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Rural Finance and Agricultural Technology Adoption in Ethiopia

Does Institutional Design Matter?

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ABSTRACT

Financial cooperatives and microfinance institutions (MFIs) are the two major sources of rural finance in Ethiopia. Whereas MFIs are relatively new, financial cooperatives have existed for centuries in various forms. The coexistence of two different institutions serving the same group of people, and delivering the same financial services, raises several policy questions. Those questions have become particularly relevant, as the government has embarked on developing a new strategy for improving rural financial services delivery. This study is expected to serve as an input to that policy discussion.

Using a unique household survey dataset and the propensity-score-matching technique, we examine the impacts of the two financial service providers on agricultural technology adoption. The results suggest that access to institutional finance has significant positive impacts on both the adoption and extent of technology use. However, when impacts are disaggregated by type of financial institution and farm size, considerable heterogeneities are observed. In particular, financial cooperatives have a greater impact on technology adoption than do MFIs, and the impacts appear to vary depending on farm size and types of inputs. The underlying implications of these results are discussed in light of the country's rural finance policies and programs.

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

JEL Classification: G21; Q14.

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1. INTRODUCTION

A large body of literature exists on the determinants of agricultural technology diffusion in developing countries. Asian experiences suggest that innovations in technology and the promotion of new technology during the Green Revolution played important roles in accelerating agricultural growth, reducing poverty, and improving the overall well-being of rural households (Fan et al. 2006; Mendola 2007; Rashid, Cummings Jr., and Gulati 2007). Although the number of studies is limited, African experiences point in the same direction. For example, using spatially explicit data from Madagascar, Minten and Barrett (2008) demonstrate that communes with higher rates of adoption of improved agricultural technologies enjoy lower food prices, higher real wages, and better livelihoods. The implications of these empirical studies are obvious: promotion of improved agricultural technology should be central to developing countries' strategies for agricultural growth and poverty reduction, especially where poverty is disproportionately high in rural areas.

Ethiopia is such an economy. About 70 percent of the country's population is employed in agriculture, of which more than 30 percent fall below the headcount poverty line (World Bank 2013; Dorosh and Rashid 2012; Ethiopia, Ministry of Finance and Economic Development 2012). The country recognizes this challenge and puts heavy emphasis on agricultural productivity growth in national policies for both economic growth and poverty reduction. Intensification of agriculture through promotion of modern inputs—such as chemical fertilizer and improved seeds—has been identified as the main pathway for achieving the productivity growth objective. To that end, government has consistently allocated more than 10 percent of public spending to agriculture and scaled up agricultural extension programs, rural finance programs, and specially designed programs for cereal system intensification (Rashid and Negassa 2013). Those investments have paid off in terms of growth in agricultural gross domestic product (GDP) and total cereal production. During 2005 and 2012, agricultural value-added almost tripled from US$6.5 billion to $19.2 billion and cereal production more than doubled from 12 million metric tons to 23 million metric tons (World Bank 2014). Yet agricultural technology adoption in the country remains low. For instance, only 30 to 40 percent of Ethiopian smallholders use fertilizer, and of those who do, the application rate is only 37 to 40 kilograms (kg) per hectare, far below the recommended rates (Spielman, Kelemwork, and Alemu 2011).

Low rates of technology adoption despite high potential gains are not unique to Ethiopia. In a recent study, de Janvry and Sadoulet (2010) argue that technology diffusion rates are slower in Africa south of the Sahara than anywhere else even though the benefits are relatively direct. Available studies suggest that incomplete markets for risk management (credit and insurance) are one of the binding constraints[1] for the lack of or slow adoption of technologies by smallholders.[2] A broad conclusion of these studies is that the differential rates of adoption can be ascribed to differential access to capital, either in the form of savings or access to credit. The underlying premise of this argument is simple: since new technologies are generally expensive and embody greater risks, farmers are reluctant to adopt them unless access to finance is available to pay for the higher costs and insure against potential risks. As a result, richer farmers generally adopt a new technology at a faster rate than resource-poor farmers, resulting in differential rates of adoption.

The conventional policy approach to overcome the adoption-discouraging effects of financial market inefficiency is subsidization of agricultural credit, mainly through state-owned development banks. Relaxing the credit constraint through subsidies was believed to have positive effects on adoption by making credit available at lower rates and minimizing the adverse effects of risks, uncertainties, and land market inefficiencies (Adams, Graham, and Von Pischke 1984). Although agricultural credit subsidies have played crucial roles in kick-starting credit markets in poor rural economies (Dorward et al. 2004), directed subsidies, such as keeping interest rates on loans to farmers unnecessarily low, have been largely criticized for generating allocative inefficiencies and failing to

[1] Other factors that inhibit adoption of agricultural technology include risk and uncertainty, imperfect information, land size, tenure structure, labor availability, insurance mechanisms, and availability of the technology itself—supply-side constraints (Fisher and Lindner 1980; Lindner 1980; Just and Zilberman 1983; Feder, Just, and Zilberman 1985; Dercon and Christiaensen 2011).

[2] A large body of literature, which grew mostly during the Asian Green Revolution, exists on the determinants of technology adoption. Selected studies include Feder and Umali (1993); Dercon and Christiaensen (2011); Lipton (1976); Bhalla (1979); and Croppenstedt, Demeke, and Meschi (2003).

achieve their primary objective of overcoming the credit constraints of small farmers (Adams, Graham, and Von Pischke 1984; Adams and Graham 1981; Binswanger, Khandker, and Rosenzweig 1993).

In recent years, there has been a shift in the agricultural finance discourse from subsidies to a more market-oriented financial system approach. Unlike the top-down government and donor credit programs, the new approach emphasizes the creation of sustainable financial institutions and the pricing of financial products and services to cover costs and associated risks (Meyer 2011). This new paradigm has guided the evolution of specialized microfinance institutions (MFIs) and the revival of financial cooperatives (that is, member-based financial institutions) across developing countries. Currently, financial cooperatives and specialized MFIs have made inroads in the agriculture sector with customized or tailored loans to meet the seasonal needs of the smallholder. And there are many examples demonstrating that such institutions have found mechanisms to deal with the costs and risks of agricultural lending.[3]

As of 2010, Ethiopia's specialized MFIs and numerous financial cooperatives have channeled about two-thirds of their loan portfolio to smallholder farmers (Amha and Peck 2010; Obo 2009). In addition, all of the financial cooperatives and the majority of the MFIs also provide saving services that allow farmers to commit savings for future investments. However, to the best of our knowledge, there is no systematic study that evaluates the effects of these institutions on farm households' technology adoption decisions. Compared with the earlier literature on access to credit and technology adoption, there is an additional (savings) dimension to this new approach, which is highlighted in Duflo, Kremer, and Robinson (2008). That study argues that such financial services can go beyond traditional credit programs by allowing farmers to save when they have cash available, such as immediately after harvest, which in turn positively affects technology adoption. However, the important additional dimensions of these programs are often ignored, as successes are often measured only in terms of repayment and disbursement rates. In other words, programs are considered successful only if they are able to expand availability of credits in rural areas and generate high repayment rates.

This paper attempts to contribute to filling this knowledge gap. Using a unique set of data, we undertake three tasks: (1) analyze the impacts of these credit and financial products on agricultural investments by smallholder farmers using propensity score matching; (2) assess these institutions' contributions to the diffusion of technology adoption; and (3) assess the importance of institutional design (that is, the way ownership of the financial services providers is organized and operated) on the farm households' technology adoption decision. The rest of the paper is organized as follows: The next section reviews the history of institutional finance provisions for smallholder agriculture in Ethiopia. Section 3 describes the survey methods and the measurement of the main variables. Section 4 discusses the methodological approach—the impact evaluation problem, propensity score matching, and propensity score estimation procedures and results. The key findings are presented in Section 5, and the paper concludes with a summary and suggested policy implications.

3 As of the end of 2006, 20 MFIs in Nicaragua reported that 47 percent of their portfolios were in agriculture and forestry. In 2007, 37 MFIs in Uganda reported that 38 percent of their total portfolios were in agricultural loans. The Economic Credit Institution in Bosnia and Herzegovina, the Banco del Estado de Chile, Small Farmer Cooperatives Ltd. in Nepal, the Cresol and SICREDI systems of savings and loan cooperatives in Brazil, Confianza in Peru, and several community-managed village savings and credit organizations in parts of West Africa have developed innovations to serve agriculture (Meyer 2011).

2. INSTITUTIONAL FINANCE AND SMALLHOLDER AGRICULTURE IN ETHIOPIA

The need for agricultural finance in Ethiopia is obvious. Most of the smallholder farmers, who represent 90 percent of the country's agricultural production, are subsistence farmers that own, on average, less than one hectare of fragmented land (Ethiopia, Central Statistical Agency 2011; 2013; Heady et al. 2013) and are characterized by their inadequate investment in productivity-enhancing inputs (Spielman, Kelemwork, and Alemu, 2011; Dercon and Christiaensen 2011). This implies that there is a large unmet demand for credit. This is mainly because of limited access, as lending to these smallholders remains unattractive to conventional commercial lenders due to small transaction size, covariant risk, and geographical remoteness of dispersed farmers (Amha and Peck 2010; Croppenstedt, Demeke, and Meschi 2003). Since the 1960s, many different policies have been tried to address this challenge, including specially designed institutions tailored for development of smallholder agriculture. However, several studies demonstrated that these subsidized credit programs neither increased productivity cost-effectively nor reduced poverty significantly (Braverman and Guasch 1986) and suffered from elite capture and institutional capacity (Admassie 1987).

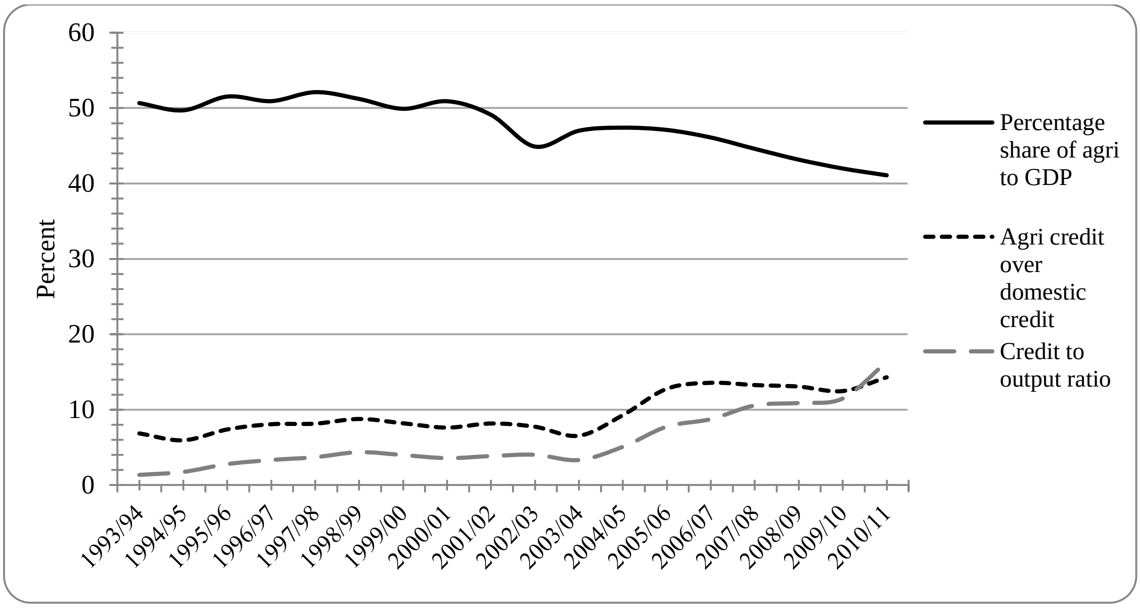
During the imperial regime (1960s–1974), about half of the total domestic credit that went to agriculture was disbursed through two intermediary institutions—the grain corporation and farmers' cooperatives. These intermediaries received credit funds from state-owned banks and extended credits to farmers at concessional rates (EEA 2000). However, as in most of the directed credit programs elsewhere in the same period, the efforts to extend agricultural credit to small farmers were not a success. During this period, between 42 and 65 percent of all total domestic loans went to agriculture and smallholder farmers received only about 7.5 percent. Most of the agricultural credits were accrued to large and influential farmers (Admassie 1987, 2004).

Although the socialist regime (1974–1991) perpetuated the tradition of assigning specialized financial institutions, smallholder farmers were not any better off during this period. They were deprived of credit because larger state-run farms received higher priority. For instance, over a 10-year period of the regime, 1974–1984, within the agriculture sector about 89 percent of the credits were channeled to state farms, while private smallholder farmers received only 9 to 11 percent (EEA 2000). Furthermore, toward the end of the socialist era, depletion of capital faced by some of these lending institutions led to the complete termination of the negligible credit shares to smallholder farmers (Amha 2010).

The postreform period, which started with the Structural Adjustment Program to reverse financial distortions of all kinds, did not do any better. As Figure 2.1 shows, during the years after the economic reform, the total share of agricultural credit shrank considerably. A recent study by Amha and Peck (2010) estimated a $3 billion credit shortage in the overall economic system. In addition, it appears that smallholder agriculture is suffering more significantly from this credit crunch than other sectors of the economy. Whereas agriculture provided about 41 percent of the total GDP in 2010/2011, the sector's share of total lending was only about 14 percent (Figure 2.1). The resulting ratio of share of lending to share of GDP was also lower—at only 34 percent. 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 2.1).

Such a gap in agricultural finance exists largely because the conventional financial institutions in Ethiopia do not provide enough credit to the agricultural sector (see Table A.3 in the appendix). Smallholder farmers, in search of financial services, mainly stumble upon MFIs and financial cooperatives. Currently, MFIs and cooperatives are the only institutions putting a clear focus on smallholder agriculture, with roughly two-thirds of their loan portfolio devoted to that sector (Obo 2009). Along with the regional governments, these financial institutions act as intermediaries between banks and small farmers. And although there have been cases of default that necessitated repayment out of the regional state budgets as well as these intermediary institutions (DSA 2010), the institutions manage to channel more credit to smallholder agriculture compared with previous regimes. As Figure 2.1 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.

Figure 2.1Percentage share of agriculture in GDP, share of agricultural credit in total domestic credit, and agricultural credit–to–output ratio



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.

Nonetheless, most MFIs and cooperatives in Ethiopia are very small in size and lack the capacity to facilitate large loans for indivisible agricultural investments (for example, tractor, tube well, oxen, and so on). Most lend small amounts aimed at increasing the productivity and income of small farmers through enabling them to adopt divisible technologies, such as improved seeds and fertilizer. Moreover, to our knowledge, there is no systematic empirical evidence that examines the adoption behaviors of the clients of these financial providers compared with independent farmers. In the absence of such evidence, the effects of credit and other financial services delivered by these institutions on farmers' agricultural investment remains an open question, as use or diversion of credit for purposes other than agriculture is not impossible.[4]

[4] For instance, a test of significance on the product-moment correlation coefficient relating average annual rate of growth in institutional credit for agriculture and average annual rate of growth in GDP from agriculture for the last two decades shows a weak interdependence. The lack of a strong relationship between growth in agricultural credit and agricultural output can be due to diversion of credit funds away from agricultural production purposes. However, the potential issue of time lag effects of credit on output complicates this conclusion.

3. SAMPLING, DATA, AND VARIABLE DEFINITION

Our data come from a three-month (April through June 2012) farm household survey of 817 households selected by stratified random sampling from 21 *kebeles* (villages) in 21 districts of Ethiopia (that is, one *kebele* from each district).[5] Two groups of *kebeles* are sampled. In one group of *kebeles*, there is no institutional financial services provider (control group), and in the other group (treatment group), there are either specialized MFIs or financial cooperatives, but not both. Of the sampled households, 54 percent belong to the former group and the remainder to the later. In the control group of *kebeles*, households were randomly selected from the complete lists of households obtained from the local administration. For the other group, for each *kebele*, a list of households that received credit was obtained from the respective MFIs and financial cooperatives, which was then used to randomly select the samples.

Variable Definition and Measurement

This study takes into account both supply-side (that is, the availability of an institution providing financial services) and demand-side (that is, the choice of farm households to participate) factors in the construction of the treatment variable—access to finance. Hence, farm households with access to finance (treatment group) are those residing in *kebeles* having an institutional finance provider and that choose to participate (that is, received agricultural credit for 2011/2012 production year). On the other hand, the comparison group constitutes farm households residing in *kebeles* where there are no formal financial service providers and that have never received institutional finance.

The outcome variables include adoption of the three most important divisible agricultural technologies in Ethiopia, namely, fertilizer, improved seeds, and pesticides. 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 that decision 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 greatly on the intensity of use (for example, kilograms of fertilizer per hectare), which is a continuous variable (Schutjer and Van der Veen 1977; Feder, Just, and Zilberman 1985). In our sample, use of pesticides was very limited. Therefore, we had to limit our intensity analysis to fertilizer and improved seeds.

Table 3.1 presents all variables used in the analysis. The selection of variables is guided by previous theoretical and empirical work on the determinants of access to finance in similar contexts by Demirgüç-Kunt and Klapper (2012), Ibrahim, Kedir, and Torres (2007), Hussien (2007), Bigsten et al. (2003), and Diagne (1999), among others.

[5] 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..

Table 3. 1 Definition of variables and measurement

Variable	Type	Definition and measurement
Treatment variable		
Access to finance	Dummy	Equal to 1 if a household has access to finance and received loan during 2011/2012 production year.
Outcome variables		
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).
Pesticide adoption	Dummy	Equal to 1 if adopted pesticide in 2011/2012 agricultural production season.
Independent variables		
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 *kebele* 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.

Source: Authors.

Note: Fertilizer includes both DAP and UREA. Improved seeds include all types of high-yield varieties used during the 2011/2012 production year. [a] TLUs are calculated based on conversion factors suggested by Jahnke et al. (1988), Chilonda and Otte (2006), and Asfaw et al. (2010). [b] Extreme-to-severe risk-averse households are dropped for reference. See Table A.1 for the risk classification.

4. EMPIRICAL MODEL AND ESTIMATION STRATEGY

Overview of Impact Evaluation and Propensity Score Matching

There is a strong theoretical basis for access to financial services having an impact on technology adoption. However, as the empirical impact evaluation literature amply demonstrates, measuring the outcomes and impacts due to access to 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 and Kremer 2005). In a cross-section study, one can only compare farm households that have received credit with those that do not have access to credit. However, the direct comparison of these two groups may be misleading, as the self-selected households that have access to finance can be generally different systematically from the comparison group (Caliendo and Kopeinig 2008; Dehejia and Wahba 2002; Heckman et al. 1998).

Therefore, in assessing the impact of access to financial services on technology adoption with cross-section data, it is important to address this statistical pitfall, particularly to isolate the effects of access to 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 finance and technology adoption as follows:

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

$$D = g(W_i) + h_i, \tag{2}$$

where Y_{Di} refers to the intensity of adoption of farm household *i* depending on whether the household has access to finance, measured by a dichotomous variable D, which takes a value equal to 1 if the household has access to credit 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 financial services. 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, which in impact evaluation terminology is the average treatment effect on the treated (ATT), and can be specified as follows:

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

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

where $E(Y_{(1)i} | D_i = 1)$ is the outcome of farm households that have access to finance and $E(Y_{(0)i} | D_i = 1)$ is the outcome if the households did not have access to institutional finance (that is, 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—that is, what would have been the farm households' decision in the absence of access to institutional finance (that is, $E(Y_{(0)i} | D_i = 1)$). 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 and 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 regression and instrumental variable (IV) estimators. If one assumes that conditioning on a vector of observable characteristics x restores the condition of randomization (that is, conditional independent assumption: $(Y_{(1)}, Y_{(0)}) \perp D|x$), the causal effect of access to finance on technology adoption can be estimated using control-function ordinary least squares (OLS) regression. However, if the conditional independent assumption does not hold, which is probable in cases where the selection into 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 parametric OLS regression is to use an IV estimator that can determine consistent estimation under the hypothesis of selection on unobservables (Caliendo and Kopeinig 2008; Heckman et al. 1998). This method also solves the problem by treating the treatment variable as endogenous. But the application of the IV requires 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 with the outcome. 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 and Ravallion 2003).

Propensity score matching (PSM) is another nonexperimental, but nonparametric approach used for causal inference under the same hypothesis for parametric OLS regression (that is, selection on observables or unconfoundedness, and 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 sample with the same set of observable parametric covariates (Dehejia and Wahba 2002; Rosenbaum and 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 and Ravallion 2003); and (3) it reduces the number of comparison groups to a subsample with characteristics more homogenous to the treated one (Cameron and Trivedi 2005).

A further distinction relates to the choice of control variables. Whereas in the parametric regression approach one naturally looks for predictors of the outcome measure and predictors that are exogenous to the outcomes that are preferred, in PSM one should consider covariates of treatment along with variables that are even poor predictors of outcomes, as the variables with a weak predictive ability for the outcome measure can still help reduce the bias in estimating causal effects (Rubin and Thomas 2000; Jalan and Ravallion 2003).

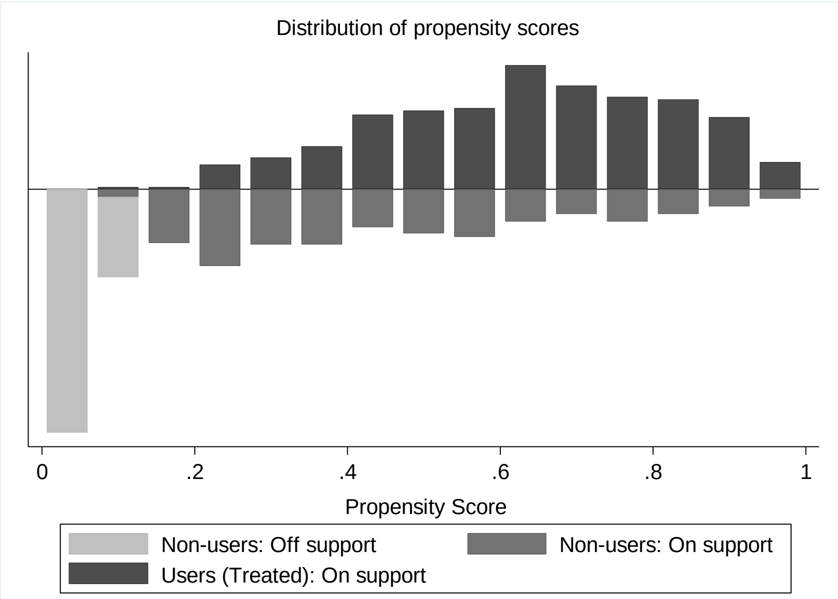
The Propensity Score Matching

Following the arguments in the literature, the conditional probability of access to finance (that is, $p(x_i) = \Pr ob(D_i = 1|x_i)$) is estimated using the predicted values from a standard probit model[6] to estimate the propensity score of each observation with and without access to finance.

[6] In our estimation of the probability of access to finance, the decision of farm households to receive a financial product (for example, credit) is analyzed using a random utility framework following similar applications by Abebaw and Haile (2013), Wollini and Zeller (2007), and Feder, Just, and Zilberman (1985) 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

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 correct prediction rate of 75 percent for the whole sample. The estimated propensity scores range from close to zero (0.000018) to close to 1 (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 finance ranges between 0.126941 and 0.982266 with a mean value of 0.634021 and a standard deviation of 0.187312. In contrast, with a mean value of 0.298779 and a standard deviation of 0.268204, the propensity scores of farm households without access to finance vary between 0.000018 and 0.966109. 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 are dropped from the analysis that follows (Figure 4.1).

Figure 4.1 Distribution of estimated propensity scores by financial access and common support



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

Table 4.1 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 policies of the MFIs in that they 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 have access to irrigated land are less likely to receive services from formal financial institutions. This

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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 β : $f_i(\beta' x_i)$, 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: $prob(access = 1) = prob(\varepsilon_i < \beta' x_i) = \beta' x_i + \varepsilon_i$, where $access = 1$ if $U_i^R > U_i^N$ and $access = 0$ if $U_i^R \le U_i^N$. The observed variables in the model include the attributes of financial services and the farm household's demographic, social, and economic variables (Tables 3.1 and 4.1). The choice of variables is guided by previous similar theoretical and empirical work (Demirgüç-Kunt and Klapper 2012; Ibrahim, Kedir, and Torres 2007; Hussien 2007; Diagne 1999; among others).

may be because such households are relatively better off and with continuous harvest have less demand for an external source of capital, as they may not be financially constrained. Finally, some variables included in the estimation of the propensity score—such as family size, remittance, participating in extension services, and household's degree of risk aversion—have no significant effect on the household's access to institutional financial services.

Table 4. 1 Probit estimation of determinants of smallholders' access to institutional finance

Variable	Coefficient	Standard error	Marginal effect
Sex	-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 or 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	0.238	0.218	0.066
Off-farm income	0.337***	0.114	0.094
Radio ownership	-0.409**	0.161	-0.113
Landholding size	0.004	0.042	0.001
Irrigations	-0.389**	0.170	-0.108
TLU[a]	-0.031**	0.015	-0.008
Safety net	-1.791***	0.580	-0.498
Extension	0.164	0.132	0.045
Farmer training center	0.530***	0.204	0.147
Risk preference[b]			
Moderate	-0.222	0.165	-0.062
Neutral	-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. [a] Tropical livestock units (TLUs) are calculated based on conversion factors suggested by Jahnke et al. (1988), Chilonda and Otte (2006), and Asfaw et al. (2010). [b] Extreme-to-severe risk averse is a reference category for the risk preference dummy. *** significant at 1%. ** significant at 5%.

After getting the predicted propensity scores from the probit model, we impose the common support or overlap condition (that is, $0 < p(D = 1|x) < 1$) 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.[7] Figure 4.1 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.

For estimating the propensity score to match households that have access to finance with their nonuser comparators, we have used three commonly applied methods—that is, nonparametric kernel-based matching, five-nearest-neighbors matching, and radius matching. The nonparametric kernel

[7] 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 and Kopeinig 2008; Heckman et al. 1997).

regression method allows matching users of technology within the whole sample of nonusers, as the technique uses the whole sample of the comparison with common support to construct a 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 find a match, 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 will be considered in the estimation of the treatment effect independently of this difference (Caliendo and Kopeinig 2008; Becker and Ichino 2002). We have used radius matching to remedy the risk of poor matching in the case of nearest-neighbors matching. Here, each treated unit is matched only with the control units 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 is the quality of the matches (Becker and 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 having similar behavioral characteristics. In other words, household preference for financial services is taken into account in evaluating financial services' causal effect on technology adoption. The point is that because it assumes access to institutional finance is random within the group of farm households that have a similar probability of access to financial services, the conditional independent assumption is now more plausible than in the case of OLS—it reduces the bias due to 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. The study performs a balancing hypothesis test of covariates within blocks and covariates across matching techniques (that is, $D \amalg x | p(x))$ 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 and Ichino 2002) and performed the mean equality test across covariates suggested by Rosenbaum and Rubin (1983). As shown in Table 4.2 and appendix Table A.2, 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 4.2, 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 systematic difference is found between users and nonusers in the majority of their observed characteristics before matching. Notice that the results of matching with the three different methods—that is, kernel-based, five-nearest-neighbors, and radius matching—do not vary in a statistically significant way. Moreover, the standardized bias,[8] another indicator to assess the balance of all covariates suggested by Rosenbaum and Rubin (1983), is found to be less than 5 percent across the covariates, except for sex and age of household head. This implies that the comparison is statistically valid.

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[8] It is the standardized mean difference between the treatment and comparison groups and can be specified as $B(x) = 100 \times \frac{\bar{x}_T - \bar{x}_C}{\sqrt{\frac{V_T(x) + V_C(x)}{2}}}$, where $\bar{x}_T$ and $\bar{x}_C$ 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 Rosenbaum and Rubin 1983 and Caliendo and Kopeinig 2008 for detailed discussions).

Table 4.2 Balancing test of matched sample

Variable	Unmatched samples			Kernel-based matching			Five-nearest-neighbors matching			Radius matching		
	Users	Nonusers	Diff: *p*-value	Users	Nonusers	Diff: *p*-value	Users	Nonusers	Diff: *p*-value	Users	Nonusers	Diff: *p*-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 significant at a 10% level or lower. [a] Tropical livestock units (TLUs) are calculated based on conversion factors suggested by Jahnke et al. (1988), Chilonda and Otte (2006), an d Asfaw et al. (2010). [b] Extreme-to-severe risk averse is a reference category for the risk preference dummy. The balancing test for the matched sample presented in is for the outcome fertilizer dummy. We estimated for all outcome variables and the results are similar.

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:

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

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 finance, but that had similar observable characteristics, respectively. As is well known, even though PSM has become popular in impact evaluation, the procedure is not free from other potential sources of bias. Such potential sources of bias identified in the literature include failure to control for local differences, not measuring the dependent variables the same way for both groups, and selection on unobservable characteristics (Heckman and Navarro-Lozano 2004; Smith and 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 safely assumed that the distribution of unobservable characteristics are the same or at least not so different for both groups independent of treatment to induce a bias (Becker and Ichino 2002). Second, it includes several relevant variables in the propensity score estimation to overcome omitted variable bias (Smith and Todd 2003). Third, we performed the Rosenbaum bounds (that is, 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).[9] Finally, the estimation 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.

[9] 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: $\pi_i = \Pr ob(D_i = 1|x_i) = F(\beta x_i + \gamma u_i)$. 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 (Rosenbaum 2002; Caliendo and Kopeinig 2008; Keele 2010).

5. RESULTS AND DISCUSSION

Descriptive Statistics

Table 5.1 presents descriptive statistics and simple means differences tests for users and nonusers of financial services. The results suggest that users and nonusers of fertilizer are significantly different in terms of both propensity (adoption) and intensity (rates of application) of fertilizer use. Of the total farm households having access to institutional finance, 99 percent used fertilizer during the 2011/2012 production year. The corresponding figure for households without access to institutional finance is 74 percent, which is still substantial. The adoption rates of improved seeds show the same pattern. Of the total sample, 63 percent of farm households among users of 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 using these technologies are using them below the recommended rates. In particular, application rates of fertilizer among households without access to institutional finance are only half of the recommended rate of 200 kg per hectare (Ethiopia, Ministry of Agriculture 2012; Spielman, Kelemwork, and Alemuet 2011; Endale 2010).

Table 5. 1 Summary statistics of sample households by access to institutional finance

Variable	Users of institutional finance (*n* = 376)		Nonusers of institutional finance (*n* = 441)		Means difference test (*p*-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**
Pesticide adoption	0.76	0.42	0.68	0.46	**0.016**
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. [a] Tropical livestock units (TLUs) are calculated based on conversion factors suggested by Jahnke et al. (1988), Chilonda and Otte (2006), and Asfaw et al. (2010). [b] Extreme-to-severe risk averse is a reference category for the risk preference dummy.

Overall, the results from the descriptive statistics on the outcome measures (that is, adoption and application rates of fertilizer, improved seeds, and pesticides) indicate statistically significant differences between households with and without access to finance. On average, households that have access to institutional finance and that choose to participate have higher rates of adoption and intensity of use.[10] Results in Table 5.1 also indicate that the users and nonusers of financial services vary significantly with regard to demographic, social, and economic variables. In particular, the results show that households with access to finance are comparatively more educated, reside closer to banks and farmer training centers, and are male-headed. Furthermore, households with access to finance are likely to have off-farm income, which goes against conventional wisdom in that off-farm income might alleviate the credit constraints that 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 further invest. Another result to highlight is that households with no access to credit are more likely to participate in safety net programs. This is contrary to one of the stated objectives of the Productive Safety Net Program—that is, increasing credit (Gilligan et al. 2008).

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

Average Impact of Access to Finance on Technology Adoption

Table 5.2 presents the estimated average effects of access to institutional finance on adoption and application rates of technologies. With the exception of pesticides, 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 more fertilizer than households without access. Given the low fertilizer use rates 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) demonstrate that fertilizer use is, in general, profitable, with value:cost ratios greater than 2. However, farmers face a number of 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 very high transaction costs. These two studies point to two different sets of constraints. Our results are more in line with the Rashid et al. (2013) conclusions.

Although overall rates of adoption are small, the results show that the adoption rates of improved seeds would be 30 to 32 percent lower in the absence of 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 highly substitutable. When faced with a financial constraint, a farmer may switch to local seeds. There is no such 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 finance using 25 kg more of improved seeds on their plots. This result also implies that households with financial access allocate a higher proportion of their lands to high-yield varieties.

[10] 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).

Table 5. 2 Effect of access to institutional finance on agricultural technology adoption

Outcome variable	Kernel-based matching (bandwidth = 0.06)		Five-nearest-neighbors matching		Radius matching (caliper = 0.05)	
	ATT (standard error)	rbound (Γ)	ATT (standard error)	rbound (Γ)	ATT (standard error)	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)
Pesticide adoption	0.01 (0.090)	-	0.00 (0.109)	-	0.01 (0.086)	-
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. 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%.

We next analyze the impact of access to institutional finance on farm households' decision to adopt fertilizer and improved seeds together. The results show significantly higher rates of combined adoption. In particular, households that have access to finance have 32 percent higher 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 results on pesticides suggest that the adoption rates do not differ significantly between the two groups. This might be because innovations or technological advances in pesticides are not aimed at increasing yields—the innovations have more to do with application techniques. Pesticide technology, rather, is used to circumvent the yield-reduction effects of pests. In other words, farmers often apply pesticides when necessary to limit economic injury rather than spraying by calendar or applying in a timely manner as they would fertilizer. Hence, the application of pesticide is not largely based on farmers' free will and can be less dependent on access to financial services and other common adoption factors.

The results presented in Table 5.2 rely heavily on the assumptions of conditional independence and of selection on observables or unconfoundedness,[11] and they are not 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 and Caliendo 2007; Rosenbaum 2002; Rosenbaum and Rubin 1983).

The incidence of this problem is examined using Rosenbaum bounds sensitivity analysis. As shown in Table 5.2 (rbound: Γ), in all cases except for the pesticide adoption estimates, 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 statistically significant effect of access to

[11] 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.

institutional finance spurious, should be higher than Γ = 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 control group). Hence, it can be concluded that the strength of the hidden bias should 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 detail discussion).

Robustness Check

Besides the rbounds sensitivity analysis, we conduct 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 that relies on the hypothesis of selection on observables like that of PSM. Table 5.3 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, off-farm income, livestock ownership, radio ownership, and degree of risk aversion. The second variation, presented in column 2, uses the whole sample that includes farm households residing in *kebeles* with access to institutional finance that choose not to participate. The balancing hypothesis is satisfied for both of these matches, and only the kernel-based matching technique is used to conserve space.

Table 5. 3 Robustness of ATT for agricultural technology adoption

Outcome variable	Treatment variable: access to institutional finance					
	Reduced probit model (kernel-based matching)		Whole sample[a] (kernel-based matching)		Control-function regression	
	ATT	Standard error	ATT	Standard error	ATT	Standard error
Fertilizer adoption	0.13***	0.040	0.05***	0.015	0.24***	0.040
Fertilizer per hectare	66.72***	14.06	24.88***	8.85	69.84***	10.81
Improved seeds adoption	0.35***	0.120	0.08*	0.047	0.34***	0.053
Improved seeds (volume)	23.74***	4.97	8.14**	3.92	24.19***	3.91
Pesticide adoption	0.03	0.113	-0.04	0.033	-0.05	0.055
Number of observations	548			814	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. 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*).

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 5.3. Notice that the results are comparable to the PSM estimates presented in Table 5.2. 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 for unobserved covariates under any of the methods presented here.

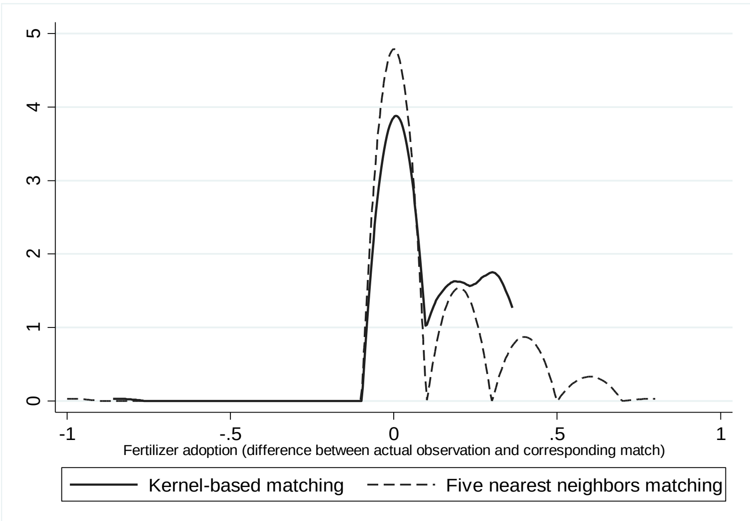
Impact Heterogeneity

We now turn to one of the central questions of the analysis: assessing the impact heterogeneity. In other words, we examine 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 5.1 is the considerable variation in user households' response to accessing institutional finance. One important implication from this analysis 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 finance. Thus, we further examine the heterogeneities to identify the sources of the variations in impact. The data allow 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 microfinance providers in rural areas (Guinnane 2001; Banerjee, Besley, and Guinnane 1994; Smith, Cargill, and 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, and Zilberman 1985; Feder and O'Mara 1981; Just and Zilberman 1983).

Figure 5. 1 Distribution of the impact of access to institutional finance across user households

(a) On fertilizer adoption and intensity of use



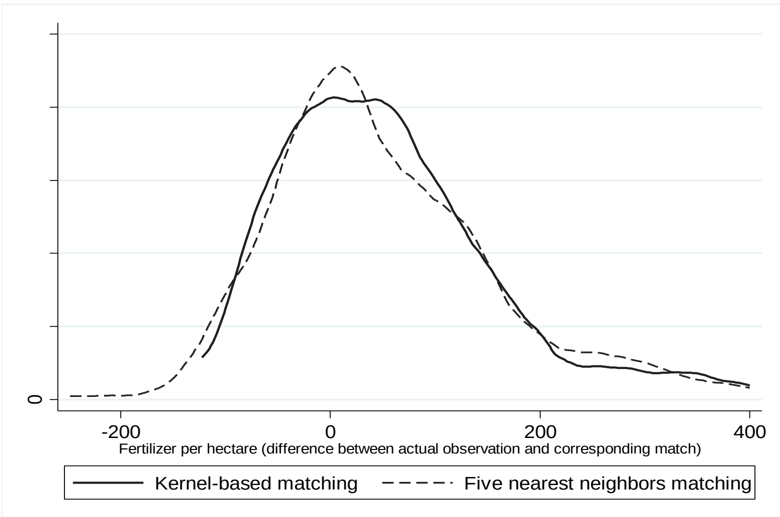
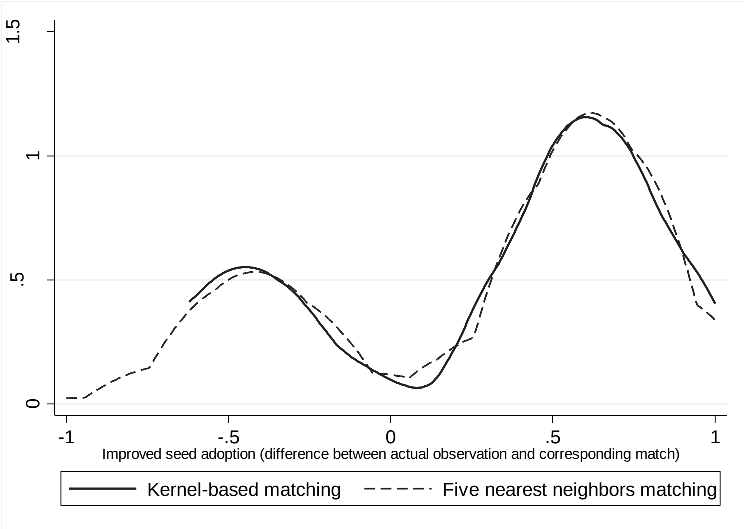
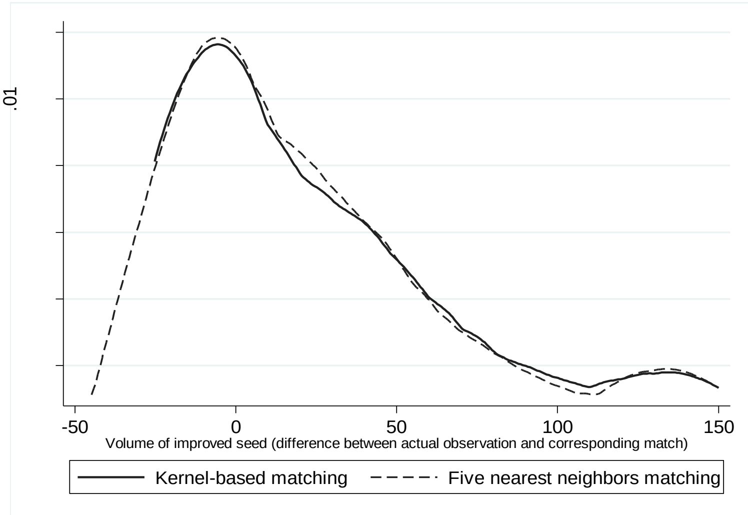


Figure 5. 2 Continued

(b) On improved seeds adoption and volume





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

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 MFI and the financial cooperative—vary considerably on 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 highly likely to induce impact variation at the household level.

Table 5.4 presents the results of this set of analyses. A take-away from this analysis is that financial cooperatives outperform the nonbank MFIs in influencing both adoption decisions and use rates. Financial cooperatives appear to significantly 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 5.4). Results also vary in terms of magnitude. While members of the financial cooperatives use more than 67 kg of chemical fertilizer relative to nonmembers, the corresponding number for the MFI members is only about 30 kg. In other words, if measured in volume of fertilizer used, the impact of financial cooperatives is twice as large as that of MFIs. The results for improved seeds are even more startling. While MFI members' seed use is not significantly better than nonmembers, financial cooperative members use 36 kg more seed per hectare relative to nonmembers.

Table 5. 4 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 (standard error)	rbound (Γ)	ATT (standard error)	rbound (Γ)	ATT (standard error)	rbound (Γ)
Panel A: Only users of financial cooperatives						
Fertilizer adoption	0.12**		0.11**		0.13***	
	(0.050)	(45–46)	(0.056)	(34–35)	(0.049)	(46–47)
Fertilizer per hectare	67.55***		65.19**		70.13***	
	(21.09)	(3.2–3.3)	(28.12)	(2.8–2.9)	(20.55)	(3.4–3.5)
Improved seeds adoption	0.42***		0.40***		0.43***	
	(0.104)	(5.9–6.0)	(0.123)	(5.3–5.4)	(0.112)	(7.0–7.1)
Improved seeds (volume)	36.02***		35.45***		36.73***	
	(5.73)	(3.6–3.7)	(5.75)	(3.7–3.8)	(5.98)	(3.6–3.7)
Number of observations	451		451		448	
Panel B: Only users of microfinance institutions						
Fertilizer adoption	0.10*		0.10		0.11**	
	(0.059)	(12–13)	(0.073)	(9–8)	(0.057)	(11–12)
Fertilizer per hectare	30.15*		29.15		27.30	
	(17.83)	(1.5–1.6)	(27.10)	(1.3–1.4)	(18.10)	(1.3–1.4)
Improved seeds adoption	0.16		0.14		0.15	
	(0.113)	(1.6–1.7)	(0.119)	(1.6–1.7)	(0.109)	(1.5–1.6)
Improved seeds (volume)	6.9		6.01		6.56	
	(6.03)	-	(5.38)	-	(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. 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. The results on pesticide adoption are similar to the estimates reported in Table 5.2 (that is, there is no statistically distinguishable difference between the treatment and control groups for pesticide adoption irrespective of institutional design of the financial service providers) and are not reported to conserve space. *** significant at 1%. ** significant at 5%. * significant at 10%.

There are two plausible interpretations for why financial cooperatives outperform MFIs. 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 ensures the use of 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 nonbank MFIs (Guinnane 2002; Smith, Cargill, and Meyer 1981). In particular, nonbank 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 and Morduch 2010). Equally important is that social sanctions are more likely to exist within the financial cooperative community in the case of members' misuse of loans for unintended purposes (Guinnane 2001; Banerjee, Besley, and Guinnane 1994).

The ATT estimates disaggregated by land size also show strong impact variations between small and larger farmers. As Table 5.5 shows, whereas the ATT results show no differential impacts on adoption rates of fertilizer by farm size, they do indicate impact heterogeneity on intensity of use. The biggest effect of access to institutional finance on intensity of fertilizer use per hectare is observed for small farmers. This suggests that access to finance can help small farmers who often cannot afford to apply the optimal amount of fertilizer.

Table 5. 5 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 (standard error)	rbound (Γ)	ATT (standard error)	rbound (Γ)	ATT (standard error)	rbound (Γ)
Panel A: Farm households with ≤ 2 hectares of land size						
Fertilizer adoption	0.10***		0.11*		0.11**	
	(0.041)	(17–18)	(0.062)	(12–13)	(0.054)	(16–17)
Fertilizer per hectare	67.19***		66.71***		67.41***	
	(22.38)	(2.9–3.0)	(24.80)	(2.7–2.8)	(21.97)	(2.7–2.8)
Improved seeds adoption	0.15		0.15		0.15	
	(0.121)	(1.7–1.8)	(0.126)	(1.7–1.8)	(0.124)	(1.7–1.8)
Improved seeds (volume)	7.51		7.66		7.60	
	(5.67)	-	(4.67)	-	(5.88)	-
Number of observations	496		496		496	
Panel B: Farm households with > 2 hectares of land size						
Fertilizer adoption	0.12**		0.11*		0.13**	
	(0.051)	(35–36)	(0.063)	(27–28)	(0.060)	(35–36)
Fertilizer per hectare	37.46**		34.11		38.86**	
	(19.13)	(1.8–1.9)	(21.97)	(1.4–1.5)	(17.96)	(1.9–2.0)
Improved seeds adoption	0.51***		0.47***		0.51***	
	(0.099)	(9.4–9.5)	(0.110)	(7.5–7.6)	(0.105)	(11.1–11.2)
Improved seeds (volume)	44.18***		42.50***		44.94***	
	(5.87)	(6.9–7.0)	(6.93)	(6.3–6.4)	(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. 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. The results on pesticide adoption are similar to the estimates reported in Table 5.2 (that is, there is no statistically distinguishable difference between the treatment and control groups for pesticide adoption irrespective of landholding size) and are not reported to conserve space. *** significant at 1%. ** significant at 5%. * significant at 10%.

Regarding improved seeds, the estimates show 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; it makes no statistically significant difference for smallholders owning less than two hectares of land. This is plausible, as small farmers' initial adoption of new, improved varieties may entail considerable risk and setup costs in terms of learning and developing or locating markets. 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. Besides credit, providing insurance products could potentially overcome the adoption-discouraging effects of farm size on use of improved varieties by small farmers. Larger landholders, on the other hand, can overcome such uncertainties and costs by piloting on small experimental plots.

6. CONCLUSION

The government of Ethiopia promotes specialized MFIs and financial cooperatives to encourage technology adoption among resource-constrained smallholders. The support ranges from creating an amicable environment for microfinance and financial cooperatives to facilitation of access to loanable funds. However, hitherto there has been little analysis as to how such institutions contribute to agricultural technology promotion in the country. A few studies have assessed the impacts of specialized MFIs, but their focus was on outcomes like income, housing, and consumption behaviors (for example, Berhane and Gardebroek 2011). Since two-thirds of the loan portfolio of these organizations is channeled to the agricultural sector, understanding the impact of their programs on technology adoption remains particularly important.

The main objective of this paper is to fill that gap. A uniquely designed survey was administered in 21 districts of the country to appropriately identify impacts with the PSM method. The results suggest that access to credit through the two types of lending organizations in general has positive impacts on the adoption and use of fertilizer and improved seeds—two key inputs that the agricultural research and extension systems actively promote. In particular, our estimates 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 access to credit through the institutions. In terms of application rates, we find that compared with the control groups, households with access to credit use 24 kg more of improved seeds and 51 kg per hectare more of chemical fertilizer. A host of tests suggest these results are robust to various specifications.

A central finding of the study is that the magnitude of impact varies considerably when disaggregated by farm size and, perhaps more important from a policy standpoint, by institutional design of the lending organization. When it comes to fertilizer, both large farmers and small farmers (owning less than two hectares of land) in our sample appear to benefit from access to credit. In particular, smallholders with access to credit apply almost 67 kg more chemical fertilizer than the control group in the same landholding categories. Large farmers with access to credit also apply fertilizer at higher rates compared with the control groups. However, consistent with the inverse size–productivity argument, the size of application is smaller at about 30 kg more than the control group. In contrast, with regard to improved seeds, our results show that only large farmers, not smallholders, benefit from access to credit. Providing insurance products in addition to credit may overcome the adoption-discouraging effects of farm size on application of improved seeds among small farmers.

Finally, we find that the institutional design of the lending institution matters most: access to credit through financial cooperatives has greater impacts on agricultural technology adoption than credit through the MFIs. An explanation lies in the historical context in which the cooperatives evolved, which in general involves a higher degree of community interaction and trust. Equally important is their institutional design—members as providers of both the demand for and the supply of loanable funds—that generates credible individual screening and monitoring incentives. MFIs, which are relatively new, can benefit by integrating some of the financial cooperatives' features to enhance their impact and effectiveness.

APPENDIX: SUPPLEMENTARY TABLES

Table A. 1Alternative 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	
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	**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 -∞	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 and Sillers (1983). Risk classification 2 is used in the analysis for analytical simplicity.

Table A. 2 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. 3 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 truism, mine, power and water resource, and personal and interbank lending.

REFERENCES

Abebaw, D., and M. G. Haile. 2013. “The Impact of Cooperatives on Agricultural Technology Adoption: Empirical Evidence from Ethiopia.” *Food Policy* 38: 82–91.

Adams, D. W., and D. H. Graham. 1981. “A Critique of Traditional Agricultural Credit Projects and Policies.” *Journal of Development Economics* 8 (3): 347–366.

Adams, D. W., D. H. Graham, and J. D. Von Pischke. 1984. *Undermining Rural Development with Cheap Credit*. Washington, DC: Economic Development Institute.

Admassie, A. 1987. “A Study of the Factors That Affect the Use of Agricultural Credit among Peasant Farmers in Ethiopia: The Case of Two Districts.” Master’s thesis, Addis Ababa University.

———. 2004. “A Review of the Performance of Agricultural Finance in Ethiopia: Pre and Post-Reform Periods.” In *Report on the Proceedings of the Agrarian Constraint and Poverty Reduction: Macroeconomic Lessons for Africa*, December 17–18, Addis Ababa. http://www.iese.ac.mz/lib/saber/eaf_025.pdf.

Amha, W. 2010. “Meeting the Financial Needs of Smallholder Farmers in Ethiopia.” In *African Smallholders: Food Crops, Market and Policy*, edited by G. Djurfeldt, E. Aryeetey, and A. C. Isinika, 156–188. DOI: 10.1079/9781845937164.0000.

Amha, W., and D. Peck. 2010. *Agricultural Finance Potential in Ethiopia: Constraints and Opportunities for Enhancing the System*. Addis Ababa: Association of Ethiopian Microfinance Institutions.

Armendáriz de Aghion, B., and J. Morduch. 2010. *The Economics of Microfinance.* Cambridge, MA, US: MIT Press.

Asfaw, S., B. Shiferaw, F. Simtowe, G. Muricho, T. Abate, and S. Ferede. 2010. *Socioeconomic Assessment of Legume Production, Farmer Technology Choice, Market Linkages, Institutions, and Poverty in Rural Ethiopia*. Research Report no. 3. Patancheru 502 324. Andhra Pradesh, India: International Crops Research Institute for the Semi-Arid Tropics.

Aterido, R., T. Beck, and L. Iacovone. 2011. *Gender and Finance in Sub-Saharan Africa: Are Women Disadvantaged?* Policy Research Working Paper WPS 5571. Washington, DC: World Bank.

Banerjee, A., T. Besley, and T. Guinnane. 1994. “Thy Neighbor’s Keeper: The Design of a Credit Cooperative with Theory and a Test.” *Quarterly Journal of Economics* 109 (2): 491–515.

Becker, S. O., and A. Ichino. 2002. “Estimation of Average Treatment Effects Based on Propensity Scores.” *Stata Journal* 2: 358–377.

Becker, S. O., and M. Caliendo. 2007. “Sensitivity Analysis for Average Treatment Effect.” *Stata Journal* 7 (1): 71–83.

Berhane. G., and C. Gardebroek, C. 2011. “Does Microfinance Reduce Rural Poverty? Evidence Based on Household Panel Data from Northern Ethiopia.” *American Journal of Agricultural Economics* 93 (1):43–55.

Bhalla, S. 1979. “Farm Size Productivity and Technical Change in Indian Agriculture.” In *Agrarian Structure and Productivity in Developing Countries,* edited by R. A. Berry and W. R. Cline, 141–193. Baltimore: Johns Hopkins Press.

Bigsten, A., P. Collier, S. Dercon, M. Fafchamps, B. Gauthier, J. Gunning, A. Oduro, R. Oostendorp, C. Patillo, M. Soderbom, F. Teal, and A. Zeufack. 2003. “Credit Constraint in Manufacturing Enterprises in Africa.” *Journal of African Economies* 12 (1): 104–125.

Binswanger, H. P., S. R. Khandker, and M. R. Rosenzweig. 1993. “How Infrastructure and Financial Institutions Affect Agricultural Output and Investment in India.” *Journal of Development Economics* 41 (2): 337–366.

Binswanger, H. P., and D. A. Sillers. 1983. “Risk Aversion and Credit Constraints in Farmers’ Decision-Making: A Reinterpretation.” *Journal of Development Studies* 20 (1): 5–21.

Braverman, A., and J. L. Guasch. 1986. “Rural Credit Markets and Institutions in Developing Countries: Lessons for Policy Analysis from Practice and Modern Theory.” *World Development* 14 (10–11): 1253–1267.

Caliendo, M., and S. Kopeinig. 2008. “Some Practical Guidance for the Implementation of Propensity Score Matching.” *Journal of Economic Surveys* 22 (1): 31–72.

Cameron, A. C., and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. Cambridge, UK: Cambridge University Press.

Chilonda, P., and J. Otte. 2006. “Indicators to Monitor Trends in Livestock Production at National, Regional, and International Levels.” *Livestock Research for Rural Development* 18 (8), article number 117.

Croppenstedt, A., D. Demeke, and M. M. Meschi. 2003. “Technology Adoption in the Presence of Constraints: The Case of Fertilizer Demand in Ethiopia.” *Review of Development Economics* 7 (1): 58–70.

De Janvry, A., and E. Sadoulet. 2010. “Agriculture for Development in sub-Saharan Africa: An update.” *AfJARE* 5 (1): 194–204.

Dehejia, R., and S. Wahba. 2002. “Propensity Score-Matching Methods for Non-Experimental Causal Studies.” *Review of Economics and Statistics* 84: 151–161.

Demirgüç-Kunt, A., and L. Klapper. 2012. *Financial Inclusion in Africa: An Overview*. Policy Research Working Paper WPS6088. Washington, DC: World Bank.

Dercon, S., and L. Christiaensen. 2011. “Consumption Risk, Technology Adoption, and Poverty Traps: Evidence from Ethiopia.” *Journal of Development Economics* 96: 159–173.

Deribie, E. 2012. “The Effects of Post 1991 Era Financial Sector Deregulations in Ethiopia: An Inspirational Guide for Agribusiness.” *Basic Research Journal of Agricultural Science and Review* 1 (4): 81–87.

Diagne, A. 1999. *Determinants of Household Access to and Participation in Formal and Informal Credit Markets in Malawi*. FCND Discussion Paper 67. Washington, DC: International Food Policy Research Institute.

Dorosh, P., and S. Rashid. 2012. *Food and Agriculture in Ethiopia: Progress and Policy Challenges*. Philadelphia: University of Pennsylvania Press.

Dorward, A., S. Fan, J. Kydd, H. Lofgren, J. Morrison, C. Poulton, N. Rao, L. Smith, H. Tchale, S. Thorat, I. Urey, and P. Wobst. 2004. “Institutions and Policies for Pro-Poor Agricultural Growth. *Development Policy Review* 22 (6): 611–622.

DSA (Development Studies Associates). 2010. *Impact Evaluation of Fertilizer Usage. Rural Capacity Building Project*. Addis Ababa: World Bank, Country Office.

Duflo, E., and M. Kremer. 2005. “Use of Randomization in the Evaluation of Development Effectiveness.” In *Evaluating Development Effectiveness*, vol. 7, edited by O. Feinstein, G. K. Ingram, and G. K. Pitman, 205–232. New Brunswick, NJ, and London, UK: Transaction Publishers.

Duflo, E., M. Kremer, and J. Robinson. 2008. “How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya.” *American Economic Review* 98 (2): 482–488.

EEA (Ethiopian Economic Association). 2000. *Annual Report on Ethiopian Economy*. V. II, 2000/2001. Addis Ababa.

Endale, K. 2010. *Fertilizer Consumption and Agricultural Productivity in Ethiopia*. Addis Ababa: Ethiopian Development Research Institute.

Ethiopia, Central Statistical Agency. 2011. “[Ethiopia] Agricultural Sample Survey 2010/11 (2003 E.C.) Volume V, Report on Area and Production of Meher Season Crops for Private Peasant Holdings.” Addis Ababa: Federal Democratic Republic of Ethiopia.

———. 2013. “[Ethiopia] Agricultural Sample Survey 2012/13 (2005 E.C.) Volume I, Report on Area and Production of Meher Season Crops for Private Peasant Holdings.” Addis Ababa: Federal Democratic Republic of Ethiopia.

Ethiopia, Ministry of Agriculture. 2012. *Ministry of Agriculture Animal and Plant Health Regulatory Directorate: Crop Variety Register*. Issue no. 15. Addis Ababa.

Ethiopia, Ministry of Finance and Economic Development. 2012. *Ethiopia’s Progress Towards Eradicating Poverty: An Interim Report on Poverty Analysis Study (2010/11).* Addis Ababa.

Fan, S., L. Xing, C. Fang, and X. Zhang. 2006. “Agricultural R&D and Urban Poverty.” *Agrotech Economics* 5: 9–15.

Feder, G. 1982. “Adoption of Interrelated Agricultural Innovations: Complementarity and the Impact of Risk Scale and Credit.” *American Journal of Agricultural Economies* 64: 94–101.

Feder, G., and G. T. O’Mara. 1981. “Farm Size and the Adoption of Green Revolution Technology.” *Economic Development and Cultural Change* 30: 59–76.

Feder, G., R. E. Just, and D. Zilberman. 1985. “Adoption of Agricultural Innovations in Developing Countries: A Survey.” *Economic Development and Cultural Change* 33: 255–298.

Feder, G., and D. L. Umali. 1993. “The Adoption of Agricultural Innovations: A Review.” *Technological Forecasting and Social Change* 43: 215–239.

Fischer, A. J., and R. K. Lindner. 1980. “The Effect of Distance to Information Source or Information Quality and the Time to Adoption.” Unpublished, University of Adelaide, Australia.

Gilligan, D. O., J. Hoddinott, and A. S. Taffesse. 2008. *The Impact of Ethiopia’s Productive Safety Net Programme and its Linkages.* IFPRI Discussion Paper 00839. Washington, DC: International Food Policy Research Institute.

Guinnane, T. W. 2001. “Cooperatives as Information Machines: German Rural Credit Cooperatives, 1883–1914.” *Journal of Economic History* 61 (2): 366–389.

———. 2002. “Delegated Monitors, Large and Small: Germany’s Banking System, 1800–1914.” *Journal of Economic Literature* 40 (1): 73–124.

Headey, D., M. Dereje, J. Ricker-Gilbert, A. Josephson, and A. S. Taffesse. 2013. *Land Constraints and Agricultural Intensification in Ethiopia: A Village-Level Analysis of High-Potential Areas.* ESSP Working Paper 58. Washington, DC: International Food Policy Research Institute.

Heckman, J., H. Ichimura, J. Smith, and P. Todd. 1997. “Matching as Econometric Evaluation Estimator: Evidence from Evaluating a Job-Training Program.” *Review of Economic Studies* 64: 605–654.

———. 1998. “Characterizing Selection Bias Using Experimental Data.” *Econometrica* 66: 1017–1098.

Heckman, J., and S. Navarro-Lozano. 2004. “Using Matching, Instrumental Variables, and Control Functions to Estimate Economic Choice Models.” *Review of Economics and Statistics* 86 (1): 30–57.

Hussien, H. K. 2007. “Farm Household Economic Behavior in Imperfect Financial Markets: Empirical Evidence and Policy Implications on Saving, Credit and Production Efficiency in Southeastern Ethiopia.” Doctoral thesis, Swedish University of Agricultural Sciences, Uppsala.

Ibrahim, G., A. Kedir, and S. Torres. 2007. *Household-Level Credit Constraints in Urban Ethiopia*. Working Paper 07/03. Leicester, UK: University of Leicester.

Jahnke, H. E., G. Tacher, P. Keil, and D. Rojat. 1988. “Livestock Production in Tropical Africa with Special Reference to the Tsetse-Affected Zone.” In *Livestock Production in Tsetse-Affected Areas of Africa.* Proceedings of a meeting held by the International Livestock Centre for Africa (ILCA) and the International Laboratory for Research on Animal Diseases (ILRAD), November 23–27, 1987, in Nairobi, Kenya. Nairobi: ILCA/ILRAD.

Jalan, J., and M. Ravallion. 2003. “Does Piped Water Reduce Diarrhea for Children in Rural India?” *Journal of Econometrics* 112: 153–173.

Just, R. E., and D. J. Zilberman. 1983. “Stochastic Structure, Farm Size, and Technology Adoption in Developing Agriculture.” *Oxford Economic Papers* 35: 307–328.

Keele, L. 2010. “An Overview of Rbounds: An R Package for Rosenbaum Bounds Sensitivity Analysis with Matched Data.” Accessed June 2012. http://www.personal.psu.edu/ljk20/rbounds%20vignette.pdf.

Lindner, R. K. 1980. “Farm Size and the Time Lag to Adoption of a Scale Neutral Innovation.” Unpublished, University of Adelaide, Australia.

Lipton, M. 1976. “Agricultural Finance and Rural Credit in Poor Countries.” World Development 4: 543–554.

Mendola, M. 2007. “Agricultural Technology Adoption and Poverty Reduction: A Propensity-Score Matching Analysis for Rural Bangladesh.” *Food Policy* 32: 372–393.

Meyer, R. L. 2011. *Subsidies as an Instrument in Agriculture Finance: A Review*. A joint discussion paper of the World Bank, BMZ, FAO, GIZ, IFAD, and UNCDF.

Miller, C. J., and J. R. Ladman. 1983. “Factors Impeding Credit Use in Small Farm Households on Bolivia.” *Journal of Development Studies* 19 (4): 522–538.

Minten, B., and C. B. Barrett. 2008. “Agricultural Technology, Productivity, and Poverty in Madagascar.” *World Development* 36 (5): 797–822.

Minten, B., K. Bethlehem, and D. Stifel. 2013. *The Last Mile(s) in Modern Input Distribution: Evidence from Northwestern Ethiopia.* ESSP Working Paper No. 51. Washington, DC: International Food Policy Research Institute.

Obo, D. D. 2009. *Microfinance in Ethiopia: Elixir or Poison?* PhD thesis, Institute of Social Studies, The Netherlands.

Rashid, S., and A. Negassa. 2013. “Policies and Performance of Ethiopian Cereal Markets.” In *Food and Agricultural Policies in Ethiopia: Progress and Challenges*, edited by Dorosh and Rashid, 123–158. Philadelphia: University of Pennsylvania Press.

Rashid, S., R. Cummings Jr., and A. Gulati. 2007. “Grain Marketing Parastatals in Asia: Results from Six Case Studies.” *World Development* 35 (11): 1872–1888.

Rashid, S., N. Tefera, N. Minot, and G. Ayele. 2013. “Can Modern Input Use Be Promoted without Subsidies? An Analysis of Fertilizer in Ethiopia.” *Agricultural Economics* 44: 595–611.

Richter, S. M. 2008. “The Insurance Role of Remittances on Household Credit Demand.” Paper prepared for presentation at the annual meeting of the American Agricultural Economics Association, Orlando, Florida, July 27–29.

Rosenbaum, P. R. 1991. “Discussing Hidden Bias in Observational Studies”. *Annals of Internal Medicine* 115 (11): 901–905.

Rosenbaum, P. R. 2002. *Observational Studies*, 2nd edition. New York: Springer.

Rosenbaum, P. R., and D. B. Rubin. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70 (1): 41–55.

———. 1985. “Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score.” *American Statistician* 39: 33–38.

Rubin, D. B., and N. Thomas. 2000. “Combining Propensity Score Matching with Additional Adjustments for Prognostic Covariates.” *Journal of American Statistical Association* 95: 573–585.

Schmidt, R. H., and E. Kropp. 1987. *Rural Finance Guiding Principles*. Eschborn: Deutsche Gesellschaft für Technische Zusammenarbeit (GTZ).

Schutjer, W. A., and M. G. Van der Veen. 1977. *Economic Constraints on Agricultural Technology Adoption in Developing Nations*. Occasional Paper 5. Washington, DC: U.S. Agency for International Development.

Smith, D., T. F. Cargill, and R. A. Meyer. 1981. “Credit Unions: An Economic Theory of a Credit Union.” *Journal of Finance* 36 (2): 519–528.

Smith, J., and P. Todd. 2005. “Does Matching Overcome Lalonde’s Critique of Non-Experimental Estimators?” *Journal of Econometrics* 125: 305–353.

Spielman D. J., D. Kelemwork, and D. Alemu. 2011. *Seed, Fertilizer, and Agricultural Extension in Ethiopia.* ESSP II Working Paper 020. Washington, DC: International Food Policy Research Institute

Wollini, M., and M. Zeller. 2007. “Do Farmers Benefit from Participating in Specialty Markets and Cooperatives? The Case of Coffee Marketing in Costa Rica.” *Agricultural Economics* 37: 243–248.

World Bank. 2013. *Ethiopia Economic Update II: Laying the Foundation for Achieving Middle Income Status.* Washington, DC.

———. 2014. *Ethiopia Economic Update III: Strengthening Export Performance through Improved Competitiveness.* Washington, DC.

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