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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 huge potential for increasing productivity and reducing poverty 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 the likelihood of adoption and use intensity of chemical fertilizers using data from large rural surveys in Ethiopia. Using a heteroscedasticity-based identification strategy to address the endogenous nature of access to credit, we find that access to credit has significant positive effects on adoption and intensity of use of chemical fertilizers. However, important heterogeneities are observed. Credit obtained from formal sources is more important for the intensity of use than for the decision to adopt chemical fertilizers. Credit taken with the primary purpose of financing agricultural inputs is more likely to promote adoption of chemical fertilizers than credit taken per se. Furthermore, reported credit effects are larger when estimated against the sample of credit-constrained non-users as compared with the pool of the whole sample of credit non-users. The results remain robust to several sensitivity analyses. Our results yield useful implications for the design, promotion, and targeting of credit services to leverage their effect on adoption of agricultural technologies.

KEYWORDS

chemical fertilizers, credit access, Ethiopia, heterogeneity analysis, heteroscedasticity-based identification, technology adoption

JEL CLASSIFICATION

G21, O12, O16, O23, Q14, Q16

Résumé

Les technologies agricoles modernes recèlent un énorme potentiel pour accroître la productivité et réduire la pauvreté dans les pays en développement.

Cependant, les niveaux d'adoption de ces technologies sont restés décevants en Afrique. Cet article analyse l'effet de l'accès au crédit sur la probabilité d'adoption et l'intensité d'utilisation des engrais chimiques en utilisant les données de grandes enquêtes rurales en Éthiopie. En utilisant une stratégie d'identification basée sur l'hétéroscédasticité pour aborder la nature endogène de l'accès au crédit, nous constatons que l'accès au crédit a des effets positifs significatifs sur l'adoption et l'intensité d'utilisation des engrais chimiques. Cependant, d'importantes hétérogénéités sont observées. Le crédit obtenu auprès de sources formelles est plus important pour l'intensité d'utilisation que pour la décision d'adopter des engrais chimiques. Le crédit contracté dans le but principal de financer les intrants agricoles est plus susceptible de promouvoir l'adoption d'engrais chimiques que le crédit contracté général. En outre, les effets de crédit signalés sont plus importants lorsqu'ils sont estimés par rapport à l'échantillon de non-utilisateurs de crédit limité par rapport à l'ensemble de l'échantillon de non-utilisateurs de crédit. Les résultats restent robustes à plusieurs analyses de sensibilité. Nos résultats ont des implications utiles pour la conception, la promotion et le ciblage des services de crédit afin de tirer parti de leur effet sur l'adoption des technologies agricoles.
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1 INTRODUCTION

Modern agricultural technologies hold huge potential for increasing farm productivity and rapidly reducing poverty in developing countries, particularly in sub-Saharan Africa where the gap between potential and actual agricultural yield is substantial (Licker et al., 2010; World Bank, 2008). However, despite considerable international and national efforts to promote their 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 (Duflo et al., 2011; Feder et al., 1985; Rashid et al., 2013; Sheahan & Barrett, 2014). For example, sub-Saharan Africa substantially lags behind other developing regions in terms of use of chemical fertilizers (World Bank, 2008).

Explaining low adoption rates of potentially productive but risky agricultural technologies remains an important empirical challenge. The literature emphasizes the roles of diverse but complementary physical, market, and institutional factors for the low uptake of agricultural technologies (de Janvry & Sadoulet, 2020; Mishra et al., 2021). Some of these explanations include low profitability (Christiaensen, 2017; Minten et al., 2013), imperfect insurance markets (Karlan et al., 2014), poor land rights or tenure insecurity (D. A. Ali, Deininger, & Duponchel, 2014), consumption risk (Dercon & Christiaensen, 2011; Engler-Palma & Hoag, 2007) and complementarity of other inputs (Bridle et al., 2020; Nakano & Magezi, 2020). For example, Minten et al. (2013) find that increasing transaction and transportation costs to distribution centers of chemical fertilizers led to a substantial rise in the price of chemical fertilizers and thereby by a reduction in their use. Alternatively, some scholars contend that modern agricultural technologies might not always yield expected returns, perhaps because of limited knowledge and education of farmers (Feder et al., 1985; Krishnan & Patnam, 2014).

Another strand of the literature emphasizes the role of credit and liquidity constraint as key deterrent to technology adoption and development in Africa (Abate et al., 2016; Giné & Klonner, 2005; Karlan et al., 2014; Lambrecht et al., 2014; Moser & Barrett, 2006; Zerfu & Larsen, 2010). In rural Africa, cash inflows do not arrive when inputs need to be purchased due to high seasonality of economic activities (Christiaensen, 2017; Fink et al., 2014). Typically, household cash resources are inadequate to finance investments in agricultural technologies, particularly when substantial investment is required (Croppenstedt et al., 2003). Under these conditions, relaxing credit constraints is expected to improve technology adoption and aggregate agricultural productivity. In line with this argument, many studies have documented positive effects of access to credit on technology adoption using various empirical strategies (Abate et al., 2016; Croppenstedt et al., 2003; Duflo et al., 2011; Giné & Klonner, 2005; Lambrecht et al., 2014; Moser & Barrett, 2006). Most of these studies report average effects of credit on technology adoption that may mask substantial heterogeneity and thus bias true effects of credit access (Suri, 2011). For example, Nakano and Magezi (2020) found that, in the aggregate, microcredit access did not have significant effects on the use of chemical fertilizer in Tanzania. However, the authors reported positive effects for farmers having access to irrigation schemes.

In this study, we argue that there may be structural heterogeneities in the effects of access to credit on technology adoption. This study contributes to the literature by highlighting important heterogeneities of effects of credit on technology adoption with regards to the type of credit (formal vs. informal), the primary purpose of credit uses (agricultural vs. non-agricultural purposes), and comparison of credit-constrained non-users as opposed to the pool of non-users. Abate et al. (2016) and Liverpool and Winter-Nelson (2010) have alluded to this argument. Abate et al. (2016) showed that the institutional design of formal lending institutions induced impact variations—credit accessed through cooperatives had a greater effect on technology adoption than that through microfinances in Ethiopia. Liverpool and Winter-Nelson (2010) found that formal credit (microfinance) has positive effect on the use of improved technology by less poor households. However, the authors did not compare the effect of credit from formal sources with informal sources. In addition, Beaman et al. (2020) report that selection into credit markets in Mali is predictive of heterogeneity, that is, returns to capital are higher for farmers who borrow than for those who do not. This suggests that distinguishing between credit-constrained and non-constrained households is critical to study the full burden of liquidity constraint on adoption of chemical fertilizers. Access to credit is expected to promote technology 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). Particularly, estimating effect of credit without differentiating between credit-constrained and non-constrained households is likely to underestimate true effect of credit access for those who want credit the most (both in credit user and non-user groups).

We study these heterogeneities through analyzing the effect of access to credit on adoption of chemical fertilizers using large and detailed farm household data collected from the four main regions in Ethiopia—Tigray, Amhara, Oromia, and Southern Nations, Nationalities and Peoples (SNNP) region in Ethiopia. The dataset uniquely contains detailed information on credit use, and its sources and purposes. The survey asked credit non-users for main reasons for not using credit, thereby allowing us to identify credit-constrained and unconstrained non-users. Chemical fertilizers (our outcome variable) are key inputs that have long been actively promoted by national agricultural research and extension systems in Ethiopia. We consider both the propensity and intensity of technology adoption. The propensity is the likelihood of a farmer to adopt a modern technology ("adoption"), and once the decision to adopt is settled, the intensity is how much of the technology to use. Conceptualizing technology adoption this way is especially useful for divisible inputs, such as chemical fertilizers, as the ultimate effect of these technologies essentially depends on the intensity of their use (Abate et al., 2016; Feder et al., 1985).

Our empirical strategy relies on heteroscedasticity-based identification to address the potential endogeneity that may otherwise bias reported results. We find that that access to credit has a positive and significant effect on adoption and intensity of chemical fertilizer use. Credit obtained from formal sources leads to higher intensity of use of chemical fertilizers but does not affect the decision to adopt. Credit taken with the primary purpose of financing agricultural inputs tends to be more important for promoting adoption of chemical fertilizers 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 non-users). This suggests that targeting credit to liquidity-constrained households would have greater effect in terms of adoption of chemical fertilizers. These results add more nuance to the effect of access to credit on technology adoption. Overall, our findings underlie the importance of accounting for important heterogeneities in assessing effects of access to credit on technology adoption. The results provide useful insights into targeting and design of credit to leverage promoting increased adoption of technologies.

The rest of the paper is organized as follows. Section 2 outlines a simple theoretical framework to help us conceptualize the nexus between access to credit and technology adoption. Section 3 provides the data and the econometric approach of the study. Section 4 presents and discusses results. Section 5 concludes.

2 | THEORETICAL FRAMEWORK

We outline a simple theoretical framework to help fix ideas about the connection between credit use and agricultural technology adoption among smallholder farmers. Adoption of agricultural technologies involves substantial costs, both fixed and variable costs. In addition to direct costs, complementary inputs and tools may also be needed to be purchased to apply the technologies. Limited household resources coupled with seasonality of agriculture activities often prevent poor households from adopting such technologies. That is why credit access to smallholder farmers has long been at the center of rural development strategies.

Theoretically, access to credit can contribute to improved technology adoption through two main channels. More directly, credit can be used to finance productive agricultural technologies, such as fertilizers, which farmers might not otherwise be able to afford (Clark et al., 2015; Diagne, 2002). Indirectly, credit use can help poor farmers to cope with *ex post* risks associated with adopting potentially productive but risky 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 (Dercon & Christiaensen, 2011; Giné & Yang, 2009). This problem is compounded by absence of formal insurance markets in rural Africa (Karlan et al., 2014). In such settings, credit access—as it relates to smoothing consumption variability—is expected to allow poor households to avoid underinvestment in productive agricultural activities (D. A. Ali, Deininger, & Duponchel, 2014; Eswaran & Kotwal, 1990).

The effect of credit on technology adoption may structurally differ for several reasons. One consideration is the type and nature of credit sources (formal or informal). In the Ethiopian context, formal credit sources include microfinance institutions, commercial banks, NGOs, and formal associations, like cooperatives. 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' liquidity 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 (Banerjee et al., 1994; Smith et al., 1981). Generally, formal credit use is limited in Ethiopia. Credit accessed from formal and informal sources can imply different costs and incentives to loanee farmers, potentially inducing impact variations for promoting technologies.

Another consideration for impact heterogeneity of credit use on technology adoption is the purpose 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 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 smallholder farmers spend credit primarily on food (Carranza & Niles, 2019). As such, the purpose for which credit is accessed can affect agricultural technology adoption.

A third potential source of heterogeneity in the assessment of effect of credit on technology adoption is the degree of households' liquidity constraint. Most studies that have looked at the effect of credit have generalized their analysis by assuming that credit access leads to positive impact outcomes. Such studies have ignored household behavior with regards to whether the household is liquidity constrained. In fact, credit access is likely to be impactful for liquidity-constrained households—those who are unable to pursue profitable opportunities for lack of financial resources. A lack of access to credit may not necessarily imply an unmet credit need (de Janvry et al., 1991). In the same way, the marginal contribution of credit is likely to be higher for households with binding liquidity constraint than for less constrained ones. However, the literature often compares credit users with non-credit users, lumping together constrained and non-constrained non-users of credit. This practice undermines the effect of credit on technology adoption. While it might be reasonable 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 from 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 & Barrett, 2017).

We distinguish between credit constrained and unconstrained non-users to understand the full burden of credit constraint on technology adoption. Credit constrained households are those who have some demand for credit but are hindered from accessing it for several reasons. Households could be credit constrained due to three major reasons: price or interest rate (too expensive); transaction costs (inadequate collateral, not knowing any lender and too long procedure); and risk (not liking to be in debt, believed it would be refused, and fear of failure to repay) (D. A. Ali & Deininger, 2012; D. A. Ali, Deininger, & Goldstein, 2014; Mukasa et al., 2017; Mushinski, 1999). Typically, unconstrained credit non-users are those that do not use credit due to availability of own adequate capital. We explore these three important heterogeneities in effects of credit access on adoption of chemical fertilizers.

3 | DATA AND ECONOMETRIC APPROACH

3.1 | Data and descriptive analysis

We use a two-wave survey data collected by the Central Statistical Agency (CSA) of Ethiopia in collaboration with the International Food Policy Research Institute (IFPRI). The data were collected for the evaluation of the Feed the Future (FtF) program in Ethiopia. FtF is 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. The main strategy is to focus attention on defined area of coverage—Zone of influence (ZOI)—in order to create and measure impact. In Ethiopia, the FtF ZOI covers 149 districts where the FtF interventions were implemented over the 5-years 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.[1] 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 6977 households in 84 districts from whom the baseline data were collected in June 2013. The follow up survey, conducted in 2015, resurveyed 6696 households that continued to live in the same districts, generating a panel data structure.[2] The survey included detailed modules on adoption and intensity of use of chemical fertilizers, credit use and relevant household and community characteristics. Community-level information on credit sources and other factors that might influence chemical fertilizers adoption, such as infrastructure and institutions, were also collected. Table A1 in the Appendix presents the description of all variables and their summary statistics by splitting the sample over the two survey years.

The credit access 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 borrowed some amount over the indicated period (see Table A1 in the Appendix). The average volume of credit for all households is 440 Ethiopian Birr (approximately \$23 based on the average exchange rate of the survey years). If non-users are excluded, the average amount among those who took credit is 3679 Ethiopian Birr (~\$193).

There is a slight increase 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 & Christiaensen, 2011). The low prevalence of credit use is attributed to lack of adequate credit supply, high cost of borrowing, inadequate collateral and risk averseness of borrowers (D. Ali, Deininger, & Goldstein, 2014; Mukasa et al., 2017). Alternatively, the low 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 the descriptive statistics and simple mean difference tests by credit use status of households. Panel A provides information on our outcome variable — chemical fertilizers (DAP, Urea and NPS). We distinguish between the propensity to adopt and the intensity of adoption of chemical fertilizers. The "propensity to adopt chemical fertilizer" variable is captured as a binary variable that takes a value of one if the household applied any amount of chemical fertilizer, zero otherwise. The intensity of adoption of chemical fertilizer is measured in terms of the amount of chemical fertilizer (kg per hectare) the household used in the previous season. For ease of interpretability, we use the log transformation of fertilizer quantity in the final analysis.

The descriptive results show that about 62% of the households adopted chemical fertilizers. However, significant differences are noted between credit users and non-users (Table 1). On average, households that have accessed credit tend

[1] 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.
[2] 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.

TABLE 1 Descriptive statistics of the study sample by credit use status

Variable	Overall sample ($N = 12{,}137$)	Credit users ($N = 1451$)	Credit non-users ($N = 10{,}686$)	Mean difference test (p-value)
Panel A: Outcome variables				
Chemical fertilizer (%)	62.4	80	60	.00
Chemical fertilizer (kg per hectare)	77.5(154.2)	112.2(152.7)	72.8(153.8)	.00
Panel B: Covariates				
Head is female, 1 = yes	0.27	0.23	0.28	.00
Age of household head in years	44(14.9)	42(13.0)	44(15.1)	.00
Household size (numbers)	4.9(2.1)	5.2(2.1)	4.9(2.1)	.00
Years of formal education of head	1.5(2.8)	1.6(2.8)	1.4(2.8)	.03
Religion-Orthodox, 1 = yes	0.53	0.64	0.51	.00
Religion-other Christian, 1 = yes	0.25	0.24	0.25	.22
Religion-others, 1 = yes	0.02	0.01	0.03	.00
Livestock owned in TLU[a]	3.3(3.9)	3.1(3.2)	3.3(4.0)	.15
Durable assets index[b]	0.05(1.4)	0.22(1.3)	0.02(1.4)	.00
Household has non-farm business, 1 = yes	0.08	0.168	0.068	.00
Household has good floor, 1 = yes	0.09	0.1	0.09	.81
Household has good roof, 1 = yes	0.43	0.52	0.41	.00
Access to electricity, 1 = yes	0.06	0.06	0.06	.26
Land size in hectares	1.6(2.6)	1.8(1.6)	1.6(2.7)	.01
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)	.00
Share of plots with plain slope	0.73(0.4)	0.74(0.4)	0.73(0.4)	.26
Share of certified plots	0.72	0.68	0.73	.00
Household owns irrigated plot, 1 = yes	0.053	0.067	0.051	.01
Production shock over 2 years, 1 = yes	0.157	0.187	0.153	.00
Marketing shock over 2 years, 1 = yes	0.019	0.026	0.019	.05
Rural saving and credit cooperatives, 1 = yes	0.427	0.513	0.415	.00
Village saving and loan association, 1 = yes	0.383	0.462	0.372	.00
Producers association, 1 = yes	0.177	0.187	0.173	.00
Access to bank/MFI, 1 = yes	0.18	0.20	0.18	.01
Access to asphalted road, 1 = yes	0.18	0.21	0.18	.01
Distance to weekly market, in Km	5.73(8.4)	5.313(6.5)	5.787(8.7)	.05
Distance to credit sources in km	4.11(12.8)	2.11(7.3)	4.38(13.3)	.00
Average size of credit in village, in Birr	439.8(895)	1,202.5(1,503)	336.3(717)	.00

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

[a]Livestock is measured using tropical livestock units (TLU).

[b]Index of durable assets owned generated using principal component analysis (PCA). FtF zone refers to whether the household lives in one of the Feed the Future zones. The results of all the IV Diagnostics tests show that our IV estimation satisfies all conditions.

TABLE 2 Mean comparisons of fertilizer adoption and use intensity over sub-sample categories

	Fertilizers use, 1 = yes	Quantity of fertilizers (kg/ha)
Purpose of credit use		
Credit taken for other purposes	0.68	61.6
Credit taken for input purposes	0.84	131.6
Mean difference test (p-value)	*.000*	*.000*
Credit accessed from informal vs. formal source		
Credit accessed from informal source	0.75	68.01
Credit accessed from formal source	0.83	133.57
Mean difference test (p-value)	*.000*	*.000*
Credit use and credit-constraint status		
Credit use: [A]	0.80	112.24
No credit, not constrained: [B]	0.72	93.61
No credit, credit constrained: [C]	0.56	64.9
Mean difference test (p-value): [A] vs. [B]	*.000*	*.000*
Mean difference test (p-value); [A] vs. [C]	*.000*	*.000*

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

to have higher rates of adoption. About 80% of the households with access to credit used chemical fertilizers, while only 60% of those without access to credit used the technology. Similarly, credit appears to be significantly correlated with the application rate of chemical fertilizers. Credit users applied, on average, 112.2 kg per hectare of chemical fertilizers as compared with 72.8 kg per hectare applied by credit non-users. However, the overall average fertilizer use per unit of land is significantly lower than recommended levels (about 200 kg/ha) (Rashid et al., 2013).

Farmers financed input purchases in several ways. They reported financing chemical fertilizer purchases primarily with cash from crop and livestock sales and nonfarm activities. Cash financing accounts for 84% among survey households (Table A2 in the Appendix). Of the total farmers who applied chemical fertilizers, 16% used credit to finance its purchases. Relatedly, households purchase fertilizers 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 (Table A2). Farmers also sparsely purchase inputs from other sources, including private traders, other farmers, NGOs, and agro-dealers.

Panel B of Table 1 presents information on other covariates. Durable assets index is generated using principal component analysis (PCA) from individual asset items owned by households. 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. The mean comparison tests show that the distributions of several covariates are significantly different between credit users and non-users. This points to the need to control for these variables in the analysis to attenuate potential sources of selection biases (see below).

Table 2 presents simple mean difference tests of adoption and intensity of use of chemical fertilizers by type of credit sources, reason for seeking credit and the extent of credit constraint. The general observation is that there appears substantial variation in adoption of chemical fertilizers across the different sub-samples. Farm households who obtained credit with the purpose of purchasing inputs were more likely to adopt and apply significantly higher rates of application of chemical fertilizers than those who accessed credit for non-agricultural purposes.[3]

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?" 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 (Appendix Table A3). Farm

[3] In Ethiopia, it is common to take credit initially to purchase inputs but ultimately use it for other purposes (e.g., consumption). In our data, about 72% of the households who accessed credit for input reported using it at least partly to finance input purchases (Appendix Table A3). The rest reported using credit for other purposes.

households who obtained credit from formal sources were significantly more likely than those who obtained credit from informal sources to adopt and apply a larger quantity of chemical fertilizers ($p < .01$) (Table 2).

Another consideration is information regarding household's credit constraint. Our data contained detailed information on main reasons for not using credit. We adopt a direct elicitation approach based on survey data to identify credit constrained households.[4] According to this approach, households are considered as credit constrained when they reported some demand for credit but were hindered from accessing it due to three major reasons: price, transaction costs and risk.[5] On the other hand, unconstrained credit non-users are those that cited availability of own capital as their main reason for not using credit. Following this procedure, about 73% of credit non-user households are credit constrained, while the rest 27% are unconstrained. The descriptive results from Table 2 show that credit users are generally more likely to use chemical fertilizers than both liquidity unconstrained and constrained credit non-user households. By contrast, credit-constrained farm households are the least to adopt chemical fertilizers. We note a similar pattern in terms of quantity of chemical fertilizers applied per hectare.

While the mean difference test results are informative, they cannot be used to make causal inferences regarding the effect of credit on chemical fertilizers adoption, since they do not account for potential confounding factors. To account for this potential endogeneity, our analysis employs a heteroscedasticity-based identification strategy.

3.2 | Econometric approach

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

$$F_{idrt} = \beta_0 + \beta_1 C_{it} + \beta_2 T_t + \beta_3 X_{idrt} + \delta_d + \rho_r + \varepsilon_{idrt} \tag{1}$$

where i, d, r, and t denote household i, district d, region r, and time t, respectively. T_t represents a binary variable that takes a value of 1 if the household was surveyed in 2015 and zero if in 2013. It may capture aggregate shifts in technology adoption or correlated shifts in the right-hand side variables. X_{idrt} is a vector of plot, household and community level characteristics. Plot level characteristics include slope of the plot, fertility of the soil, access to irrigation, certification status, and average distance of the plots from residence. For the analysis, these plot characteristics are aggregated to household level. Household characteristics cover household size, religion and education level of the household head, value of durable assets, size of livestock owned in TLU, land size, exposure to shocks, ownership of non-farm business, and other wealth indicators (e.g., housing quality). Community level characteristic include access to public services such as asphalted road and weekly market. We also controlled for differences in access to rural saving and credit cooperatives, village saving and loan association, producer association, and urban areas.

δ_d and ρ_r denote the district and region fixed effects, respectively. Regional fixed effects capture policy and institutional differences across the regions. Administrative regions in Ethiopia are semi-autonomous, and policies and institutions have the potential to vary across the regions. For instance, each region has its own legislative and directive for establishing and regulating microcredit institutions and (financial) cooperatives. Further, the district fixed effects represents a set of (more than 75) districts (woredas) that allow to capture time-invariant differences in fertilizer use among households living in different districts. They are added in to control for observed and unobserved agro-ecological and other characteristics associated with each district. The last term in the equation, ε_{idrt}, is the random error term. Standard errors are clustered at the village level.

In Equation (1), β_1 captures the main relationship of interest: the effect of access to credit on adoption and intensity of chemical fertilizer use. Our central hypothesis is that credit relaxes households' liquidity constraint to finance adoption of chemical fertilizers and, hence, β_1 is positive. However, as indicated before, access to credit might be endogenous due to potential reverse causality and omitted variables that could drive both credit use and technology adoption. When access to credit is endogenous, $corr(C_{it}, \varepsilon_{idrt}) \neq 0$ and β_1 would be biased. Typically, instrumental variables (IV) method that relies on exclusion restriction is used to address such endogeneity concern with (non-experimental) cross-section data. In our

[4] Other two common approaches are detection via the violation of the life-cycle hypothesis (Browning & Lusardi, 1996) and tcredit limit approach (Diagne et al., 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.

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

case, however, this method is not feasible since it was proved difficult to find appropriate instrument(s) for credit use. Instead, we employ a heteroscedasticity-based identification strategy proposed by Lewbel (2012). This approach allows identification where other traditional sources of identification, such as standard IV approach or panel data method, are not available or unable to credibly address the problem.

To intuitively expound the model based on Equation (1), let's suppose that Z_{it} represents the vector of exogenous variables and C_{it}, representing credit use and intensity, is endogenous. In the first stage, each endogenous variable in C_{it} is regressed on the exogenous variables, Z, and the vector of residuals $\hat{\varepsilon}$ is retrieved. Next, the instruments are obtained as $(Z—E(Z))\hat{\varepsilon}$, where E(Z) is the expected value of Z. The basic requirement of the model is that there is heteroscedasticity in $\hat{\varepsilon}$ (i.e., $cov(\hat{\varepsilon}^2, Z_{it}) \neq 0$). Based on this relationship, internally generated instruments are used in estimation without imposing any exclusion restrictions (Lewbel, 2012).

For Equation (1) above, we first run separate regressions of credit access and log of quantity of credit used (in Ethiopian Birr) on a set of exogenous variables (Z) and then retrieved the residuals ($\hat{\varepsilon}$). The included exogenous variables include plot level characteristics (share of plots with fertile soil, share of plots with plain slope, and proportion of certified land), and community level infrastructure (distances of the village from the nearest town in km, quality of road in the village, distance of the village from the nearest credit sources, and availability of credit in the village). The Breusch–Pagan test rejects the null of homoscedasticity at the 1% level for both the propensity of credit use as well as quantity of credit used. As per the literature, we selected the exogenous variables so that the residuals become heteroskedastic. Further, IV-Diagnostics tests reported with the results in Section 4 support the validity of the approach. The critical values of the Cragg-Donald test statistic reject the null hypothesis that the endogenous regressor (credit access) is weakly identified. The Kleibergen-Paap test also rejects the hypothesis of under-identification, that is, the minimal canonical correlation between the endogenous variable and the instruments is statistically different from zero. The Hansen test statistics of over-identification fail to reject the null hypothesis that our over-identifying restrictions are valid across the different IV regressions, that is, we cannot reject the null hypothesis of zero correlation between the instruments and the error term.

4 | RESULTS AND DISCUSSION

4.1 | Basic results

To set the stage for our analysis, we first estimate the association between access to credit and adoption of chemical fertilizers through estimating a simple Linear Probability Model (LPM).[6] Results presented in Column (a) of Table 3 show that access to credit is positively associated with the propensity of adoption of chemical fertilizers. The results in Column (c) suggest that farmers who used credit are more likely to apply higher amount of fertilizer per hectare than those who did not use credit.

However, as discussed earlier, access to credit may be endogenous in the models explaining adoption and intensity of use of chemical fertilizers. To attenuate this concern, we employ a heteroscedasticity-based identification strategy using relatively exogenous variables to internally instrument for credit access. The results for adoption and intensity of use of chemical fertilizers based on the IV estimations are presented, respectively, in Columns (b) and (d) of Table 3. The results show that access to credit has causally contributed to increasing propensity of adoption and intensity of use of chemical fertilizers. Specifically, compared to their counterparts, access to credit led to about 6.4 percentage point increase in the adoption of chemical fertilizer and about 35.7 percentage increase in the quantity of fertilizer applied by households that had access to credit. To put this into perspective, the average baseline propensity and use intensity of fertilizer by credit non-users are, respectively, 60% and 72.8 kg/ha (see Table 1). Therefore, the 6.4 percentage change effect of credit use on the adoption rate implies a 10.7 percent higher probability of adoption of chemical fertilizer by credit users compared to their counterparts. Similarly, 35.7% change in quantity of chemical fertilizer implies 26 kg/ha more application of fertilizer by credit users than non-credit users. Furthermore, while the results of the simple OLS regressions and the IV estimations are largely consistent, the coefficients of the access to credit variable are generally higher for the OLS estimates than their corresponding values from the IV regressions, suggesting the correction of the endogeneity biases in the simple regressions by the IV strategy.

[6] Despite the censored nature of our outcome variable (quantity of chemical fertilizer), we report here the OLS model to be consistent with the results based on IV (2SLS). However, our results remain qualitatively similar when we use tobit model (see also the sensitivity analysis Section).

TABLE 3 Effect of access to credit on chemical fertilizer adoption and intensity of application

	Propensity of adoption		Intensity of adoption	
	(a)	(b)	(c)	(d)
	OLS	IV (2SLS)	OLS	IV (2SLS)
Access to credit, yes = 1	.101***	.064***	.441***	.357***
	(0.012)	(0.015)	(0.055)	(0.073)
Survey round, 2015	.048***	.050***	.171***	.176***
	(0.013)	(0.013)	(0.058)	(0.058)
Head is female	-.051***	-.051***	-.271***	-.271***
	(0.011)	(0.011)	(0.049)	(0.048)
Log(age of household head)	-.025*	-.027**	-.167***	-.169***
	(0.014)	(0.014)	(0.060)	(0.060)
Household size, number	.010***	.010***	.049***	.050***
	(0.002)	(0.002)	(0.010)	(0.010)
Number of years formal education	.003*	.003*	.016**	.016**
	(0.002)	(0.002)	(0.007)	(0.007)
Religion (reference = Muslim)				
Religion-orthodox	.192***	.193***	.881***	.884***
	(0.050)	(0.050)	(0.203)	(0.202)
Religion-Other Christian	.135***	.137***	.626***	.630***
	(0.044)	(0.044)	(0.182)	(0.181)
Religion-others	0.032	0.032	0.214	0.214
	(0.058)	(0.058)	(0.273)	(0.273)
Non-farm business	0.022	0.026	0.026	0.035
	(0.016)	(0.016)	(0.071)	(0.071)
Log(land size in hectares)	.060***	.062***	-.333***	-.330***
	(0.020)	(0.020)	(0.083)	(0.083)
Livestock ownership, TLU[a]	-0.001	-0.001	0.011	0.011
	(0.002)	(0.002)	(0.010)	(0.010)
Ownership of durables, PCA[b]	.016***	.016***	.069***	.069***
	(0.005)	(0.005)	(0.021)	(0.021)
Household has good floor	-0.008	-0.008	-0.086	-0.088
	(0.016)	(0.016)	(0.072)	(0.072)
Household has good roof	.117***	.116***	.553***	.551***
	(0.018)	(0.018)	(0.079)	(0.079)
Access to electricity	-.093**	-.093**	-.354**	-.353**
	(0.041)	(0.041)	(0.177)	(0.177)
Log(Plot distance from residence (Km)	.029***	.029***	.165***	.165***
	(0.006)	(0.005)	(0.026)	(0.026)
Production shock over past 2 years	0.010	0.012	-0.040	-0.037
	(0.021)	(0.021)	(0.090)	(0.090)
Marketing shock over past 2 years	-0.037	-0.037	-0.096	-0.096
	(0.034)	(0.034)	(0.146)	(0.146)
Share of plots with fertile soil	-.032*	-.033*	-0.105	-0.107
	(0.018)	(0.018)	(0.079)	(0.079)

(Continues)

TABLE 3 (Continued)

	Propensity of adoption		Intensity of adoption	
	(a)	(b)	(c)	(d)
	OLS	IV (2SLS)	OLS	IV (2SLS)
share of plots with plain slope	0.036	0.036	.202*	.203*
	(0.025)	(0.025)	(0.110)	(0.110)
Owns irrigated plot	.080**	.080**	.398**	.398**
	(0.036)	(0.036)	(0.200)	(0.199)
Proportion of certified land	.040**	.039**	.176**	.175**
	(0.018)	(0.018)	(0.075)	(0.075)
Rural saving & credit coops available	0.038	0.039	0.071	0.071
	(0.030)	(0.030)	(0.140)	(0.139)
Village saving & loan association available	-0.002	-0.001	0.023	0.025
	(0.022)	(0.022)	(0.101)	(0.100)
Producer association available	-0.004	-0.004	-0.040	-0.040
	(0.027)	(0.027)	(0.125)	(0.125)
Log(distance to nearest town, in Km)	-0.005	-0.005	-0.026	-0.027
	(0.014)	(0.014)	(0.066)	(0.066)
Road is asphalted	-0.002	-0.001	0.016	0.018
	(0.030)	(0.030)	(0.139)	(0.139)
Distance to weekly market in km	-.002*	-.002*	-.014**	-.014**
	(0.001)	(0.001)	(0.005)	(0.005)
FtF zone	.077**	.077**	.511***	.513***
	(0.039)	(0.039)	(0.177)	(0.176)
Regions (reference = Tigray)				
Region is Amhara	-.577***	.632***	-2.292***	2.782***
	(0.070)	(0.108)	(0.356)	(0.535)
Region is Oromia	0.095	.760***	-1.613***	3.485***
	(0.075)	(0.095)	(0.474)	(0.387)
Region is SNNP	.340***	1.135***	-2.166***	4.929***
	(0.078)	(0.100)	(0.476)	(0.408)
District fixed effects	yes	yes	yes	yes
Constant	.312***	-.277**	1.599***	-0.825
	(0.115)	(0.132)	(0.549)	(0.559)
Number of observations	11,528	11,528	11,526	11,526
R^2	0.349	0.348	0.395	0.395
Adjusted R^2	0.345	0.344	0.392	0.392
IV Diagnostics				
Kleibergen-Paap LM statistic		67.84		67.83
Kleibergen-Paap *p*-value		.000		.000
Cragg-Donald test		1082.6		1082.0
Hansen-J test		10.02		4.31
Hansen-J *p*-value		.349		.890

(Continues)

TABLE 3 (Continued)

Notes: Standard errors clustered at the village level in parentheses. The outcome variable in Columns (a) and (b) is whether the famer used chemical fertilizers 1 = yes; while the outcome variable in Columns (c) and (d) is the log transformation of the amount of chemical fertilizers the household used in kgs per hectare (ln(kg/ha)).

[a]Livestock is measured using tropical livestock units (TLU).

[b]Index of durable assets owned generated using principal component analysis (PCA). FtF zone refers to whether the household lives in one of the Feed the Future zones. The results of all the IV Diagnostics tests show that our IV estimation satisfies all conditions.

***$p < .01$,

**$p < .05$,

*$p < .1$.

Overall, we contend that the main findings support the argument that improving credit availability leads to increased adoption and application rates of chemical fertilizers. Meaning, where credit is severely lacking, smallholder farmers may not be able to adopt and properly apply productivity boosting chemical fertilizers. These results are consistent with previous studies that reported that credit constraint is an apparent reason for variations in adoption rates of agricultural technologies in Africa and beyond (Abate et al., 2016; Karlan et al., 2014).

Table 3 also reveals that adoption of chemical fertilizers is significantly correlated with many other covariates. Consistent with other empirical studies, standard wealth indicators, such as type of roof and durable assets, appear to be important covariates of adoption of chemical fertilizers. Household size and demographic characteristics of the household head are also found to have significant association with adoption of chemical fertilizers. Both propensity of adoption and intensity of use of fertilizer are positively and significantly associated with plot distance from residence. At glance, this positive correlation between adoption of chemical fertilizers and plot distance from residence appears counter intuitive. However, the positive correlation 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 implying that chemical fertilizers are more likely to be used on plots that are farther from residence. Proportion of certified land by the household is positively correlated with the propensity and intensity of use of chemical fertilizers. Consistent with the literature, this suggests the role of tenure security in improving adoption of technologies.

The regional dummies are interpreted relative to the reference region, Tigray. Estimation results from our preferred models show that both the propensity and intensity of chemical fertilizer use are relatively higher in Amhara, Oromia and SNNP regions, as compared with Tigray region. The survey round dummy appears with a positive and significant coefficient in both the propensity and intensity of chemical fertilizer use models (Table 3). This indicates that the propensity and intensity of adoption of chemical fertilizers 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, the share increasing from 8% to 16% between the years (Appendix Table A1).

4.2 | Heterogeneity analyses of effects of access to credit

We now turn to assessing heterogeneity of effects of access to credit. The foregoing analysis shows that credit availability increases both the likelihood of adoption and the intensity of use of chemical fertilizers. In this section, we examine whether the effect of credit access on adoption and use intensity of chemical fertilizers varies with respect to the type of credit and the purpose for which households had sought credit. 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 chemical fertilizer use. Throughout, we assess heterogeneity by interacting access to credit with our variables of interest. We expect these interaction terms to be potentially endogenous as is the access to credit variable. Therefore, we extend the heteroscedasticity-based identification strategy used in the basic model for this part as well. In each regression, we now have two endogenous variables: the credit use variable and the interaction term. Fortunately, our internal IV generates enough instruments to address the endogeneity in both variables.

First, we estimate the basic model by including both the access to credit dummy and a dummy variable indicating if the credit was obtained to purchase inputs as regressors. The regression results in Columns (a) and (b) of Table 4 largely corroborate the findings of the sub-sample mean difference test results (Table 2). The full model results are presented in the Supplementary Materials (Table S1). The results show that famers who took credit for agricultural use are about

TABLE 4 Heterogeneity in effects of credit access based on purpose and sources of credit: IV (2SLS)

Variables	Credit purpose		Credit source	
	(a)	(b)	(c)	(d)
	Propensity of adoption	Intensity of adoption	Propensity of adoption	Intensity of adoption
Access to credit, yes = 1	0.028	0.093	.068**	0.141
	(0.04)	(0.16)	(0.03)	(0.15)
Access to credit*credit used for input	.093**	.351**		
	(0.04)	(0.16)		
Access to credit*credit from formal sources			-0.006	.270**
			(0.04)	(0.16)
Plot & Household controls	Yes	Yes	Yes	Yes
Community controls	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Constant	.467***	-0,827	-.277**	-.790***
	(0.128)	(0.56)	(0.133)	(0.274)
Number of observations	11,528	11,526	11,528	11,526
R^2	0.163	0.396	0.348	0.395
Adjusted R^2	0.16	0.392	0.344	0.391
IV Diagnostics				
Kleibergen-Paap LM statistic	47.84	48.81	37.11	33.32
Kleibergen-Paap *p*-value	.00	.00	.00	.00
Cragg-Donald test	331.8	327.38	230.08	229.99
Hansen-J test	16.47	16.47	15.59	10.29
Hansen-J *p*-value	.56	.56	.622	.922

Notes: Standard errors clustered at the village level in parentheses. Coefficients of plot, household, community and regional controls not reported to conserve space. Table S1 in the supplementary material contains full list of the covariates.

***$p < 0.01$,

**$p < .05$,

*$p < 0.1$.

9 percentage point more likely to adopt chemical fertilizers than those who took credit for non-agricultural purposes. Similarly, famers who took credit for agricultural purposes used about 35 percent more quantities of chemical fertilizers than those who took credit for other purposes. Thus, the purpose to which credit was committed is more important for adoption of chemical fertilizers than taking credit per se. This speaks to the fact that growth in the volume of credit to smallholder farmers may not necessarily translate into investments in agricultural technologies. Credit funds are fungible, and evidence from low income countries has shown that smallholder farmers spend credit primarily on food (Carranza & Niles, 2019). Given such observations, our result reinforces the notion that the purpose for which credit is accessed can considerably affect agricultural technology adoption. From a policy perspective, this can provide tentative support that well-designed input voucher systems can promote adoption of improved technologies more than conventional credit schemes of directly providing monetary credit.

We next investigate if the type of credit matters for adoption and intensity of use of chemical fertilizers. Table S1 in the Supplementary Materials contains the full model regressions. We similarly estimate the basic model by including indicators for both the availability and the source of credit. The results in Columns (c) and (d) of Table 4 show that credit accessed from formal sources leads to 27 percentage increase in the intensity of use of chemical fertilizer ($p < .1$) but it does not enter significantly at the conventional significance levels in the model for the likelihood of adopting chemical fertilizers. Plausible explanations for these differences may root from availability and scale variations between the two credit sources. In general, while formal credit sources more often attract wealthier and more connected households, informal credit sources represent a major source of credit for poor households because of several complementary reasons, including information asymmetry, limited supply of formal credit, stringent collateral requirements from formal sources, and the political and economic segmentation of local financial markets.

On the other hand, formal and informal credit types differ notably in terms of the volume and predictability of loanable funds. Informal loans are usually short-term, small, characterized by high flexibility, and are largely used for immediate consumption smoothing (Boucher & Guirkinger, 2007). In fact, many of the informal credit sources (e.g., Iddir, equb) are driven by community level goals to meet unexpected expenses and to cope with risk. While they provide many benefits, including capacity for small loans in a timely manner (Yami & van Asten, 2018), they might not be suitable to finance large agricultural investments as they are small in size and subject to seasonal fluctuations. Contrarily, formal loans are primarily used for business and are more frequently used for financing agriculture inputs (Carranza & Niles, 2019), and thus are more likely to play an important role in the decision about how much fertilizer to use.

The broader implication here is that improving access to and use of credit from formal sources may particularly spur the intensity of use of chemical fertilizers in Ethiopia. Together with the finding that access to credit is important for both adoption and intensity of use of chemical fertilizers, this result suggests that credit from formal and informal sources may play different roles in households' chemical fertilizers adoption process.

In Table 5, we present results for the effect of credit on adoption of chemical fertilizers based on: (a) full model (comparing credit users with the pool of credit non-users); (b) comparison of credit users with credit-constrained non-users; and (c) comparison of credit users with credit unconstrained non-users. Table S2 in the Supplementary Materials reports results from full models. Results show that credit users are generally more likely to adopt and use more chemical fertilizers than the pool of credit non-users. However, credit effects are considerably larger when estimated against liquidity-constrained credit non-user households (Columns (b) and (e)) as compared to the pool of credit non-users as one group (Columns (a) and (d)).

As expected, the magnitude of the coefficient for access to credit is larger for both adoption and intensity of use of fertilizers in the sub-sample that excludes unconstrained non-users (Columns (b) and (e)). This is intuitive as it now represents the difference in the likelihood of adoption and intensity of use between those who used credit and those who 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 (see Chi-square values in Table 5). This suggests that effects of credit would be higher if credit services target liquidity-constrained households. To put it positively, one important implication of this finding is that targeting credit to liquidity constrained farm households is more likely to promote adoption of improved technologies.

A less obvious result is the comparison between credit users and unconstrained credit non-users. The standard regressions do not imply statistical differences at conventional significance levels. However, the descriptive statistical analysis and the comparison of estimated coefficients imply some level of subtle differences. The later test suggests that credit users are more likely to use more quantities of chemical fertilizers than unconstrained credit non-user households ($p < .2$). This may tentatively imply that participation in a credit market may play other roles in addition to capital supply. Participation in the credit market may induce a dynamic incentive to loan repayment—the prospect a borrower will be offered a larger loan by a lending institution once she has been able to repay the current loan. Participation in the credit market may also induce adoption due to peer effects. 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 repercussions on social capital and status. Informal lenders also closely monitor borrowers to secure their money back, extending both incentive and peer pressure roles with credit services. Evidence also shows that using microfinance for agricultural loans increased purchasing of agricultural products when compared to cash grants, showing a higher return to capital on credit (Beaman et al., 2014).

4.3 | Sensitivity analyses

We assess the robustness of the basic results in several ways. First, rather than using access to credit dummy, we use (log of) quantity of credit as an explanatory variable in the regressions. The results are presented in Table 6. Table S3 in the Supplementary Materials provides full model regressions. Columns (a) and (b) report that the propensity of adoption of fertilizer increases with the size of credit. Specifically, doubling the quantity of credit leads to an increase in the adoption

TABLE 5 Heterogeneity in effects of credit based on liquidity-constraint status of households: IV (2SLS)

Variables	Propensity of adoption			Intensity of adoption		
	(a) Full model	(b) Constrained non-users	(c) Unconstrained non-users	(d) Full Model non-users	(e) Constrained non-users	(f) Unconstrained non-users
Access to credit, yes = 1	.064***	.098***	0.018	.357***	.494***	0.152
	(0.015)	(0.020)	(0.027)	(0.073)	(0.094)	(0.133)
Plot & Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Community controls	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-.277**	-.364**	-.111	-0.825	-1.158*	-0.225
	(0.132)	(0.142)	(0.129)	(0.559)	(0.604)	(0.585)
Number of observations	11,528	8,721	4,207	11,526	8,720	4,206
R^2	0.348	0.360	0.363	0.395	0.409	0.407
Adjusted R^2	0.344	0.355	0.353	0.392	0.402	0.397
Chi-square value		54.81	33.9		39.32	26.12
p-value		.000	.000		.000	.000
IV Diagnostics						
Kleibergen-Paap LM statistic	67.84	71.07	30.76	67.83	71.06	30.76
Kleibergen-Paap p-value	.000	.000	.000	.000	.000	.000
Cragg-Donald test	1082.6	698.6	77.78	1082	698.26	77.82
Hansen-J test	10.02	14.49	8.14	4.305	7.833	6.456
Hansen-J p-value	.349	.106	.520	.890	.551	.694

Notes: Standard errors clustered at the village level in parentheses. Coefficients of plot, household, community and regional controls not reported to conserve space. Columns (b) and (e) compare credit users with credit-constrained non-users; Columns (c) and (f) compare credit users with credit-unconstrained non-users. Table S2 in the supplementary material contains full list of the covariates.

***$p < .01$,

**$p < .05$,

*$p < .1$.

TABLE 6 Effect of quantity of credit on chemical fertilizers application: IV (2SLS)

Variables	Propensity of adoption		Intensity of adoption	
	(a) OLS	(b) IV (2SLS)	(c) OLS	(d) IV (2SLS)
Log (amount of credit)	.013***	.008***	.060***	.049***
	(0.002)	(0.002)	(0.007)	(0.009)
Plot & Household controls	Yes	Yes	Yes	Yes
Community controls	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Constant	.313***	-.279***	1.600***	-.849***
	(0.115)	(0.132)	(0.547)	(0.560)
Number of observations	11,528	11,528	11,526	11,526
R^2	0.348	0.348	0.396	0.396
Adjusted R^2	0.345	0.344	0.392	0.392
IV Diagnostics				
Kleibergen-Paap LM statistic		64.00		63.99
Kleibergen-Paap *p*-value		.000		.000
Cragg-Donald test		1420.2		1419.8
Hansen-J test		11.837		5.597
Hansen-J *p*-value		.223		.779

Notes: Standard errors clustered at the village level in parentheses. Coefficients of plot, household, community and regional controls not reported to conserve space. Table S3 in the Supplementary material contains full list of the covariates.
***$p < .01$,
**$p < .05$,
*$p < .1$.

of chemical fertilizer by 0.8 percentage point. Given that the baseline adoption rate of chemical fertilizer by non-credit users is 60%, this translates to a 1.3 percentage change in the adoption of chemical fertilizer. Similarly, columns (c) and (d) present results from the simple OLS and 2SLS regressions for quantity of chemical fertilizers used on amount of credit obtained by the households. Doubling the quantity of credit leads to an increase in the quantity of chemical fertilizer used by households by about 5%. Credit size appears with positive and statistically significant coefficients in both models. Generally, the basic results remain qualitatively similar and robust.

Second, the basic results assumed the outcome variables as linear variables. However, since the fertilizer use indicator is a binary variable and the quantity of fertilizer per hectare is left censored (due to non-adopters), using a linear model may not be unequivocally appropriate. Linear models are preferable due to their simplicity and interpretability, and because they provide a host of specification tests to assess the validity of the IV strategy (Angrist & Pischke, 2009; Caudill, 1988). However, for limited dependent outcomes, a linear model may be unreliable (Wooldridge, 2002). Therefore, we assess the robustness of the basic findings using tobit regressions. As in the basic model, the estimate from the tobit regression may be biased due to the potential endogeneity of credit access in model explaining technology adoption. To address this challenge, we rely on instrumental variables (IV) strategy. 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. 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. Both instruments pass the standard tests for instruments, including the relevance criterion, weak instruments and overidentification. Despite this, we realize that concerns may remain related to the admissibility of the exclusion restrictions, and clean causal inference might be compromised.[7]

[7] Unlike the approach used for the basic model, to the best of our knowledge, the heteroscedasticity-based identification strategy could not be combined with the tobit model.

TABLE 7 Effect of credit use on intensity of adoption of chemical fertilizers, Tobit regressions

Variables	(a) Tobit	(b) IV Tobit
Credit access, yes = 1	.637***	7.373***
	(0.079)	(1.803)
Plot & Household controls	Yes	Yes
Community controls	Yes	Yes
Regional dummies	Yes	Yes
District fixed effects	Yes	Yes
Constant	-3.874	-6.266
	(1.118)	(1.542)
Adjusted/ Pseudo R^2	0.130	
Number of observations	11,526	11,526

Notes: Standard errors clustered at the village level in parentheses. Coefficients of plot, household, community and regional controls not reported to conserve space. Table S4 in the Supplementary material contains full list of the covariates.
***$p < .01$,
**$p < .05$,
*$p < .1$.

TABLE 8 Effect of credit use on input use, chemical fertilizer users only, IV (2SLS)

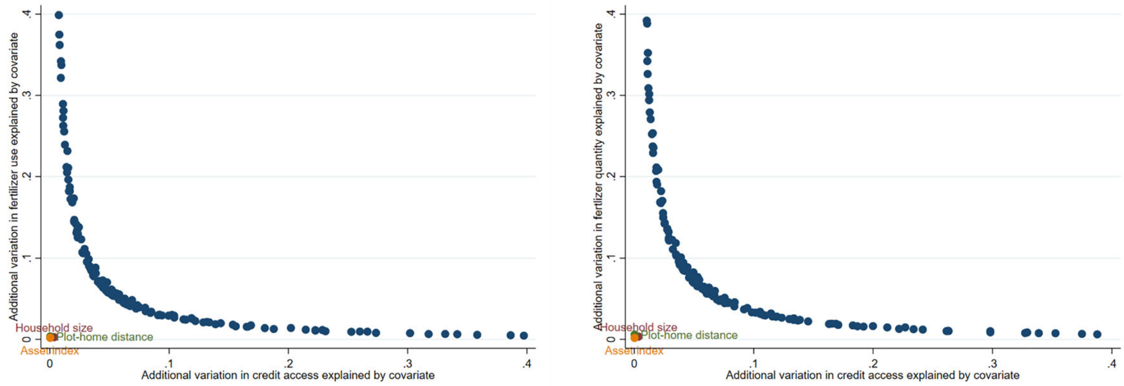
Variables	(a) OLS	(b) IV (2SLS)
Credit access, yes = 1	.063*	.767**
	(0.038)	(0.341)
Plot & Household controls	Yes	Yes
Community controls	Yes	Yes
Regional dummies	Yes	Yes
District fixed effects	Yes	Yes
Constant	4.181	4.195
	(0.328)	(0.275)
Adjusted R^2	0.298	0.160
Number of observations	7,296	7,296

Notes: Standard errors clustered at the village level in parentheses. Coefficients of plot, household, community, and regional controls not reported to conserve space. Table S5 in the Supplementary material contains full list of the covariates.
***$p < .01$,
**$p < .05$,
*$p < .1$.

Table 7 reports the result of the tobit regressions along with the respective IV approach to account for the endogeneity of access to credit, while Table S4 in Supplementary Materials contains full model regressions. The results remain robust and do not seem to be driven by the non-linear nature of the outcome variables.

Third, we re-estimated our basic model for the intensity equation including only households that applied non-zero values of chemical fertilizers. This strategy can be thought to exploit the variation in the intensity of chemical fertilizer use among households that used fertilizer in response to access to credit. In other words, this estimation measures effect for households who change the intensity of chemical fertilizer use triggered by access to credit. Therefore, the estimates can be interpreted as local average treatment effects. The results are reported in Table 8, and they remain once more robust and consistent with results from the basic model. Full model regressions are presented in Table S5 in the Supplementary Materials.

Finally, omitted variables could remain a concern with our estimation of the effect of credit on technology adoption if the omitted variables are significantly correlated with both credit and chemical fertilizer. To attenuate this concern, we control for district fixed effects and regional dummies throughout our regressions that could partially account for observed and unobserved 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



Panel (a) outcome variable – propensity of fertilizer use

Panel (b) outcome variable – use intensity fertilizer

FIGURE 1 Sensitivity of estimated effect to omitted variable bias.

heterogeneities. Despite these control measures, it is virtually impossible to control for every possible household-specific factor that might be correlated with both technology adoption and access to credit, given the observational nature of the data. Thus, omitted variable bias could still remain a real concern. For example, it is plausible that those who use input more are more productive that could translate into higher income and thereby better credit rating. We formally assess the degree of omitted variable bias using the sensitivity analysis proposed by Imbens (2003). The test helps us examine whether our results are appreciably affected by omitted variable bias by estimating the degree of correlation a missing variable should have with both the outcome and explanatory variables to substantially change the estimated effect.

To implement this procedure, we take our preferred specifications (the IV results in Table 3) and consider the correlation between credit access and unobserved covariates that are also correlated with the outcome variables—adoption and intensity of chemical fertilizer use. By generating pseudo-observables over 200 iterations, Figure 1 shows a series of points representing the combination of R-squared values that would lead to a reduction of the size of the effect coefficient by half. On the vertical axis, we plot the marginal increase in R-squared that results when an unobserved covariate is added to a regression of the outcome variables on our full set of significant controls. The horizontal axis plots the marginal increase in R-squared from adding the covariate to a regression of credit access on our full set of controls. Panel A and Panel B present this analysis separately for adoption and use intensity of fertilizer, respectively.

From the figure, we can see that a correlation between credit access and an omitted variable would only be problematic if the correlation between the same omitted variable and the outcome variables was very high. To illustrate this finding made by a hypothetical omitted covariate, we also plot the partial correlation between credit access and the outcome variables for three significant control variables (household size, household asset index, and plot distance from household residence). The results show that none of the three controls even approaches the threshold that reduces our estimated effect of credit on the outcome variables by half. Therefore, an omitted variable would have to be much more important than our existing controls to invalidate our results. This gives us confidence that our main result, that is, credit access promotes fertilizer use and intensity, is unlikely to have been driven by omitted variable bias.

5 | CONCLUSION AND DISCUSSIONS

Increasing agricultural productivity and reducing poverty through promoting the use of modern inputs, such as chemical fertilizers, has long been at the center of development policies in developing countries. In this paper, we study the effect of access to credit on smallholder households' adoption decision and intensity of use of chemical fertilizers using large survey data in Ethiopia. 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 development strategies and reform packages for pro-poor growth.

Using a heteroscedasticity-based identification strategy to account for the potential endogeneity, we find evidence that access to credit has a positive and significant effect on both adoption and intensity of use of chemical fertilizers. We also document substantial heterogeneity in the effects of credit. Credit accessed from formal sources is more significant for the intensity of chemical fertilizers than for the decision to adopt per se. 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 the likelihood to adopt new technologies. Equally, credit taken with the primary purpose of financing agricultural inputs is more important in promoting adoption of chemical fertilizers than credit accessed per se. 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). Thus, effect of credit is greater when credit services target liquidity-constrained households. Furthermore, our findings indicate that differentiating between the likelihood of adoption and intensity of adoption can reveal important insights into the decision-making process of farmers.

The findings of this study have important implications for policymaking geared towards promoting increased adoption and the intensity of use of agricultural technologies. More broadly, our results support the argument that 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 strong association between credit accessed with the purpose of agricultural inputs and adoption of chemical fertilizers suggests that simple growth in the volume of credit may not necessarily translate into a higher rate of agricultural technology adoption. This provides tentative support that credit supply earmarked to input financing may be more effective to promote adoption of improved technologies. The finding that credit accessed from formal sources is more important for the intensity of use of chemical fertilizers underlies the importance of encouraging penetration of formal financial services into rural areas and/or mitigating factors that prohibit smallholder farmers from accessing credit from formal sources. Finally, our result that credit access has greater effect on technology adoption and use intensity for liquidity-constrained households points to the need to design credit policies targeting these households.

Finally, while our results are informative and relevant, it is important to note that credit access is one of many impediments to the adoption of improved agricultural technologies in poor countries. Such factors as production risk, transaction costs, weak access to both input and output markets and other institutional conditions are proven to play important roles in technology adoption (de Janvry & Sadoulet, 2020). This implies that capital constraints alone are not enough to explain the low adoption of technologies. In other words, expanding credit to farmers who are otherwise credit-constrained will not suffice to generate higher farm investment and thus improved income and growth (Karlan et al., 2014). Similarly, unfavorable physical, market, and institutional conditions undermine the profitability of investments in agricultural technologies, like fertilizer and improved seeds, ultimately leading to low adoption rates (de Janvry & Sadoulet, 2020). Thus, complementary measures at multiple fronts are likely needed to address multiple market failures to increase the uptake of agricultural technologies in developing countries (Mishra et al., 2021).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

TABLE A1 Summary of key variables by survey years

Variables	Overall sample (N = 12,137)	2013 (N = 6111)	2015 (N = 6026)	Mean difference test (p-value)
Panel A: Outcome variables				
Chemical fertilizers	62.4	58.2	66.6	.00
Chemical fertilizers (kg per hectare)	62.8 (98.9)	61.4 (99.3)	64.2 (98.5)	.11

(Continues)

TABLE A1 (Continued)

Variables	Overall sample (N = 12,137)	2013 (N = 6111)	2015 (N = 6026)	Mean difference test (p-value)
Panel B: Main explanatory variables				
Access to credit	0.12	0.08	0.16	.00
Credit amount (Birr)	439.8	256.6	625.7	.00
Average size of credit in village, in Birr	440(895)	257 (563)	626 (1,106)	.00
Distance to credit sources in km	4.11(12.8)	4.89 (16.6)	3.36 (7.2)	.00
Panel C: Other covariates				
Head is female	0.27	0.27	0.27	.34
Age of household head	44(14.9)	43(14.8)	45(14.8)	.00
Household size	4.9(2.1)	4.8(2.1)	5(2.2)	.00
Education level of head	1.5(2.8)	1.3(2.7)	1.6(2.8)	.03
Land size in hectares	1.6(2.6)	1.5(3.2)	1.7(1.8)	.01
Livestock owned, in TLU	3.3(3.9)	3.2(4.3)	3.3(3.4)	.42
Durable assets owned	0.05(1.4)	0.04(1.4)	0.05(1.4)	.69
Household has good floor	0.09	0.09	0.1	.65
Household has good roof	0.43	0.38	0.47	.00
Access to electricity	0.06	0.04	0.07	.00
total land size in ha	1.63(2.62)	1.52(3.20)	1.73 (1.84)	.00
Log(Plot distance from residence (km)	1.95(1.33)	1.90(1.36)	2.01(1.29)	.00
Share of plots with fertile soil	0.71(0.41)	0.74(0.40)	0.69(0.41)	.00
Share of plots with plain slope	0.73(0.39)	0.75(0.39)	0.71(0.40)	.00
Proportion of certified plots	0.72(0.41)	0.73(0.41)	0.72(0.40)	.03
Share of irrigated plots	0.05(0.22)	0.05(0.21)	0.06(0.23)	.02
Distance to weekly market in km	5.73 (8.43)	5.45(9.46)	6.00(7.30)	.00
Distance to nearest town, km	12.95(11.83)	12.82(11.03)	13.09(12.60)	.20
Average credit in the village	440 (895)	257(563)	626(1,106)	.00
Distance to credit source in Km	4.11(12.77)	4.85(16.48)	3.36 (7.21)	.00
HH faced production shock over past 2 years	0.16	0.16	0.16	.87
HH faced marketing shock over past 2 years	0.02	0.02	0.02	.96
Road is asphalted, yes = 1	0.18	0.18	0.19	.20
Access to rural saving and credit coop	0.43	0.44	0.41	.00
Access to village saving and loan association	0.38	0.37	0.40	.00
Access to producer association	0.18	0.15	0.20	.00
FtF zone, yes = 1	0.64	0.64	0.64	.84

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

TABLE A2 Sources and methods of financing chemical fertilizers, by %HHs

Method of financing chemical fertilizers	Percentage of households
Cash	84
Credit	9
Partly credit	7
Source of chemical fertilizers	
Service cooperatives	39.0
Government extension agents	26.6
Producers cooperatives/Association	16.7
Local market (retailors)	12.7
Private trader	5.3
Development organizations (NGO)	1.3
Farmers in the village	1.2
Dealers	0.3
Others	0.8

Source: Ethiopian FtF survey (2013, 2015).

TABLE A3 Details of households who took credit, percentage of households

Explanatory variables	Total	2013	2015
Proportion of HHs who took credit	12.0	8.1	15.2
Source of credit-Formal	67.5	74.7	63.2
Source of credit-Informal	35.2	26.7	40.2
Proportion of HHs taking credit for input	72.4	79.9	68.1

Source: Ethiopian FtF survey (2013, 2015).