ABSTRACT

It has now become almost a stylized fact that sustained agricultural growth is central to rapid poverty reduction and economic development. Yet, world poverty is largely concentrated in the agrarian societies, which have the potential for agricultural productivity growth. This is particularly true for Sub-Saharan African countries, where the gaps between potential and actual yields remain high. Minimizing this gap through the promotion of modern inputs—such as fertilizer and modern seeds—has been at the core of almost all development strategies in Ethiopia. Among other initiatives, the country has promoted microfinance institutions and member-owned financial cooperatives to alleviate credit constraints of the smallholder farmers. This paper analyzes the impacts of these institutions. Using household survey data and a propensity-score-matching technique, we examine the effects that institutional financial services have on farmers' adoption of agricultural technology in Ethiopia. The results suggest that access to institutional finance has a significant positive impact on both the adoption and extent of technology use. However, when impacts are disaggregated by type of financial institution and farm size, heterogeneities are observed. In particular, financial cooperatives have a greater impact on technology adoption than microfinance institutions, and the results appear to vary depending on farm size and types of inputs. The paper concludes with implications for policies to promote adoption of modern agricultural inputs.

Keywords: institutional finance; agricultural technology adoption; impact analysis, propensity score matching; Ethiopia

JEL Classification: G21; Q14.

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Rural Finance and Agricultural Technology

Adoption in Ethiopia

Does the Institutional Design of Lending Organizations Matter?

1. INTRODUCTION

Historical evidence suggests that in most countries, sustained agricultural growth in the early stages of development was central to rapid economic growth and poverty reduction (Timmer, 2014; Hazell et al., 2007; Johnston & Mellor, 1961). This has been true for the industrialized countries of Europe (Lains & Pinella, 2010) and North America (Timmer, 2014), as well as Japan and the emerging countries of East Asia (Johnston, 1951; Hayami & Ruttan, 1971). The most recent example is the Green Revolution in Asia, where the introduction of improved farm technologies led to an increase in agricultural production, which helped fuel overall economic growth, reduce poverty, and improve the livelihoods of rural households (Fan et al. 2006; Mendola 2007; Rashid, Cummings Jr., & Gulati 2007). More importantly, consumers benefited as supply outpaced demand, which drove down real food prices and led to an improvement in caloric intake by the poor households (Evenson & Gollin 2003).¹

However, this historical regularity is yet to manifest in many African countries, especially in countries south of the Sahara. Although modern technologies— such as improved seeds, fertilizer, and agro-chemicals— are readily available, their rates of adoption have been the lowest in Africa (Jayne & Rashid, 2013; and de Janvry & Sadoulet, 2010). Currently, the continent has the largest yield gaps (i.e. the difference between possible and actual yields) in major cereals. For example, maize and wheat yields are consistently lower than their yield potential by 63 and 52 percent, respectively (Licker et al., 2010; Nkonya et al., 2013). As demonstrated in Asia, this yield gap can be closed with widespread adoption of available improved technologies. According to the FAO, farmers in Africa apply 21.1 kgs of nutrients per hectare of land, which compare with 135.6 kgs in South Asia and 195.3 kgs in developed countries. Several national and continent-wide initiatives—such as the Comprehensive African Agricultural

¹ Although the number of studies is limited, African experiences also point into the same direction. For example, using spatially explicit data from Madagascar, Minten & Barrett (2008) demonstrate that communes with higher rates of adoption of improved agricultural technologies enjoy lower food prices, higher real wages, and better livelihoods.

Development Program (CAADP) of the New Partnership for African Development (NEPAD)—have set targets to improve the application rates in Africa.

Ethiopia is on the forefront for tackling these challenges in its agriculture sector. The government has allocated more than 10 percent of public spending to agriculture, invested in scaling up its agricultural extension and rural finance programs, and has given special attention to programs that support increased production of cereal crops (Rashid & Negassa 2013). These investments have paid off in terms of increasing both cereal production and the growth of the agricultural gross domestic product (AGDP). Between 2005 and 2012, the value-added from agriculture almost tripled from US\$6.5 billion to \$19.2 billion, and cereal production grew from 12 million metric tons to 23 million metric tons (World Bank 2014). Despite these impressive achievements, the country still has a large yield gap. One explanation for such a gap is the low technology adoption. For instance, one study finds that only 30 to 40 percent of Ethiopian smallholders apply fertilizer, and of those who do, the rate of application is only 37 to 40 kgs per hectare, which is far below the recommended rates (Spielman, Kelemwork, & Alemu 2013). Sheahan & Barrett (2014) found slightly higher estimates of fertilizer use (45kgs /ha), but low estimates of modern seed use for barley (3.2%), maize (34%), wheat (12%), and coffee (1.5%).

Ethiopia has much to gain by promoting widespread use of modern input use. The broader constraint, however, has the deficient markets for risk management (credit and insurance), which, to a large extent, is responsible for slow adoption of technologies by smallholders.² The conventional policy approach to addressing this challenge has been to provide subsidized credit through state-owned banks. However, it has been well documented that this policy has either failed or has had limited success (Adams, Graham, & Von Pischke 1984; Binswanger, Khandker, & Rosenzweig 1993). Recently, Ethiopia has adopted a new approach by moving away from subsidies to a more market-oriented financial system.

² A large body of literature, which grew mostly during the Asian Green Revolution, exists on the determinants of technology adoption in the presence of market failures. Selected studies include Feder, Just, & Zilberman 1985; Dercon & Christiaensen (2011); Feder & Umali (1993); Lipton (1976).

As of 2010, Ethiopia's specialized Microfinance Institutions (MFIs) and Financial Cooperatives (FCs) have become the primary source of credit for smallholders, with about two-thirds of their loan portfolio channeled to smallholders (Amha & Peck 2010; Obo 2009).

To the best of our knowledge, there is no systematic study that evaluates the effects of these institutional credit provisions on farmers' decisions to adopt new technology. This paper attempts to fill this knowledge gap. Using survey data, we undertake two main tasks: (1) analyze the effect of access to institutional credit on smallholders adoption and application rates of agricultural technology by using propensity score matching; and (2) assess whether the institutional design of the lending organizations (i.e. the way ownership of the financial services providers is organized and operated) makes a difference in promoting agricultural technologies.

The remainder of the paper is organized as follows: Sections 2 reviews the history of institutional finance provisions for smallholder farmers in Ethiopia. Section 3 presents a brief summary of the characteristics and lending approaches of FCs and MFIs in Ethiopia. Section 4 describes the survey methods and the measurement of the main variables and the estimation strategy—i.e. the impact evaluation problem, propensity score matching, and propensity score estimation procedures and results. The main findings are presented in Section 5, and the paper concludes with a summary and a discussion on policy implications in Section 6.

2. INSTITUTIONAL FINANCE AND SMALLHOLDER AGRICULTURE IN ETHIOPIA

There is a clear need for a robust agricultural finance system in Ethiopia. Even though smallholder farmers produce 90 percent of the country's agricultural production, they are resource-poor and on average, own less than one hectare of land (Ethiopia, Central Statistical Agency 2011; 2013; Headey et al. 2013). Furthermore, they are characterized by their inadequate investment in productivity-enhancing inputs (Dercon & Christiaensen 2011; Spielman, Kelemwork, & Alemu, 2013). This implies that there is a potentially large credit demand from smallholders that is unlikely to be met by the formal banking system because smallholders require smaller transactions, have large covariant risk, and live in rural areas that lack access to a bank (Amha & Peck 2010; Croppenstedt, Demeke, & Meschi 2003). Since the 1960s, there have been several policies designed to address this challenge, including institutions tailored for smallholder agriculture. Evaluations of these programs, however, have shown that they neither increased productivity nor reduced poverty (Braverman & Guasch 1986). Instead they suffered from elite capture and institutional capacity constraints (Admassie, 1987).

During the imperial regime (1960s–1974), about half of the total domestic credit that went to agriculture was disbursed through two intermediary institutions—the grain enterprises and primary cooperatives. These intermediaries received funds from state-owned banks to provide credit to farmers at concessional rates (EEA 2000). However, like most of the government controlled credit programs elsewhere in the same period, the efforts to extend agricultural credit to smallholders did not succeed. During 1960-74 period, between 42 and 65 percent of all total domestic loans went to agriculture. Of this total, smallholders received only a fraction (7.5 percent) compared to the wealthier and influential farmers (Admassie 1987; 2004).

The socialist regime (1974–1991) perpetuated the tradition of instituting specialized financial institutions, but it did not translate into greater access to credit by smallholders. Instead, they were deprived of credit because larger state-run farms received higher priority. For instance, during the first 10

years of the regime (1974—1984), about 89 percent of the agricultural credit was extended to state farms, while private smallholder farmers received only 9-11 percent (EEA 2000).

Smallholder farmers did not fare any better by the reforms under the Structural Adjustment Program. As Figure 1 shows, during the years after the economic reform, the share of agricultural credit shrank considerably. A recent study by Amha & Peck (2010) estimated a \$3 billion credit shortage in the overall economic system. The smallholders suffered more severely due to this shortage than the other sectors. Although agriculture accounted for 41 percent of the total GDP in 2010/2011, the sector's share in overall loan disbursement was only about 14 percent (Figure 1). The ratio of the share of total agricultural lending to the share of agriculture to GDP was also low at only 34 percent, which was also more or less the case for most of Ethiopia's neighboring countries³. Moreover, the credit-to-output ratio for the same period indicates a substantial credit shortage in agriculture—the mean credit-to-aggregate value of total agricultural production over the last two decades is only 6 percent (Figure 1).

(Figure 1 here)

The existence of large credit gap reflects the fact that the conventional financial institutions in Ethiopia do not provide enough credit to smallholder agriculture (see Table A.4 in the appendix). Currently, MFIs and FCs are the only institutions that focus on smallholder lending, allocating about two-thirds of their loan portfolio to smallholders (Amha & Peck 2010; Obo 2009). Along with the regional governments, these financial institutions act as an intermediary between banks and smallholders. As Figure 1 shows, since the revival of cooperatives and the spread of microfinance in 2000, the share of agricultural credit and the credit-to-output ratio have steadily grown.

³ The share of total lending to agriculture is also very low compared to lending to manufacturing, trade, and other service sectors in neighboring Eastern African countries too. Our calculation of the ratio of the share of agricultural lending to the share of agriculture to output for Kenya, Uganda, Tanzania, Ghana, and Sudan indicates comparable credit-to-output ratio—i.e. the credit-to-output ratio during the same period (i.e. 2010/11) was about 23, 45, 51, 23, and 48 percent for Kenya, Uganda, Tanzania, Ghana, and Sudan, respectively.

However, growth in the volume of credit to smallholder farmers may not necessarily translate into a higher rate of agricultural technology adoption. Funds are fungible and it is possible that the farmers use their credit for purposes other than agriculture. A quick analysis of aggregate data suggests that this is a possibility. For instance, product-moment correlation between the average annual growth rate in agricultural credit and agricultural GDP for the 1980s and 1990s is very low, suggesting the possibility of credit diversion. However, firm conclusions cannot be drawn without establishing the causal relationship through survey data, which, to the best of our knowledge, is very limited.

3. FCs AND MFIs IN ETHIOPIA

Similar to other developing countries, the mainstream financial institutions in Ethiopia lack the capacity to serve resource-poor households and smallholder farmers (Obo 2009; Amha & Peck 2010). Therefore, besides informal sources⁴, low-income households and smallholders heavily rely on FCs and microfinance institutions, which are now the forerunners in delivering financial services to farmers. Their contributions are notable in lending small-uncollateralized loans, in savings mobilization, and in inculcating financial literacy in society (Degefe & Nega, 2000).

As of 2012, there were over 7,000 primary saving and credit cooperatives that provided financial services (i.e., saving, loans, and insurance) to about one million members in Ethiopia (FCA, 2012). Similar to most credit cooperatives elsewhere, FCs in Ethiopia are organized by individuals (i.e., farmers, laborers, employees, etc.) working or living in the same localities and they themselves are the providers of both the demand for and the supply of loanable funds. FCs mainly uses standard bilateral lending contracts between the cooperative and a member-borrower. Liability for repaying the loan rests with the individual borrower and the co-signer, who must also be a member of the same cooperative.

Aside from FCs, the development of institutional finance in Ethiopia also rely on the national and international NGOs and government credit programs. Specialized MFIs emerged during the 1990s as a result of the transformation of government and non-government credit providers following the economic reform in 1991. In addition to shareholder-owned microfinance institutions, which evolved from previous NGOs and government credit programs, the industry also witnessed the start-up of investor-owned microfinance providers. In 2012, a total of 30 MFIs in Ethiopia served over 2.3 million clients, with total loans amounting to 6.5 billion *birr*⁵ – or about \$365 million.

⁴ In Ethiopia, informal or non-institutional sources of financial services are a source of credit services for more than 80 percent of the rural borrowers and approximately accounts for about 20 percent of the total credit in the country (Amha and Peck, 2010; Ayalew 2003).

⁵ *Birr* is the Ethiopian currency. Exchange rate in December 2012 was 18.18 Birr to US dollar.

MFIs in Ethiopia are share companies that are registered and regulated by the National Bank of Ethiopia (NBE). They are owned by individuals, public bodies, NGOs or by a combination of the three. Most of them are commercial lenders that aim to achieve financial self-sufficiency in serving the poor. Unlike FCs, which are confined to specific locations, MFIs operate in larger areas and rely heavily on external funding. They use both bilateral individual lending contracts and contracts based on joint liability lending. In the case of group lending, which is the main lending contract of MFIs in Ethiopia, loans are made to individuals, but the group of borrowers shoulder responsibility for the loan if one of the members defaults.

In summary, while FCs and MFIs resemble each other in terms of the target group they are serving (i.e. low-income clients and smallholder farmers); they differ in their ownership and governance structure, source of funding, lending approach, and appropriation of earnings (Table 1).

(Table 1 here)

4. DATA AND METHODOLOGY

4.1 Sampling Design and Data

The data used in this paper come from a specially designed survey of 817 farm households conducted during April – June of 2012. The sample was drawn from 21 *kebeles* (villages) in 21 districts of Ethiopia (i.e. one *kebele* from each district) using a stratified random sampling.⁶ Two groups of *kebeles* were sampled⁷. In the first group of *kebeles*, there was no institutional financial services provider (control group), and in the other group of *kebeles* (treatment group), there was either a specialized MFI or FC, but not both. It is worth noting that the control *kebeles* were shortlisted by microfinance institutions as potential areas of future expansion of their programs. Of the sampled households, 54 percent belong to the control group (i.e. group of households with no access to institutional financial services) and the remainder to the treatment group (i.e. group of households who have received institutional credit from the aforementioned institutional financial service providers).

In the control group, households were randomly selected from the complete lists of households obtained from the local administration. For the treatment group, for each *kebele*, a list of households that received credit was obtained from the respective MFIs and FCs, which was then used to randomly select the samples. We also randomly selected non-beneficiary households from the treatment *kebeles* (i.e. control households within treatment *kebele*) using household lists maintained by *kebele* authorities (after excluding those who received institutional credit) to examine potential spillover effect.

⁶ The data were collected with the financial and technical support of the European Research Institute on Cooperative and Social Enterprises and the International Food Policy Research Institute, Research for Ethiopia's Agriculture Policy (REAP) project.

⁷ The sampled group of treatment and control *kebeles* are from Eastern Gojjam zone of Amhara region and Western and Eastern Shewa zones of Oromia region. And the *woredas* from where the treatment and control group of *kebeles* were selected are comparable in their production potential, agro-ecology, input and output market opportunities, and on average landholding size, distance to district centers and markets and access to farmer training centers and extension services (see Table 4 and Table 5 for some of *kebele* related variables).

Variable Definition and Measurement

This study takes into account both supply-side (i.e. the availability of an institution providing financial services) and demand-side (i.e. the choice of farm households to participate) factors in the construction of the treatment variable—the use of institutional finance. The farm households in the treatment group are those that reside in *kebeles* that have an institutional finance provider and who choose to participate (i.e. received agricultural credit for 2011/2012 production year). On the other hand, the comparison group constitutes farm households that reside in *kebeles* where there are no formal financial service providers and that didn't receive institutional finance.

The outcome variables include the adoption of the two most important agricultural technologies in Ethiopia, fertilizer and improved seeds. Following Feder (1982), we define adoption of technology as a two-level decision-making process. At the first level, a farmer decides whether to adopt a technology; once the decision to adopt is made, the next (second-level) decision is to determine how much modern input to use. Defining adoption this way is particularly important for divisible inputs like fertilizer and seed because the impact of such technology depends on the intensity of use (for example, kilograms of fertilizer per hectare), which is a continuous variable (Feder, Just, & Zilberman 1985; Schutjer & Van der Veen 1977).

Table A. 1 in the appendix presents all the household and *kebele*-level variables used in the analysis. The selection of variables is guided by previous theoretical and empirical work on the determinants of access to and usage of institutional financial services in similar contexts by Bigsten et al. (2003); Demirgüç-Kunt & Klapper (2012), Diagne (1999); Hussien (2007); and Ibrahim, Kedir, & Torres (2007), among others.

4.2 Estimation Strategy

Impact Evaluation Problem and Propensity Score Matching

There is a strong theoretical basis to support the connection between access to financial services and the level of technology adoption. However, measuring the outcomes and impacts due to access (or a lack thereof) to institutional finance is complicated by the fact that the counterfactuals are almost always missing. The advantage of the randomized control trial in addressing this particular challenge is the reason behind that method's increasing popularity in impact evaluation (Duflo & Kremer 2005). In a cross-section study, one can only compare farm households that received credit with those who did not. However, the direct comparison of these two groups may be misleading, as the self-selected households that have received institutional finance can be inherently different from the comparison group (Caliendo & Kopeinig 2008; Dehejia & Wahba 2002; Heckman et al. 1998).

Therefore, in assessing the impact of usage of institutional finance on technology adoption with cross-sectional data, it is important to address this statistical pitfall, particularly to isolate the effects of institutional finance from other socioeconomic determinants of households' technology adoption (for example, education, landholding, risk preference, and so on). Following Mendola (2007), we define household access to institutional finance and technology adoption as follows:

$$Y_{Di} = f_D(x_i) + \varepsilon_{Di} \quad D = 0,1, \quad \text{and} \quad (1)$$

$$D = g(W_i) + h_i, \quad (2)$$

where Y_{Di} refers to the intensity of adoption of agricultural technologies of farm household i depending on whether the household has access to institutional finance, measured by a dichotomous variable D , which takes a value equal to 1 if the household has received institutional finance and zero otherwise. x_i and ε_{Di} are vectors of observed and unobserved variables, respectively. Finally, W_i is a subset of x_i and

includes observable explanatory variables that determine the use of institutional financial services and η_i represents the other, unobservable household-specific characteristics that influence households' access to financial services.

Our interest is to determine the magnitude of the average impact of access to institutional finance on intensity of technology adoption, or the average treatment effect on the treated (ATT), and can be specified as follows:

$$\tau_{ATT} = E(Y_{(1)i} - Y_{(0)i} | D_i = 1) \quad , \text{ and}$$

$$\tau_{ATT} = E(Y_{(1)i} | D_i = 1) - E(Y_{(0)i} | D_i = 1) \quad , \quad (3)$$

where $E(Y_{(1)i} | D_i = 1)$ is the outcome of farm households that have access to institutional finance and $E(Y_{(0)i} | D_i = 1)$ is the outcome if the households did not have access to institutional finance (i.e. nontreatment outcome of treated units).

The basic problem in estimating the causal effect specified in Equation 3 is that one can only observe $E(Y_{(1)i} | D_i = 1)$ from households that have access to institutional finance. We cannot observe the counterfactual—i.e. what would have been the farm households' decision in the absence of access to institutional finance (i.e. $E(Y_{(0)i} | D_i = 1)$). In observational studies like this, the outcome of farm households that do not have access to institutional finance ($E(Y_{(0)i} | D_i = 0)$) is often used to overcome the 'missing observation problem' and approximate $E(Y_{(0)i} | D_i = 1)$. However, approximating the nontreatment outcome of treated units using self-selected nonusers will have a selection bias (B) = $E(Y_{(0)i} | D_i = 1) - E(Y_{(0)i} | D_i = 0)$ (Caliendo & Kopeinig 2008; Heckman et al. 1998).

There are both parametric and nonparametric estimation methods that can be applied to reduce the bias arising from such an approximation. The commonly used parametric methods include control-function regressions and instrumental variable (IV) estimators. If one assumes that conditioning on a vector of observable characteristics x restores the condition of randomization (i.e. conditional independent assumption: $(Y_{(1)}, Y_{(0)}) \perp D | x$), the causal effect of access to finance on technology adoption can be estimated using a control-function ordinary least squares (OLS) regression. However, if the conditional independent assumption does not hold, which is probable in cases where the selection of the treatment is due not only to observable variables but also to characteristics unobservable to the analyst, OLS regression could lead to biased estimates.

A variation on a parametric OLS regression is to use an IV estimator that can determine consistent estimation under the hypothesis of selection on unobservable (Caliendo & Kopeinig 2008; Heckman et al. 1998). This method also solves the problem by treating the treatment variable as endogenous. The application of the IV, however, requires the availability of at least one valid instrument Z that is relevant and exogenous (that is, $Cov(Z, D) \neq 0$ but $Cov(Z, e) = 0$)—the basic exclusion restriction under which the IV estimator works. While this approach has the advantage of restoring the conditions in a ‘natural experiment’, it is fairly difficult to find a variable that explains the selection and at the same time has no relation to the outcome. Additionally, when such a variable is available, its exclusion restriction is not easily testable. Furthermore, the validity of the causal inference using these commonly used regression methods rests on ad hoc functional form assumptions required by standard parametric approaches (Jalan & Ravallion 2003).

Propensity score matching (PSM) is another nonexperimental, but nonparametric approach used for causal inference under the same hypothesis as parametric OLS regression (i.e. selection on observables or unconfoundedness/conditional independence). PSM substitutes for the absence of experimental comparison units by using a set of potential control units that are not drawn from the population treatment group, but instead from independent samples with the same set of observable

parametric covariates (Dehejia & Wahba 2002; Rosenbaum & Rubin 1983). PSM is generally preferred over parametric regression for at least three reasons: (1) it does not require a parametric model linking treatment to outcome (Smith and Todd 2005); (2) it can impose a common support condition that improves the quality of the match (Jalan & Ravallion 2003); and (3) it reduces the number of comparison groups to a subsample with characteristics more homogenous to the treated one (Cameron & Trivedi 2005).

The Propensity Score Matching Procedure

Following the arguments in the literature, the conditional probability of access to finance (i.e.

$p(x_i) = \Pr ob(D_i = 1 | x_i)$) is estimated using the predicted values from a standard probit model⁸ to estimate the propensity score of each observation with and without access to credit.

⁸ In our estimation of the probability of access to finance, the decision of farm households to receive a financial product (in this case, credit) is analyzed using a random utility framework following similar applications by Abebaw & Haile (2013), Feder, Just, & Zilberman (1985), and Wollini & Zeller (2007) on decisions by farmers to adopt technologies and to participate in cooperatives, among others. We assume that the willingness, or the decision, to receive financial services is based on the maximization of an underlying utility function. Even though the actual utility function of each farm household U_i is unknown, farm households choose to receive a financial product if the utility gain from receiving finance (U_i^R) is greater than the utility of not receiving it (U_i^N). Hence the utility gain from receiving financial services (that is, $U_i^R - U_i^N$) can be expressed as a function of a vector of observable variables x_i and a vector of parameters to be estimated $\beta : f_i(\beta'x_i)$, where $U_i = f_i(\beta'x_i) + \varepsilon_i$. Following the random utility framework, the probability of a farmer receiving financial services can be given by $prob(\varepsilon_i < \beta'x_i)$. The error term in the model is assumed to have a standard normal distribution, thus validating the use of a probit model. The empirical probit model estimated can be specified as follows:

$$prob(access = 1) = prob(\varepsilon_i < \beta'x_i) = \beta'x_i + \varepsilon_i, \text{ where } access = 1 \text{ if } U_i^R > U_i^N \text{ and } access = 0 \text{ if } U_i^R \leq U_i^N.$$

The observed variables in the model include the attributes of financial services and the farm household's demographic, social, and economic variables (Tables A. 1 and 2). The choice of variables is guided by previous similar theoretical and empirical work (Demirgüç-Kunt & Klapper 2012; Diagne 1999; Hussien 2007; and Ibrahim, Kedir, & Torres 2007, among others).

The estimated probit model is statistically significant at the 1 percent level, and the model correctly classified 74 percent of farm households among users and 76 percent of farm households among nonusers, with a total accurate prediction rate of 75 percent for the entire sample. The estimated propensity scores range from close to zero (0.000018) to close to one (0.982266) with a mean value of about 0.45 and a standard deviation of 0.288. The propensity score of farm households with access to institutional finance ranges between 0.126941 and 0.982266, with a mean value of 0.634021 and a standard deviation of 0.187312. In contrast, the propensity scores of farm households without access to finance vary between 0.000018 and 0.966109, with a mean value of 0.298779 and a standard deviation of 0.268204. Hence, following the minima and maxima criterion, the common support region for the distribution of estimated propensity scores of farm households, with and without access to finance, would range between 0.126941 and 0.966109. About 20 percent of farm households whose propensity scores lie outside this range were dropped from the analysis that follows (Figure 2).

Table 2 summarizes the results from the probit estimation. They are not surprising, but a couple of points are worth highlighting. First, female-headed households are 13.5 percent more likely to participate in formal financial institutions, which is consistent with the policies of the MFIs which target female-headed households. Second, literate households have a 6.5 percent higher probability than illiterate households to borrow from such institutions. This is consistent with the assumption that education helps households manage financial resources. Third, somewhat surprisingly, households that are relatively wealthy (as measured by livestock ownership and ownership of durable assets) and that have access to irrigated land are less likely to receive services from formal financial institutions.

A striking result in Table 2 is the opposite signs for the distance of two different institutional financial service providers (i.e. bank vs. nonbank financial institutions). While the distance to the bank has the inverse relationship with access and use of credit, which is expected, distance to nonbank financial institutions has a positive correlation with credit use. This could be because of the differences in the mode of operation between these two types of financial service providers. Unlike banks (where customers have

to visit the bank to receive a service), microfinance institutions send credit officers to villages that are unreachable by banks. Thus, in districts where microfinance programs operates, farm households can access to credit regardless of the distance from their village to the location of the microfinance office. The negative sign for radio ownership is plausible, since households who own a radio are often well-off, and hence, less financially constrained. Finally, some variables included in the estimation of the propensity score—such as family size, remittances, participation in extension services, and a household’s degree of risk aversion—have no significant effect on the household’s access to institutional financial services.

(Table 2 here)

After obtaining the predicted propensity scores from the probit model, we imposed a common support or overlap condition to improve the quality of the match, as it drops the comparison value of those for whom $P(x)$ is higher or smaller than that of the treated.⁹ Figure 2 shows the density distribution of propensity scores for users and nonusers of institutional financial services by common support. The results suggest that there are sufficient common support regions for matching. In addition, the difference in propensity score distribution between users and nonusers validates the use of matching techniques to ensure comparability.

(Figure 2 here)

For estimating the propensity score to match households that have access to institutional finance with their nonuser comparators, we used three commonly applied methods—that is, nonparametric kernel-based matching, five-nearest-neighbors matching, and radius matching. The nonparametric kernel regression method provides a means to match the users of technology within the entire sample of nonusers. This technique uses the entire sample of the comparison with common support to construct a

⁹ By the common support condition, the propensity score is bounded away from 0 and, excluding the tails of the distribution, $P(x)$ —between 0.126941 and 0.966109 in our case. This condition rules out the phenomenon of perfect predictability of D given X and ensures that farm households with the same X value have a positive probability of being either users or nonusers of institutional financial services (Caliendo & Kopeinig 2008; Heckman et al. 1997).

weighted average match for each treated (Heckman et al. 1997; 1998). On the other hand, the five-nearest-neighbors matching is used to match each user with the mean of the five nonusers who have the closest propensity score. In this method, while all treated units are matched, some of the matches can be fairly poor. This is because for some treated units, the nearest neighbors may have a very different propensity score even though the unit is considered in the estimation of the treatment effect independently of this difference (Becker & Ichino 2002; Caliendo & Kopeinig 2008). We have used radius matching to remedy the risk of poor matching in the case of nearest-neighbors matching. In the case of radius matching, each treated unit is matched only with the control unit whose propensity score falls in a predefined neighborhood of the propensity score of the treated unit. The smaller the dimension of the radius, the higher the possibility of unmatched treated units and the better the quality of the matches (Becker & Ichino 2002).

Note that since households are ranked based on propensity scores ($p(x)$), matching based on $P(x)$ implies evaluating the effect of access to institutional finance on a group of households that have similar characteristics. In other words, a household's preference for financial services is taken into account when evaluating financial services' causal effect on technology adoption. Because matching based on $P(x)$ assumes access to institutional finance is random in a group of farm households that have similar access to financial services, the conditional independent assumption is now more plausible than in the case of OLS which reduces the bias from observable heterogeneity.

However, the validity of this assumption relies on the extent to which the matching techniques construct a comparison group that resembles the treatment group. We perform a balancing hypothesis test of covariates within blocks and covariates across matching techniques (that is, $D \perp x | p(x)$) to ensure that farm households with a similar probability of access to financial services have the same distribution of pre-exposure characteristics, x . In conducting the balancing tests, we made sure that balancing across inferior bounds prevails in the estimation of the probability model (Becker & Ichino 2002) and performed the mean equality test across covariates suggested by Rosenbaum & Rubin

(1983). As shown in Table 3 and Appendix Table A. 3, the balancing property is satisfied in both cases. In particular, the test based on the mean equality test of covariates between households with access to finance and corresponding households without access to finance shows that the two groups are comparable.

As one can see in Table 3, the unmatched sample fails to satisfy the balancing property. Although the groups are found to be comparable in terms of age, family size, landholding, livestock ownership, and risk preference, a noticeable difference is found between users and nonusers in the majority of their observed characteristics before matching (i.e. for the unmatched sample). Notice that the results of matching with the three different methods—i.e. kernel-based, five-nearest-neighbors, and radius matching—do not vary in a statistically significant way. Moreover, the standardized bias,¹⁰ another indicator to assess the balance of all covariates suggested by Rosenbaum & Rubin (1983), is found to be less than 5 percent across the covariates after matching, except for gender and age of the household head. This implies that the comparison is statistically valid.

(Table 3 here)

Since the tests do conform to statistically valid methods of comparison, the estimated average effect of access to institutional finance for farm households with ‘similar’ propensity scores can be specified as follows:

¹⁰ It is the standardized mean difference between the treatment and comparison groups and can be specified as

$$B(x) = 100 \times \frac{\bar{x}_T - \bar{x}_C}{\sqrt{\frac{V_T(x) + V_C(x)}{2}}}, \text{ where } \bar{x}_T \text{ and } \bar{x}_C \text{ are the sample means for the treatment and comparison}$$

groups, respectively. $V_T(x)$ and $V_C(x)$ are the corresponding sample variances. Total standardized bias is estimated as an

unweighted average of all covariates x , and the percentage bias reduction can be calculated as $BR = 100 \times \left(1 - \frac{B_{after}}{B_{before}} \right)$. A

standardized bias below 5 percent after matching is seen as sufficient (see and Caliendo & Kopeinig 2008 and Rosenbaum & Rubin 1983 for detailed discussions).

$$\tau_{ATT}^{PSM} = E_{P(x)|D=1} [E(Y_{(1)i}|D_i = 1, p(x)) - E(Y_{(0)i}|D_i = 0, p(x))], \quad (4)$$

where $E(Y_{(1)i}|D_i = 1, p(x))$ and $E(Y_{(0)i}|D_i = 0, p(x))$ are the outcomes of households that did and did not have access to institutional finance, but that had similar observable characteristics, respectively. As is well known, even though PSM has become popular in impact evaluations, the procedure is not free from other potential sources of bias. Potential bias could include failing to control for local differences, not measuring the dependent variables the same way for both groups, and selection on unobservable characteristics (Heckman & Navarro-Lozano 2004; Smith & Todd 2005).

However, the matching analysis we have conducted addresses most of these concerns. First, since PSM compares treatment and control groups with propensity scores of the same distribution, it can be assumed that the distribution of unobservable characteristics is the same or at least not so different for both groups independent of treatment to create a bias (Becker & Ichino 2002). Second, the analysis includes several relevant variables in the propensity score estimation to overcome omitted variable bias (Smith & Todd 2005). Third, we performed the Rosenbaum bounds (i.e. rbounds) sensitivity analysis to test the sensitivity of the results to possible hidden biases due to unobservable household characteristics when this assumption was relaxed (Rosenbaum 2002).¹¹ Fourth, we conducted a series of triangulation or

¹¹ Given multiple variations of sensitivity tests for matching analysis, the basic issue addressed by the rbounds approach is whether inference about the treatment effects may be changed by unobserved covariates. To check for the sensitivity of the matching analysis for unobserved heterogeneity, it is assumed that the participation probability π_i is not only determined by observable covariates X_i but also by unobservable factors u_i : $\pi_i = \text{Prob}(D_i = 1|X_i) = F(\beta X_i + \gamma u_i)$. u_i is the vector of unobserved variables, and γ is the effect of u_i on the decision to participate (that is, on the decision to receive institutional finance in our case). If the study is free from hidden bias, γ will be equal to zero and the participation probability will only be determined by X_i . However, if there is a hidden bias, two individuals with the same observed characteristics X have a differing probability of receiving a treatment. Varying the value of γ assesses the sensitivity of the results with respect to hidden bias. Based on that, for each value of γ , bounds for significant levels of the treatment effect under the assumption of selection on unobservables in the treatment status and confidence intervals can be derived (Caliendo & Kopeinig 2008; Keele 2010; Rosenbaum 2002).

robustness checks for sample and estimation methods. Finally, in our estimation we also checked for possible heterogeneous effects by plotting the impact distribution of access to institutional finance on agricultural technology adoption for user households and disaggregating the impact estimates using surrogate variables. This method potentially captures households and institutional factors that influence farmers' adoption decisions.

5 RESULTS AND DISCUSSION

Descriptive Statistics

Table 4 presents descriptive statistics and simple means differences tests for institutional financial services user and nonuser farm households. The results suggest that users and nonusers of institutional financial services are significantly different in terms of both propensity (adoption) and intensity (rates of application) of fertilizer use. Of the total farm households that have access to institutional finance, 99 percent used fertilizer in the 2011/12 planting season, while only 74 percent of households without access to institutional finance used fertilizer, which is substantial. The adoption rates of improved seeds show a similar pattern. Of the total sample, 63 percent of farm households that accessed institutional finance and 42 percent of nonusers adopted one or more varieties of improved seed. However, when looking at the intensity of use, the majority of households in the sample that used improved seeds applied them below the recommended rate. In particular, the application rates of fertilizer among households without access to institutional finance are only half of the recommended rate of 200 kg per hectare. (Endale 2010; Ethiopia, Ministry of Agriculture 2012; Spielman, Kelemwork, & Alemu 2013).

Overall, the results from the descriptive statistics on the outcome measures (i.e. adoption and application rates of fertilizer and improved seeds) indicate statistically significant differences between households with and without access to institutional finance. On average, households that have access to institutional finance and that choose to access credit have higher rates of adoption and intensity of use.¹² Results in Table 4 also indicate that the users and nonusers of financial services vary significantly with regards to demographic, social, and economic variables. In particular, the results show that households with access to finance are comparatively more educated, reside closer to financial service providers and

¹² However, as stated in the previous sections, these results cannot be used to make inferences regarding the impact of access to finance on improved agricultural technology adoption since the results do not account for potential confounding factors (that is, factors that are correlated with access to finance and, independent of access, that are causally related to agricultural technology adoption).

farmer training centers, and are male-headed. Furthermore, households with access to finance are likely to have non-farm income, which goes against conventional wisdom that non-farm income might alleviate the credit constraints and lead to lower credit demand. However, the positive correlation between off-farm income and access to finance is also plausible, as credit is fungible, and the security of one's own capital can inspire households to invest further. In addition, households that lack access to credit are more likely to participate in safety net programs, which is contrary to one of the stated objectives of the Productive Safety Net Program—that is, increasing credit (Gilligan et al. 2008).

(Table 4 here)

For all other variables (i.e. family size, remittance, landownership, livestock ownership, and risk preference), the differences between the two groups are not statistically significant, implying that there is no selection bias in receiving institutional financial services, for instance, by wealth status and degree of risk aversion. Overall, the results from the descriptive statistics are consistent with those in literature on the determinants of access to institutional finance (see Aterido, Beck, & Iacovone 2011; Bigsten et al. 2003; Demirgüç-Kunt & Klapper 2012; Miller & Ladman 1983; Richter 2008; Schmidt & Kropp 1987, among others).

We also describe the characteristics of sample *kebeles* by treatment status in Table 5 to understand the similarities and differences between the treatment and control groups of *kebeles* in their local contexts that might affect the link between access to institutional finance and agricultural technology adoption. Table 5 shows that *kebeles* with access to institutional finance are more or less comparable with the comparison group of *kebeles* in several ways: agricultural potential, agro-ecology, input and output marketing systems, and access to farmer training centers (a center that works on promotion of agricultural technologies and best agronomic practices). The two groups of *kebeles* are also similar in terms of remoteness as measured by their proximity to *woreda* or district centers.

(Table 5 here)

Average Impact of Access to Finance on Agricultural Technology Adoption

Table 6 presents the estimated average effects of access to institutional finance on adoption and application rates of technologies. The results across the three matching algorithms consistently show positive and statistically significant impacts of access to institutional finance on smallholders' adoption and application rates of agricultural technologies. Households with access to finance are 11 percent more likely to adopt fertilizer and, on average, use 51 kg/ha more fertilizer than households without access to institutional credit. Given the low rates of fertilizer use in the country, this result has important implications. Recent studies have presented some interesting results on the adoption of fertilizer in Ethiopia. Rashid et al. (2013) demonstrates that fertilizer use is, in general, profitable, with value cost ratios greater than two. However, farmers face some constraints, including access to credit and policy-induced bottlenecks in the supply chain. On the other hand, using a unique survey in one of the remote parts of the country, Minten et al. (2013) argued that fertilizer use could not be profitable in Ethiopia's remote areas because of high transaction costs. These two studies point to two different sets of constraints. Our results are more in line with the findings and conclusions of Rashid et al. (2013).

Although overall rates of adoption are low, the results show that the adoption rates of improved seeds would be 30 to 32 percent lower without institutions providing agricultural finance. One explanation for the greater impact of access to institutional finance on adoption rates of improved seeds, compared with fertilizer use, is that improved seeds are substitutable. When faced with a financial constraint, a farmer may switch to local seeds. There is no cheap substitute for chemical fertilizer. The proxy measure of improved seeds use rates also indicates a statistically significant difference between the two groups, with households having access to institutional finance using 25 kg more improved seeds on their plots (Table 6). This result also implies that households with access to financial resources allocate a higher proportion of their land to high-yield varieties.

(Table 6 here)

Next, we analyzed the impact of access to institutional finance on farm households' decision to adopt fertilizer and improved seeds together (i.e. seed—fertilizer technology). The results show significantly higher rates of combined adoption. In particular, households that have access to credit have a 32 percent higher rate of joint adoption. Put differently, the combined adoption rate of fertilizer and improved seeds would have been 32 percent lower in the absence of access to institutional finance. The magnitude of impact on the joint adoption decision is somehow higher than the impact on the adoption of individual technologies. This suggests that the effect of access to institutional credit on joint adoption decisions is greater among farm households who are less likely to adopt complementary technologies in the absence of institutional credit services. Overall, the positive effect of access to institutional credit on technology adoption is consistent with recent studies by Lambrecht et al. (2014) and Liverpool & Winter-Nelson (2010), among others.

The results presented in Table 6 rely heavily on the assumptions of conditional independence and selection on observables or unconfoundedness,¹³ and it may not be robust against possible hidden biases. If unobserved covariates exist that affect access to institutional finance and adoption of agricultural technologies simultaneously, unobserved heterogeneity that influences the significance of the estimates might arise (Becker & Caliendo 2007; Rosenbaum 2002; Rosenbaum & Rubin 1983).

The incidence of this problem was examined by using Rosenbaum bounds sensitivity analysis. As shown in Table 6 (rbound: Γ), in all cases, the estimates are found to be strong, or insensitive to a bias that would double the odds of access to institutional finance. The majority of the results are insensitive to unobserved heterogeneity. The magnitude of hidden bias, which would make our finding of a positive and

¹³ Conditional independence or unconfoundedness in our case denotes that access to institutional finance does not depend on farm households' technology adoption, after controlling for the variations in adoption induced by differences in observable covariates. It is a strong assumption, which implies that access to institutional finance is based on observable covariates and that variables simultaneously influencing access to finance and agricultural technology adoption are observable. Thus, systematic differences in adoption and application rates of technologies between farm households that are users and nonusers of institutional finance with the same value of covariates are ascribed to access to institutional finance.

statistically significant effect of access to institutional finance spurious, should be higher than $\Gamma = 2.5$ (meaning, the results remain the same for unobservable characteristics that would increase the probability of receiving financial services among treatment group by about twice and half compared to the control group). Hence, we conclude that the strength of the hidden bias would need to be sufficiently high to undermine the conclusion of a positive and statistically significant effect of access to institutional finance on smallholders' agricultural technology adoption and application rates (see Rosenbaum 1991 for a detailed discussion).

Robustness Check

Besides the rbounds sensitivity analysis, we conducted further robustness checks of the estimated ATT by using variations in the specification of the probit model and in the sample used, and by using a control-function regression model and instrumental variable estimation. Table 7 shows the ATT results from these variations. The first variation, reported in column 1, uses the reduced probit model specification for the estimation of propensity score, which excludes potentially endogenous variables, including household literacy status, landholding size, non-farm income, livestock ownership, radio ownership, and degree of risk aversion. The second variation, presented in column 2, uses the entire sample that includes farm households residing in *kebeles* with access to institutional finance that choose not to take institutional credit. The balancing hypothesis is satisfied for both of these matches, and only the kernel-based matching technique is used to conserve space. The control-function regression and the instrumental variable estimation are two additional robustness check reported in column 3 and 4 and provides estimations of the effects of institutional finance on technology adoption under the hypotheses of 'selection-on-observables' and 'selection-on-unobservables', respectively.

(Table 7 here)

Comparisons of the results suggest that the estimates are insensitive to the probit specification and the sample used. A reduced probit model generates results that are similar, both in magnitude and significance, to those of the base model. Likewise, the results from the whole sample reveal similar signs

and levels of statistical significance, albeit with lower impact in magnitude. A relatively lower impact for the whole sample is plausible, as possible spillover effects could exist that can undermine the impact. Moreover, the comparable results observed from disaggregated samples, while checking impact heterogeneity in the next section, ensure the insensitivity of the results for the samples considered. The results of the third robustness check, the control-function regression, are presented in the third column of Table 7. The results are comparable to the PSM estimates presented in Table 6.

Similarly, the results from the two-stage least squares (2SLS) estimation that account for selection-on-unobservable indicates a positive impact of institutional credit on adoption and intensity of use of agricultural technologies. As shown in the last column of Table 7, the magnitude of the impact from the two-stage estimation is higher for fertilizer adoption and application rates compared to the estimates from the PSM. This suggests that farmers who receive institutional credit are less likely to adopt fertilizer in their unobservable attributes (factors not accounted in the PSM). Hence, the effect of institutional credit on fertilizer adoption and application rate is greater among farm households who are less likely to adopt in the absence of credit services. In sum, the robustness checks indicate that the positive and statistically significant impact of access to institutional finance on agricultural technology adoption is not sensitive to unobserved covariates under any of the methods presented here.

Impact Heterogeneity

We now turn to one of the central questions of the analysis: assessing the impact heterogeneity (i.e. whether the impact of access to finance varies across households with respect to their demographic, social, and economic characteristics). To begin with, we plot the impact distribution of access to institutional finance on agricultural technology adoption by type of technology both for adoption rate and intensity of use.

A key observation from Figure 3 is the considerable variation in user households' response to accessing institutional finance. One important implication of this finding is that for the majority of households, the adoption and application rates of fertilizer and improved seeds would have been lower in

the absence of access to institutional finance. Thus, we further examine the heterogeneities to identify the sources of the variations in impact. The data allows us to disaggregate the ATT estimates by the institutional design of the financial service providers and landholding size—a potential surrogate variable for other factors affecting agricultural technology adoption. Theoretical and empirical studies indicate that the way ownership is organized and practiced has a considerable effect on the monitoring and enforcement abilities of micro-finance providers in rural areas (Banerjee, Besley, & Guinnane 1994; Guinnane 2001; Smith, Cargill, & Meyer 1981). Likewise, many empirical studies show a strong relationship between adoption rates, intensity, and the time pattern of adoption and farm size (Feder, Just, & Zilberman 1985; Feder & O'Mara 1981; Just & Zilberman 1983).

(Figure 3 here)

The principal variable used to assess impact heterogeneity is the institutional design of the lending agency. This is particularly important because the terms and conditions of the two lending organizations in our sample—the specialized nonbank MFI and the FCs—vary considerably in their approaches (savings-led versus credit-led), size and coverage, and monitoring and follow-up efforts. Thus, the ways in which the financial institutions are designed and operated are likely to induce impact variation at the household level.

Table 8 presents the results of this set of analyses. FCs outperform the nonbank MFIs in influencing both adoption decisions and use rates. FCs appear to affect both adoption and use rates of fertilizer and improved seeds, which is robust in all three different specifications. By contrast, only fertilizer adoption and use are significant for the MFIs—and only under one of the three specifications, namely the kernel-based matching (panel B of Table 8). Results also vary in terms of magnitude. While members of the FCs use more than 67 kg of chemical fertilizer relative to independent farmers, the corresponding number for MFI members is only about 30 kg. In other words, if measured in volume of fertilizer used, the impact of FCs is twice as large as that of MFIs. The results for improved seeds are even more startling. While seed use among MFI clients is not significantly better than that of independent

farmers, financial cooperative members use 36 kg more seed compared to independent farmers who have no access to institutional financial services.

(Table 8 here)

There are two plausible explanations for why FCs outperforms MFIs in terms of enhancing technology adoption by their clients. First, financial cooperative members act as borrowers and lenders, providing both the demand for and supply of loanable funds. So, there is a built-in individual selection and monitoring incentive mechanism, which reduces information asymmetries and ensures the use of the loans for their intended purpose. In other words, the fear of losing their savings encourages depositors to be actively involved in screening potential borrowers and in monitoring those who have received loans. This stands in contrast to the supply-only specialized MFIs (Guinnane 2002; Smith, Cargill, & Meyer 1981). In particular, MFIs are commonly attached to international donors or parastatals and rely on external sources of capital for lending. MFIs, based on extensive outside financial sources, might be less effective in overcoming ex-post moral hazards. For instance, in the case of joint liability lending, group members can collude against the lenders by collectively deciding to avoid social sanctions (Armendáriz de Aghion & Morduch 2010). In comparison, social sanctions are more likely to exist within the FC community in the case of members' misuse of loans for unintended purposes (Banerjee, Besley, & Guinnane 1994; Guinnane 2001).

The ATT estimates disaggregated by land size also show strong impact variations between small and large farmers. As Table 9 shows, whereas the ATT results show no differential impacts on adoption rates of fertilizer by farm size, they do indicate impact heterogeneity on the intensity of use. The biggest effect of access to institutional finance on the intensity of fertilizer use per hectare is observed for small farmers. This suggests that access to finance can help smallholder farmers who often cannot afford to apply the optimal amount of fertilizer.

Regarding improved seeds, the estimates show that impacts vary by farm size for both adoption and application rates. In particular, the results suggest that whereas access to institutional finance has a

significant effect on large farms' improved seed use; there is no statistically significant difference for smallholders owning less than two hectares of land. Though improved seed is a divisible technology and hence neutral to scale, the results indicate that adoption rates are related to farm size. This is plausible, as smallholders' initial adoption of new, improved varieties may entail considerable risk and setup or fixed costs in terms of learning and developing or locating markets (Feder & O'Mara 1981). Moreover, limited farm size for experimentation coupled with fear of the welfare consequences if the improved seeds result in a poor harvest can push small farmers to stick with conventional low-risk and low-return agricultural practices (Dercon & Christiaensen 2011). Thus, besides credit, providing insurance products could potentially overcome the adoption-discouraging effects of farm size on the use of improved varieties by smallholders. Landowners with larger plots, on the other hand, can overcome such uncertainties and costs by piloting on small experimental plots.

(Table 9 here)

Overall, the main findings of the analysis support the argument that improving rural financial services leads to improved adoption and application rates of modern agricultural technologies —i.e. where credit is severely limited, smallholder farmers may not be able to adopt and properly apply productivity enhancing inputs. These results are consistent with prior studies by Croppenstedt, A., Demeke, D., & Meschi, M. M. (2003), Feder & O'Mara (1981), Lambrecht et al. (2014), and Liverpool & Winter-Nelson (2010), among others, that conclude that facing a credit constraint is an apparent reason for differential adoption rates of agricultural technologies. Yet, the incomplete nature of agricultural technology packages in Ethiopia, as they often lack credit components, remains a critical constraint to further enhance adoption and application rates of agricultural technologies, especially among smallholder farmers.

Although financial inclusion estimates indicate low overall access to finance in Ethiopia (only 27 percent of the population over the age of 15 hold an account with a formal financial institution including MFIs and FCs), financial provision in rural areas is disproportionately lower—i.e. the rural based MFIs

and FCs account for only one-quarter of adults who access financial service, which is only about 6.75 percent of the adult population (Demirgüç-Kunt & Klapper 2012). This clearly shows the need to improve access to financial services in the rural sector to meet the substantial capital requirements needed for the adoption of new agricultural technologies. That said, the ongoing effort to establish and widely promote rural financial services providing institutions in the country could thus be considered an important development towards addressing such constraints.

Furthermore, the differential nature of adoption and use intensity impact by the design of lending institutions may suggest the need to target interventions in promoting the development of financial institutions, without necessarily discriminating between the different service provider institutions. The results show that FCs can have more impact in terms of agricultural technology adoption and intensity of use. Since such financial institutions have relatively long history of providing financial services to smallholder farmers in Ethiopia, and they have a wider presence in different parts of the country, promoting and revitalizing FCs can enhance smallholders' investment in productivity-enhancing modern agricultural inputs. The revitalization of FCs, however, may require addressing both structural (e.g. governance) and service quality issues, aside from expanding the breadth and depth of the financial services they are currently providing to their members.

6 CONCLUSION

Agriculture is the cornerstone of Ethiopia's growth and poverty reduction strategies. There are special programs, such as the Participatory Demonstration and Training Extension System, which are specifically designed to increase cereal production through the demonstration of seed–fertilizer technology. However, modern inputs use remains low, and yield gaps in the cereal systems continue to be high. One of the programs to address this challenge has been the promotion of specialized MFIs and FCs to help alleviate smallholders' credit constraints in technology adoption. While these programs have expanded rapidly, with two-thirds of the loans channeled to smallholder farmers there has been little systematic analysis of their impacts. This paper has attempted to fill that gap. The PSM method is applied to a specially designed farm survey and administered in 21 districts of the country to identify the impacts of MFIs and FCs on smallholders' technology adoption.

Three broad sets of results emerged from this analysis. First, credit through these two lending organizations has had a positive impact on the adoption and use of fertilizer and improved seeds—the two key inputs that the national agricultural research and extension system has actively promoted. The results suggest that both adoption and application rates of fertilizer and modern seeds would have been significantly lower—by 11 and 32 percent, respectively—in the absence of lending through these institutions. Financial services through these institutions have contributed to increasing intensity of input use as well. Compared to the control groups, households with access to credit apply 24 kgs more improved seeds and 51 kgs more chemical fertilizer per hectare of cultivated land. A host of diagnostics tests suggests that these results are robust to various specifications and estimation methods. The broader implication of these results is that improving access and use of formal financial services can spur adoption and application rates of modern agricultural inputs in Ethiopia, which will in turn, lead to productivity improvements.

Second, although both large and small-scale farmers (owning less than two hectares of land) in the sample appear to benefit from access to credit, the magnitude of impacts varies considerably

depending on the farm size. Smallholder farmers that have access to credit apply almost 67 kgs / hectare more chemical fertilizer than the control group, which compares with only about 30 kgs more per hectare for large farmers relative to the corresponding control groups. The results for improved seed are the opposite: only large farmers with access to credit appear to use a significantly higher rate of improved seed compared to the control. The difference in improved seed application rates between smallholders with and without credit access is statistically insignificant. Thus, in addition to credit, providing insurance products could potentially overcome the adoption-discouraging effects of farm size on the use of improved varieties among smallholders.

Finally, we find that the design of the lending institution matters: access to credit through FCs has a greater impact on agricultural technology adoption than through the MFIs. Two proximate reasons for differential impacts are discussed: (a) the greater degree of trust among the FCs members and (b) better screening and incentive compatibility. Historically, the cooperatives evolved as a community response to risk management, and, therefore, members or clientele in FC have more social interactions than in MFIs, which are relatively new and often top down. Unlike MFIs, the FC's members are providers of both the demand and supply of loanable funds and, hence, have greater incentives to screen, monitor, and enforce effective use of funds. In scaling up their programs, MFIs can benefit by incorporating some of the features of FCs to enhance their impact. To that end, future research should focus on systematically identifying why FCs outperforms MFIs in Ethiopia or elsewhere in Africa south of the Sahara.

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Table 1 *Main differences between financial cooperatives and MFIs in Ethiopia*

	Financial cooperatives (FCs)	Microfinance institutions (MFIs)
Ownership	Owned by members/clients	Owned by investors/NGOs/State
Governance	Governed by voluntary board of directors and on the basis of one-man-one-vote principle	Governed by appointed board of directors and on the basis of one-share-one-vote principle
Clientele	Low-income clients and small farmers that share common bond	Low-income clients and small farmers (mostly women) who belong to the same community
Source of fund for lending	Members deposit	External loans, grants, and/or investors
Products and services	Full range of financial services (primarily saving and credit)	Focus on microcredit
Lending approach	Individual lending and saving precedes credit	Primarily follow group lending and credit precedes saving
Earnings	Net income divided among members (often in the form of lower interest on loans and higher interest on savings)	Net income either builds reserve or is divided among investors

Source: Authors, based on discussion with the Association of Ethiopian Microfinance Institutions (AEMFI) and Federal Cooperative Agency (FCA).

Table 2 *Probit estimation of determinants of smallholders' access to institutional finance*

Variable	Coefficient	Standard error	Marginal effect
Sex (<i>Male=1, Female=0</i>)	-0.486***	0.149	-0.135
Age	-0.002	0.005	-0.000
Literacy	0.234**	0.115	0.065
Family size	0.030	0.027	0.008
Distance to FC/MFI	0.011***	0.001	0.003
Distance to bank	-0.049***	0.003	-0.013
Distance to road	-0.005***	0.001	-0.001
Remittance (<i>Yes=1, No=0</i>)	0.238	0.218	0.066
Off-farm income (<i>Yes=1, No=0</i>)	0.337***	0.114	0.094
Radio ownership (<i>Yes=1, No=0</i>)	-0.409**	0.161	-0.113
Landholding size	0.004	0.042	0.001
Irrigations (<i>Yes=1, No=0</i>)	-0.389**	0.170	-0.108
TLU ^a	-0.031**	0.015	-0.008
Safety net (<i>Yes=1, No=0</i>)	-1.791***	0.580	-0.498
Extension (<i>Yes=1, No=0</i>)	0.164	0.132	0.045
Farmer training center (<i>Yes=1, No=0</i>)	0.530***	0.204	0.147
Risk preference ^b			
Moderate (<i>Yes=1, No=0</i>)	-0.222	0.165	-0.062
Neutral (<i>Yes=1, No=0</i>)	-0.111	0.159	-0.030
Constant	0.928**	0.420	
Pseudo- R^2	0.286		
LR chi-square (18)	322.55		
Prob > chi-square	0.000		
Number of obs.	817		
Sensitivity (%)			
(Percentage correctly classified among users)	74.20		
Specificity (%)			
(Percentage correctly classified among nonusers)	75.74		
Total correctly classified (%)	75.03		

Source: Authors' calculations based on primary data collected between April and June 2012.

Note: FC = financial cooperative; MFI = microfinance institution. ^aTropical livestock units (TLUs) are calculated based on conversion factors suggested by Asfaw et al. (2010), Chilonda & Otte (2006), and Jahnke et al. (1988). ^bExtreme-to-severe risk averse is a reference category for the risk preference dummy. *** significant at 1%. ** significant at 5%.

Table 3 *Balancing tests for matched sample*

Variable	Unmatched samples			Kernel-based matching			Five-nearest-neighbors matching			Radius matching		
	Users	Nonusers	Diff: <i>p</i> -value	Users	Nonusers	Diff: <i>p</i> -value	Users	Nonusers	Diff: <i>p</i> -value	Users	Nonusers	Diff: <i>p</i> -value
Sex	0.88	0.77	0.000	0.78	0.85	0.015	0.78	0.84	0.031	0.78	0.85	0.016
Age	41.94	42.96	0.161	41.98	43.73	0.018	41.98	43.81	0.014	41.98	43.75	0.017
Literacy	0.63	0.46	0.000	0.63	0.65	0.597	0.63	0.63	0.964	0.63	0.65	0.542
Family size	5.99	6.18	0.242	6.01	6.15	0.400	6.01	6.12	0.504	6.01	6.14	0.412
Distance to FC or MFI	60.17	53.54	0.099	60.11	58.81	0.774	60.11	59.38	0.873	60.11	58.62	0.742
Distance to bank	15.02	30.62	0.000	15.11	14.75	0.740	15.11	14.47	0.561	15.11	14.76	0.746
Distance to road	65.21	69.44	0.289	65.62	60.66	0.150	65.62	62.33	0.343	65.62	60.55	0.140
Remittance	0.06	0.04	0.140	0.06	0.07	0.576	0.06	0.07	0.554	0.06	0.07	0.598
Off-farm income	0.46	0.34	0.000	0.46	0.44	0.518	0.46	0.44	0.528	0.46	0.44	0.528
Radio ownership	0.84	0.92	0.000	0.84	0.85	0.901	0.84	0.86	0.632	0.84	0.85	0.864
Landholding size	2.39	2.27	0.346	2.39	2.47	0.512	2.39	2.51	0.311	2.39	2.46	0.547
Irrigation	0.09	0.16	0.003	0.09	0.09	1.000	0.09	0.08	0.817	0.09	0.09	0.987
TLU ^a	6.43	6.64	0.508	6.45	6.84	0.189	6.45	6.97	0.079	6.45	6.82	0.206
Safety net	0.002	0.045	0.000	0.002	0.001	0.423	0.002	0.00	0.318	0.002	0.00	0.417
Extension	0.76	0.72	0.286	0.75	0.75	0.974	0.75	0.76	0.810	0.75	0.76	0.959
Farmer training center	0.93	0.86	0.001	0.93	0.94	0.610	0.93	0.94	0.608	0.93	0.94	0.548
Risk preference ^b												
Moderate	0.37	0.36	0.614	0.38	0.36	0.707	0.38	0.36	0.694	0.38	0.36	0.736
Neutral	0.47	0.49	0.704	0.47	0.47	0.951	0.47	0.47	0.861	0.47	0.47	0.736

Source: Authors' calculations, based on primary data collected between April and June 2012.

Note: FC = financial cooperative; MFI = microfinance institution. Bold *p*-value indicates differences are significant at a 10% level or lower. ^a Tropical livestock units (TLUs) are calculated based on conversion factors suggested by Asfaw et al. (2010), Chilonda & Otte (2006), and Jahnke et al. (1988). ^b Extreme-to-severe risk averse is a reference category for the risk preference dummy. The balancing tests for the matched sample presented here is for the outcome fertilizer dummy. The results for the other outcome variables are similar and hence not reported to conserve space. .

Table 4 *Summary statistics of sample households by access to institutional finance*

Variable	Users of institutional finance (<i>n</i> = 376)		Nonusers of institutional finance (<i>n</i> = 441)		Means difference test (<i>p</i> -value)
	Mean	Standard deviation	Mean	Standard deviation	
Fertilizer adoption	0.99	0.07	0.74	0.43	0.000
Fertilizer per hectare (kilograms)	157.27	91.65	95.06	90.31	0.000
Improved seeds adoption	0.63	0.48	0.42	0.49	0.000
Volume of improved seeds (kilograms)	36.21	42.67	17.86	30.65	0.000
Sex	0.88	0.32	0.77	0.41	0.000
Age	41.94	10.14	42.96	10.54	0.161
Literacy	0.63	0.48	0.46	0.49	0.000
Family size	5.99	2.10	6.18	2.46	0.242
Distance to FC or MFI	60.17	66.89	53.54	47.25	0.098
Distance to bank	15.02	16.80	30.62	16.65	0.000
Distance to road	65.21	44.77	69.44	65.32	0.289
Remittance	0.06	0.24	0.04	0.20	0.140
Off-farm income	0.46	0.49	0.34	0.47	0.000
Radio ownership	0.84	0.36	0.92	0.25	0.000
Landholding size	2.39	1.54	2.27	1.87	0.346
Irrigations	0.90	0.28	0.16	0.36	0.002
TLU ^a	6.43	3.58	6.64	5.30	0.507
Safety net	0.002	0.05	0.04	0.20	0.000
Extension	0.76	0.42	0.72	0.44	0.286
Farmer training center	0.93	0.24	0.86	0.34	0.000
Risk preference ^b					
Moderate	0.37	0.48	0.36	0.48	0.613
Neutral	0.47	0.50	0.49	0.50	0.704

Source: Authors' calculations, based on primary data collected between April and June 2012.

Note: FC = financial cooperative; MFI = microfinance institution. Bold *p*-value indicates differences significant at a 10% level or lower. ^aTropical livestock units (TLUs) are calculated based on conversion factors suggested by Asfaw et al. (2010), Chilonda & Otte (2006), and Jahnke et al. (1988). ^bExtreme-to-severe risk averse is a reference category for the risk preference dummy.

Table 5 *Summary statistics of sample kebeles by access to institutional finance*

Variable	<i>Kebeles with institutional finance (n=13)</i>		<i>Kebeles without institutional finance (n=8)</i>		Means difference test (<i>p</i> -value)
	Mean	Standard deviation	Mean	Standard deviation	
Distance to nearest market (<i>in minutes</i>)	56.06	28.83	83.22	69.45	0.223
Number of input suppliers	1.47	0.45	1.60	0.61	0.597
Number of output buyers	2.11	0.63	2.26	1.22	0.722
Agricultural potential (<i>1=High, 0=Otherwise</i>)	1.00	0.00	0.87	0.35	0.210
Agro-ecology (<i>1=Yes, 0=No</i>)					
Dega (cool)	0.15	0.37	0.13	0.35	0.863
Woina dega (subtropical)	0.85	0.37	0.75	0.46	0.607
Kolla (tropical)	0.00	0.00	0.12	0.35	0.210
Altitude (<i>in meters</i>)	2277	379	2410	709	0.581
Farmers training center (<i>1=Yes, 0=No</i>)	0.92	0.27	0.87	0.35	0.731
Distance to district center (<i>in KM</i>)	6.43	7.79	4.04	3.60	0.428

Source: Authors' calculations, based on primary data collected between April and June 2012.

Table 6 *Effect of access to institutional finance on agricultural technology adoption*

Outcome variable	Treatment variable: institutional credit					
	Kernel-based matching (bandwidth = 0.06)		Five-nearest- neighbors matching		Radius matching (caliper = 0.05)	
	ATT	rbound (Γ)	ATT	rbound (Γ)	ATT	rbound (Γ)
Fertilizer adoption	0.11** (0.057)	(31–32)	0.11** (0.050)	(23–24)	0.12** (0.048)	(31–32)
Fertilizer per hectare	53.15*** (18.12)	(2.4–2.5)	51.32** (21.71)	(2.2–2.3)	53.89*** (17.14)	(2.5–2.6)
Improved seeds adoption	0.32*** (0.105)	(3.8–3.9)	0.30*** (0.111)	(3.5–3.6)	0.32*** (0.107)	(3.9–4.0)
Improved seeds (volume)	24.83*** (5.01)	(2.4–2.5)	24.12*** (5.07)	(2.3–2.4)	25.28*** (5.40)	(2.3–2.4)
Number of observations	548		548		541	

Source: Authors' calculations, based on primary data collected between April and June 2012.

Note: Bootstrap with 100 replications is used to estimate the standard errors reported in parentheses. Common support condition is imposed across the three matching estimators. Rosenbaum bounds, rbound (Γ), are estimated to determine critical values of hidden bias. The matched sample includes 252 users of institutional finance (treatment) and 296 nonusers (control) for kernel and nearest-neighbors matching and 245 users (treatment) and 296 nonusers (control) for radius matching. ATT = average treatment effect on the treated. *** significant at 1%. ** significant at 5%.

Table 7 *Robustness of ATT for agricultural technology adoption*

Outcome variable	Treatment variable: institutional credit			
	Reduced probit model (kernel based matching)	Whole sample ^a (kernel-based matching)	Control-function regression	Instrumental variable (2SLS)
	ATT	ATT	ATT	Coefficients
Fertilizer adoption	0.13*** (0.040)	0.05*** (0.015)	0.24*** (0.040)	0.40*** (0.032)
Fertilizer per hectare	66.72*** (14.06)	24.88*** (8.850)	69.84*** (10.81)	97.67*** (7.851)
Improved seeds adoption	0.35*** (0.120)	0.08* (0.047)	0.34*** (0.053)	0.18*** (0.051)
Improved seeds (volume)	23.74*** (4.97)	8.14** (3.920)	24.19*** (3.910)	24.43*** (3.347)
Number of observations	548	814	672	672

Source: Authors' calculations, based on primary data collected between April and June 2012.

Note: Bootstrap with 100 replications is used to estimate the standard errors in parentheses. Common support condition is imposed across for the matching estimators. The matched sample includes 252 users of institutional finance (treatment) and 296 nonusers (control) for the matching based on the reduced probit model and 373 users of institutional finance (treatment) and 441 nonusers (control) for the matching based on the whole sample. ATT = average treatment effect on the treated. ^a Whole samples include farm households residing in *kebeles* with access to institutional finance and choose 'not' to participate meaning, untreated units in treatment *kebele*. IV: distance to the institutional financial service provider (i.e. usage of institutional credit is instrumented with access to financial service as measured by the distance to the institutional financial service provider).

Table 8 *Impact of access to institutional finance on agricultural technology adoption disaggregated by institutional design of the lending organization*

Outcome variable	Kernel-based matching (bandwidth = 0.06)		Five-nearest-neighbors matching		Radius matching (caliper = 0.05)	
	ATT	rbound (Γ)	ATT	rbound (Γ)	ATT	rbound (Γ)
Panel A: Only users of financial cooperatives						
Fertilizer adoption	0.12** (0.050)	(45–46)	0.11** (0.056)	(34–35)	0.13*** (0.049)	(46–47)
Fertilizer per hectare	67.55*** (21.09)	(3.2–3.3)	65.19** (28.12)	(2.8–2.9)	70.13*** (20.55)	(3.4–3.5)
Improved seeds adoption	0.42*** (0.104)	(5.9–6.0)	0.40*** (0.123)	(5.3–5.4)	0.43*** (0.112)	(7.0–7.1)
Improved seeds (volume)	36.02*** (5.73)	(3.6–3.7)	35.45*** (5.75)	(3.7–3.8)	36.73*** (5.98)	(3.6–3.7)
Number of observations	451		451		448	
Panel B: Only users of microfinance institutions						
Fertilizer adoption	0.10* (0.059)	(12–13)	0.10 (0.073)	(9–8)	0.11** (0.057)	(11–12)
Fertilizer per hectare	30.15* (17.83)	(1.5–1.6)	29.15 (27.10)	(1.3–1.4)	27.30 (18.10)	(1.3–1.4)
Improved seeds adoption	0.16 (0.113)	(1.6–1.7)	0.14 (0.119)	(1.6–1.7)	0.15 (0.109)	(1.5–1.6)
Improved seeds (volume)	6.9 (6.03)	-	6.01 (5.38)	-	6.56 (5.06)	-
Number of observations	393		393		389	

Source: Authors' calculations, based on primary data collected between April and June 2012.

Note: ATT = average treatment effect on the treated. Bootstrap with 100 replications is used to estimate the standard errors reported in parentheses. Common support condition is imposed across the three matching estimators. rbound (Γ) is the estimated Rosenbaum bounds for critical values of hidden bias. The matched sample for panel A includes 155 users of institutional finance (treatment) and 296 nonusers (control) kernel and nearest-neighbors matching and 152 users (treatment) and 296 nonusers (control) for radius matching. The matched sample for panel B includes 97 users (treatment) and 296 nonusers (control) for kernel and nearest-neighbors matching and 93 users (treatment) and 296 nonusers (control) for radius matching. *** significant at 1%. ** significant at 5%. * significant at 10%.

Table 9 *Impact of access to institutional finance on agricultural technology adoption disaggregated by landholding size*

Outcome variable	Kernel-based matching (bandwidth = 0.06)		Five-nearest-neighbors matching		Radius matching (caliper = 0.05)	
	ATT (	rbound (Γ)	ATT	rbound (Γ)	ATT	rbound (Γ)
Panel A: Farm households with ≤ 2 hectares of land size						
Fertilizer adoption	0.10*** (0.041)	(17–18)	0.11* (0.062)	(12–13)	0.11** (0.054)	(16–17)
Fertilizer per hectare	67.19*** (22.38)	(2.9–3.0)	66.71*** (24.80)	(2.7–2.8)	67.41*** (21.97)	(2.7–2.8)
Improved seeds adoption	0.15 (0.121)	(1.7–1.8)	0.15 (0.126)	(1.7–1.8)	0.15 (0.124)	(1.7–1.8)
Improved seeds (volume)	7.51 (5.67)	-	7.66 (4.67)	-	7.60 (5.88)	-
Number of observations	496		496		496	
Panel B: Farm households with > 2 hectares of land size						
Fertilizer adoption	0.12** (0.051)	(35–36)	0.11* (0.063)	(27–28)	0.13** (0.060)	(35–36)
Fertilizer per hectare	37.46** (19.13)	(1.8–1.9)	34.11 (21.97)	(1.4–1.5)	38.86** (17.96)	(1.9–2.0)
Improved seeds adoption	0.51*** (0.099)	(9.4–9.5)	0.47*** (0.110)	(7.5–7.6)	0.51*** (0.105)	(11.1–11.2)
Improved seeds (volume)	44.18*** (5.87)	(6.9–7.0)	42.50*** (6.93)	(6.3–6.4)	44.94*** (6.61)	(6.7–6.8)
Number of observations	472		472		472	

Source: Authors' calculations, based on primary data collected between April and June 2012.

Note: ATT = average treatment effect on the treated. Bootstrap with 100 replications is used to estimate the standard errors reported in parentheses. Common support condition is imposed across the three matching estimators. rbound (Γ) is the estimated Rosenbaum bounds for critical values of hidden bias. The matched sample for panel A includes 200 users of institutional finance (treatment) and 296 nonusers across all the matching techniques. The matched sample for panel B includes 176 users (treatment) and 296 nonusers across all the matching techniques. *** significant at 1%. ** significant at 5%. * significant at 10%.

Source: The percentage share of agriculture in GDP is collected from the yearly national account statistics published by the Ministry of Finance and Economic Development (2012). The total domestic credit and amount of credit channeled to agriculture are obtained from the National Bank of Ethiopia.

Figure 1 *Percentage share of agriculture in GDP; share of agricultural credit in total domestic credit; and agricultural credit-to-output ratio*

Source: Authors' calculations based on primary data collected between April and June 2012.

Figure 2 *Distribution of estimated propensity scores by financial access and common support*

(a) On fertilizer adoption and intensity of use

(b) On improved seeds adoption and volume of use

Source: Authors' calculations, based on primary data collected between April and June 2012.

Figure 3 *Distribution of the impact of access to institutional finance across user households*

APPENDIX

Table A. 1 *Definition of variables and measurement*

Variable	Type	Definition and measurement
<i>Treatment variable</i>		
Access to institutional finance	Dummy	Equal to 1 if a household has access to institutional financial services and received loan during 2011/2012-production year.
<i>Outcome variables</i>		
Fertilizer adoption	Dummy	Equal to 1 if adopted fertilizer in 2011/2012 agricultural production season.
Fertilizer per hectare	Continuous	Volume of fertilizer applied per hectare (in kilograms).
Improved seeds adoption	Dummy	Equal to 1 if adopted improved seeds in 2011/2012 agricultural production season.
Volume of improved seeds	Continuous	Volume of improved seeds used (in kilograms).
<i>Independent variables</i>		
Sex	Dummy	Equal to 1 if male-headed and 0 if female-headed.
Age	Continuous	Age of household head in number of years.
Literacy	Dummy	Equal to 1 if the household head can read and write.
Family size	Continuous	Number of household members.
Distance to FC or MFI	Continuous	Walking distance from home to the savings and credit cooperative or MFI (in minutes).
Distance to bank	Continuous	Distance from home to the nearest commercial bank (in kilometers).
Distance to road	Continuous	Walking distance from home to the nearest road (in minutes).
Remittance	Dummy	Equal to 1 if the household received remittance during 2011/2012 year.
Off-farm income	Dummy	Equal to 1 if the household generates off-farm income.
Radio ownership	Dummy	Equal to 1 if the household owns a radio.
Landholding size	Continuous	Size of landholding in hectares.
Irrigation	Dummy	Equal to 1 if the household owns irrigated land.
Tropical livestock unit (TLU) ^a	Continuous	Livestock ownership in TLUs.
Safety net	Dummy	Equal to 1 if the household participates in safety net program.
Extension	Dummy	Equal to 1 if the household participates in government extension program.
Farmer training center	Dummy	Equal to 1 if there is a farmer-training center in the <i>kebele</i> where the household resides.
Risk preference ^b		
Moderate	Dummy	Equal to 1 if the household is moderately risk averse.
Neutral	Dummy	Equal to 1 if the household is risk preferring to neutral.
Distance to nearest market	Continuous	Distance between the <i>kebele</i> and the nearest market (in minutes).
Number of input suppliers	Continuous	Number of input suppliers in the <i>kebele</i> .
Number of buyers	Continuous	Number of output buyers in the <i>kebele</i> .
Agricultural potential	Dummy	Equal to 1 if the agri. potential of the <i>kebele</i> is high.
Agro-ecology		
Dega (cool)	Dummy	Equal to 1 if the <i>kebele</i> is cool in its climate zone.
Woina dega (subtropical)	Dummy	Equal to 1 if the <i>kebele</i> is subtropical in its climate zone.
Kolla (tropical)	Dummy	Equal to 1 if the <i>kebele</i> is tropical in its climate zone.
Altitude	Continuous	Elevation of the <i>kebele</i> above sea level in meters.
Distance to district center	Continuous	Distance between the <i>kebele</i> and district in kilometers.

Source: Authors.

Note: Fertilizer includes both DAP and UREA. In terms of NPK, while DAP contain 18 percent of nitrogen (N) and 46 percent of phosphorus (P₂O₅); Urea contains only 46 percent of nitrogen (N). Both don't contain Potassium (K) and other micronutrients and the reminders in both cases are fillers and carrier materials. Improved seeds include all types of high-yield varieties used during the 2011/2012-meher season. ^a TLUs are calculated based on conversion factors suggested by Asfaw et al. (2010), Chilonda & Otte (2006), and Jahnke et al. (1988). ^b Extreme-to-severe risk-averse households are dropped for reference. See Table A.2 for the risk classification.

Table A. 2 *Alternative gambles, payoffs, and corresponding risk classification*

Option	Expected gain (E)	Standard deviation (SD)	Approximate partial risk-aversion coefficient (θ)	Risk classification 1	Risk classification 2
Option 1: 2.5 birr, 2.5 birr	2.5	0	∞ to 7.51	Extreme	Extreme to severe
Option 2: 2.25 birr, 4.75 birr	3.5	1.25	7.51 to 1.74	Severe	
Option 3: 2 birr, 6 birr	4	2	1.74 to 0.81	Intermediate	Moderate
Option 4: 1.75 birr, 6.25 birr	4	2.25		Inefficient	
Option 5: 1.5 birr, 7.5 birr	4.5	3	0.81 to 0.32	Moderate	
Option 6: 1 birr, 8 birr	4.5	3.5		Inefficient	
Option 7: 0.5 birr, 9.5 birr	5	4.5	0.32 to 0	Slight to neutral	Risk-preferring to neutral
Option 8: 0 birr, 10 birr	5	5	0 to $-\infty$	Neutral	

Source: Authors' calculations based on primary data collected between April and June 2012.

Note: Farm households' level of risk aversion is directly measured via a gambling experiment with a real payoff following Binswanger & Sillers (1983). Risk classification 2 is used in the analysis for analytical simplicity.

Table A. 3 *Number of users and nonusers of institutional finance in each block of the propensity scores (inferior bound of propensity score)*

Block of propensity score	Users	Nonusers	Total
0.126	32	2	34
0.2	98	44	142
0.4	68	104	172
0.6	47	142	189
0.8	27	84	111
Total	272	376	648

Source: Authors' calculations, based on primary data collected between April and June 2012.

Note: The common support condition is imposed.

Table A. 4 *Commercial and private banks' loan composition by economic sector (in percentage), 2011*

Economic sector	CBE	BOA	Awash	NIB	United	Bunna	OIB	LIB	Birhan	AdIB	Dashen
Agriculture	10.5	0.2	2.2	4.5	0	0	2.2	3	0.5	0.7	2
Industry/ Manufacturing	11.5	9.3	5.8	25.7	16.7	3.3	4.7	2.6	10.2	11.1	22.8
Domestic trade	4.5	35	26.4	19.4	21	32.4	51.1	56	30.1	13.7	31.8
International trade	13.9	29	35.3	28.1	36.2	27.1	19.4	29	27.1	39.9	14.9
Import	-	14	14.2	13.9	21.1	19.3	4	24.7	19.3	12.4	8.8
Export	-	15	21.1	14.2	15.1	7.8	15.4	4.3	7.8	27.5	6.1
Others	59.6	26.5	30.3	22.3	26.1	37.2	22.6	9.4	32.1	34.6	28.5

Source: Deribie (2012) and annual reports of respective banks.

Note: CBE = Commercial Bank of Ethiopia; BOA = Bank of Abyssinia; NIB = Nib International Bank; OIB = Oromia International Bank; LIB = Lion International Bank; AdIB = Addis International Bank. *Others* include government deficit financing, hotel and tourism, mine, power and water resource, and personal and interbank lending.