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Credit constraint and agricultural technology adoptions: evidence from Ethiopia

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Abstract

Purpose – This paper investigates constraints to yield enhancing technology adoptions, highlighting credit using data pooled from the first three waves of the Ethiopian socio-economic surveys.

Design/methodology/approach – Direct elicitation methodology is used to identify household's non-price credit rationing status. The panel selection model specified to examine causal effects of credit constraint on adoption variables allows us to tackle self-selection into adoptions and potential endogeneity of credit constraint while controlling for unobserved heterogeneity in both the selection and main equations.

Findings – Results show that about 54% of sample households face credit rationing, predominantly demand-side risk rationing. There is a negative association between measures of credit constraint status and adoption variables. The effect is stronger when the demand-side credit rationing is accounted for and when within household variation in credit constraint status overtime is considered as opposed to across constrained and unconstrained households.

Practical implications – Expanding physical access to institutional credit alone may not necessarily spur increased uptake of credit and instant investment by farm households. For a majority of them to take advantage of available credit and improved technology, interventions should also aim at minimizing downside risks.

Originality/value – This paper incorporates the role of downside risk in influencing farmer's decisions to uptake credits and subsequently his/her adoption behaviors. The researcher approached the topic by state-of-the-art method which allows obtaining more reliable results and hence more specific contributions to research and practice.

Keywords Direct elicitation methodology, Credit constraint, Agricultural technology adoptions, Panel selection model, Ethiopia

Paper type Research paper

1. Introduction

Agriculture contributes approximately 40% to Ethiopia's GDP, 80% to its export and employs an estimated 75% of its workforce. About 74% of farm households in Ethiopia live on small farms of which nearly 67% living under the national poverty line (Kirchner, 2021). The nation has managed to increase agricultural output since early 2000s contributing to national poverty reduction and an overall improvement in well-being. However, the long-awaited agricultural transformation is yet to happen necessitating substantial rise in the productivity of smallholder farmers, bridging the yield gap. Ethiopia's cereal yield amounted to 42% of Vietnam and 33% of Egypt as of 2018 (World Bank, 2021). Increasing agricultural productivity and ensuring food security remained at the top of government's development

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agendas. More recently, the government has consistently allocated and channeled more than 10% of its total budget to the agricultural sector; drew special attention to programs that support productivity growth such as extension services and rural finance (Rashid and Negassa, 2013; Bachewe *et.al.*, 2015) [1]. Farmers are highly encouraged to utilize modern technologies such as fertilizer [2]. Recently available micro-evidence shows that many farmers in Ethiopia use fertilizer than is often acknowledged. But there exists immense variation across farmers in the intensity of use, even among those with similar biophysical endowments (Sheahan and Barrett, 2017).

It is imperative to identify critical drivers of farmers' adoption decisions in low income contexts. Conceptually, the relative importance of potential constraints could be confounded. Well acknowledged is for credit constraints and risk aversion (Chaudhuri and Osborne, 2002), but few empirical studies examine directly how these factors interact and affect the process of technology adoption itself in poor agrarian settings (Foster and Rosenzweig, 2010). Ample literature exists documenting that poor farm households suffer the most from credit constraints and incomplete insurance. Credit availability can facilitate the adoption and increased use of improved technology via two channels. ex ante credit availability allows resource poor, but productive households to finance lucrative investment opportunities that may otherwise relinquished. Ex-post credit availability enables them to smooth consumption once input allocation decision is made and thus induce even highly risk averse households to take this advantage. Conversely, technology adoption increases farmer's risk and uncertainties, perpetuating low demand for credits, low rates of adoption and limited productivity gains. According to Jayne *et al.* (2006) risk averse farmers tend to reduce their exposure to risk by investing less in the production of a crop than risk-neutral return maximization might indicate. However, many households in low income agrarian settings possess low levels of assets and little or no access to credit and safety nets and are usually prone to imperfect informal insurance pooling. For them the issue is more of their ability to bear risk than their attitude toward it. Their downside risk may often be catastrophic (loss of land or even starvation) and hence has to be avoided, even at the expense of forsaking opportunities for large gains (Schneider, 2010, p. 7). This partly explains why limited households use credit to finance inputs purchase (Christiaensen, 2017), albeit significant advance in the physical access to microcredit.

In this paper, we provide empirical evidence on constraints to adoption of relatively risky, but potentially productivity enhancing technology in Ethiopia underscoring credit. Our analysis of household technology adoption decisions focuses on inorganic fertilizer (henceforth fertilizer). Using detailed household survey data we basically try to address two sequential research questions: whether there is any credit rationing in rural Ethiopia and whether Ethiopian farm households' technology adoption decisions are affected by this rationing [3]. One challenge in adoption studies using observational data is disentangling the contribution of one constraint from others. To make a meaningful link between lack of technology adoption and credit constraints, we need to observe variation in the latter that was not associated with variation in other constraints." . . . This is unlikely to be covered by survey without explicit sampling practices and questionnaire design meant to elicit that variation" (Magruder, 2018, p. 2). Moreover, measuring access to credit is not an easy task. Many existing studies used a measure of credit availability that is learned to be problematic (see Doss, 2006). One measure frequently used is whether the household has access to credit-a yes/no response. They largely focused on capturing the effects across constrained vs. unconstrained farmers.

The sample available to us allows for making some important contributions to the literature on constraints to adoption of agricultural technologies in low-income countries (briefly reviewed in section 2). We take advantage of the Ethiopian socio-economic surveys (ESS) - large and nationally representative panel of households obtained from rural Ethiopia as part of the World Bank's LSMS-ISA in 2011/12, 2013/14 and 2015/16. Direct elicitation methodology is employed to identify household's non-price credit rationing status. We specify panel selection model to examine causal effects of credit constraint on both the dichotomous adoption and the continuous conditional intensification decisions. To the best of our knowledge, this is one of the first studies that attempt to tackle self-selection into adoptions and potential endogeneity of credit constraint while controlling for unobserved heterogeneity in both the selection and main equations. An attempt is made to incorporate the role of risk and uncertainties in influencing farmer's decisions to uptake credit and subsequently his/her adoption behaviors. An alternative instrumental variable is used to assess the robustness of our results.

The remainder of this paper is structured as follows: literature review focusing on the main empirical issues in modeling agricultural technology adoption decisions is discussed in brief in section 2. Panel selection model is specified in section 3. Section 4 describes the ESS dataset and introduces direct elicitation methodology with some descriptive evidence. This is followed by presentation of results and discussion in section 5. Section 6 concludes the paper.

2. Literature review

A large body of empirical literature has attempted to understand constraints to agricultural technology adoptions in low-income countries at least since Feder *et al.* (1985). In trying to understand constraints to adoptions, the literature has taken two different stands on the interpretation given to farmers' behavior. The first emphasizes profitability, that is, adoption may not be optimal for every farmer (Suri, 2011; Liu, 2013; Matsumoto and Yamano, 2011; Sheahan *et al.*, 2013). Thus, observed technology uptake may represent quite rational response by farmers to the problems of lower rates of return to adoptions and input use and highly variable profit. If farmers find it profitable to adopt divisible technologies such as fertilizer, they can obtain the little cash needed to purchase them by any means necessary. The second, more in line with the current work, emphasizes some form of market failures and the resulting seemingly inefficient behavior of the farmers to explain deviations from optimal adoptions and inputs use: capital and credit constraints (Croppenstedt *et al.*, 2003; Duflo *et al.*, 2011; Holden and Lunduka, 2013; Lambrecht *et al.*, 2014); risk and uncertainties (Alem *et al.*, 2010; Dercon and Christiaensen, 2011); accessibility or supply shortages (Moser and Barrett, 2006; Minten *et al.*, 2013, De Janvry *et al.*, 2016) or information failures and the role of learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010). An important implicit assumption here is that under the right conditions, farmers are ready to take risk and invest.

There has been considerable research on constraints to agricultural technology adoption in the Ethiopian context too. Lack of access to institutional credits remained a major drag to technical improvement in the Ethiopian smallholder agriculture (Assefa, 1987, 2004; Croppenstedt *et al.*, 2003; Zerfu and Larson, 2010; Abate *et al.*, 2016; Mukasa *et al.*, 2017) [4]. The consequence of covariate shocks such as droughts, are acute in Ethiopia, often affecting household's welfare many years after the shock (Dercon, 2004; Dercon and Christiaensen, 2011).

Existing studies approached the topic with different econometric methodologies. Some (including Croppenstedt *et al.*, 2003) applied double hurdle model using cross-sectional data. Observed zero-value on the intensity of fertilizer use is interpreted as if it is an optimal outcome for the household. In a two-stage investigation approach, a probit model of adoption decisions and truncated model of intensity of use are estimated. Some others, more in line with our approach, (including Zerfu and Larson, 2010), employ panel selection model using a sample of farm households different and quite smaller than the sample available to us. In this case, the non-zero population varies over time, making the distinction between the hurdle and selection models less clear (Ahn, 2004). Panel selection model allows for the possibility of rationality thesis, that is, farmers respond to lower expected net return/utility from using fertilizer while exploring the effects of market imperfections and constraints on household's adoption decisions. Panel data allows for the analysis of household behavior through time. For instance, it is interesting to analyze how access to finance changes over time and how these changes affect adoption decisions. Yet at least two additional issues arise: unobserved heterogeneity and potential endogeneity of variable of interest, making the estimation strategy complex. Our identification strategy makes this paper also different from Zerfu and Larson (2010).

3. Empirical strategy

One overarching goal in this paper is to obtain more reliable estimates of causal effects of credit constraint on both adoption and intensification decisions. A basic theoretical model linking farmer's optimization behaviour and financial market imperfections (Karlan *et al.*, 2014; Magruder, 2018) serve as our basis. Binding credit constraint and incomplete informal insurance pooling can lead to a less risky household investment portfolio choice.

$$adopts_{it} = 1\left[\theta IV_{it}^{CC} + \boldsymbol{\pi} \boldsymbol{z}_{it} + b_i + v_{it} > 0\right] \tag{3.1}$$

$$fertr_{it} = \alpha CC_{it} + \boldsymbol{\beta} \boldsymbol{x}_{it} + a_i + u_{it} \tag{3.2}$$

$$a_i = \overline{\boldsymbol{x}}_i + \gamma_{ai} \tag{3.3}$$

$$b_i = \overline{IV}_{it}^{CC} + \overline{\boldsymbol{z}}_i + \gamma_{bi}$$

Where i denotes the household, t denotes time (wave), $fertr_{it}$ is fertilizer application rate, CC_{it} is potentially endogenous dummy signifying credit constraint status, $\boldsymbol{x}_{it}$ is a vector of control variables that explain the intensity of use with associated vector of parameters β, a_i is time invariant household unobserved effects, u_{it} is standard error term. $adopts_{it}$ is a binary indicator of adoption status with $adopts_{it} = 1$ if the unobserved $adopts_{it}^{*} > 0$ or an indicator function 1[.] is equal to one, in which case the household adopts fertilizer and $adopts_{it} = 0$ otherwise. IV_{it}^{CC} is instrumental variable for CC_{it}, $\boldsymbol{z}_{it}$ is a vector of exogenous explanatory variables that explain technology adoption decisions with associated vector of parameters $\boldsymbol{\pi}$, b_i is time invariant household unobserved effects and v_{it} is error term with zero mean and unit variance.

The dichotomous adoption decision of the farmer is represented by a probit selection Equation (3.1). Equation (3.2) is a conditional demand function of the farmer. There is at least one important potential source of bias in the estimation of Equation (3.1): in most settings, adoption of one technology depends on the availability/adoption of the other, a typical example being improved seeds and fertilizer. A farmer may perceive that using fertilizer boosts her returns from adopting improved seeds. If this is the case, then a univariate probit selection model used to examine single input adoption decisions may lead to results that are apparently subject to simultaneous equation bias and inconsistency (Feder *et al.*, 1985; Abay *et al.*, 2018). It may also be the case that the farmer finds it more profitable to use fertilizer along with improved seeds, but constraints posed by elements of the enabling environment such as credit constraint force her to adopt sequentially rather than using the two inputs simultaneously (Feder, 1982). These elements of the enabling environment influence the extent and incidence of complementarity. This implies that complementarity effect is likely to be confounded with the effect of both observable and unobservable sources of heterogeneity across farm households in Equation (3.1). The latter might be driven by, among others, differences in return to adoption (Suri, 2011) and/or differences in risk preferences (Liu, 2013). However, household fixed effect included in the estimation should take care of complementarity effect.

Two main sources of bias can also be mentioned in the estimation of the conditional demand Equation (3.2). First, unobserved factors in the selection equation are likely to be correlated with unobserved factors in the main equation. Put it differently: farmers may self-select into adoption. For instance, households closer to major urban centers may benefit from better infrastructure and social networks, which enhance their consciousness about technology adoption and profitability as well as market conditions. The second issue is potential endogeneity of credit constraint status. Omitted variables such as managerial quality might influence both credit constraint status and intensity of inputs use decisions. But reverse causality might also be at play here: good harvest resulting from fertilizer use may determine credit market participation decisions and outcomes of the farmer, including credit constraint status. We employ an estimator developed by Semykina and Wooldridge (2010) to address these two potential sources of bias while controlling for unobserved time invariant household specific effects in both equations. The presence of unobserved heterogeneity also in the selection equation makes consistent estimates of the main equation complicated. Simply adding the inverse Mills ratio obtained from the first stage and using simple fixed effects estimator may not achieve consistent estimates (Semykina and Wooldridge, 2010).

In this approach, Mundlak's (1978) modeling solution is used to model a_i and b_i as in Equation (3.3). Where the bar indicates the time average for exogenous time varying covariates in each equation, which are likely correlated with the time constant unobservables. These variables are set to vary only across households, not over time for a given household. γ_{ai} and γ_{bi} are assumed to be normally distributed with mean equal to zero and variance $\sigma_{\gamma bi}$ and $\sigma_{\gamma bi}$ and independent of $\boldsymbol{z}_{it}$, IV_{it}^{CC} and $\boldsymbol{x}_{it}$. In other words, b_i is assumed to relate to $\boldsymbol{z}_{it}$ and IV_{it}^{CC} only through their time averages. Similarly, a_i is assumed to relate to $\boldsymbol{x}_{it}$ only through its time averages. γ_{ai} and γ_{bi} are allowed to be correlated with u_{it} and v_{it} across the two equations. The time averages for explanatory variables in Equation (3.3) are computed from the entire sample (including both users and non-users) and as such is free of selection bias (Semykina and Wooldridge, 2010). The advantages of modeling the unobserved heterogeneity this way are twofold. First, it avoids the problem of incidental parameters (Mundlak, 1978) while doing the jobs of simple fixed effects estimator. Second, it allows measurement of the effects of time invariant explanatory variables as in the simple random effect estimator (Wooldridge, 2010).

Parameters of main interest are α and θ respectively capturing the effect of potentially endogenous credit constraint in the main and selection equations. We hypothesize that there are smallholder farmers who still wish to benefit from the advantages of fertilizer adoption and its optimal usage, but unable to do so due to credit market imperfections. Thus, we expect the sign of α and θ to be negative and statistically significant. IV_{it}^{CC} is generated as the fitted probability from a probit regression of CC_{it} on an appropriate instrument capturing exogenous variation in the category of credit rationing considered plus the controls in $\boldsymbol{x}_{it}$ and their time averages (Wooldridge, 2010). All the variables in $\boldsymbol{x}_{it}$ are also in $\boldsymbol{z}_{it}$, but the latter includes at least one additional variable that is not in the former as an exclusion restriction tackling selection bias. It must be the case that this exclusion restriction variable captures factors that influence the decisions to adopt fertilizer, but not necessarily subsequent intensification decisions.

Procedure 4.1.1 in Semykina and Wooldridge (2010) is closely followed to estimate the main equation. First, inverse mills ratio (IMR) is generated from a probit estimation of the selection equation augmented with time averages of all time varying variables in $\boldsymbol{z}_{it}$ and IV_{it}^{CC}, taking all observations in the sample (including both users and non-users) [5]. Moreover, regional and time dummies are included in the estimation. Standard errors are adjusted for the effect of clustering at the enumeration areas. Then, the main equation is estimated via pooled 2SLS-IV augmented with time averages of all time-varying variables in

$\boldsymbol{x}_{it}$ and time averages of the generated instruments taking all observations in the sub-sample (only users). IMR generated from step one, time dummies and interactions of IMR with time dummies are also included in the estimation. The generated instruments and IMR as well as all variables in $\boldsymbol{x}_{it}$ and their time averages are used as instruments. Standard errors are adjusted for clustering at household level [6]. Standard errors associated with average partial effects are bootstrapped with 500 replications.

There are certain nice features of this identification procedure (Wooldridge, 2010; Secchi *et al.*, 2016). It is robust to misspecification of the first stage probit model. It is also more efficient than directly including the chosen instrument into standard IV procedure. More to these, adjustment for 2SLS-IV standard error is not required. Yet, one needs to rely on goodness of fit from the fitted probability of potentially endogenous variables on selected instruments to validate the suitability of external instruments instead of standard weak instrument test procedures.

3.1 The dependent variables

Applied researchers define adoption variables in many different ways depending on contexts. In this study, if the household is using any amount of fertilizer on its plot during a given agricultural season, irrespective of history of use, the household is an adopter or user of this input/technology. This definition is not inconsistent with the fact that farmers keep using and discarding technologies or inputs over time. For users, the next important measure is the proportion of land applied to fertilizer. The intensity of adoption is measured at the household level in a given time period by the per hectare quantity of fertilizer used.

3.2 The control variables

The choice of control variables focused on household, their farm and community level characteristics that help them cope with decision making in a highly constrained environment. Their definition is provided in Table A1. Households devise various strategies of their own to mitigate welfare loses posed by market failures and constraints.

We included a common set of control variables in both the main and selection equations. The latter also includes regional dummies as an exclusion restriction, assuming that lack of fertilizer supply locally, late delivery and inadequate infrastructure can be captured by regional dummies. This is in line with previous studies in the Ethiopian context (for example, Croppenstedt *et al.*, 2003). Substantial investment in infrastructure made over the last two decades, especially in all-weather roads is anticipated to make local accessibility of technologies and inputs much easier. According to Moneke (2020) Ethiopia managed to expand all-weather road network roughly four-fold between the late 1990s and today, from approximately 16,000 km to approximately 70,000 km. Therefore, one may attach less weight to accessibility as limiting factor in adoption decisions. Yet, starting from low base and geographic distribution of this expansion ought to be borne while considering regional dummies for this purpose.

We used two alternative instruments for potentially endogenous credit constraint variables. Our first instrument is having certificate of land right. There is an ongoing large-scale rural land certification programs in Ethiopia. The most recent one is land investment for transformation (LIFT), a second-round registration and certification program launched in 2013 [7]. The program provides farmers with the legal certificate of right to use plots under their control. In most of the cases, the aim also includes improving smallholder farmers' access to finance (Ghebru and Girmachew, 2019). Albeit poor collateral laws in the country, there is evidence that some farmers in some localities use this certificate as a guarantee to obtain credits.

Notwithstanding much improvement in the physical access to credit over the last two decades, most rural poor still have no or limited access to institutional credit.

Thus, whether formal credit providers are present in a village and distance to these institutions could be one potential source of heterogeneity across households with regard to their decisions to participate in the credit market and the resulting equilibrium outcomes. Widely documented thin and imperfect agricultural markets in Ethiopia reinforce the validity of these instruments. Land, labour, credit and insurance as well as output markets are far from being complete. Land is state-owned and it is allocated to farmers by a local council, with only usufruct right. Land buying and selling as well as rent in or rent out is hardly practiced and wage labour in rural areas is rare. So, for instance, it is very difficult if not impossible for the farmer to consider a strategy of relocation to areas where access to credit is better.

4. Data

The ESS is a multi-topic, nationally representative panel household survey with a focus on agriculture. It contains detailed post-planting and post-harvest information; information on socio-economic variables as well as community-level and location-specific variables.

Households in the survey were visited three rounds so far: first in 2011/12 and then a follow-up survey in 2013/14 and 2015/16 [8]. The survey uses a two-stage probability sampling. In the first stage the enumeration areas (EAs) - primary sampling units-are selected for the rural, small and large town areas samples. This is followed by the selection of households included in the survey from each EA in the second stage. For the rural samples, 290 EAs were selected based on probability proportional to size of the total EAs in each regional state. A total of 12 households were sampled in each EA (without replacement) of which 10 were randomly selected out of the total households engaged in farming and/or livestock rearing activities and the other two out of the remaining households, that is, those which are not engaged in either activity. In case there were less than two households from the latter category, more households from the former category were surveyed. For a small-town sample, a total of 43 EAs were selected in the first stage. In the second stage, 12 households-irrespective of their agricultural activities-were selected randomly from a list of each EA without replacement. Accordingly, a total of 3,969 households were visited during the first round with a response rate of 99.3% [9]. Similarly, a total of 5,262 and 4,954 households were visited respectively during the second and third round with a response rate of 96.2 and 85% [10].

For the current purpose we considered only samples from rural and rural town areas, extracting an unbalanced panel of farm households which are engaged in crop production. All households observed at least twice and for which we are able to identify their credit constraint status are included in the sample of data used in the econometric exercises. Only limited households are dropped due to missing information on other important variables included in the estimations. Borrowing households with no clear information concerning the sources and purpose of loans as well as no information on the amount of loans and an amount of loans obtained below 150 Ethiopian Birr are dropped.

4.1 Direct elicitation methodology

To identify non-price credit constraint status of the household we used direct elicitation methodology (Boucher *et al.*, 2009) which relies on borrowing incidence. Available information is adequate to identify the incidence of credit constraint, but not necessarily its level. The dividing line is that not all households which reported credit constrained are necessarily creditworthy clients from lenders' perspectives. Yet, the incidence of credit constraint provides an upper-bound measure of the extent of true credit constraint (Sanchez and Love, 2009).

Table 1 summarizes information on household's credit market participation decisions and the resulting equilibrium outcomes. Accordingly, on average, about 23% of sample respondents have no demand for credit and did not participate in the credit market during the period from 2012 to 16. There is, however, noticeable regional variation and an upward trend in the share of households which do not demand any credit. Quite similar share of households managed to obtain the full amount of loans requested (accessed) during the same period. Contrary to one's expectation, partially accessed and rejected loan requests account for limited share (a little larger than two percent and four percent) of the total loan incidence. To put it another way, about 78% of households which applied for loans obtained the full amount requested with another more than eight percent obtaining partial amount. At first glance, this figure gives a wrong impression that credit constraint is less prevalent in rural Ethiopia. The picture becomes clearer when we account for the demand-side credit rationing.

There is a downward trend and regional variation in the share of households which denied access to credit by lenders with above average rejection rate in Tigray and the SNNP. More than 51% of borrowing households reported to face demand-side credit rationing albeit substantial variation across regions. This provides one explanation for the current paradox in rural credit markets of developing countries: limited uptake of credit albeit significant improvement in the physical access to microcredit. Risk rationing is more prevalent in the SNNP. As expected, transaction costs rationing is exceptionally high in regionO. It is expected that formal lenders' penetration in regionO is low in part due to limited economic activities in the regions.

5. Results and discussion

Table 2 reports summary statistics on adoption variables, variables of main interest and control variables. Contained in the table are mean, standard deviation, minimum and maximum of each variable dividing the entire sample into two, depending on fertilizer adoption status during the period covered in the sample. About 50.5% of sample households are non-users [11]. Credit constraint is more prevalent among non-users. This is so irrespective of how one defines it. Data confirms non-trivial heterogeneity between users and non-users in terms of credit constraint status, but also control variables. While only 17% of non-users reported to face quantity rationing this share increases to 60% if a broader

% Share (incidence)	No demand	Accessed	Unsatisfied	Rejected	Certainly rejected	Transaction costs rationed	Risk rationed
Period							
2012	17.9	21.7	2.7	4.6	7.6	11.4	34.1
2014	23.9	23.7	3.1	4.0	8.8	8.1	28.4
2016	28.0	22.9	1.3	3.4	8.8	5.6	29.9
Average	23.3	22.8	2.4	4.0	8.4	8.4	30.8
Region:2012–16							
Tigray	26.7	32.1	2.5	5.1	3.4	1.5	28.8
Amhara	25.1	29.6	2.4	2.5	6.4	2.1	31.8
Oromia	24.0	22.4	2.7	3.6	10.2	8.0	29.3
SNNP	22.8	18.5	2.9	5.0	8.7	4.0	38.0
RegionO	21.2	17.3	1.3	4.1	11.0	22.7	22.5

Source(s): Own computations based on ESS dataset
RegionO-stands for a group of smaller regional states of Ethiopia: Afar, Benishangul Gumuz, Gambella, Harari and Somali regional states plus Diredawa

Table 1.
Sample household's credit market participation decisions and outcomes

Inorganic fertilizer status Variables	(1) N	(2) Mean	(3) Non-users Sd	(4) min	(5) Max	(6) N	(7) Mean	(8) Users Sd	(9) min	(10) Max
Inorganic fertilizer rate						3,822	4.900	1.762	−3.9	11.0
Credit constraint_q	3,901	0.171	0.377	0	1	3,842	0.122	0.327	0	1
Credit constraint_qrtc	3,901	0.599	0.490	0	1	3,842	0.461	0.499	0	1
Household member	3,901	5.671	2.470	1	16	3,842	6.140	2.270	1	17
Land right	3,901	0.351	0.477	0	1	3,842	0.634	0.482	0	1
Improved seeds	3,901	0.053	0.224	0	1	3,842	0.330	0.470	0	1
Extension reach	3,901	0.094	0.291	0	1	3,842	0.735	0.441	0	1
Adult equivalent	3,901	4.077	1.893	0.7	13.1	3,842	4.480	1.749	0.7	12.6
Female	3,901	0.231	0.422	0	1	3,842	0.174	0.379	0	1
Education	3,901	0.342	0.475	0	1	3,842	0.445	0.497	0	1
MFIs	3,901	0.264	0.441	0	1	3,842	0.262	0.440	0	1
Oxen	3,901	0.689	1.074	0	12	3,842	1.246	1.216	0	11
Roof	3,901	0.384	0.486	0	1	3,842	0.538	0.499	0	1
Non-farm	3,901	0.311	0.463	0	1	3,842	0.281	0.449	0	1
Banks	3,901	0.042	0.201	0	1	3,842	0.029	0.167	0	1
Distance banks	3,901	29.57	30.09	0	246	3,842	21.72	23.13	0	246
Banks*distance banks	3,901	0.004	0.120	0	5	3,842	0.012	0.230	0	5
Livestock, per adult	3,901	0.592	0.914	0	24.8	3,842	0.660	1.337	0	73.0
Woreda	3,901	0.096	0.295	0	1	3,842	0.070	0.254	0	1
Distance woreda	3,901	22.05	25.13	0	264	3,842	19.49	21.98	0	264
Woreda*distance woreda	3,901	0.764	6.671	0	120	3,842	0.365	2.949	0	36
Area planted	3,901	0.573	0.542	0	3.0	3,842	0.894	0.603	0	3.0
Livestock	3,901	1.193	0.926	0	4.9	3,842	1.467	0.780	0	6.8
Labor time	3,901	4.602	1.161	0	9.7	3,842	5.361	0.904	1.4	9.9
Age	3,901	3.786	0.337	2.6	4.6	3,842	3.785	0.309	2.8	4.6
Non-farm*Tigray	3,901	0.013	0.115	0	1	3,842	0.035	0.183	0	1
Non-farm*Amhara	3,901	0.033	0.177	0	1	3,842	0.066	0.248	0	1
Tigray	3,901	0.066	0.248	0	1	3,842	0.144	0.351	0	1
Others	3,901	0.283	0.451	0	1	3,842	0.069	0.253	0	1
Amhara	3,901	0.202	0.402	0	1	3,842	0.236	0.425	0	1
Oromia	3,901	0.153	0.360	0	1	3,842	0.249	0.432	0	1
SNNP	3,901	0.296	0.457	0	1	3,842	0.303	0.460	0	1

Note(s): Only those households observed at least twice are considered in the estimation of the main equation of interest-input intensification equation. As such the users' sub-sample in this table doesn't much the number of observations in the estimation. All households represented in this table are also observed at least twice. A value of zero observed for area planted is due to very insignificant value after area is transformed to hectare and does not necessarily corresponds to zero. A zero value for labor time is likely to be due to sharecropping practiced among limited share of smallholder farmers

Table 2. Summary statistics: sample households' fertilizer adoption decisions

definition is considered. The corresponding share is only 12 and 46% among users. Average intensity of fertilizer use among users stood at 134 kg/ha. Sample data also reveals substantial variation across regions as far as fertilizer use is concerned.

Majority of non-users of fertilizer are found to be female headed households, illiterate, poorer and less endowed compared to users. Around 23 and 17% of non-users and users are female headed households respectively. Only 34% of non-users can read and write in any language while this share stood at 44.5% among users. A variable used to proxy wealth status (roof) shows that the roof of the main dwelling of 38% of non-users is predominantly made of corrugated iron sheet while this share is 54% among users. Around 63% of users have certificate of land right, but only 35% of non-users have the same documentation.

More bank branches are present in rural villages where non-users reside compared to users, but the latter are, on average, closer to available bank branches. Majority of Ethiopian farmers are smallholders; holding less than two hectares of land, but this is even lower among non-users. On average, non-users and users cultivate respectively 1.8 hectares and 2.4 hectares of land. Users have more labour (measured in labour time, but also in terms of household members) and capital inputs (oxen, livestock). Non-users have limited alternative to fertilizer such as compost if having fewer livestock corresponds to less availability of the latter. Given that they are relatively less endowed and poorer; non-users are observed to engage more in non-farm activities. Only nine percent of non-users have access to extension services compared to 73% among users, showing severe information constraint/limited managerial ability among the former. Moreover, only five percent of non-users adopted improved seeds compared to 33% among users.

It must be mentioned that the effects of both versions of credit constraint variables are considered in both the selection and main equations of fertilizer adoption decisions. The estimated coefficients can be interpreted as causal effects on adoption variables of within household changes in credit constraint status. IV probit or biprobit specification is estimated for the selection equation. Estimation results for fertilizer use decisions are reported in Table 3. Narrowly defined credit constraint is statistically insignificant in explaining fertilizer use decisions when treated as an exogenous. But it is highly significant when treated as an endogenous (column (3)). As expected, the estimated average partial effect (APE) is negative and stands at 0.213 implying that the probability of adopting inorganic fertilizer is 21.3% points lower for quantity rationed household ceteris paribus. Irrespective of its treatment in the selection equation, credit constraint defined broadly is highly significant (column (6)). However, its treatment as an endogenous dummy result in an estimated partial effect of about 32% points more (from just 0.04 to 0.36). If the estimated partial effect is to be trusted-which makes sense given that the broader definition is considered-the probability of adoption is 36% points lower for credit constrained households.

As expected, extension service and adoption decisions are positively associated. Albeit weak effect, households with larger cultivated land size are more likely to use fertilizer implying that less endowed households keep relying on traditional farming technique reinforcing rural poverty. Cultivated land size is expected to be more important in explaining variation in the intensity of fertilizer use across farmers. However, given incomplete or missing land market and the narrow range on cultivated lands, as many argue it makes no sense to treat land size as a choice variable in the Ethiopian context (Croppenstedt *et al.*, 2003) [12]. Households that use improved seeds are more likely to use fertilizer on their plots. Results for education and oxen are also in line with previous studies in the Ethiopian context. The variable we use to proxy education captures households' literacy status and may not necessarily capture actual formal educational effect that lessens information barrier. As such its effect might be diffused by interaction with some variables that proxy wealth.

The chosen instrument-land right-does not explain the dependent variable in the selection equation in both cases, and results remain robust to its inclusion in the estimations (columns (1) and (4)). However, it explains variation in credit constraint status irrespective of how one defines the latter (Table A2: columns (1) and (2)).

Estimation results for the conditional demand equation are reported in Table 4. The demand equation is estimated via pooled 2SLS tackling both sources of bias whilst controlling for time-invariant unobserved effects (column (4)). As expected, credit constraint affects the intensity of use negatively and the point estimate is −1.45 with a 95% confidence interval between −0.454 and −2.447 and it is highly significant. Accordingly, credit constraint could reduce the amount of fertilizer applied per hectare by more than 36.5% all other variables held constant. The coefficient on IMR is significant, implying that controlling for selection bias is appropriate.

Panel selection Variables	(1) APE	Probit (2) APE	(3) IV probit APE	(4) APE	Probit (5) APE	(6) IV probit APE
Credit constraint_q	−0.015	−0.017	−0.213***			
	(0.015)	(0.015)	(0.062)			
Credit constraint_qrtc				−0.039***	−0.040***	−0.363***
				(0.010)	(0.010)	(0.031)
Land right	0.003			0.003		
	(0.017)			(0.016)		
MFIs				0.017	0.018	0.013
				(0.017)	(0.017)	(0.011)
Female	0.013	0.010	−0.002	0.016	0.013	0.006
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.032)
Education	−0.023	−0.024*	−0.023	−0.024	−0.025*	−0.027*
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
Extension reach	0.294***	0.293***	0.281***	0.313***	0.312***	0.226***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.018)
Oxen				0.013*	0.013*	0.010
				(0.007)	(0.007)	(0.006)
Area planted	0.065***	0.067***	0.075***	0.063***	0.065***	0.061***
	(0.016)	(0.016)	(0.021)	(0.016)	(0.016)	(0.013)
Non-farm	0.009	0.011	0.010			
	(0.021)	(0.021)	(0.023)			
Improved seeds	0.059***	0.058***	0.061***			
	(0.021)	(0.021)	(0.020)			
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,743	7,743	7,743	7,743	7,743	7,743

Note(s): Variable selected as an instrument for potentially endogenous credit constraint_q and credit constraint_qrtc is land right. Columns (3) and (6) are estimation results that take care of the endogeneity of credit constraint in the selection equation. Standard errors adjusted for clustering at enumeration areas are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 3. Probit and IV probit results for the effect of credit constraint on inorganic fertilizer use decision

While it does not explain fertilizer adoption decisions, non-farm activities strongly affects fertilizer intensification decisions. This association can be explained by the role of family labour time in the intensification decisions and by immaterial return from non-farm activities in most rural settings. Farm households usually opt for non-farm activities to smooth consumption particularly during the lean seasons (which coincides with main planting season in agriculture), but only at the costs of family labour time used to operate on farm. As such, there is little cash to generate from these activities to use for the purchase of agricultural inputs. This is in line with findings in similar studies, for example, Croppenstedt *et al.* (2003) who find quite strong effect of family labour availability on fertilizer adoption and intensification decisions. Substantial heterogeneity in fertilizer intensification decision is driven by cultivated land area. The result suggests that farmer's intensity of fertilizer use negatively responds to additional hectare of cultivated land. Evidence on the association between the intensity of use and farm size remained largely inconclusive in earlier literature (Feder *et al.*, 1985). While many studies indicate lack of significant association, some others find positive or negative link between the two. However, this result is consistent with the one reported by Croppenstedt *et al.* (2003) and Zerfu and Larson (2010) in the Ethiopian context. Zerfu and Larson (2010) rule in the possibility of smaller holding farmers invest greater time and effort into their limited holdings. But, if this was the case, we presume that we would have seen positive association between non-farm activities (mostly practiced by smaller holding farmers) and intensity of use.

Panel selection Variables	(1) Simple OLS Coefficient	(2) Pooled OLS Coefficient	(3) Coefficient	(4) Pooled 2SLS Coefficient
Credit constraint_qrtc	−0.231***	−0.217***	−0.225***	−1.450***
	(0.044)	(0.044)	(0.044)	(0.508)
IMR				−0.177**
				(0.071)
Banks		0.434**		
		(0.195)		
Distance banks		0.004***		
		(0.001)		
Banks*distance banks		0.062		
		(0.051)		
Non-farm	−0.083	−0.238**	−0.254***	−0.235**
	(0.057)	(0.097)	(0.098)	(0.119)
Oxen	0.195***	0.0183	0.021	−0.012
	(0.028)	(0.037)	(0.037)	(0.043)
Female	0.102	0.072	0.058	−0.009
	(0.064)	(0.174)	(0.176)	(0.202)
Education	−0.038	0.075	0.078	0.133
	(0.051)	(0.076)	(0.076)	(0.096)
Roof	0.174***	0.189*	0.189*	0.174
	(0.050)	(0.108)	(0.108)	(0.120)
Livestock	−0.010	0.125**	0.123**	0.083
	(0.036)	(0.056)	(0.056)	(0.059)
Area planted	−0.699**	−0.872***	−0.865***	−0.802***
	(0.060)	(0.077)	(0.077)	(0.093)
Labor time	0.161***	0.207***	0.211***	0.233***
	(0.031)	(0.042)	(0.042)	(0.048)
Constant	4.281***	4.653***	4.590***	5.028***
	(0.323)	(0.371)	(0.367)	(0.427)
Household FE	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,342	3,342	3,342	3,342
R-squared	0.482	0.492	0.490	0.369

Note(s): That time averages of interaction terms are not included in the estimation. Variables selected as instruments for the potentially endogenous credit constraint_qrtc are: Banks, Distance banks and Banks*distance banks. IMR interacted with time dummies are also included in the estimation under column (3). Standard errors adjusted for clustering at household level are in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Other variables included in the estimation, but not reported here are age and household member

Table 4.
Instrumental variable estimation results for the effect of credit constraint on intensity of inorganic fertilizer use

A study by Nkonya *et al.* (1997) attach greater weight to risk associated with fertilizer adoption in explaining the inverse relationship between land size and intensity of use observed in Tanzania. Farmers with larger holding may hedge risks by applying on portion of their land. In any case, as we tried to elaborate earlier, current land distribution among smallholder farmers and incomplete land market ought to be borne while interpreting this finding. Livestock is used to proxy for availability of organic fertilizer. While livestock explains intensification decisions positively it is not significant in the empirical specification of main interest. The positive association between the two is in line with finding in Zerfu and Larson (2010). Effectiveness with chemical fertilizer critically depends on the organic content of the soil. Traditionally farmers in Africa use manure to build depleted soil contents. However, it could be the case that its effect diffused by interaction with other variables such oxen, roof and education as all may capture wealth effects as well. Due to that, we do not assert that estimated coefficients on control variables correspond to causal effects on adoption and intensification decisions.

We used presence of formal lenders in the village and community's distance to the nearest formal lenders (or their branches) as external instruments in the conditional demand equation. Both MFIs and commercial banks were considered, but the performance of the former in explaining potentially endogenous variable and in satisfying the exclusion restriction is poor. This is in part due to non-trivial missing information on community's distance from MFIs variable for which we also tried to impute from similar information. Both the presence of commercial bank branches in the village and community's distance to the nearest branch explain variation in the intensity of fertilizer use (Table 4: column (1)). Nevertheless, the interaction between the two does not. Estimation results in Table A2, columns (3) and (4) on the other hand show that the former explains variation in credit constraint status only in the sub-sample of fertilizer users. Distance to the nearest branch does not explain variation in credit constraint in both full and sub-samples. In contrast, the interaction between the two explains variation in credit constraint in both full and sub-samples and statistically significant.

In fact, there is not much information to lose by not using the presence of MFIs in a village and community's distance from the nearest MFIs branches. Most prominent MFIs are concentrated in major urban areas (district towns) just like banks. Given that only limited share of farm households have access to bank credit and bank branches are predominantly concentrated in urban areas, one must be curious if this instrument capture only remoteness and not necessarily the extent of credit constraint [13]. It could be the case that these variables capture factors other than credit constraint which influence intensification decisions thus violating the exclusion restriction. By controlling for selection bias and unobserved time-invariant household effects our estimation must curtail factors which may contaminate the exclusion restriction requirements. In addition, we used alternative instrumental variables to assess the robustness of our results.

5.1 Robustness check

In this sub-section, we provide further results and robustness checks of our baseline estimates reported so far in this section. Probit specification is used to test the robustness of our baseline specification for the selection equation – IV probit. Results reported in Table 3 show that the estimates are consistent albeit the magnitudes of the coefficients being different. To be more precise, when matching results reported in Table 3 columns (2) and (3), the coefficient on narrowly defined credit constraint is larger and statistically significant under the baseline specification. The same holds true for the coefficient on broadly defined credit constraint (Table 3, columns (5) & (6)) with the exception that it remains significant irrespective of the specification. Measurement errors are common in the survey data. Therefore, it is possible that large differences in the coefficient estimates and hence in APEs for both measures of credit constraint variables reveal significant attenuation bias towards zero in the probit estimation. In addition, irrespective of how one defines credit constraint status, estimates remain robust to the inclusion of the instrument in the probit specification.

As regard to the conditional demand equation, we test the sensitivity of panel selection estimates obtained using fixed-effect two-stage least square estimator approach across different estimation methods. In one case, the conditional demand equation is estimated using simple OLS ignoring the endogeneity of credit constraint status, selection bias and time-invariant unobserved effects. In addition, pooled fixed effect is estimated ignoring any potential bias due to self-selection and endogeneity of credit constraint status. Results reported in Table 4 reveal that the estimates are consistent across the estimation methods considered including the baseline specification. However, the coefficient of the credit constraint – irrespective of its definition – is underestimated for the simple OLS and pooled fixed effect (columns (1) and (3)), signifying sizable bias including attenuation bias towards zero, which also provides a justification for the use of pooled 2SLS. Again, estimates remain robust to the inclusion of the instruments used in the pooled OLS specification.

We also used variables that capture remoteness-if the community is in a woreda (district) town and community's distance from the nearest woreda town, including interaction between the two-as alternative instruments in the conditional demand equation. Estimation results for the conditional demand equation with alternative instruments are reported in Table 5. Only the former explains variation in credit constraint status in the sub-sample and neither the latter nor the interaction between the two explains variation in credit constraint in both the sub-sample and full sample probit estimations (columns (1) and (2)). Yet, the former also explains variation in the dependent variable in the conditional demand equation (column (3)). The estimation of conditional demand equation via pooled 2SLS using these instruments leads to overestimated point estimate on credit constraint, insignificant IMR and close to zero R^2, among others.

We also attempted to establish a link between narrowly defined credit constraint and intensity of use using total livestock per adult equivalent household as an external instrument. This instrument satisfies all criteria to be a candidate except that it is likely to be

	(1)	(2)	(3)	(4)	(5)
Panel selection	Probit		Pooled OLS		Pooled 2SLS
Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Credit constraint_qrtc			−0.215***	−0.223***	−2.472**
			(0.044)	(0.044)	(0.993)
IMR					−0.138
					(0.088)
Woreda	−0.383**	−0.196*	0.663***		
	(0.184)	(0.116)	(0.185)		
Distance woreda	0.002	−0.0006	−0.00004		
	(0.002)	(0.001)	(0.001)		
Woreda*distance woreda	−0.014*	0.006	−0.005		
	(0.007)	(0.006)	(0.010)		
Area planted	0.131	0.027	−0.866***	−0.865***	−0.752***
	(0.102)	(0.070)	(0.077)	(0.077)	(0.121)
Labor time	0.042	0.024	0.213***	0.211***	0.249***
	(0.047)	(0.029)	(0.042)	(0.042)	(0.059)
Constant			4.593***	4.590***	5.401***
			(0.370)	(0.367)	(0.583)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Regional FE	Yes	Yes	No	No	No
Observations	3,342	7,743	3,342	3,342	3,342
R-squared			0.493	0.490	0.075

Note(s): Columns (1) and (2) depict a fitted probability from a Probit regression of potentially endogenous variable (credit constraint_qrtc) on the selected instruments (Woreda, Distance woreda and Woreda*distance woreda) respectively in the sub-sample and full sample. Time averages of interaction terms are not included in the estimations. IMR interacted with time dummies are also included in the estimation under column (5). Standard errors adjusted for clustering at various level are in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Other control variables included in the estimation, but are not reported here: Non-farm, Oxen, Female, Education, Roof, Livestock, Household member, Age

Table 5.
Instrumental variable results for the effect of credit constraint on intensity of inorganic fertilizer use: with alternative instruments

weak. It is also one of the instrumental variables frequently used in the literature on credit constraint in low income settings. Relatively wealthier households are expected to face less binding quantity rationing compared to their poorer counterparts. Either they have sufficient own resources or face less difficulty due to collateral in case they wish to borrow. This instrument explains variation in credit constraint in both sub-sample and full sample probit estimation taking households' quantity rationing status as a dependent variable (Table 6: columns (1) & (2)). On the other hand, the instrument does not explain variation in the dependent variable in the demand equation and estimation results from pooled OLS remains robust to its inclusion in or exclusion from the estimation (Table 6: columns (3) & (4)). Estimation results from pooled 2SLS using this instrument signify that the selected instrument is potentially weak – the sign on the credit constraint coefficient is as expected, but it is not significant (inflated standard error) with significant IMR. However, estimation results reported in Table 6 indicate that failure to consider a broader definition may lead to underestimation of the true effects of credit constraint on farm households' livelihood strategies, fertilizer intensification decisions in particular.

6. Concluding remarks

In this paper, we used recently available ESS dataset to investigate the effects of credit constraint on farm household's investment decisions in a risky, but potentially productivity enhancing technology. On average, about 54% of farm households visited during the surveys reported to face credit rationing predominantly demand-side, which many previous studies overlooked. State-of-the-art estimation strategy - fixed-effect two-stage least square estimator

	(1)	(2)	(3)	(4)	(5)
	Probit		Pooled OLS		Pooled 2SLS
Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Credit constraint_q			−0.172***	−0.172***	−0.266
			(0.067)	(0.067)	(3.949)
IMR					−0.250***
					(0.085)
Livestock, per adult	−0.101**	−0.251**	0.0006		
	(0.045)	(0.100)	(0.014)		
Area planted	0.015	−0.032	−0.852***	−0.852***	−0.852***
	(0.079)	(0.126)	(0.075)	(0.075)	(0.082)
Labor time	−0.021	−0.106*	0.213***	0.213***	0.214**
	(0.036)	(0.059)	(0.043)	(0.043)	(0.099)
Constant			4.542***	4.542***	4.582***
			(0.368)	(0.368)	(1.008)
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	7,743	3,342	3,342	3,342	3,342
R-squared			0.486	0.486	0.488

Note(s): Columns (1) and (2) respectively depicts a fitted probability from a probit regression of potentially endogenous variable (credit constraint_q) on the selected instrument (livestock per adult) in the full and sub-samples. Time averages of interaction terms are not included in the estimation. IMR interacted with time dummies are also included in the estimation under column (5). Standard errors adjusted for clustering at household level is in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Other control variables included in the estimation, but are not reported here: Non-farm, Oxen, Female, Education, Roof, Age and Interaction term between IMR and time dummies (only in the estimation under column (5))

Table 6. Instrumental Variable results for the effect of credit constraints on intensity of inorganic fertilizer use: with alternative measure of credit constraint and instrument

approach-is employed to obtain more reliable results. This estimation strategy tackles major empirical challenges one may encounter in this area of inquiries: complementarity effects in input adoption decisions of the selection model; selection bias and endogeneity and/or reverse causality in input intensification decisions of the conditional demand model. Measurement error is another potential source of bias in survey data analysis leading to considerable attenuation bias towards zero for some estimators.

Consistent with theoretical arguments and many existing empirical findings, results in this study suggest that credit constraint can deter adoption and optimal use of farm technology, contributing to poverty perpetuation. We find stronger effect when the uninsured risk that implicitly lies between adoption and credit use decisions is accounted for. Estimation results are consistent across several alternative estimators: simple Probit vs. IV Probit for the selection model; simple pooled OLS (comparing across constrained and unconstrained households) vs. Pooled FE (that ignores selection bias and endogeneity) vs. pooled FE-IV (that tackles all potential sources of bias) in the conditional demand model. The effect is stronger when within household variation in credit constraint status overtime is considered as opposed to across constrained and unconstrained households. One possible explanation for this is that market failure is household specific in the sense that they selectively fail for a particular household. For coefficients of main interest in this study, it is not easy to make direct comparison with findings in existing literature mainly due to different credit and adoption variables used in empirical exercises. However, the finding that credit constraints may limit the adoption of chemical fertilizers in Ethiopia is largely in line with existing studies (for instance, Croppenstedt *et al.*, 2003; Zerfu and Larson, 2010; Abate *et al.*, 2016). While it is largely consistent with findings in existing empirical literature we do not claim that coefficient estimates on control variables represent casual effects.

Results in this paper highlight that policy discussions that ignore the demand-side credit rationing is likely to underestimate the true detrimental effects of credit constraint on farm household's livelihood strategies, particularly technology adoptions. More importantly, expanding physical access to institutional credit alone may not necessarily spur increased uptake of credit and instant investment by farm households. For a majority of rural poor to take advantage of available credit and improved technology, interventions should also aim at minimizing downside risks, which is more rampant than emphasized in existing literature.

Notes

1. The government considers microcredit as a key policy instrument in combating poverty, especially among the poorer, but productive farm households (Amha, 2003, 2011).
2. The government sets (and subsidizes) fertilizer prices, but does not consider it a formal subsidy programme (Rashid *et al.*, 2013)
3. We use credit constraint and credit rationing jargons interchangeably
4. Assefa (1987, 2004) provides historical overview and documents that ensuring adequate and timely flow of institutional credit to rural areas, particularly which tailored to the need of small and marginal farmers remained largely a challenge in Ethiopia.
5. As an alternative, IMR is generated by estimating the selection equation for each wave (period) separately (including both users and non-users). The sub-sample used in the estimation of the main equation is regenerated from a pooled sample. Results remain almost the same.
6. Standard errors adjusted for clustering at enumeration area is also considered given that the instrument used varies only among clusters and not within household in the same cluster. However, the effect on results is negligible.
7. The first round of this program took place in the last decade and covered some 20 million plots over five years. One of the core objectives of this program was to strength women's land holding rights

and to boost land related investments. There is some evidence of positive impacts of this land reform in terms of increased investment, land productivity and land rental market activities (Deininger *et al.*, 2008).

8. The 2018/19 ESS is not a follow-up of the previous ESS waves.
9. The first round was designed in such a way that it represents rural and small-town areas of Ethiopia. Thus, it excludes samples from major urban areas.
10. Attrition in major urban areas was 15% due to consent refusal and inability to trace the whereabouts of sample respondents during the third wave.
11. Albeit from a low base and at a decreasing rate, there is a growing share of households using fertilizer: about 46%, 50 and 52% respectively in 2012, 2014 and 2016.
12. Most households own land size less than two hectares and land is state owned in Ethiopia and farmers enjoy only usufruct right. Dercon (2001) documents that land buying and selling as well as rent in and rent out is hardly practiced, making cultivated land and land owned remain closely correlated. He estimates that the correlation between household land holdings suitable for cultivation and actual land size cultivated per household (after transactions) is 0.92.
13. Survey data shows that, on average, credit provided by the MFIs and banks respectively account for only 29.6 and 0.4% of the total credit supplied (including semi-formal and informal sources) during the years included in the sample.

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Appendix

Variables	Variable definitions
Inorganic fertilizer use	1 if the household uses any inorganic fertilizer
Inorganic fertilizer rate	Rate of fertilizer application (kgs/ha, winsorized top 1%, in logs)
Improved seeds	1 if the household uses improved seeds
Extension reach	1 if the household is reached by extension services
Credit constraint_q	1 if constrained (quantity rationing)
Credit constraint_qrtc	1 if constrained (quantity rationing, transaction costs rationing and risk rationing)
Female	1 if female headed household
Household member	Household size
Adult equivalent	Household size in adult equivalent scale
Education	1 if the household head can read and write in any language
Age	household head age (in logs)
Labour time	Total labour days at the planting stage (family plus hired) in logs
Area planted	Total area planted (winsorized top and bottom 1%, in arcinh transformation)
Livestock	Total household livestock holdings (in TLU, in arcinh transformation)
Livestock, per adult	Livestock holding per adult equivalent scale
Oxen	Number of oxen owned by the household in the main season
Roof	1 if the roof of the main dwelling is predominantly made of corrugated iron sheet
Non-farm	1 if anyone in the household owned non-farm enterprise, 12 months prior to the survey
Land right	1 if the household has legal documentation of land right (at least one plot)
Microfinance	1 if there is microfinance institutions in the community (at cluster level)
Banks	1 if there is commercial bank in the community(at cluster level)
Distance banks	Distance to the nearest commercial bank (in km) at community level
Banks*distance banks	An interaction term between banks and distance to banks
Woreda	1 if the community is in the woreda(district) town
Distance woreda	Distance to the nearest woreda (district) town (in km) at community level
Woreda*distance woreda	An interaction term between woreda and distance to woreda
Tigray	1 if the household resides in Tigray regional state
Amhara	1 if the household resides in Amhara regional state
Oromia	1 if the household resides in Oromia regional state
SNNP	1 if the household resides in SNNP regional state
Others	1 if the household resides in the rest regional states
Non-farm*Tigray	Interaction term between non-farm enterprises and Tigray regional state
Non-farm*Amhara	Interaction term between non-farm enterprises and Amhara regional state

Source(s): Arcinh-inverse hyperbolic sine transformation (Bellemare and Wichman, 2020); TLU- tropical livestock unit

Table A1.
Variable definitions

Variables	(1) Selection model Coefficient	(2) Coefficient	(3) Intensification model Coefficient	(4) Coefficient
Land right	−0.150**	−0.141**		
	(0.076)	(0.068)		
Banks			−0.494***	−0.214
			(0.177)	(0.205)
Distance banks			0.0002	0.0004
			(0.002)	(0.001)
Banks*distance banks			−0.480***	−0.261***
			(0.099)	(0.029)
Household FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Pseudo R^2	0.018	0.021	0.026	0.021
Observations	7,743	7,743	3,342	7,743

Note(s): Columns (1) and (2) respectively depict fitted probability from a probit regression of credit constraint_q and credit constraint_qrtc. Similarly, columns (3) and (4) respectively depict a fitted probability from a probit regression of credit constraint_qrtc in the sub-sample and full sample. Time averages of interaction terms are not included in the estimation. Standard errors adjusted for clustering at enumeration area level are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Other control variables included in the estimation, but not reported here are: Non-farm, Oxen, Female, Education, Roof, Livestock, Area planted, Labour time, Household member, Age, Extension reach, Improved seeds, MFIs, Non-farm* Tigray, Non-farm *Amhara

Table A2. Fitted probability from a probit regression of endogenous variables on instruments

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