Does Technology Adoption Promote Commercialization? Evidence from Chickpea Technologies in Ethiopia

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Abstract

This paper evaluates the adoption determinants and casual impact of adoption of improved chickpea technologies on market integration in rural Ethiopia. The article makes use of data obtained from a random cross-section sample of 700 small-scale farmers in Ethiopia. We apply augmented double hurdle model to analyze the determinants of the intensity of variety adoption conditional on overcoming seed access constraints. We estimate the causal impact of technology adoption on market integration by utilizing treatment effect model, regression based on propensity score as well as matching techniques to assess results robustness. Results show that knowledge of existing varieties, perception about the attributes of improved varieties, household wealth (livestock and land) and availability of active family labor force play a significant role in enhancing the level of adoption of improved chickpea varieties. Our analysis also reveals that the adoption of improved agricultural technologies has a significant positive impact on marketed surplus and the findings are consistence across the three models suggesting the robustness of the results. Integration into output market is also positively associated with household wealth and availability of active family labor force and negatively associated with age of household head and distance to main market. Results confirm the potential direct role of technology adoption on market integration among the rural households, as higher productivity from improved technology translates into higher output market integration.

JEL classification: C13, C15, C34, C52, O32, O38

Keywords: Commercialization; Double hurdle model; improved *c*hickpea varieties; technology adoption; treatment effect model; Ethiopia

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1. Introduction

Today, about 1.1 billion people continue to live in extreme poverty on less than US$ 1 a day. Another 1.6 billion live on between US$ 1–2 per day. Three out of four poor people in developing countries- (83 million people) lived in rural areas in 2002 (WDR 2008). Most depend on agriculture for their livelihoods, directly or indirectly. Unlike almost all other regions of the world, poverty in Sub-Saharan Africa (SSA) has been rising over the last decade. The share of people living on less than $1 a day in this region exceeds that in the next poorest region of South Asia by about 17 percentage points. In 2003 about 46 percent of the population in SSA lived on less than $1 a day—slightly more than in 1980 and in 1990 (ECA, 2005). The pathway out of poverty trap in these countries depends on the growth and development of the agricultural sector since agriculture is the predominant sector in the economies of many African countries and underpins the livelihood of the majority of the poor. So a more dynamic and inclusive agriculture is required to accomplish the Millennium Development Goals (MDGs) and to get more people out of poverty. The first MDG goal, to eradicate extreme poverty and hunger, in particular depends on raising the productivity of agriculture. Achieving agricultural productivity growth and development will not be possible without yield enhancing technical options because it is no longer possible to meet the needs of increasing numbers of people by expanding areas under cultivation. Agricultural research and technological improvements are therefore crucial to increase agricultural productivity and thereby reduce poverty and meet demands for food without irreversible degradation of the natural resource base. However, in today's more integrated world economy, success in productivity-based agricultural growth crucially depends on the expansion of 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 Ethiopia grain legumes production presents an opportunity in reversing the trends in productivity, poverty and food insecurity. In part, this is because legumes have the capacity to fix atmospheric nitrogen in soils and thus improves soil fertility and save fertilizer costs in subsequent crops (Serraj, 2004). Hence, the rotation of cereal crops with legumes is essential if soil fertility, soil health, and the sustainability of production systems are to be maintained. Second, it improves more intensive and productive use of land, particularly in areas where land is scarce and the crop can be grown as a second crop using residual moisture. Third, it reduces malnutrition and improves human health especially for the poor who cannot afford livestock products. It is an excellent source of protein, fiber, complex carbohydrates, vitamins, and minerals. Fourth, the growing demand in both the domestic and export markets provides a source of cash for smallholder producers.

Despite the crucial role of dryland legumes like chickpea for poverty reduction and food security in Ethiopia, lack of technological change 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 variety dominates the local and export markets, however; low productivity of the variety limits the farmers' competitiveness in these markets. The structure and functioning of marketing system in the country is constrained by factors including small quantity supplies, lack of grading and quality control systems, lack of well-coordinated supply chain, lack of efficient market information delivery mechanisms, underdeveloped infrastructure and high transaction costs (Shiferaw and Teklewold, 2007). As a result, market integration of the smallholder farmers 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 commercialization 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, the national agricultural research organization of Ethiopia in collaboration with International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) have developed and released 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 by the end of 2005 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 chickpea seeds in 2001/02 (CSA, 2002).

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 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 study seeks to provide answers to the following research questions. Which farmers are using improved technologies? What are the main factors that influence farmers to adopt improved/intensity technologies under seed access constraints using augmented double hurdle model and the main factors that affect seed access? The findings have implications for designing appropriate development oriented policy. Besides the linkage between technology adoption, productivity gain and market integration are scanty or relatively thin in economic literatures especially in developing country settings where significant frictions make this question most salient (Edmeades, 2006; Balagtas et. al, 2007; Bellemare and Barrett, 2006).

Thus using farm-level data collected from a random cross-section sample of 700 Ethiopia small-scale producers, this paper deals with the following objectives: (a) assess the role of market institutions, infrastructural and household assets in determining improved chickpea technology adoption for small farmers (b) identify determinants of market integration of chickpea and (c) assess the impact of improved chickpea technology adoption on market integration. Agricultural commercialization (market integration) 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 (Zeller et al., 1997). This article analyzes how technology adoption relates to output market integration. Technology adoption and market integration have no clear casual relationship. There seems to be a two-way link between market integration and technology adoption. Increased market integration may facilitate the adoption of new varieties and increase yield for small producers but it may also be that adoption of new varieties and greater yield leads to more integration. The two-way relationship or endogeneity problem can be corrected by instrumenting the endogenous variable using instrumental variable techniques.

The remainder of the paper is organized as follows. Section two shows the data collection methodology and the econometric model used for estimation. Section three presents the estimation results and in section four conclusions are drawn and some further implications are noted.

2. Data and methods

2.1 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). The primary survey was done in two stages. First, a reconnaissance survey was conducted by a team of scientists to have a broader understanding of the production and marketing conditions in the survey areas. During this exploratory survey, discussions were held with different stalk holders including farmers, traders and extension staff working directly with farmers. The findings from this stage were used to refine the study objectives, sampling methods and the survey instrument. The household survey was then carried out in March, 2008. 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*[3] and farm households. In the first stage, three districts namely Minjar-Shenkora, Gimbichu and Lume-Ejere were 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 around Debre Zeit which is 50 kms 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 fertilizer use, quality seed, 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 hectares whereas chickpea production in Minjar-Shenkora ranges from 15,000 to 17,500 hectares.

Eight *kebeles* from each of Gimbichu and Lume-Ejere districts and ten *kebeles* from Minjar-Shenkora district were randomly selected from where a random sample of 700 households was selected for detailed household survey. The three districts, Gimbichu, Lume-Ejere and Minjar-Shenkora constitute 21%, 43% and 36% of the total sampled households, respectively as presented in Table 1.

[3] It is usually named peasant association and is the lowest administrative unit in the country.

Table 1here

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, varieties 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.

2.2 Empirical models

Our empirical model specifications are divided into two parts. First, the intensity of variety adoption conditional on overcoming seed access constraints is investigated by making use of augmented double hurdle model. Second, the causal impact of technology adoption on market integration is analyzed by utilizing two-stage standard treatment effect model, regression based on propensity score as well as matching techniques.

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 understand the intensity of adoption. We applied the Double-Hurdle (DH) model for this purpose. The Tobit model has been popular for the two stage analysis. In the Tobit model, decisions whether to adopt or not 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? ii) If yes, do you have improved seed, land, credit, labor, etc constraints? The intensity of adoption is therefore modeled conditional on the constraints. The Tobit model, however, assumes a zero amount of adoption of improved chickpea variety as a corner solution. However, the augmented 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 old and new cultivars. Access to information is critical in facilitating this process however actual adoption and planting of improved varieties depend on the availability of improved seeds and the ability of the farmers to access this input. In this study, we have information whether the smallholder farmers are constrained or not. The households were asked why they had not planted the improved chickpea varieties. Access to improved seeds was the key constraints that farmers with positive desired demand had to overcome. 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 studies including Shiferaw et al. (2008), Coady (1995) and Croppenstedt et al. (2003) to model constrained technology adoption when there are farmers with constrained positive demand to the new technology.

Assume that the latent desired demand for improved variety of chickpea 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, β is a vector of parameters to be estimated, and *u* is a normal 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 of 0 and variance of 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 have positive desired demand and access to improved seed ($i.e.\ D_i^* > 0$ and $A_i^* > 0$) and hence they actually adopt the new technology

ii) Farmers in group 2 do not want the improved variety regardless of their access to the improved seed ($i.e.\ D_i^* < 0$ and $A_i^* > 0$ or $A_i^* < 0$)

iii) Farmers in group 3 have positive desired demand but cannot get it because they don't have access to the improved seed ($i.e.\ D_i^* > 0 \ and \ A_i^* < 0$)

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

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

The above 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, i.e. the farmer has desire to plant the improved seed, and the access threshold, i.e. the farmer has access to the improved seed. Studies by Jones (1992), Kimhi (1999) and Moffatt (2005) showed that the participation and access thresholds are independent, we also assume their independence. The log-likelihood function for the observed demand can thus be written as

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

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

Treatment effect model and propensity score methods

Estimation of the casual impact of technology adoption on market integration (marketed surplus) based on non-experimental observations is not trivial because of the need of finding on counterfactual of intervention. 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 had adopt (or the converse). In experimental studies, this problem is addressed by randomly assigning improved seeds to treatment and control status, 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 is not randomly distributed to the two groups of the households (adopters and non-adopters), but rather the households themselves deciding to adopt or not to adopt based on the information they have. Therefore, adopters and non-adopters may be systematically different; this difference may manifest themselves in differences in access to market, infrastructure, access to institutions and household asset holdings 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 occurred when there are unobservable characteristics that affect both the probability of adoption and outcome variable, marketed surplus.

Following Rosenbaum and Rubin (1983), Green (1997), Angrist (2001) and Fernandez-Cornejo (2005), different econometric techniques are applied to correct for potential selection bias in estimating the impact of technology adoption on level of market integration. Formally, given the unobserved variable and its observed counterpart, the treatment-effect equation can be expressed as:

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

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

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

where G_i^* is the unobservable or latent variable for technology adoption, G_i is its observable counterpart (dummy for adoption of new chickpea varieties), H_i is a vector denoting the commercialization (marketed surplus), J_i are vectors of exogenous variables thought to affect commercialization and Y_i are non-stochastic vectors of observed farm and non-farm characteristics determining adoption. e_i and u_i are random disturbances associated with the commercialization model and the adoption of new technology. In Equation (5), the dependent variable adoption of new 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 level of market integration. If this is the case, the error terms in Equation (5) and (6) will be correlated, leading to biased estimates of γ, the impact of technology adoption.

In fact, we have performed a Wu-Hausman specification test [Hausman, 1978] to test the null hypotheses that adoption variable is exogenous in the market integration function. The exogeneity of technology adoption on market integration 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 new chickpea varieties are endogenous in the market integration 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).

For the first stage, our identification strategy is based on variations in the knowledge and perception of new technology enjoyed by different households. Our hypothesis is that the probability of a household adopting new technology is an increasing function of its knowledge and attitude, reflected by two instrumental variables: the number of improved varieties known by farmers and farmers' perception about the new verities during the previous cropping year[4]. These variables do not have any direct effect on the level of market integration, although they are hypothesised to affect the probability that the household adopts new technology. The validity of our results depends to a large extent on the quality of these instruments. We assess the quality of our instruments by using an F-test of the joint significance of the excluded instruments. According to Stock and Staiger (1997), the weak instrument hypothesis will be rejected if an F-test is greater than 10. Additionally, as part of a robustness check, we also perform overidentification tests of the model.

Econometric literature suggests two other methods to correct for observable selectivity bias, namely propensity score methods and matching techniques. To complement the two-stage model and to assess consistency of results two additional models were applied. For these

[4] Both of the instruments used reflect knowledge and perception of farmers during the previous year. We used the lagged variable to avoid potential endogeneity problem.

techniques to be valid, the fundamental assumption is the ignorable treatment assignment (Rosenbaum and Rubin, 1983) which can formally be represented by:

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

where H_1 and H_2 are the outcomes of interest (level of market integration) 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 new varieties). In the second model considering the underlying assumption of ignorability of treatment, we use the propensity score as control function to overcome the endogeneity problem of the adoption variable. The propensity score is estimated using probit model and indicates the conditional probability of adoption given observable regressors Y. The structural equation then is expressed as:

$$H_i = \alpha J_i + \gamma G_i + \mu Pscore + e_i \tag{9}$$

Where

$$Pscore(Y) = \Pr(G_i = 1 / Y) \tag{10}$$

The third model bases 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 (2005) 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. Therefore, impact estimate 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 was used.

3. Results and discussion

3.1 Descriptive statistics

Table 2 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 these, about 32% are adopters i.e. 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) however adopters have higher proportion of household heads with secondary education. This suggests that education might be uncorrelated 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 suggesting 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 main market is significantly lower 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 knowledge of the existing improved chickpea varieties and 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 of smallholders suggests that adopters and non-adopters differ significantly in some proxies of physical, human and social capital.

Table 2 Here

The adopters groups are also significantly distinguishable in terms of level of market integration measured as 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 varieties might have achieved a higher level of market integration even if they had not adopted.

3.2 Econometric results

3.2.1 Determinants of seed access

The jointly estimated double-Hurdle model results for seed access are provided in the bottom half of Table 3. Most of the variables in the model have the expected signs. Seven variables were found to be statistically significant in explaining the farmer access to improved seed.

The likelihood of accessing improved seed for a household is hypothesized to increase with higher ownership of wealth assets. As expected, the household wealth proxies 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 positive role of household wealth in accessing seed. Oxen-based farming is basically the one practiced in the study area and that is why we used oxen (the number of oxen the household owns) 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. Information effect is captured by ownership of information-transmission equipments 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 to extension agents and education dummy) explained the variation in access to 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 suggesting that men and women farmer's are tendency to have similar chance 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 seed compared with 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 located on across region roads and that might make the farmers in the district more advantaged in terms of access to information, access to improved seed and other market related factors. Lume-Ejere is also closer to national research center compared to the other two and this makes the farmers in this district beneficiaries of pre-extension demonstration and improved seed distribution (popularization) trials.

3.2.2 Determinants of variety adoption

The estimated results for Double-Hurdle and Tobit models on the demand for improved varieties are presented on the upper section of Table 3. 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 had the same directional effects in all of the two models. The likelihood ratio test statistic specified above favored the DH model over the Tobit. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) estimates also confirmed the same 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 wealth), pervious 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 and 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. Farmers' awareness about the available improved varieties is an important factor for the adoption to take place. Our results confirm with this preposition. Knowledge of improved varieties was statistically significant in explaining the level of adoption. Those farmers who knew more number of 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 Shiferaw (2008) for pigeonpea varieties, Kristjanson et al. (2005) for cowpea varieties and Kaliba et al. (2000) for maize varieties.

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.

Results 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.

This shows the importance of wealth/poverty level in production and technology decision behavior of farmers. This could be the case when the unobserved constraints and shadow prices systematically differ across farmers with ownership of key assets. Ownership of these assets eases the access of households to improved seed and credit. Livestock ownership also helps farmers spread some of the risks they face. Similar results were found by Shiferaw et al. (2008) for improved pigeonpea varieties in Tanzania and Kristjanson et al. (2005) for cowpeas in Nigeria. Beside socio-economic characteristics and farmer's perception about the improved varieties had an effect on the level of adoption of the varieties. In line with our expectation the perception of producers towards quality of production for improved chickpea is positive and significant. Household head attributes indexing age, gender and education were not significant.

The level of adoption of improved chickpea varieties were found to vary across difference agro-ecological zones. District dummies included in the models were found to be highly statistically significant (the point of reference is Lume-Ejere district). The empirical results confirmed that the demand for improved chickpea varieties was the highest in Lume-Ejere district. Farmers in Gimbichu and Minjar-Shenkora districts adopted at lower level compared to their counterparts in Lume-Ejere district. Lume-Ejere is located on across region roads and also closer to agricultural research centre compared to the other two and this makes the farmers in this district beneficiary of pre-extension demonstration and improved seed distribution trials.

Table 3 Here

3.2.3 The causal impact of technology adoption on market integration

The mean comparison between adopters and non adopters demonstrate that the adopters groups are significantly distinguishable in terms of level of market integration. The outcome proxy variable, percentage of total production actually commercialized was computed as the ratio of total chickpea sale to total production in the previous crop season. To verify whether this difference can be attributed to adoption of improved technologies, the impact model is estimated using different econometric procedures (Table 4 and 5) [5]. Table 4 presents the results of two-stage treatment effect model and regression based on propensity score. Test results of the model show that the assumptions of normality and homoskedasticity of the error terms are violated. Thus, 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 per cent level of

[5] Results of first stage adoption equation are not discussed here and could be available on request.

significance and the Wald Chi-square is 73.49. Overidentification 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.

Our hypothesis was that adoption of improved chickpea varieties improves the level of market integration of smallholder farmers. 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 surpluses 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 Here

Table 5 report the estimation results for the average treatment effect on the treated (ATT) of the outcome variable using propensity score matching techniques. We applied the common support option for computing the propensity score and the ATT. The balancing property of the propensity score was tested and satisfied. Different specifications of the probit model were fitted until the balancing property was satisfied. The whole sample of households were used for this purpose and adoption status of the households was taken to be the treatment variable. This makes clear that some observations with no chickpea production will have invalid values for the outcome variable (252 observations were dropped). As a result, we used only 448 observations for estimation of the ATT by the matching algorithms. 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 1% for all the matching methods. This indicates that (assuming there is no selection bias due to unobservable farm and farmer specific factors) market integration level of smallholder farmers who adopted improved chickpea varieties is significantly higher than the non adopters.

Table 5 Here

3.2.4 Determinants of market integration

As shown in Table 4, there are more variables other than adoption that affect marketed surplus. The coefficient of the active family labor force is positive and strongly correlated with marketed surplus. Those households with more active labor force are expected to have higher crop productivity, and therefore be more likely to participate in market at higher intensity. The degree of participation in crop market is negatively influenced by age of household head. Younger households are more likely to participate as sellers than are older households. The coefficient of livestock ownership is positive and significant in both models, which suggest that farmers with more livestock tend to have higher market integration. The income from livestock production may help farmers to minimize their liquidity constraint to adopt new technologies that increases productivity and sales. Perhaps due to the availability of more manure, which can have positive impact on productivity and further livestock can be used as collateral to get credits. Marketed surplus was also positively affected by farm size, which might have facilitated in boosting production. In line with our expectation, distance to main market variable is negatively correlated with marketed surplus because of the increased transaction costs associated with marketing of the farmers' agricultural produce. This is also related to better access to improved seeds and other key agricultural inputs. Investment policies aimed at building up more rural road networks and improving the quality of roads may increase the level of market integration. Contrary to our expectation, education level of household head, membership in farmer association and ownership of information-transmission equipments are not significant in explaining the variation in marketed surplus.

4. Summary and conclusions

This paper has been aimed to analyze the adoption determinants and estimate the causal effect on marketed surplus of adopting improved chickpea varieties in rural Ethiopia. The data have shown that several households are constrained from adopting new varieties due to seed access constraints that prevent some potentially adopting farmer from planting new varieties. Adoption of improved chickpea varieties was therefore modeled as a two-stage (two hurdles), which distinguishes the seed access and the areas of land allocated to the new technology. In particular, the adoption model applied in this paper, the DH model, avoids the assumption that all non adopters do not want to adopt and 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 were strongly related to a range of household wealth indicator variables. Those households with more family labor force, livestock and land allocated more land for the improved chickpea varieties. Ownership of these assets eases the access of households to improved seed and credit. Livestock ownership also helps farmers spread some of the risks they face. A policy of enhancing better credit system and designing risk coping strategies may help farmers to build assets that enhance the level of adoption of the new technology. Knowledge and perception about the improved varieties were also found to be the limiting factors for adoption despite positive demand for new cultivar. The implication is that there is a need to strengthen and leverage government extension service and rural institutions to promote awareness creation of the existing improved 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 be the highest in Lume-Ejere district as compared to Gimbichu and Minjar-Shenkora. This implies that agricultural research institutions should expand their pre-extension and popularization trials to the relatively remote districts too. The office of agriculture should also make concerted effort to address all the villages through community-based extension services and improved seed distribution scheme.

The relationship between agricultural technology and market integration is complex. Though, the potential for increasing marketed surplus through the diffusion of modern farming technology is substantial. In this paper we have used a two stage treatment effect model, regression based on propensity score and matching method to estimate the casual effect of technology adoption on marked surplus. The empirical results show that adoption of improved chickpea varieties has a positive and robust effect on marketed surplus. These results generally underscore that a household’s production technology choices fundamentally affect its level of market integration 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 pent up demand for financial services to which they have no access. This indicates that promoting adoption of improved production technologies is essential to inducing broader-based market participation in a well-integrated markets that transmit excess supply to distant locations because the returns to increased output diminish less quickly there than they do in segmented or poorly integrated markets and the potential for adverse welfare effects on non- adopters is likewise lower.

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Table 1. Sampled Communities and Households

Districts	Total households	Total Kebeles	Sampled Kebeles	Sampled households
	Number	Number	Number	Number
Gimbichu	12316	10	8	149
Lume-Ejere	14563	13	8	300
Minjar-Shenkora	14991	18	10	251
Total	41,870	41	26	700

Table 2. 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***
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 head 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**

Note: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels.

Table 3. Estimation results of Double Hurdle and Tobit model

Variables	Double hurdle Coef. (Std. Err.)	Tobit model coef. (Std. Err.) [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)**
Perception of farmers (overall score)	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)***
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

Note: Numbers in parentheses are robust standard errors. *, ** , *** coefficients are significantly different from zero at the 99% (***), 95% (**) and 90% (*) confidence levels, respectively.

Table 4. Impact on commercialization using treatment effect and propensity score regression
Dependent variable: share of total chickpea marketed

	Two-stage standard treatment effect (model 1)	Regression based on propensity-score (model 2)	
		Without Control Variables	With Control Variables
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)
Number of observation	448		
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 overidentification			
Chi2	0.78		
P-values	0.38		

Note: Numbers in parentheses are robust standard errors. *, ** , *** coefficients are significantly different from zero at the 99% (***), 95% (**) and 90% (*) confidence levels, respectively.

Table 5. Impact on commercialization using PPS matching methods (model 3)

Variable	Adopters	Non-adopters	Difference = average treatment effect on the treated (ATT)	t-stat.
Method 1: Stratification matching	Stratification with 5 blocks under common support			
Number of observation	217	222		
Share of total chickpea marketed	-	-	0.196	7.072*** (0.028)
Method 2: Radius matching	Non-adopters within 0.1 PPS under common support			
Number of observation	229	210		
Share of total chickpea marketed	-	-	0.20	4.97*** (0.040)
Method 3: Kernel matching	Kernel-weighted average of all control farmers under common support			
Number of observation	217	222		
Share of total chickpea marketed	-	-	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			
Number of observation	217	51		
Share of total chickpea marketed	-	-	0.161	3.022*** (0.053)

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