effect of credit use on propensity of adoption of agricultural technologies, IV

Outcome variables	**Chemical Fertilizer**	**Improved seed**	**Agricultural Chemicals**	**Other technologies**
Access to credit	1.087***	0.219**	0.472**	0.626**
	(0.267)	(0.096)	(0.214)	(0.286)
Plot and household characteristics	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.018	0.289	0.261	0.089
Weak-identification tests				
Cragg-Donald test	69.11	69.11	69.11	69.11
Kleibergen-Paap LM statistic	32.9	32.9	32.9	32.9
Kleibergen-Paap p-value	0.000	0.000	0.000	0.000
Over-identification test				
Hansen-J test	1.562	0.003	0.202	10.582
Hansen-J p-value	0.211	0.957	0.653	0.001
Number of observations	11,871	11,871	11,871	11,871

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

Table 6: Effect of credit use on intensity of agricultural technology use, IV

Outcome variables	**Chemical Fertilizer (kg per ha)**	**Improved seed (kg per ha)**	**Agricultural Chemicals (liter per ha)**
Access to credit	3.899***	0.189	0.806**
	(1.158)	(0.491)	(0.328)
Plot and household characteristics	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes
Adjusted R^2	0.219	0.244	-0.019
Weak-identification tests			
Cragg-Donald test	69.04	69.04	69.04
Kleibergen-Paap LM statistic	32.87	32.87	32.87
Kleibergen-Paap p-value	0.000	0.000	0.000
Over-identification test:			

Hansen-J test	2.355	1.473	0.106
Hansen-J p-value	0.125	0.225	0.744
Number of observations	11,869	11,869	11,869

**** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.*

Finally, all standard tests for valid instruments indicate that the performance of our instruments is reasonably good. As shown in the first-stage regression, our instruments are relevant (i.e. good predictors of credit use), and the associated partial F-statistic for the model with only the instruments as explanatory variables ($F = 474.9$) is way above the minimum 10 threshold value of the "rule of thumb" for valid instruments (Staiger and Stock, 1997). Tables 5 and 6 also provide further qualifications for the performance of our instrumental variables in the IV-diagnostics. The critical values of the Cragg-Donald test statistic reject the null hypothesis that the endogenous regressor is weakly identified. The Kleibergen-Paap test also rejects the hypothesis of under-identification, i.e. the minimal canonical correlation between the endogenous variable and the instruments is statistically different from zero. The Sargan test statistics of over-identification fail to reject the null hypothesis that our over-identifying restrictions are valid across the different IV regressions, i.e. we cannot reject the null hypothesis of zero correlation between the instruments and the error term.

Overall, we contend that the instrumentation strategy is credible, and the main findings support the argument that improving credit availability leads to increased adoption and application rates of modern agricultural technologies. Meaning, where credit is severely lacking, smallholder farmers may not be able to adopt and properly apply productivity boosting modern technologies. These results are consistent with previous studies by Croppenstedt et al. (2003), Giné and Klonner (2005), Moser and Barrett (2006), Duflo et al. (2011), Lambrecht et al. (2014) and Abate et al. (2016) that reported that credit constraint is an apparent reason for variations in adoption rates of agricultural technologies in Africa and beyond.

3.2. Analyses of heterogeneous effects of credit

We now turn to one of the central objectives of this paper: assessing heterogeneous effects of credit use. The foregoing analysis shows that credit availability increases both the likelihood of adoption of modern agricultural technologies and the intensity of their use. In this section, we present a critical analysis of effect heterogeneities and identify the relevant sources of the heterogeneities. More precisely, we examine whether the effect of credit use on technology adoption varies with respect to the source of credit and the purpose for which credit has been sought by households. Further, we disaggregate credit non-users into credit-constrained and unconstrained, and study if and how they differ in terms of their adoption behavior and intensity of technology use. To begin with, we summarize the heterogeneous patterns of agricultural technology adoption by type of credit sources, reason for seeking credit and the extent of credit constraint (Table 7). The global observation from these sets of sub-sample analyses is that there appears substantial variation in technology adoption across the different sub-samples, though not equally across all technology types (see below).

For conciseness, we report results from the more formal parametric analyses only for chemical fertilizer — a key input that has long been actively promoted by national agricultural research and extension systems in Ethiopia. Our data also show that chemical fertilizer is the prominently adopted improved technology among surveyed farm households (Table 1). In addition, reporting results only for chemical fertilizer allows us to tell consistent story across the set of heterogenous analyses. Throughout, we assess heterogeneous effects by interacting credit use with our variables of interest. We expect these interaction terms to be potentially endogenous as is the credit use variable. In theory, correcting for the endogeneity requires using the same instruments for credit use to instrument for the interactions. However, this would make the analyses less straightforward, and the interpretation of the results somewhat complicated. As a result, the reported regression coefficients should be interpreted as correlations rather than causal effects.[9]

Table 7: Mean comparison of propensity of technology adoption and intensity of use over sub-sample categories

	Credit used for inputs			Credit accessed from formal source			Credit use and credit-constraint status				
	No	Yes	Mean difference test (p-value)	No	Yes	Mean difference test (p-value)	Credit use	No credit, not constrained	No credit, constrained	Mean difference test (p-value)	
							[A]	[B]	[C]	[A] vs [B]	[A] vs [C]
Panel A: Propensity of technology adoption											
Inorganic Fertilizer	0.68	0.84	0.00	0.75	0.83	0.00	0.80	0.72	0.56	0.00	0.00
Improved seeds	0.35	0.51	0.00	0.38	0.50	0.00	0.46	0.33	0.27	0.00	0.00
Agricultural chemicals	0.30	0.37	0.01	0.36	0.35	0.87	0.35	0.33	0.25	0.10	0.00
Other technologies	0.59	0.59	0.92	0.62	0.57	0.11	0.59	0.51	0.45	0.00	0.00
Panel B: Intensity of technology use											
Inorganic Fertilizer	61.58	131.59	0.00	68.01	133.57	0.00	112.24	93.61	64.90	0.00	0.00
Improved seeds	16.90	18.19	0.73	16.78	18.34	0.66	17.83	20.29	15.33	0.41	0.22
Agricultural chemicals	4.03	1.13	0.07	1.13	2.32	0.44	1.93	3.62	1.69	0.20	0.74

Source: Authors' computation based on Ethiopian FtF survey (2013, 2015)

We start by reporting heterogeneous effects based on purposes for which households accessed credit. We differentiate between credit obtained for agricultural investments and non-agricultural purposes (e.g. food consumption and non-agricultural business). As much as developing countries do not often provide enough credit to smallholder agricultural sector, growth in the volume of credit to smallholder farmers may not necessarily translate into investments in agricultural technologies. Credit funds are fungible, and it is possible that farmers use their credit for purposes other than agriculture. It has been observed that, while many farm households overwhelmingly reported using credit at least partially for input, many of them also reported using part of their credit for consumption and other purposes. About 72% of the households who accessed credit reported using it at least partly to finance input purchases. About 67% of the households did not repay their credit as per original schedules. Using credit

9 For completeness, we run these regressions instrumenting for the interactions and results remained robust and consistent with results from the simple regressions.

for unintended purposes was the main reason for not repaying credit for 35% of the sampled households.

Table 7 shows that farm households who obtained credit initially to purchase inputs are more likely to adopt and, have significantly higher rates of application of chemical fertilizer and agricultural chemicals than do those who accessed credit for non-agricultural purposes. For improved seed, while targeted credit demand is more effective to enhance propensity of use, it is weakly correlated with the quantity of use per hectare. Perhaps, one reason could be that many farmers use second-generation improved seeds saved from previous harvest years.

We estimate the basic parametric model by including both the credit use dummy and a dummy variable indicating if the credit was obtained to purchase inputs as regressors and the regression results in Table 8 largely corroborate the findings of the sub-sample heterogeneity analysis. Thus, the purpose to which credit was committed to is as important for adoption of chemical fertilizer as taking credit itself. Decisively, its effect is even more robustly important for the quantity of fertilizer used by farm households. From a policy perspective, this can provide tentative support that input voucher systems can promote adoption of improved technologies more rather than conventional credit schemes of directly providing monetary credit.

Table 8: Heterogeneous impact of purpose of credit use on fertilizer use

Outcome variables	**Propensity of adoption**	**Quantity (kg per hectare)**
Access to credit	0.061***	0.132
	(0.021)	(0.087)
Access to credit*credit used for input	0.038*	0.310***
	(0.021)	(0.093)
Plot and household characteristics	Yes	Yes
Woreda fixed effects	Yes	Yes
Adjusted R^2	0.415	0.463
Number of observations	11,871	11,869

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

We next investigate if the source of credit matters for technology adoption and intensity of use. We differentiate between formal and informal sources of credit based on households' response to the survey question: "*From whom or which institution was the application made for a loan?*". Formal sources include microfinance institutions, commercial banks, NGOs, and formal associations, like cooperatives. On the other hand, informal sources include relatives and friends, groceries/local merchant, moneylenders, and informal associations like rotating saving groups (Eqqub) and social insurance groups (Iddir). Access to credit, whether from formal or informal sources, can potentially alleviate smallholder farmers' credit constraints. However, credit from these two sources is likely to differ in terms of approaches, terms and conditions of credit, size and coverage, and screening and enforcement mechanisms (Smith et al., 1981; Banerjee et al., 1994; Guinnane, 2001). These differences can imply different costs and incentives to loanee farmers, inducing impact variations for promoting technologies.

In Ethiopia, formal and informal sources continue to be major sources of agricultural credit, though their share differs. Of the total farm households that had access to credit, about 67% took credit from formal sources, while about 35% took credit from informal sources. Farm households who obtained credit from formal sources are significantly more likely to adopt chemical fertilizer and improved seeds than those who accessed credit from informal sources ($p<0.01$) (Table 7). As for the intensity of input use, impact heterogeneities appear to exist only for chemical fertilizers—those accessing credit from formal source tend to use more quantities of fertilizer per hectare as compared to those accessing credit from informal sources. Again, no differential effects were observed on adoption of other technologies.

For the parametric analysis, we estimate the basic model by including indicators for both the availability and the source of credit. The results are shown in Table 9. Credit from formal sources is not important in explaining the likelihood of adopting chemical fertilizer. But it is positively and significantly correlated with the intensity of use of chemical fertilizer. The broader implication here is that improving access and use of credit from formal sources may particularly spur the intensity of use of modern agricultural inputs in Ethiopia. Together with the finding that credit use is important for both adoption and intensity of use of chemical fertilizer, this result suggests that credit from formal and informal sources plays different roles in households' technology adoption process. Plausible explanations for these differences may root from scale variations between the two credit sources. The volume and availability of loanable funds from informal sources are usually subject to seasonal fluctuations. Credit from such sources is not only inadequate, but also exploitative and costly (Setargie, 2013). Credit from informal sources is more likely to be used for consumption smoothing and meeting unexpected expenses. In fact, many of the informal credit sources (e.g., Iddir) are driven by community level goals to meet unexpected expenses and to cope with risk. Yet, informal credit sources represent a major source of credit for poor households because of several complementary reasons, including limited supply of formal credit, stringent collateral requirements from formal sources, and the political and economic segmentation of local financial markets (Tsai, 2004).

Thus far, we have principally been comparing adoption behavior of households that took credit with those that did not. However, lumping constrained and non-constrained non-users of credit together is likely to undermine the effect of credit on technology adoption. While it might be reasonably fair to consider households that took credit had some demand for it, one could not necessarily assume that all non-credit users are liquidity constrained. Indeed, recent evidence in Africa highlights that a large proportion of farmers often finance modern input purchases with cash from non-farm activities and crop sales (Adjognon et al., 2017; Sheahan and Barrett, 2017). This statement is also supported by our data, where cash is the primary means of financing input purchases.

Table 9: Heterogeneous impact of credit sources on fertilizer use

Outcome variables	**Propensity of adoption**	**Quantity (kg per hectare)**
Access to credit	0.095***	0.259***
	(0.018)	(0.076)
Access to credit*credit from formal sources	-0.012	0.157*
	(0.020)	(0.083)
Plot and household characteristics	Yes	Yes
Woreda fixed effects	Yes	Yes
Adjusted R2	0.414	0.489
Number of observations	11,871	11,871

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

To examine the full burden of credit constraint on technology adoption, we distinguish between credit constrained and unconstrained non-users. Credit constrained households are those who have some demand for credit but are hindered from accessing it for several reasons. We adopt a direct elicitation approach based on survey data to identify credit constrained households.[10] Our data contained detailed information on main reasons for not using credit. According to this approach, households could be credit constrained due to three major reasons: price (too expensive), transaction costs (inadequate collateral, not knowing any lender and too long procedure) and risk (not liking to be in debt, believed would be refused, and fear of failure to repay) (Ali and Deininger, 2012; Ali et al., 2014b; Mukasa et al., 2017)[11]. Typically, unconstrained credit non-users are those that cited availability of capital as their main reason for not using credit. This procedure showed that 73% of credit non-user households are credit constrained, while the rest 27% are unconstrained.

Results from Table 7 show that credit users are generally more likely to adopt agricultural technologies than both liquidity unconstrained and constrained credit non-user households. By contrast, credit-constrained farm households are the least to adopt most of the agricultural

[10] Other two common approaches are detection via violation of the life-cycle hypothesis (Browning & Lusardi, 1996) and credit limit approach (Diagne, Zeller, & Sharma, 2000). While the life-cycle hypothesis uses the dependence of consumption on transitory income as evidence of credit constraint, the credit limit approach uses the gap between supply of and demand for credit for identification.

[11] Our data shows that the share of these three reasons is as follows: risk (62.7%), transaction cost (29.7%) and price (7.7%)

technologies, particularly those that require substantial investments. In Table 10, we present results for the effect of credit on technology adoption based on a) full model (comparing credit users with credit non-users); b) comparison of credit users and constrained credit non-users; and c) comparison of credit users and credit unconstrained non-users. We provide test statistics for differences in effect magnitudes of credit in these regressions (Table 10).

Table 10: Heterogeneous impact of credit constraint on fertilizer use

Outcome variable	Propensity of adoption			Quantity (kg per hectare)		
	Full model	excl. unconstrained non-users	excl. constrained non-users	Full model	excl. unconstrained non-users	excl. constrained non-users
Access to credit	0.088***	0.116***	0.051**	0.353***	0.457***	0.166***
	(0.012)	(0.014)	(0.021)	(0.053)	(0.059)	(0.063)
Plot and household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.414	0.426	0.127	0.463	0.478	0.454
Number of observations	11,871	8,996	4,306	11,869	8,995	4,305
Credit coefficient difference with full model						
Chi-square value		37.3	24.9		22.1	20.2
p-value		0.00	0.00		0.00	0.00

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

As expected, the magnitude of the coefficient for credit is larger for both adoption and intensity of use of fertilizer in the sub-sample that excludes unconstrained non-users[12]. This is intuitive as it now represents the difference in likelihood of adoption and intensity of use between those that used credit and those that both did not take credit and were not able to afford to finance on their own. In all cases, the differences in the magnitudes of the coefficients are significantly different from zero at conventional levels of significance, suggesting that credit constrained non-users are significantly more disadvantaged than both credit users and unconstrained non-users. For example, if measured in the likelihood of adoption of fertilizer, the effect of credit use is about 3% larger when assessed against credit-constrained non-users than when it is estimated against the whole sample of non-users. To put it positively, one important implication

[12] These basic results similarly hold for other technologies (see Table A4 in the appendix)

of this finding is that targeting credit to liquidity constrained farm households is more likely to promote adoption of improved technologies.

The finding that credit users are more likely to adopt agricultural technologies than unconstrained credit non-user households suggests that participation in a credit market may play other roles in addition to capital supply. Participation in credit market could provide additional incentives and play disciplining roles (peer pressure) to increase the likelihood of adopting more technology. For instance, microcredit services in rural Ethiopia are often provided in a group lending scheme with other packages, like information provision and networking (Tarozzi et al., 2015). Group liability tends to increase the likelihood of using credit for intended purposes as group members engage in disciplining each other. Defaulting on loan repayment in a group lending scheme has also a negative repercussion on social capital and status. Informal lenders do also closely monitor borrowers to secure their money back, extending both incentive and peer pressure roles with credit services.

4. Sensitivity analysis

In this section, we assess the robustness of the basic results in several ways. First, rather than using a credit use dummy, we use quantity of credit and examine its association with propensity of adoption and intensity of inputs used. Panel A of Table 11 reports that the propensity of adoption increases with the size of credit, but the magnitudes of the corresponding coefficients are rather small. Panel B presents results from regression of quantity of inputs used on amount of credit obtained by the households. Credit appears with positive and statistically significant coefficient for chemical fertilizer and improved seed. The magnitudes of the corresponding coefficients are, again, relatively small. This might be due to the fact that both the average quantity and variability of borrowed amount is very low. Otherwise, the results remain robust.

Table 11: Association between credit amount and propensity of adoption and quantity of inputs used

Outcome variables	Fertilizer	Improved seed	Chemicals	Other technologies
Panel A: Propensity of Adoption				
Log (amount of credit in Birr)	0.011***	0.006***	0.005***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Plot and household characteristics	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes	Yes
Adjusted R2	0.414	0.306	0.344	0.207
Panel B: Quantity (kg per hectare)				
Log (amount of credit in Birr)	0.047***	0.011**	-0.000	
	(0.007)	(0.005)	(0.003)	
Plot and household characteristics	Yes	Yes	Yes	
Woreda fixed effects	Yes	Yes	Yes	
Adjusted R2	0.463	0.245	0.122	
Number of observations	11,869	11,869	11,869	11,869

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

Second, we used an OLS—a linear probability model (LPM)—in our basic specification to estimate propensity of adoption. Using the linear model may not be unequivocally appropriate as the outcome variable for the propensity to adopt is essentially a binary. LPM is advantageous owing to its simplicity, interpretability and because it provides a host of specification tests to assess the validity of the IV strategy (Angrist and Pischke, 2008; Caudill, 1988). However, some question the dependability of a linear model for limited dependent outcomes (Wooldridge, 2002). We, therefore, assess the robustness of our findings using a probit regression. The results from normal probit and IV models are presented in Tables 12 and Table 13, respectively. We can see that the results remain robust and do not seem to be driven by the non-linear nature of our outcome variables. Moreover, the Wald test of exogeneity for the IV probit model rejects the null hypothesis that the residuals from the first-stage are not correlated with those from the second-stage model, suggesting the appropriateness of using IV estimation strategy and the admissibility of the excluded instruments.

Table 12: Association between credit use and propensity of technology adoption, probit model

Outcome variables	Fertilizer	Improved seed	Chemicals	Other technologies
Access to credit	0.404***	0.170***	0.186***	0.181***
	(0.054)	(0.051)	(0.057)	(0.046)
Plot and household characteristics	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes	Yes
Constant	1.343***	-1.219***	-0.236	-0.473**
	(0.277)	(0.241)	(0.232)	(0.214)
Pseudo R2	0.373	0.299	0.320	0.174
Log-likelihood ratio	-4861.9	-4234.1	-4736.2	-6791.4
Number of observations	11,707	11,618	11,555	11,871

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

Third, if we remain skeptical about whether our instruments fully satisfy the exclusion restriction, then the main concern regarding our instruments is that they may be correlated with some unobserved heterogeneity that could induce self-selection bias. For instance, distance from the nearest formal credit source could affect technology adoption via a host of different channels other than through the credit channel. Some of these channels may reflect non-credit attributes that can challenge the exclusion restriction between distance to a credit source and technology adoption. One concern, for instance, is that many formal credit sources are in district towns. While none of our respondents come from such towns, households residing close to formal credit sources, and hence to these towns, may have broader opportunities to access market information and infrastructure and learn about improved technologies through social networks. If so, our distance instrument may pick effects of potentially relevant omitted variables, thus violating the exclusion restriction. But households who are not using credit could also be randomly exposed to similar social networks and interactions to some extent when they travel to markets for shopping or other social reasons, as major markets are also found in these district towns. Ultimately, this can lessen the level of concern to a certain degree.

Table 13: Effect of credit use on propensity of technology adoption, probit IV

Outcome variables	Fertilizer	Improved seed	Chemicals	Other technologies
Access to credit	2.801***	1.094**	1.803***	2.027***
	(0.123)	(0.431)	(0.284)	(0.319)
Plot and household characteristics	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes	Yes
Wald test of exogeneity				
chi2(1)	98.50	4.11	21.77	19.59
Prob > chi2	0.000	0.04	0.00	0.00
Log-likelihood ratio	-7436.2	-6788.5	-7276.3	-9386.1
Number of observations	11,707	11,618	11,555	11,871

**** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.*

While the econometric tests suggest that this problem is less of a concern with our instruments, our data allow us to formally explore this unobserved heterogeneity problem to some extent. We exploit the panel nature of the data and estimate fixed effect estimators that can help in cancelling out selection bias based on unobserved covariates. A crucial cautionary note here is that fixed effect models mitigate only time-invariant unobserved heterogeneity. Tables 14 and 15 report the results, respectively, for the propensity to adopt and the intensity of use of the various agricultural technologies. The results remain robust and qualitatively similar to those of the base models. This suggests that our results are not sensitive at least to time invariant unobserved heterogeneities.

Table 14: Effect of credit use on propensity of adoption of agricultural technology, FE

Outcome variables	Fertilizer	Improved seed	Chemicals	Other technologies
Access to credit	0.076***	0.080***	0.060***	0.097***
	(0.016)	(0.024)	(0.019)	(0.024)
Plot and household characteristics	Yes	Yes	Yes	Yes
Adjusted R^2	0.044	0.043	*0.027*	0.032
Number of observations	11,871	11,871	*11,871*	11,871

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

Finally, our results are not driven by observed and unobserved district characteristic as we control for district fixed effects throughout our regressions, and thus all reported effects are not expected to pick up location specific characteristics. Moreover, our regressions also control for many time varying demographic and socioeconomic household covariates that can further lessen concerns with time varying unobserved heterogeneities

Table 15: Effect of credit use on intensity of agricultural technology use, FE

Outcome variables	Fertilizer (kg per ha)	Improved seed (kg per ha)	Chemicals (liter per ha)
Access to credit	0.268***	0.144**	0.045
	(0.072)	(0.057)	(0.030)
Plot and household characteristics	Yes	Yes	Yes
Adjusted R^2	0.028	0.012	0.009
Number of observations	11,869	11,869	11,869

*** p<0.01, ** p<0.05, * p<0.1; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

5. Conclusion and discussion

Increasing agricultural productivity and reducing poverty through promoting the use of modern inputs, such as fertilizer and improved seeds, has long been at the center of development debates in developing countries. In this paper, we study the effect of credit on smallholder households' adoption decision and intensity of use of modern agricultural technologies using large survey data in Ethiopia. In Africa, credit constraints present a critical challenge for smallholder farmers in the process of adoption of agricultural technologies (e.g., Zerfu and Larsen, 2010; Lambrecht et al., 2014). In the context of smallholder agriculture, credit constraint arises because cash resources are limited for farmers or cash inflows do not arrive when inputs are needed to be purchased. Credit constraint can also arise due to imperfect information and adverse selection effects that are strong enough to exclude some households from credit markets (Aryeety and Udry, 1997; Stiglitz and Weiss, 1981). There are good reasons to believe that access to credit can facilitate technology adoption. First, it guarantees the availability of liquid resources to finance purchase of inputs. Second, it enables poor households to smooth consumption in the face of idiosyncratic and/or covariate production risks, which frees up cash from precautionary saving and encourages capital formation as well as improves marketing efficiency. Third, in the specific context of Ethiopia, access to credit can complement existing development strategies and reform packages for pro-poor growth.

We use instrumental variables (IV) approach to account for the potential reverse-causality and non-random take-up of credit. Consistent with theoretical arguments, we find evidence that credit constraint is an apparent reason for differential adoption and application rates of agricultural technologies. Particularly, we find that access to credit has a positive and significant effect on both adoption and intensity of use of many improved technologies. But the results appear to vary depending on types of inputs. The strongest and consistent effect is observed for chemical fertilizer—the most important input that national agricultural research and extension systems have actively promoted in Ethiopia. Recognizing that IV results rely on satisfying the relevance and uncorrelatedness criteria, we subject our results to a battery of different robustness checks and sensitivity analyses. Our results turn out to be robust.

We also document substantial heterogenous effects of access to credit based on the nature of the source of credit and the primary purpose for which credit is taken. We find that the nature of the source of credit matters for technology adoption. Specifically, credit accessed from formal sources is more significant for the intensity of agricultural inputs than for the decision to adopt. Perhaps, this is because credit accessed from formal sources generally tends to be larger in volume, which is more important for intensity of technology use than for propensity to use new technologies. Equally, credit taken with the primary purpose of financing agricultural inputs is more important in promoting technology adoption than total credits taken *per se*. This suggests that growth in the volume of credit may not necessarily translate into a higher rate of agricultural technology adoption, as farmers may use credit for purposes other than agriculture. Finally, the effect of credit on those who used credit is significantly greater when effect is estimated against credit-constrained non-users as compared with the pool of credit non-users (both constrained and non-constrained). This suggests that lack of access to credit has the strongest negative effect on credit-constrained non-users. At the same time, credit users are more likely to adopt improved technologies than liquidity unconstrained credit non-users, suggesting that access to credit may also promote technology adoption via other mechanisms (e.g. incentive and peer pressure).

Overall, the main findings of this paper support the argument that smallholder farmers may not be able to adopt and properly apply modern inputs when they are severely constrained by lack of access to credit. In other words, improving access and use of credit can spur the adoption and intensity of use of modern agricultural inputs in Ethiopia, which ultimately can lead to productivity gains and poverty reduction. The broader implication of these results is that policies and interventions aiming at promoting adoption of improved technologies need to be complemented by efforts to improve access to credit. For optimal effect, credit services need to target liquidity-constrained households. Our results also have implications for the design of credit: voucher-based input credit may specifically be useful to promote adoption of improved technologies.

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Appendices

Table A1: Summary of key variables by survey years

Variable	Overall sample N=12,137	2013 N=6,111	2015 N=6,026	Mean difference test (p-value)
Panel A: Covariates				
Access to credit, yes=1	0.12	0.08	0.16	0.00
Head is female, yes=1	0.27	0.27	0.27	0.34
Age of household head	44(14.9)	43(14.8)	45(14.8)	0.00
Household size	4.9(2.1)	4.8(2.1)	5(2.2)	0.00
Education level of head	1.5(2.8)	1.3(2.7)	1.6(2.8)	0.03
Land size in hectares	1.6(2.6)	1.5(3.2)	1.7(1.8)	0.01
Livestock owned, in TLU	3.3(3.9)	3.2(4.3)	3.3(3.4)	0.42
Durable assets owned	0.05(1.4)	0.04(1.4)	0.05(1.4)	0.69
Household has good floor, yes=1	0.09	0.09	0.10	0.65
Household has good roof, yes=1	0.43	0.38	0.47	0.00
Access to electricity, yes=1	0.06	0.04	0.07	0.00
Average size of credit in village, in Birr	440(895)	257 (563)	626 (1,106)	0.00
Distance to credit sources in km	4.11(12.8)	4.89 (16.6)	3.36 (7.2)	0.00
Panel B: Outcome variables				
Propensity of input adoption (% HHs)				
Chemical Fertilizer	62.4	58.2	66.6	0.00
Improved seeds	20.8	14.9	26.9	0.00
Agricultural chemicals	28.1	25.4	30.9	0.00
Other technologies	48	44.2	51.7	0.00
Quantity of inputs used				
Chemical Fertilizer (kg per hectare)	62.8(98.9)	61.4(99.3)	64.2(98.5)	0.11
Improved seeds (kg per hectare)	5.14(22.9)	4(21.3)	6.3(24.4)	0.00
Agricultural chemicals (liters per hectare)	1.4(9.9)	1.6(10.9)	1.1(8.9)	0.00

Source: Ethiopian FtF survey (2013, 2015). Note: Standard deviations are presented in parentheses.

Table A2: Association between credit use and propensity of adoption of agricultural technologies

Outcome variable:	**DAP**	**UREA**	**Improved seed**	**Herbicides**	**Fungicides**	**Pesticides**
Access to credit, yes=1	0.073***	0.053***	0.043***	0.039***	0.013	0.014*
	(0.014)	(0.014)	(0.013)	(0.015)	(0.008)	(0.007)
Plot and Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Woreda Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	11,871	11,871	11,871	11,871	11,871	11,871
R^2	0.405	0.348	0.312	0.353	0.093	0.148
Adjusted R^2	0.400	0.343	0.306	0.348	0.085	0.141

Source: Ethiopian FtF survey (2013, 2015). Note: Standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1; Coefficients omitted to preserve space.

Table A3: Association between credit use and intensity of technology uses

Outcome variable:	DAP	UREA	Improved seed	Herbicides	Fungicides	Pesticides
Access to credit, yes=1	0.264***	0.185***	0.094**	-0.009	-0.008	0.009
	(0.053)	(0.050)	(0.039)	(0.014)	(0.007)	(0.015)
Plot and Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Woreda Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	11,869	11,869	11,869	11,869	11,869	11,869
R^2	0.459	0.366	0.251	0.132	0.048	0.094
Adjusted R^2	0.455	0.361	0.245	0.125	0.040	0.087

Source: Ethiopian FtF survey (2013, 2015). Note: Standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1; Coefficients omitted to preserve space.

Table A4: Heterogeneous effect of credit constraint on input use

Outcome variables:	Improved seed		Agricultural chemicals		Other technologies	
	excl. unconstrained non-users	excl. constrained non-users	excl. unconstrained non-users	excl. constrained non-users	excl. unconstrained non-users	excl. constrained non-users
Access to credit, yes=1	0.058***	0.014	0.066***	0.015	0.065***	0.039**
	(0.014)	(0.014)	(0.016)	(0.018)	(0.018)	(0.019)
Plot and Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Woreda Fixed Effects*	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,996	4,306	8,996	4,306	8,996	4,306
R^2	0.316	0.371	0.380	0.334	0.216	0.263
Adjusted R^2	0.309	0.356	0.373	0.319	0.208	0.246
Credit coefficient difference with full model						
Chi-square value	9.39	9.25	14.75	8.75	0.30	2.60
p-value	0.00	0.00	0.00	0.00	0.59	0.11

Source: Ethiopian FtF survey (2013, 2015). Note: Standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1; Coefficients omitted to preserve space.