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Full Length Research Paper

Agricultural technology adoption, seed access constraints and commercialization in Ethiopia

Solomon Asfaw[1]*, Bekele Shiferaw[2], Franklin Simtowe[3] and Messia Hagos[4]

[1]Food and Agricultural Organization of the United Nations, Agricultural Development Economics Division (ESA), Viale delle Terme di Caracalla, 00153 Rome, Italy.
[2]International Maize and Wheat Improvement Centre (CIMMYT), UN Avenue, Gigiri P. O. Box, 30677-00100 Nairobi, Kenya.
[3]International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), UN Avenue, Gigiri, P. O. Box 39063-00623, Nairobi, Kenya.
[4]Ethiopian Economics Association (EEA), P. O. Box 34282, Addis Ababa, Ethiopia.

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This article examines the driving forces behind farmers' decisions to adopt agricultural technologies and the causal impact of adoption on farmers' integration into output market using data obtained from a random cross-section sample of 700 farmers in Ethiopia. We estimate a Double-Hurdle model to analyze the determinants of the intensity of technology adoption conditional on overcoming seed access constraints. We estimate the impact of technology adoption on farmers' integration into output market by utilizing treatment effect model, regression based on propensity score as well as matching techniques to account for heterogeneity in the adoption decision, and for unobservable characteristics of farmers and their farm. Results show that knowledge of existing varieties, perception about the attributes of improved varieties, household wealth (livestock and land) and availability of active labor force are major determinants for adoption of improved technologies. Our results suggest that the adoption of improved agricultural technologies has a significant positive impact on farmers' integration into output market and the findings are consistent across the three models suggesting the robustness of the results. This confirms the potential direct role of technology adoption on market participation among rural households, as higher productivity from improved technology translates into higher output market integration.

Key words: Commercialization, chickpea, double-hurdle model, improved varieties, grain legumes, technology adoption, treatment effect model, Ethiopia.

INTRODUCTION

Agricultural research and technological improvements are crucial to increase agricultural productivity to meet demand for food and thereby reduce poverty. However, in today's more integrated world economy, success in productivity-based agricultural growth crucially depends on market opportunities. Improving the competitiveness of developing countries agricultural products in international, regional, and domestic markets is the key to expanding market opportunities (WDR, 2008). In recent years, governments of developing countries have sought to promote the diversification of production and exports away from the traditional commodities in order to accelerate economic growth, expand employment opportunities, and reduce rural poverty. In a country like Ethiopia, grain legumes production presents an opportunity in reversing the negative trends in productivity, poverty and food insecurity. First, this is because legumes have the capacity to fix atmospheric nitrogen in soils and thus facilitates soil fertility and save fertilizer costs in subsequent crops. Secondly, it improves more intensive and productive use of land, particularly in areas

*Corresponding author. E-mail: Solomon.Asfaw@fao.org. Tel: +390657055504.

where land is scarce and the crop can be grown as a second crop using residual moisture. Thirdly, it reduces malnutrition and improves human health, especially for the poor who cannot afford livestock products. Fourth, the growing demand in domestic and export markets provides a source of cash for smallholders.

Despite the crucial role of cereal legumes like chickpea, pigeonpea and groundnuts for poverty reduction and food security, lack of technological improvement and market imperfections have often locked small producers into subsistence production and contributed to stagnation of the sector (Shiferaw and Teklewold, 2007). Often, the traditional varieties dominate the local and export markets; but low productivity of these varieties limits the farmers' competitiveness in these markets. The structure and functioning of marketing system is often constrained by factors including small quantity of supplies, lack of grading and quality control systems, lack of well-coordinated supply chain, lack of efficient market information delivery mechanisms, underdeveloped infra-structure and high transaction costs (Shiferaw and Teklewold, 2007). As a result, integration of smallholder farmers into output markets in the area is limited. The cumulative effect of these factors is low adoption of improved technologies, low competitiveness and inability to penetrate high-value markets that offer premiums for quality. In the last few years, research and development interventions have attempted to understand these constraints and facilitated the development of new technologies and market linkages for small producers. The opportunities for market development and comer-cialization are particularly favorable for legume crops which tend to have higher domestic, regional and international demand. To harness the untapped potential of legumes for the poor, International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in collaboration with the Ethiopian Institute of Agricultural Research (EIAR) has developed several high-yielding and stress tolerant varieties of chickpea with desirable agronomic and market traits. A total of eleven improved chickpea varieties had been released as a result of this research program.

However, the adoption rate of these varieties is very low. Official estimates from the Central Statistics Authority (CSA) show that, of the total chickpea cultivated area (194,981 ha) only 0.69% was covered by improved seeds in 2001/02 (Dadi et al., 2005). It has long been recognized that the continuous use of traditional, low yielding crop varieties is a major cause of low crop productivity, but correctly identifying the factors that prevent smallholder farmers from adopting improved, high yielding crop varieties remains a challenge. Besides, knowledge is still lacking about the actual on-farm performance of the introduced varieties across a large span of environments. Therefore, it is imperative to examine and identify the extent to which farmers have adopted improved chickpea technologies under market imperfection and information asymmetry. The findings have implications for designing appropriate development oriented policy. Moreover, there is lack of empirical evidence, especially for legumes in Africa, on the linkage between technology adoption, productivity gain and market participation (Balagtas et al., 2007; Bellemare and Barrett, 2006; Bernard et al., 2008; Edmeades, 2006; Gebremedhin et al., 2009).

Thus, using farm-level data collected from a random cross-section sample of 700 small-scale producers in Ethiopia, this paper deals with the following objectives:

(a) To assess the role of market institutions, infrastructure and household assets in determining adoption of improved chickpea technology among small farmers;
(b) To identify determinants of market participation for chickpea; and
(c) To assess the impact of improved chickpea technology adoption on integration of smallholders into rural output markets.

Agricultural commercialization can be conceptualized as the process by which farm households are increasingly integrated into different markets such as input markets, food and non-food consumption markets, output markets and labor markets. The analytical portion of this article however, primarily focuses on the integration of farmers into output markets, because this is the typical indicator for the process of agricultural commercialization (Wooldridge, 2005).

SURVEY DESIGN AND DATA

The data used for this paper originates from a survey conducted by the International Crop Research Institute for Semi-Arid Tropics (ICRISAT) and Ethiopian Institute of Agricultural Research (EIAR) in 2008. The primary survey was done in two stages. First, a reconnaissance survey was conducted by a team of scientists to have an understanding of the production and marketing conditions in the survey areas. During this exploratory survey, discussions were held with different stakeholders including farmers, traders and extension staff working directly with farmers. Second, the findings from the first stage were used to refine the study objectives, sampling methods and the survey instrument. A formal survey instrument was prepared and trained enumerators collected the information from the households via personal interviews. A multi-stage sampling procedure was used to select districts, *kebeles* and farm households. *Kebeles* refers to peasant associations (rural communities) which represent the lowest administrative unit in the country. In the first stage, three districts namely Minjar-Shenkora, Gimbichu and Lume-Ejere were purposively selected from the major legume producing area based on the intensity of chickpea production, agro-ecology and accessibility. These districts represent one of the major chickpea growing areas in the country where improved varieties are beginning to be adopted by farmers. The districts are in the Shewa region in the central highlands of the country and are located north east of Debre Zeit which is 50 km south east of the capital, Addis Ababa. Debre Zeit Agricultural Research Centre (DZARC) is also located in the area and is a big asset to the districts in terms of information on quality seed,agronomic practices, marketing, storage, introducing new crop varieties and other relevant information.

Chickpea production in Gimbichu and Lume-Ejere districts ranges from 12,500 to 15,000 ha whereas chickpea production in Minjar-Shenkora ranges from 15,000 to 17,500 ha per year. The crop is grown during the post-rainy season on black soils using residual moisture. A random sample of 8 to 10 *kebeles* growing chickpea were selected from each district for the survey. This was followed by random sampling of 150 to 300 farm households from each district. A slightly higher sample was taken from Lume-Ejere district mainly because of large number of households growing chickpea in this district. The survey collected valuable information on several factors including household composition and characteristics, land and non-land farm assets, livestock ownership, household membership in different rural institutions, crop varietal choice and area planted, costs of production, yield data for different crop types, indicators of access to infrastructure, household market participation, household income sources and major consumption expenses. The economic traits and preference for different improved chickpea cultivars and reasons for adoption and dis-adoptions of new varieties were also included in the data collected.

Methods

Constrained technology adoption - the Double-Hurdle (DH) model

Unlike the typical binary dependent variable models applied for studying the dichotomous issue of the probability of adopting a new technology or not, our objective goes beyond that and helps in understanding the intensity of adoption. We applied the Double-Hurdle (DH) model for this purpose. Conventionally, the Tobit model has been popular for the two stage analysis. In the Tobit model, decisions whether or not to adopt and how much to adopt are assumed to be made jointly and hence the factors affecting the two level decisions are taken to be the same. However, the decision to adopt may well precede the decision about the intensity of use and hence the explaining variables in the two stages may differ. In the DH model, the parameters in the second stage can freely vary from those in the first stage. The two-stage questions in a typical DH model are:

i) Do you want to adopt improved chickpea varieties?; and
ii) If yes, do you face constraints in accessing improved seed, land, credit, labor and other resources needed to adopt the new varieties?

The intensity of adoption is therefore modeled conditional on these constraints. The Tobit model, however, assumes a zero amount of adoption of improved chickpea variety as a lack of positive demand for new technology. However, the DH model separates the sampled households into three distinct groups. At first stage, farmers need to develop a positive desired demand for improved varieties based on their evaluation of benefits from comparing traditional and new cultivars. Access to information is critical in facilitating this process. However, actual adoption and planting of improved varieties will depend on the availability of improved seeds and the ability of the farmers to access this input. Access to improved seed was the key constraint that farmers with positive desired demand had to overcome. This is mainly due to imperfections in local seed markets and lack of availability of seed of improved varieties in the desired quality and time.

In this study, we have information whether the smallholder farmers face seed access constrain or not. Using this information, the DH model can capture the demand for improved chickpea varieties better than the Tobit model specification (Blundell and Meghir, 1987; Croppenstedt et al., 2003). A similar model has been used by other studies to estimate technology adoption, when there are farmers with constrained positive demand to adopt the new technology (Shiferaw et al., 2008; Coady, 2003; Croppenstedt et al., 2003). Assume that the latent desired demand for improved variety of chickpea D^* for any farmer *i* is given by:

$$D_i^* = \beta X_i + u_i \tag{1}$$

where the vector X includes variables that determine the demand function (e.g., wealth related variables, information, perception of improved seeds, household and location specific variables etc.), β is a vector of parameters to be estimated, and *u* is a random variable with mean 0 and variance σ_u^2.

The model for the individual farmer's access to the improved seed can be given by:

$$A_i^* = \alpha Z_i + e_i \tag{2}$$

where A^* is the latent variable underlying the i^{th} farmer access to improved seed, α is the parameter vector, Z is a vector of variables that determine access, and *e* is a random normal variable with mean 0 and variance 1.The interaction of Equations (1) and (2), imply the observed model of improved seed demand, which is a composite model of three sub-sample groups. The three groups include:

i) Farmers in group 1 (G1) have positive desired demand and access to improved seed $(i.e.\ D_i^* > 0 \text{ and } A_i^* > 0)$ and hence they actually adopt the new technology;
ii) Farmers in group 2 (G2) do not want the improved variety regardless of their access to the improved seed $(i.e.\ D_i^* < 0 \text{ and } A_i^* > 0 \text{ or } A_i^* < 0)$; and
iii) Farmers in group 3 (G3) have positive desired demand, because they do not have access to the improved seed and hence they do not adopt the new technology $(i.e.\ D_i^* > 0\ and\ A_i^* < 0)$.

Assuming the demand and access equations are mutually exclusive, we can express the observed improved seed demand model as:

$$\begin{aligned} D_i &= \beta X_i + u_i \, for\ (farmers\ \ in\ group\ 1) \\ D_i &= 0\ for\ (farmers\ \ in\ group\ 2) \\ D_i &= 0\ for\ (farmers\ \ in\ group\ 3) \end{aligned} \tag{3}$$

The aforestated equation tells us that two thresholds should be passed in order to observe a positive level of improved seed use. These are the participation threshold, that is the farmer has the desire to plant the improved seed, and the access threshold, that is the farmer has access to the improved seed. The assumption that the participation and access thresholds are independent is supported by numerous studies (Jones, 1992; Kimhi, 1999; Moffatt, 2005) and hence we also assume their independence. The log-likelihood function for the observed demand can thus be written as:

$$\ln(L) = \sum_{G1=1} \{\ln[\Phi(\alpha' Z_i / \sigma_u] + \ln \phi[(D_i - \beta_i X)(1/\sigma_u)]\} + \sum_{G2=1} \ln[1 - \Phi(\beta' X / \sigma_u)] + \sum_{G3=1} \ln[\Phi(\beta' X_i / \sigma_u)(1 - \Phi(\alpha' Z_i)] \tag{4}$$

where ϕ and Φ, respectively, are the probability density function (*pdf*) and the cumulative distribution function (*cdf*) of the standard normally distributed random variable.

Farmers' integration into markets - treatment effect and propensity score methods

Estimation of the causal impact of technology adoption on farmers' integration into output market (marketed surplus) based on non-experimental observations is not trivial because of the difficulties in finding a counterfactual. What we cannot observe is the marketed surplus for adopters of improved chickpea varieties in case they did not adopt. That is, we do not observe the marketed surplus of households that adopt improved technologies had they not adopted (or the converse). In experimental studies, this problem is addressed by randomly assigning improved seeds to treatment and control groups, which assures that the marketed surplus observed on the control households and that adopt improved chickpea are statistically representative of what would have occurred without adoption. However, improved chickpea seeds are not randomly distributed to the two groups of the households (adopters and non-adopters), but rather the households themselves decide to adopt or not to adopt based on the information and preference they have. Therefore, adopters and non-adopters may be systematically different; this difference may manifest itself in terms of differences in access to market, infrastructure, access to institutions and asset endowments and characteristics.

Thus, it is difficult to perform ex-post assessment of gains from adoption using observational data, because of possible selection bias due to observed and unobserved household characteristics. Failure to account for this potential selection bias could lead to inconsistent estimates of the impact of adoption. In other words, this bias occur when there are unobservable characteristics that affect both the probability of adoption and outcome variable that is farmers' integration into output market. Following other studies, different econometric techniques are applied to correct for potential selection bias in estimating the impact of technology adoption on farmers' integration into output market (Angrist, 2001; Fernandez-Cornejo et al., 2005; Greene, 1997; Rosenbaum and Rubin, 1983). Formally, given the unobserved variable and its observed counterpart, the treatment-effect equation can be expressed as:

$$G_i^* = \theta + \beta Y_i + u_i \tag{5}$$

$$H_i = \chi + \alpha J_i + \gamma G_i + e_i \tag{6}$$

$$G_i = \begin{cases} 1 & if\ G_i^* > 1 \\ 0 & otherwise \end{cases} \tag{7}$$

where G_i^* is the unobservable or latent variable for technology adoption, Y_i are non-stochastic vectors of observed farm and non-farm characteristics determining adoption, G_i is its observable counterpart (dummy for adoption of improved chickpea varieties), H_i is a vector denoting marketed surplus, J_i are vectors of exogenous variables thought to affect marketed surplus and u_i and e_i are random disturbances associated with the adoption of improved technology and the marketed surplus model, respectively. Beta, alpha and gamma are parameters to be estimated and our main interest is to estimate gamma which represents impact of technology adoption on market integration. In Equation (5), the dependent variable adoption of improved chickpea varieties equals one, if the farmer has adopted at least one improved chickpea varieties during 2006/07 cropping season, and zero otherwise. It is generally assumed that the household's aim to maximize its expected utility subject to various constraints determines the decision to adopt new varieties. Note that we cannot simply estimate Equation (6) because the decision to adopt may be determined by unobservable variables that may also affect marketed surplus. If this is the case, the error terms in Equations (5) and (6) will be correlated, leading to biased estimates of γ, the impact of adoption.

In fact, we have performed a Wu-Hausman specification test to test the null hypotheses that adoption variable is exogenous in the marketed surplus equation (Hausman, 1978). The exogeneity of technology adoption on market surplus is tested by using the residuals from the reduced form equations (adoption regressed on its instruments) as explanatory variables in the structural equations (with marketed surplus as the dependent variable). If technology adoption is endogenous, then the residual variable of the reduced form equation correlate with the dependent variable in the structural equation. The P-values of the estimated F-test statistics show that the exogeneity hypothesis is rejected at the 5% level of significance. The test suggests that farmers' decisions to adopt improved varieties are endogenous in the marketed surplus function and need to be accounted for to obtain efficient and consistent estimates. However, whether or not the effect of a treatment (adoption) can be correctly estimated using an instrumental variable regression, importantly depends on the validity of the exclusion restriction. Hence, for identification purposes, we followed the usual order condition that Y_i contains at least one element not in J_i imposing an exclusion restriction in Equation (6). Our identification strategy is based on variations in the knowledge and perception of improved technology exhibited by different households.

Our hypothesis is that the probability of a household to adopt improved technology is an increasing function of its prior knowledge and attitude, reflected by two instrumental variables: the number of improved varieties known by farmers (knowledge) and farmers' perception about the improved verities during the previous cropping year (attitude). We used the lagged variable to avoid potential endogeneity problem. Wu-Hausman specification test were also carried out to check if the selected instruments are exogenous and the results support the exogeneity hypothesis. These variables do not have any direct effect on the marketed surplus, although they are hypothesised to affect the probability that the household adopts improved technology. The validity of our results depends to a large extent on the quality and relevance of these instruments. We assess the quality of our instruments by using an F-test of the joint significance of the excluded instruments. As discussed earlier an instrumental variable must not be correlated with the equation's disturbance process and it must be highly correlated with the included endogenous regressor. According to Staiger and Stock, the weak instrument hypothesis will be rejected if an F-test is greater than 10 (Staiger and Stock, 1997). Additionally, as part of a robustness check, we also perform over-identification tests of the model. Econometric literature suggests two other methods to correct for observable selectivity bias, namely regression based on propensity score and matching techniques. To complement the two-stage instrumental variable (IV) technique and to assess consistency of the results to different assumptions, two additional models were applied. For these techniques to be valid, the fundamental assumption is the ignorable treatment assignment (Rosenbaum and Rubin, 1983) which can formally be represented by:

$$(H_1, H_2) \perp G_i \,\big|\, Y \tag{8}$$

where H_1 and H_2 are the outcomes of interest (farmers' into output market) for adopters and non-adopters, respectively.This assumption states that, conditional on a set of observables Y, the respective treatment outcome is independent of actual treatment status (adoption of improved varieties). In the second model, considering the underlying assumption of ignorability of treatment, we use the propensity score as control function in case the adoption variable interact with unobserved heterogeneity (Wooldridge, 2005) – a method pioneered by Rosenbaum and Rubin (1983). The structural equation then is expressed as:

$$H_i = \chi + \gamma G_i + \mu PPS + e_i \tag{9}$$

Where:

$$PPS(Y) = \Pr(G_i = 1 \,|\, Y) \tag{10}$$

The propensity score (PPS) is the conditional probability of adoption given observed covariates Y and can be estimated by a Probit model. The estimated propensity score is used in the structural equation as a control function for selection bias. The third model is based on matching techniques, which have to deal with the challenge of defining an observationally similar group of non-adopters to that of adopters. Smith and Todd demonstrate that impact estimates calculated using matching methods are highly sensitive to matching method itself, but robustness can be improved by restricting matches only to those adopters and non-adopters who have a common support in the distribution of propensity scores (Smith and Todd, 1997). Therefore, the difference in the observed outcome (farmers' integration into output market) was estimated by applying the common support condition. Further checking for robustness by using four different methods for selecting matched non-adopters, namely stratification matching, nearest neighbour matching, radius matching and Kernel matching were used.

RESULTS AND DISCUSSION

Descriptive statistics

Table 1 presents the t-test and chi-square comparison of means of selected variables by adoption status for the surveyed 700 households. Some of these characteristics are the explanatory variables of the estimated models we present further on. The dataset contains 700 farm households and of which about 32% are adopters that is planted at least one of the improved chickpea varieties during 2006/07 cropping season. The area planted of improved chickpea varieties is about 0.6 ha for adopters. Average age of sample household head is about 47 years and about 9% are female-headed. No significant difference is observable in the age and gender of the household head although the groups vary in terms of their marital status. Adopter categories do not seem to significantly vary in terms of primary and junior level of education (1 to 8 years) although adopters have higher proportion of household heads with at least secondary education. This suggests that education might be correlated with decision to adopt. The average active family labor force is 3.7 persons for adopters and 3.4 for non-adopters and the difference is statistically significant supporting the importance of family labor for adoption of new technologies. The adopter groups are distinguishable in terms of asset holding whereby adopters own more livestock per capita, land per capita and farm asset per capita. No significant difference is observable in access to off-farm activities and practicing water conservation and soil fertility.

Average walking distance to the main market is significantly higher for adopters and they seem to have also more access to extension service, media service and official positions. However, there is no significant difference in terms of household membership in different rural institutions. The result also depicts that the adopter categories are distinguishable in terms of their greater knowledge of the existing improved chickpea varieties and positive perception about those varieties. Adopters have more experience in chickpea farming, as well as farmer to farmer seed exchange. This simple comparison of the two groups suggests that adopters and non-adopters differ significantly in some proxies of physical, human and social capital. The adopters groups are significantly distinguishable in terms of farmers' integration into output market, measured both as amount sold and share of total chickpea produced marketed. In the subsequent part of the chapter, a rigorous analytical model is estimated to verify whether these differences in mean marketed surplus remains unchanged after controlling for all confounding factors. To measure the impact of adoption, it is necessary to take into account the fact that individuals who adopt improved chickpea varieties might have achieved a higher level of market participation even if they had not adopted.

Table 1. Descriptive summary of variables used in estimations (N = 700).

Variables	Unit	Adopters (N =222)	Non-adopters (N = 478)	t-stat (chi-square)
Dependent variables				
Area planted of improved chickpea varieties	ha	0.6	0.0	24.7***
Share of total chickpea marketed	ratio	0.40	0.23	6.27***
Amount sold	kg	1209	475	7.14***
Household characteristics variables				
Age of the household head	years	47.6	46.7	0.9
Gender of household head (male = 1)	1/0	0.95	0.92	1.1
Marital status (married =1)	1/0	0.94	0.88	4.61**
Household head education 1-4 years (yes = 1)	1/0	0.44	0.41	0.7
Household head education 5-8 years (yes = 1)	1/0	0.12	0.11	0.1
Household head education greater than 8 years (yes = 1)	1/0	0.06	0.02	5.8**
Active family labour force	count	3.7	3.4	2.6***
Household wealth variables and farm characteristics				
Oxen per capita	count	0.55	0.45	3.87***
Non-oxen tropical livestock unit per capita	TLU	0.89	0.62	6.24***
Farm size per capita	ha	0.42	0.34	3.39***
Value of farm asset owned per capita	Birr	263.9	156.2	2.52**
Access to off-farm activities (yes = 1)	1/0	0.35	0.40	1.49
Farming main occupation (yes = 1)	1/0	0.94	0.94	0.10
Lentil share in total cultivated area	ratio	0.06	0.07	-0.7
Practice soil and water conservation (yes = 1)	1/0	0.40	0.40	0.00
Soil quality (ranked above average =1)	1/0	0.90	0.89	0.13
Institutional and access related variables				
Contact with government extension agents	count	28.5	18.4	4.2***
Own radio or TV or mobile phone (yes = 1)	1/0	0.84	0.75	7.36***
Number of improved varieties known in previous cropping year	count	1.86	1.08	11.09***
Members of input supply cooperatives (yes = 1)	1/0	0.87	0.88	0.07
Member of farmer association (yes = 1)	1/0	0.27	0.22	1.6
Household heads hold official position (yes = 1)	1/0	0.34	0.25	6.89***
Walking distance to main market	km	12.8	9.3	2.8***
Distance to extension service	km	2.5	2.5	-0.08
Experience of growing chickpea in years	year	22.6	19.3	3.3***
Farmers perception of improved varieties (ranked above average = 1)	1/0	0.83	0.29	179.5***
Own donkey for transport (yes = 1)	1/0	0.89	0.82	5.31**
Used recycled saved seed (yes = 1)	1/0	0.54	0.50	0.99
Experience in farmer to farmer seed exchange (yes = 1)	1/0	0.26	0.18	5.18**

Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. T-test and chi-square are used for continuous and categorical variables, respectively.

Estimation of Results

Determinants of seed access

The jointly estimated DH model results for seed access are provided in the bottom half of Table 2. Most of the variables in the model have the expected signs. Seven variables were found to be statistically significant in explaining farmer access to improved seed. The likelihood of accessing improved seed for a household is hypothesized to positively increase with ownership of wealth assets. As expected, the proxies for household wealth such as ownership of oxen, non-oxen livestock assets (TLU), farm size and monetary value of farm assets take a positive sign, all suggesting the contributing role of household wealth in accessing improved seed. The results suggest that the relatively affluent farmers have better access to seed perhaps due to their ability to travel to other areas to purchase seed. This might also suggest rich farmers may have been targeted more than others through the extension system. Oxen-based farming is commonly practiced in the study area and that is why we used oxen (the number of owned oxen) as a separate explanatory variable in model. Livestock was the economic variable that was highly significant in explaining the likelihood of access of improved seed.

Access to information is also expected to positively affect the likelihood of accessing improved seed. This effect is captured by ownership of information supporting assets like TV, radio or mobile phone, education level of the household head and contact with extension agents. All of the variables have the expected sign although only two variables (contact with extension agents and education) explained the variation in access to improved seed significantly. This may actually show that information was the major limiting factor determining the farmer's ability to get hold of improved seeds. We find no significant variation in seed access across age and gender categories suggesting that men and women farmers do not vary significantly in accessing improved seed. Both of the district dummy coefficients have a negative sign and statistically significant. These indicate that farmers in the Lume-Ejere district (reference district) have significantly more access to improved seed compared to those in Gimbichu and Minjar-Shenkora. These dummies capture many district specific characteristics like population density, soil type and/or fertility, rainfall availability, etc. Modjo, which is the capital town of Lume-Ejere, is strategically located on the inter-regional cross road and which might give farmers in the district more advantage in terms of access to information, access to improved seed and other market related factors. Lume-Ejere is also closer to the national research center compared to the other districts and this may enable the farmers in this district to receive benefits of pre-extension demonstration and improved seed distribution (popularization) trials.

Determinants of technology adoption

The estimated results for the DH and Tobit models on the demand for improved varieties are presented on the upper section of Table 2. We are presenting the Tobit model results for comparison purpose. The results from the two models were comparable which shows the robustness of our results to model specification. All the statistically significant variables have the same directional effects in both models. The likelihood ratio test statistic favored the DH model over the Tobit. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) estimates also confirmed the same DH model to better fit the data. Henceforth, we base our discussion on the results from the DH model. Seven variables were found to have significant effects in explaining the level of adoption, measured in term of area planted under improved chickpea varieties.These included active family labor force, per capita asset (farm size and non-oxen livestock), previous year knowledge about improved varieties, perception of farmers about the technology attribute and the district dummies. To adopt the newly introduced varieties, farmers need to be aware of the available varieties as adoption is sometimes hampered not only by the inherent characteristics of the varieties themselves but also by lack of awareness of the end users of the technologies.

Hence, farmers' awareness about the available improved varieties is an important factor for the adoption to take place. Our results confirm this preposition. Knowledge of improved varieties was statistically significant in explaining the level of adoption. Those farmers who knew more varieties during preceding year probably have better information about the advantages of the varieties and are likely to adopt and allocate more land during the current year. This positive effect of farmer technology awareness variable is consistent with studies for pigeonpea varieties Tanzania (Shiferaw et al., 2008), cowpea varieties in Nigeria (Kristjanson et al., 2005) and maize varieties in Tanzania (Kaliba et al., 2000). Active family labor force had significantly and positively affected the level of adoption of improved chickpea varieties. This would reflect the importance of family labor (as proxied by the number of worker family members) in cultivating the new chickpea varieties. The significant positive effect also shows how family labor is important in developing countries where moral hazard associated with hired labor is common. This makes hiring labor costly for households with small family labor force. It is also possible that new varieties may require more labor. They may require improved agronomic practices (e.g. weeding, plowing etc) and more labor in harvesting and threshing. In addition, new varieties are sweet and tasty at green stage and many farmers need labor to watch the fields at night to control from thieves. Some of the green chickpea sold along roadside is stolen from unguarded farm. The positive effect of family labor variable is also consistent with other studies (Gebremedhin et al., 2009).

Results also confirmed that the level of adoption of improved varieties was strongly related to household wealth indicator variables such as per capita farm size and non-oxen livestock wealth. However, this shows the importance of wealth/poverty level in production and technology choice decision behavior of smallholder farmers. This could be the case when the unobserved constraints and shadow prices of inputs systematically differ across farmers with ownership of key assets. Ownership of these assets eases the access of households to improved seed and credit. Livestock

Table 2. Estimation results of the Double-Hurdle and Tobit model.

Variables	Double-Hurdle coef. (Std. Err.)	Tobit model coef. (Std. Err.)[a]
A) Area planted with improved varieties		
Gender of household head	0.161 (0.13)	0.175 (0.16)
Age of household head	0.002 (0.00)	0.002 (0.00)
Head education 1 to 4 years	-0.038 (0.07)	-0.085 (0.08)
Head education 5 to 8 years	-0.018 (0.10)	0.100 (0.12)
Head education greater than 8 years	0.084 (0.16)	-0.038 (0.19)
Active family labour force	0.062 (0.02)***	0.049 (0.03)*
Value of farm asset owned per capita	0.000 (0.00)	0.000 (0.000
Oxen per capita	0.132 (0.10)	0.238 (0.12)*
Farm size per capita	0.315 (0.13)**	0.193 (0.14)
Non-oxen tropical livestock unit per capita	0.115 (0.06)*	0.161 (0.07)**
Walking distance to the main market	0.004 (0.00)	0.005 (0.00)*
Contact with government extension agents	0.001 (0.00)	0.002 (0.00)*
Number of improved varieties known in previous year	0.212 (0.04)***	0.107 (0.04)**
Farmers perception of improved varieties	0.169 (0.07)**	0.646 (0.09)***
Access to off-farm activities	-0.003 (0.06)	-0.050 (0.07)
Lentil share in total cultivated area	-0.117 (0.23)	-0.108 (0.27)
Wheat share in total cultivated area	-0.011 (0.06)	0.104 (0.07)
Practice soil and water conservation	-0.020 (0.06)	-0.054 (0.07)
Soil quality	-0.005 (0.09)	-0.012 (0.11)
Lume-Ejere district (Reference)		
Minjar-Shenkora district	-0.249 (0.08)***	-0.415 (0.10)***
Gimbichu district	-0.370 (0.09)***	-0.404 (0.11)***
Constant	-1.045 (0.23)***	-1.429 (0.28)***
B) Seed access		
Gender of household head	0.285 (0.38)	
Age of household head	0.000 (0.01)	
Head education 1 to 4 years	-0.049 (0.20)	
Head education 5 to 8 years	0.997 (0.41)**	
Head education greater than 8 years	-0.082 (0.48)	
Active family labour force	-0.045 (0.06)	
Value of farm asset owned per capita	0.000 (0.00)	
Oxen per capita	0.753 (0.29)**	
Farm size per capita	-0.078 (0.30)	
Non-oxen tropical livestock unit per capita	0.360 (0.20)*	
Own radio or TV or mobile phone	0.210 (0.14)	
Contact with government extension agents	0.010 (0.00)**	
Own donkey for transport	0.161 (0.26)	
Use saved recycled seed	0.164 (0.20)	
Experience in farmer-farmer seed exchange	0.049 (0.23)	
Lume-Ejere district (Reference)		
Minjar-Shenkora district	-1.110 (0.22)***	
Gimbichu district	-0.642 (0.24)***	
Constant	0.028 90.64)**	
Number of observation	677	677
Log likelihood	-588.05	-371.32
Wald chi2(19), LR chi2 (19)	200.54	286.81
Prob > chi2	0.000	0.000
Akaike Information Criterion (AIC)	1401.85	1078.46
Bayesian Information Criterion (BIC)	1546.24	1164.33

Numbers in parentheses are robust standard errors. *, **, *** coefficients are significantly different from zero at the 99, 95 and 90% confidence levels, respectively. [a] Note that the area allocated to improved chickpea varieties are not observed for farmers not planted chickpea, thus make the variable truncated for the use of Tobit model.

ownership also helps farmers to spread some of the risks they face. Similar results were found for improved pigeonpea varieties in Tanzania (Shiferaw et al., 2008) and for cowpeas in Nigeria (Kristjanson et al., 2005). Besides, farmer's perception about the improved varieties had also an effect on the level of adoption. As expected, higher preferences of producers attitude towards selected quality traits of improved chickpea varieties is positively correlated with higher adoption. However, household head attributes indexing age, gender and education were not significant. The level of adoption of improved chickpea varieties were found to vary across different agro-ecological zones. District dummies included in the models were found to be highly significant (the point of reference is Lume-Ejere district). The empirical results confirmed that the land allocated for improved chickpea varieties was highest in Lume-Ejere district. Lume-Ejere is located on the main inter-state road and also closer to national agricultural research centre that develop improved chickpea varieties.

Impact of technology adoption on farmers' integration into markets

The simple comparisons between adopters and non adopters demonstrate that the adopters groups are significantly distinguishable in terms of farmers' integration into output market (marketed surplus). The outcome proxy variable that is, share of total production actually commercialized, was computed as the ratio of total chickpea sold to total production during the previous cropping season. To verify whether this difference can be attributed to adoption of improved technologies, the impact model is estimated using different econometric procedures (Tables 3 and 4). Results of first stage adoption equation are not discussed here but are available upon request. Table 3 presents the results of two-stage treatment effect model and regression based on propensity score. To correct for potential violation of normality and homoskedasticity of the error terms assumptions, robust standard errors are estimated using White's heteroskedasticity consistent standard errors. The null-hypothesis that all variables can be dropped is rejected at less than the one percent level of significance and the Wald Chi-square is 73.49. Over-identification tests support the choice of the instruments, as do the F-test values for the first stage technology adoption. The F statistic of joint significance of the excluded instruments is greater than 10, thus passing the test for weak instruments. The null hypothesis in the over identification test is that the instruments are valid and this cannot be rejected.

Our hypothesis was that adoption of modern chickpea varieties improves the level of integration of smallholder farmers into local markets. Our results support this proposition. The marketed surplus was overwhelmingly explained by adoption of improved varieties as indicated by the positive and significant coefficient of adoption variable in the three econometric models pointing to the robustness of the results. *Ceteris paribus*, adoption of improved technologies results in an increase in marketed surplus by about 19% in the treatment effect model. In the case of the regression based on propensity score (model 2), two alternative specifications are estimated. First only the propensity score and the adoption variables are included in the equation and in the second part other control variables in addition to the propensity score are included. Both estimation results show a positive and strong effect of adoption on marketed surplus. Table 4 reports the estimation results for the average treatment effect on the treated (ATT) of the outcome variable, using propensity score matching techniques (PSM). In our application of PSM, we first estimate a Probit regression in which the dependent variable equals one, if the household adopted at least one improved chickpea varieties, zero otherwise. We then check the balancing properties of the propensity scores. The balancing procedure tests whether or not adopters and non-adopters observations have the same distribution of propensity scores. When balancing test failed, we tried alternative specifications of the Probit model; the specification used in this paper is the most complete and robust specifications that satisfied the balancing tests. The quality of the match can be improved by ensuring that matches are formed only when the distribution of the density of the propensity scores overlaps adopters and non-adopters observations—that is, when the propensity score densities have "common support." For this reason, we used the common support approach for all PSM estimates. For the common support sample, the Probit model was estimated again to obtain a new set of propensity scores to be used in creating the match. We also retested the balancing properties of the data. All results presented in the following pages are based on specifications that passed the balancing tests. We matched adopters and non-adopters observations by four PSM techniques as discussed earlier. The standard errors of the impact estimates are calculated by bootstrap using 100 replications for each estimate.

The estimated results based on the four matching algorithms showed that our ATT estimate is robust. The overall average gain in the percentage of total chickpea production sold ranges from 0.16 to 0.20. The estimated gain was statistically significant at 99% confidence level for all the matching methods. This indicates that (assuming there is no selection bias due to unobservable factors) level of integration into chickpea market for farmers who adopted improved chickpea varieties is significantly higher than the non adopters. We reached the same conclusion using endogenous switching regression to control for the unobserved farm and household characteristics.

CONCLUSIONS AND POLICY IMPLICATIONS

This paper analyzes the adoption determinants and

Table 3. Impact on marketed surplus - treatment effect and propensity score regression results. Dependent variable: share of total chickpea marketed.

Variables	Two-stage standard treatment effect (model 1)	Regression based on propensity-score (model 2)		
		Without control variables		With control variables
	Coef. (Rob. Std. Err.)	Coef. (Rob. Std. Err.)		Coef. (Rob. Std. Err.)
Gender of household head	-0.011 (0.05)			-0.009 (0.06)
Age of household head	-0.002 (0.00)*			-0.003 (0.00)
Head education 1 to 4 years	-0.009 (003)			-0.006 (0.03)
Head education 5 to 8 years	-0.022 (0.06)			-0.021 (0.05)
Head education greater than 8 years	-0.020 (0.11)			-0.011 (0.09)
Active family labour force	0.029 (0.01)**			0.028 (0.01)**
Value of farm asset owned per capita	0.000 (0.00)			0.000 (0.00)
Oxen per capita	0.084 (0.08)			0.083 (0.06)
Farm size per capita	0.133 (0.08)*			0.133 (0.07)*
Non-oxen tropical livestock unit per capita	0.126 (0.04)***			0.119 (0.03)***
Walking distance to the main market	-0.002 (0.00)*			-0.002 (0.00)*
Access to off-farm activities	-0.043 (0.03)			-0.038 (0.03)
Own radio or TV or mobile phone	-0.020 (0.04)			-0.019 (0.04)
Member of farmer association	-0.014 (0.03)			-0.023 (0.04)
Lume-Ejere district (Reference)				
Minjar-Shenkora district	-0.011 (0.05)			0.000 (0.05)
Gimbichu district	-0.052 (0.34)			-0.048 (0.05)
Adoption	0.191 (0.10)*	0.072 (0.04)*		0.090 (0.04)**
Propensity score		0.337 (0.66)***		0.133 (0.10)
Constant	0.134 (0.10)	0.161 (0.03)***		0.139 (0.11)
Log likelihood	-307.77	F-test	33.48	6.19
Wald chi2(17)	73.49	Prob>F	0.000	0.000
Prob > chi2	0.000	Adj R2	0.13	0.17
Test of instruments				
F-test (first stage)	11.12			
P-value	0.00			
Test of over-identification				
Chi2	0.78			
P-values	0.38			

Numbers in parentheses are robust standard errors. *, **, *** coefficients are significantly different from zero at the 99, 95 and 90% confidence levels, respectively. In the two-stage standard treatment effect model, the predicted probability from the first-stage Probit adoption model is used instead of the actual dummy variable.

estimates the causal effect of adopting improved chickpea technologies on smallholder farmers' integration into output market in rural Ethiopia. The data showed that several households were constrained from adopting improved varieties due to seed access limitations that prevent some potentially adopting farmers from planting new varieties. Adoption of improved chickpea varieties was therefore modeled as a two-stage (DH model), which distinguishes demand for improved varieties from seed access and the areas of land allocated to the improved technology. As opposed to conventional Tobit model, the DH adoption model applied in this paper, avoids the assumption that all non adopters do not want to adopt and that the same factors affect the probability to adopt and intensity of use in the same direction. Results confirmed that the level of adoption of improved chickpea varieties was strongly related to a range of household wealth indicator variables. Those households with more family labor force, livestock and land were considerably more likely to allocate extra land for the improved chickpea varieties. Ownership of these assets seems to ease the access of households to improved seed, some of which may be due to its potential effect on accessing credit. Livestock ownership may also help farmers spread some of the risks they face.

A policy for provision of better credit services and increased supply of seed to local markets may help farmers enhance the level of adoption of the new technology. Knowledge and perception about the improved varieties were also found to be the supporting factors

Table 4. Impact on marketed surplus using PPS matching methods (model 3).

Variable	Adopters	Non-adopters	Difference = average treatment effect on the treated (ATT)	t-stat.
	Dependent variable: share of total chickpea marketed			
Method 1: Stratification matching	**Stratification with 5 blocks under common support**			
	217	222	0.196	7.072*** (0.028)
Method 2: Radius matching	**Non-adopters within 0.1 PPS under common support**			
	224	210	0.20	4.97*** (0.040)
Method 3: Kernel matching	**Kernel-weighted average of all control farmers under common support**			
	217	222	0.188	6.044*** (0.031)
Method 4: Nearest neighbour matching	**Only 51 non-adopters have bee matched to the 217 adopters under common support**			
	217	51	0.161	3.022*** (0.053)

Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. The number in brackets shows bootstrapped standard errors with 100 replication samples.

for adoption despite limited access. This implies the need for policy to strengthen and leverage government extension services and rural institutions to promote and create positive awareness about the existing improved chickpea technologies. The government will need to take the lead in technology promotion and dissemination at the initial stages and in creating an enabling environment for effective participation of the private sector. The other significant variables in both the first and second hurdles of the adoption model were the district dummies. The likelihood of seed access and level of adoption of improved chickpea varieties were found to vary across districts; highest in Lume-Ejere district as compared to Gimbichu and Minjar-Shenkora. This implies that agricultural research institutions should expand their pre-extension trials and demonstration efforts to the relatively remote districts too. Policy makers need to encourage and assist private seed companies and community seed producer associations by improving access to agri-business development services and empowering cooperatives and village agro-dealers.

The very limited numbers of private seed enterprises and the low attention accorded to the informal seed sector narrowed the options available to farmers for obtaining modern varieties at affordable prices, at the right place and time. A more flexible seed system which is financially and institutionally sustainable, that meets the needs of a diverse group of farmers, and reduces the current seed supply shortage is crucial in Ethiopia to accelerate agricultural growth and commercialization. This requires lifting the entry barriers for participation of the private seed industry and encouraging the growth of the informal sector by providing adequate access to basic or foundation seed and extension advice on seed production, processing, treatment and storage. The private sector lack the incentive to participate in the enhanced delivery of seeds of these crops as the size of the market is small and farmers are able to use saved and recycled seed for 3 to 5 years. Strengthening the farmer based seed production program and revolving seed scheme by improving farmers' skills in seed multiplication can assist in increasing the supply of seed for improved varieties both within communities and the formal seed system.

The revolving seed loan scheme where target farmers often organized into groups or cooperatives access a certain amount of seeds of improved varieties from a supplier (e.g. NGO or ministry of agriculture) and return at least the same amount of seed in-kind is an important mechanism in the absence of adequate supply of improved seeds to reach all farmers. This scheme was initially proposed for forage seeds distribution but recently grain seeds are also distributed through this system. Unlike the formal seed system, this scheme does not involve many transactions. The great advantage of this system is that it benefits resource-poor farmers who may otherwise have poor access to or lack adequate cash to buy seed from the formal seed system. This study also investigated the causal impact of improved agricultural technology on farmer integration into output market. We have used econometric estimation approaches that explicitly address endogeneity and selection problems such as two-stage treatment effect model, regression based on propensity score and matching method to achieve this objective. The empirical results showed that adoption of improved chickpea varieties had a positive and robust effect on farmers' integration into output market. These results generally underscore that a household's production technology choices, fundamentally affect its level of market participation, primarily by affecting its productivity. Households operating rudimentary agricultural productivity technologies may participate in markets, but often only because they must use commodity markets as a way to resolve cash constraints under conditions where they have no access to financial services. This indicates that promoting adoption of improved production technologies is essential for inducing broad-based market participation that transmits excess supply to distant locations.

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