The Impact of improved maize varieties on farm productivity and wellbeing: evidence from the East Hararghe Zone of Ethiopia

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ABSTRACT

The aim of this study is to measure the impact of improved maize varieties on farm productivity and smallholders’ wellbeing using data collected from the East Hararghe Zone of Ethiopia. We combined propensity score matching method with endogenous switching regression to estimate the impact on the welfare of farmers and we applied the stochastic frontier corrected for sample selection to measure the impact on farm productivity. The results show that adoption of improved maize varieties leads to significant gains in wellbeing and improves farm productivity.

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1. Introduction

Poor communities in developing countries live disproportionately in rural areas and directly or indirectly depend on subsistence and small scale agriculture, which are partially integrated into markets, for their food, income and livelihoods (Mendola 2007; Minten and Barrett 2008; Fischer and Qaim 2012; Larsen and Lilleør 2014). Hence, progress in the agriculture sector is seen as vital for sustainable pro-poor economic development, food security and poverty alleviation in affected areas (Ligon and Sadoulet 2007; Asfaw et al. 2012; Kassie et al. 2013). Nevertheless, in Africa, the performance of the agricultural sector is disappointing and its growth is lagging behind population growth.

Though there is an increase in agricultural production in Africa, much of this growth comes from the expansion of cultivated land. As such, there exists a significant productivity gap between Africa and the rest of the world (Dzanku, Jirström, and Marstorpe 2015). Most of the countries located in Sub-Saharan Africa (SSA) have not been able to ensure food security at either national or household level (Kassie et al. 2013; Bezu et al. 2014). Their agricultural systems are generally rain-fed and productivity is well below its productive potential (Tittonell and Giller 2013).

Ethiopia is one such SSA country still suffering from persistent and widespread poverty and food insecurity (Husmann 2016). More importantly, poverty is disproportionately affecting people in the rural areas of the country where agriculture is the main economic activity (Diao and Pratt 2007; Dercon, Hoddinott, and Woldehanna 2012; Abro, Alema, and Hanjra 2014). Hence, to tackle poverty, the link between agricultural growth, rural development, and poverty reduction has to be given due attention (Minten and Barrett 2008). This calls for the adoption of productivity enhancing technologies and improvement in the efficiency and productivity of the sector as it is becoming no longer possible to increase output by expanding the area under cultivation (Asfaw et al. 2012; Headay, Dereje, and Taffesse 2014). Nevertheless, the adoption rates of agricultural technologies in Africa in general and Ethiopia in particular, remains quite low (Feleke and Zegeye 2006; Abebe et al. 2013; Jayne and Rashid 2013; Pamuk, Bulte, and Adebunju 2014; Abate et al. 2016; Wainaina, Tongruksawattana, and Qaim 2016). For instance, in Ethiopia, though more than 40 improved varieties of maize have been developed and released over the last four decades (Zeng et al. 2015), the adoption of improved maize varieties is very low (Jaleta, Kassie, and Marenya 2015). It is thus critical to examine the constraints and incentives influencing the adoption of agricultural technologies, and to measure their impact on smallholders’ agricultural productivity and wellbeing.
Though several studies have attempted to measure the impacts of improved agricultural technologies, the vast majority of these relied on single econometric models and do not properly control for potential differences between adopters and non-adopters. For instance, the large proportion of studies (e.g. Mendola 2007; Becerril and Abdulai 2010; Wu et al. 2010; Kassie, Shiferaw, and Muricho 2011; Awotide et al. 2013) relied on the propensity score matching (PSM) approach. However, this technique only works if the difference between the two groups can be captured by using only observable variables. If there are unobservable characteristics, which can influence adoption decisions and the outcome variable, the result from the PSM is likely to be biased (Ma and Abdulai 2016).

A similar knowledge gap exists in studies on the impact of agricultural technologies on farm productivity. Most previous studies do not pay due attention to seed types (e.g. Seyoum, Batte, and Fleming 1998; Liu and Zhuang 2000; Binam et al. 2004; Bozoğlu and Ceyhan 2007; Chen, Huffman, and Rozelle 2009; Abdulai and Abdulai 2016). Even those that consider improved varieties (for instance Hossain, Bose, and Mustafi 2006) either rely on a single production frontier by assuming that adopters and non-adopters have similar production characteristics, or overlook a selection bias, particularly from unobserved characteristics (e.g. Alene and Hassan 2006). The reported impacts from studies which do not account for a selection bias are likely to be biased (Bravo-Ureta, Greene, and Solís 2012; González-Flores et al. 2014).

Hence, unlike previous works, this study tries to control for both observed and unobserved heterogeneities on production, adoption and the outcome variables. Accordingly, we combined PSM method with endogenous switching regression (ESR) to estimate the impact of improved maize varieties on the welfare of farmers (consumption per adult equivalent) and we applied PSM and the recently introduced Greene (2010) frontier model that corrects for sample selection bias to estimate the impact of adoption of improved maize varieties on farm productivity (technical efficiency [TE] in maize production).

2. Conceptual framework and estimation strategies

2.1. Technology adoption decision and impact evaluation

Following Becerril and Abdulai (2010) and Khorje et al. (2015), we modeled a households’ decision to adopt improved maize varieties using a random utility framework. Let $M_i$ represent the difference between the utility from the adoption of improved maize varieties ($U_{i1}$) and the utility from the conventional seeds ($U_{i0}$). The farmer chooses to adopt improved maize varieties if the utility from adoption is greater than the utility of the conventional seeds; $U_{i1} - U_{i0} > 0$. However, the two utilities are non-observable and the net benefit, $W_i$, that the farmer gains from adoption is a latent variable determined by observed and unobserved characteristics given in Equation (1)

$$M_i = X_i \beta + \varepsilon_i \text{ With } M_i = \begin{cases} 1 & \text{if } M_i > 0 \\ 0 & \text{otherwise} \end{cases}$$

where $M_i$ is a binary variable representing the adoption of improved maize varieties; $\beta$ is a vector of parameters to be estimated; $X$ stands for a vector of household, socioeconomic, location and institutional characteristics that influence farmers adoption decision and $\varepsilon_i$ represents the random error term. Moreover, the relationship between the adoption of improved maize seed varieties and its impact on welfare (measured as consumption per adult equivalent, for our case) can be modeled, along with a vector of other explanatory variables ($Z$) as follows:

$$W_i^* = Z_i \psi + \theta M_i + \mu_i,$$

where $W_i^*$ represents the welfare (consumption per adult equivalent), $M_i$ stands for the adoption of improved maize varieties, $\psi$ and $\theta$ are vectors of parameters to be estimated, and $\mu_i$ is an error term. The impact of the adoption of improved maize varieties on the well-being of farmers is therefore measured by the estimations of the parameter $\theta$ if farmers are randomly assigned to adopter or non-adopter groups (Faltermeier and Abdulai 2009; Khorje et al. 2015). However, since farmers themselves decide to adopt the technology based on the information they have, adopters and non-adopters may not be randomly distributed to the two groups as they may be systematically different (Amare, Asfaw, and Shiferaw 2012). In this case the mean outcome of the two groups differs even in the absence of the treatment. Hence, this initial bias has to be solved. To do so, we have combined ESR technique with PSM. Combining the two models will strengthen the estimates as each model has its own limitations which cannot be individually corrected (Khorje et al. 2015).

2.1.1. ESR models

In addition to the selection bias associated with non-randomness in technology adoption, heterogeneity of technology impacts is another important econometric problem. Under such conditions the standard
econometric method of using a pooled sample of adopters and non-adopters might be inappropriate as it assumes that the set of regressors have the same impact on adopters and non-adopters (Kassie, Shiferaw, and Muricho 2010). Besides, a number of recent empirical analyses that measured the impact of agricultural technologies (e.g. Asfaw et al. 2012; Khonje et al. 2015) also indicated the significance of unobservable factors under impact evaluation. Hence we implemented ESR to control for unobservable variables that affect both the adoption and outcome variables.

The ESR framework follows two stages. The first stage is estimation of the selection equation, the decision to adopt improved maize varieties. Following Khonje et al. (2015), the selection equation for the adoption of improved maize varieties is specified as:

$$ M_1^i = \beta X_i + u_i \text{ with } M_1 = \begin{cases} 1 & \text{if } M_1^i > 1 \\ 0 & \text{otherwise} \end{cases} $$

(3)

where $M_1^i$ is the latent variable for the adoption of improved maize variety and $M_1$ is its observable counterpart, $X_i$ are vectors of observed characteristics determining the adoption of improved maize varieties and $u_i$ is the error term. This stage of the ESR framework is estimated using a probit model. For the ESR model to be identified, it is important to include selection instruments that affect the adoption decision but not the welfare outcome variable (Shiferaw et al. 2014). Accordingly, we included agricultural cooperative membership, social responsibility of the head and frequency of extension contact as selection instruments by conducting a simple falsification test following Di Falco, Veronesi, and Yesuf (2011) and Khonje et al. (2015). The test results show that the identified instruments are jointly significant in explaining adoption [$\chi^2 = 147.12 \ (p = .000)$] but are not jointly significant in the outcome equation $[F = 1.72206 \ (0.1622)]$.

In the second stage of the ESR framework, an Ordinary Least Squares regression with selectivity correction is used to examine the relationship between the outcome variable and a set of explanatory variables conditional on the adoption decision. The two outcome regression equations faced by the farmers: to adopt (regimes 1) and not to adopt (regimes 2) conditional on adoption can be expressed as:

Regime 1 (Adopters): $w_{1i} = \alpha_1 J_i + e_{1i} \text{ if } M_1 = 1$, (4a)

Regime 2 (nonadopters): $w_{2i} = \alpha_2 J_{2i} + e_{2i} \text{ if } M_1 = 0$, (4b)

where $w_i$ is the consumption per adult equivalent in each regime, $J_i$ represents a vector of exogenous variables expected to affect consumption per adult equivalent and $e_i$ are random disturbances. The error terms given under Equations (3) and (4) are assumed to have a trivariate normal distribution, with zero mean and non-singular covariance matrix expressed as:

$$ \text{cov}(e_{1i}, e_{2i}, u_i) = 
\begin{pmatrix}
\sigma^2_{e1} & \sigma_{e1u} & 0 \\
\sigma_{e1u} & \sigma^2_{e2} & 0 \\
0 & 0 & \sigma^2_u
\end{pmatrix},
$$

where $\sigma^2_{e1}$ is the variance of the error term in the selection, $\sigma^2_{e2}$ are the variances of the error terms in the outcome functions, and $\sigma_{e1u}$ and $\sigma_{e2u}$ represent the covariance of $u_i e_{1i}$ and $e_{2i}$ (Khonje et al. 2015). An important implication of the error structure is that because the error term of the selection equation is correlated with the error terms of the outcome functions given under Equation (4a) and (4b), the expected values of $e_{1i}$ and $e_{2i}$ conditional on the sample selection are non-zero (Asfaw et al. 2012):

$$ E[e_{1i}|M_1 = 1] = \sigma_{e1u} \varphi(\beta X_i) - \Phi(\beta X_i) = \sigma_{e1u} \lambda_{1i}, $$

(5)

$$ E[e_{2i}|M_1 = 0] = \sigma_{e2u} \frac{\varphi(\beta X_i)}{1 - \Phi(\beta X_i)} = \sigma_{e2u} \lambda_{2i}, $$

(6)

where $\varphi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative density function, and $\lambda_{1i} = \frac{\varphi(\beta X_i)}{\Phi(\beta X_i)}$ and $\lambda_{2i} = \frac{\varphi(\beta X_i)}{1 - \Phi(\beta X_i)}$. $\lambda_{1i}$ and $\lambda_{2i}$ represent the inverse mills ratio calculated from the selection equation.

The average treatment effect of the treated, (ATT), and of the untreated, (ATU), can be obtained from the above ESR framework by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios. Following Di Falco, Veronesi, and Yesuf (2011) and Asfaw et al. (2012), the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios are computed as follows:

Adopters with adoption (observed in the sample)

$$ E[w_{11}|M_1 = 1; X] = X_{1i} \beta_1 + \sigma_{e1} \lambda_{1i}. $$

(7a)

Non-adopters without adoption (observed in the sample)

$$ E[w_{12}|M_1 = 0; X] = X_{1i} \beta_1 + \sigma_{e2} \lambda_{2i}. $$

(7b)

Adopters had they decided not to adopt (counterfactual)

$$ E[w_{21}|M_1 = 1; X] = X_{1i} \beta_2 + \sigma_{e2} \lambda_{1i}. $$

(7c)

Non-adopters had they decided to adopt (counterfactual)

$$ E[w_{21}|M_1 = 0; X] = X_{1i} \beta_2 + \sigma_{e1} \lambda_{2i}. $$

(7d)

Then ATT, which represents the effect of improved maize varieties on the consumption expenditure of the farm households that actually adopted the technology, is
calculated as the difference between (7a) and (7c):

$$\text{ATT} = E[w_{1i}|M_i = 1; X] - E[w_{2i}|M_i = 1; X]$$

$$= X_1\beta_1 + \sigma_1 \lambda_1 - X_1\beta_2 + \sigma_2 \lambda_1. \quad (8)$$

Similarly, we can calculate the ATU for the farm households that actually did not adopt improved maize varieties as the difference between (7d) and (7b) will give ATU:

$$\text{ATU} = E[w_{1i}|M_i = 0; X] - E[w_{2i}|M_i = 0; X]$$

$$= X_2\beta_1 + \sigma_1 \lambda_2 - X_2\beta_2 + \sigma_2 \lambda_2. \quad (9)$$

2.1.2. Propensity score matching

In addition to ESR, we also used PSM to check the robustness of the estimated treatment effect results from ESR for different assumptions. PSM helps to adjust for initial differences between the two groups by matching each adopter unit to a non-adopter unit based on similar observable characteristics (Rosenbaum and Rubin 1983). Therefore, the first step in PSM is to predict the propensity scores for each observation using a probit model using characteristics that are not affected by the treatment variable. The predicted propensity score indicates the probability of receiving treatment.

After predicting the scores, imposing the common support region is the next step in the PSM framework. The common support region is the area within the minimum and maximum propensity scores of treated (adopters) and comparison groups (non-adopters). This stage is followed by identification of an appropriate matching estimator. Caliendo and Kopeinig (2008) listed a number of matching estimators including the Nearest Neighbor (an individual from a comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score), Caliper (where an individual from the comparison group is chosen as a matching partner for a treated individual that lies within a given caliper) and Kernel (a non-parametric matching estimator use weighted averages of all individuals in the control group to construct the counterfactual outcome). The finally step is checking for matching quality whether the matching procedure can balance the distribution of different variables or not. If the matching quality is satisfied, ATT can be specified as the mean difference of consumption per adult equivalent of the adopters matched with non-adopters who are balanced on the propensity scores and fall within the region of common support, expressed as:

$$\text{ATT} = E(W_1|M = 1, M(X)) - E(W_0|M = 1, M(X)). \quad (10)$$

2.2. Estimation of TE under impact evaluation framework

To measure the impact of improved maize varieties on farm productivity, we considered the TE of farmers in maize production as our outcome variable. TE refers to the ability to produce the maximum feasible output from a given bundle of inputs (Farrell 1957; Xiaogang, Skully, and Brown 2005). Any deviation from this maximal output is considered as technical inefficiency (Coelli 1995).

Following the works of González-Flores et al. (2014) and Bravo-Ureta, Greene, and Solís (2012), we measured the impact of improved maize varieties on TE by combining the PSM technique with the Greene (2010) model to correct biases from observed and unobserved variables, respectively. Hence, the first step in this framework is to fit the stochastic production frontier (SPF) function. According to Greene (2010), the sample selection and SPF models, along with their error structures, can be expressed as follows:

Sample Selection: $M_i = 1[\alpha'z_i + \omega_i > 0]$, $\omega_i \sim N(0, 1)$

$$\text{SPF}: y_i = \beta'x_i + \epsilon_i, \epsilon_i \sim N(0, \sigma^2)$$

$(y_i, x_i)$ observed only when $M_i = 1$

Error Structure: $\epsilon_i = v_i - u_i$

$$u_i = |\sigma_0 U_i| = \sigma_0 |U_i|, \text{ where } U_i \sim N(0, 1)$$

$$v_i = \sigma_v V_i, \text{ where } V_i \sim N(0, 1)$$

$$(\omega_i, v_i) \sim N_2(0, 1), (1, \rho \sigma_0, \sigma^2_v), \quad (11)$$

where $M$ is a binary variable equal to one for adopters and zero for non-adopters, $y$ is the amount of maize produced, $z$ is a vector of covariates included in the sample selection equation, and $x$ is a vector of inputs in the production frontier, $\alpha$ and $\beta$ are parameters to be estimated; $V_\iota$ is the stochastic effects beyond the farmer’s control, measurement errors as well as other statistical noises and $u_i$ is the nonnegative random variable assumed to account for technical inefficiency in production. It is useful to underscore that the parameter $\rho$ captures the presence or absence of selectivity bias.

Since the stochastic frontier approach requires prior specification of the functional form of the production function, a log-likelihood ratio (LR) test was conducted to choose from Cobb–Douglas and Translog functional forms by testing the null hypothesis that the coefficients of all interaction terms and square specifications in the Translog functional forms are equal to zero using the following LR formula given by Coelli (1998):

$$LR = -2(LnL_{TL} - LnL_{CB}), \quad (12)$$
where $\ln L_{TL}$ and $\ln L_{CB}$ represent the log-likelihood function values obtained from the Translog and the Cobb–Douglas production function, respectively. The test result indicated that the coefficients of the interaction terms and the square specifications of the input variables under the Translog specifications are not significantly different from zero ($\chi^2 = 14.98$ ($p = 0.1328$)). As a result, the null hypothesis was accepted and the Cobb–Douglas functional form is selected for this study. Several studies have utilized Cobb–Douglas production including Bozoğlu and Ceyhan (2007); and González-Flores et al. (2014). The linear form of Cobb–Douglas production function is represented in Equation (13).

$$\ln y_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln x_{ij} + v_i - u_i$$

(13)

where $\ln$ denotes the natural logarithm; $y_i$ is the observed maize production of the $i$th farmer, $x_i$ is a vector of inputs used by the $i$th farmer, $\beta_j$ is a vector of unknown parameters while the characters in the error structure correspond to the typical characterization of a stochastic frontier model.

### 2.3. Measuring welfare

Welfare can be measured either from income or consumption expenditure perspectives. However, it is advised to measure welfare based on consumption expenditure in less-developed countries such as Ethiopia. This is because a household’s income is hard to measure in less-developed countries as much of it comes from self-employment. Besides, income can be a misleading indicator as it fluctuates due to transitory events such as layoffs or changes in family status, but such changes do not necessarily show changes in well-being (Wemmerus and Porter 1996). Whereas consumption is relatively less erratic, hence it is easier to estimate.

Consumption data also have additional information because consumption decisions are related to other household decisions such as nutrition and health (Atkinson 1992). Moreover, reports of household income are likely to be understated compared to consumption expenditures (Getahun and Villanger 2015). For instance, households may not remember everything they have sold, or money they have earned, within a year. They may also be unwilling to reveal their entire income for fear of taxation (Meyer and Sullivan 2003). Hence, they are more likely to report their expenditures than their income, as they are principally taxed on their income rather than their expenditures. Income measures may also be restricted by an unwillingness to reveal incomes earned from illegal and illicit activities such as contraband, corruption, prostitution etc.

The other candidate, consumption expenditure, is also not free from criticism. For instance, households are likely to understate what they have spent on luxuries and items such as alcohol, cigarettes, prostitution etc. (Meyer and Sullivan 2003).

Considering the strengths and drawbacks of each of the indicators, we measured welfare by using consumption expenditure per adult equivalent. To estimate the households’ consumption expenditure, we asked our respondents a range of questions on aggregate consumption expenditure on both food and non-food items. In this regard, both products that are purchased, and those that are consumed from own production are considered. The aggregated figure then re-estimated in a per-adult-per-annum basis. Previous works that used consumption per adult equivalent to measure wellbeing in Ethiopia include Abro, Alemu, and Hanjra (2014) and Alem and Söderbom (2012).

### 3. Study areas, sampling, data and description of variables

This study is undertaken in the eastern part of Ethiopia specifically in the East Hararge zone of Oromia regional state. The zone produces different types of agricultural products including cereals, pulses, oilseed, vegetables, fruits and cash crops such as coffee and khat. Among the cereal crops, maize is the dominant crop as both the size of land allocated to it and the number of households producing it was the highest compared to other crops produced. For instance, there were 424,811 farmers producing 1.33 million qt of maize on 55,380 ha of land with an average productivity of 24.06 qt/ha in 2014/15 production season (CSA 2015).

From the selected zone, two districts namely Haramaya and Girawa were selected for this study based on their extent of maize production. There are 33 and 19 rural kebeles3 in Haramaya and Girawa districts, respectively. From those kebeles, four kebeles were randomly picked from each district namely Jiru Gemechu, Hula Jeneta, Lencha and Rusu Jeneta were selected from Haramaya districts and Damota, Gobe Salma, Addele Waltaha and Tuji Gebisa are from Girawa district. Finally, 355 households (211 adopters and 144 non-adopters) were selected, using the simple random sampling technique with replacement4. The list of kebeles selected and size of sample size selected from each kebeles are indicated in Table 1.
4. Results and discussions

4.1. Descriptive statistics

Before embarking to the econometrics results, it is important to provide information regarding the sample respondents and variables used in the econometrics model. Accordingly, Table 2 presents the descriptive statistics of variables used for this study. The mean age of the sample respondents is about 38 years and on average they have cultivated maize for more than 16 years. Nearly 90% of the sample households are headed by males. Concerning their educational status, 63.1% of the respondents and 24.2% of the spouses are literate and, at least, are capable of writing and reading. The mean family size of the respondents is 6.81.

As far as their asset ownership, on average, they have 0.576 quintal of land per adult equivalent and 0.582 units of livestock measured by tropical livestock units (TLU) per adult equivalent. With reference to institutional variables, 37.2% of the respondents are facing credit constraints (they need credit but they are not getting it). About 22% of respondents are members of agricultural cooperatives and 31% of them have social responsibilities such as leadership in local institutions. Almost all of the respondents indicated that they have access to extension contact though the frequency of their contact differs. Accordingly, the mean frequency of extension contact is about 51 days per year. Among our respondents, 70.7% of them have confidence on the skill of the extension works. About half of them indicated that they have access to market information and nearly 60% of them have got training regarding maize production. The sample respondents, on average, travel about 35 and 20 minutes to reach the nearest market and farmers training center respectively.

4.2. Econometrics results

4.2.1. Estimation of the impact of adoption on welfare

In this subsection we will present results from both the ESR and PSM techniques. The result of the ESR model is reported in Table 3. The first and second column presents the consumption expenditure per adult equivalent for non-adopters and adopters, respectively; and the third column presents the estimated coefficients of selection on adopting improved maize varieties or not. The estimated coefficients of the selection terms are significantly different from zero suggesting both observed

| Variable                  | Combined (355) | Adopter (211) | Non-adopter (144) |
|---------------------------|---------------|---------------|-------------------|
|                          | Mean          | Std. Dev.     | Mean              | Std. Dev.     | Mean              | Std. Dev.     |
| Improvedseed              | 0.594         | 0.492         | 1                 | 0             | 0                 | 0             |
| Age_HH                    | 37.93         | 8.804         | 38.109            | 9.17          | 37.667            | 8.262         |
| Sex_HH                    | 0.896         | 0.306         | 0.91              | 0.287         | 0.875             | 0.332         |
| Education HH              | 0.631         | 0.483         | 0.668             | 0.472         | 0.576             | 0.496         |
| Education of spouse       | 0.242         | 0.429         | 0.237             | 0.426         | 0.25              | 0.435         |
| Maize Experience          | 16.4          | 9.194         | 16.564            | 9.323         | 16.16             | 9.028         |
| Agri Cooperative          | 0.217         | 0.413         | 0.261             | 0.44          | 0.153             | 0.361         |
| Confidence on Extension   | 0.707         | 0.456         | 0.834             | 0.373         | 0.521             | 0.501         |
| Social Responsibility     | 0.31          | 0.463         | 0.318             | 0.467         | 0.299             | 0.459         |
| Extension contact         | 50.921        | 40.672        | 57.322            | 44.358        | 41.542            | 32.503        |
| Access to Market info     | 0.487         | 0.501         | 0.578             | 0.495         | 0.354             | 0.48          |
| Training                  | 0.594         | 0.492         | 0.706             | 0.457         | 0.431             | 0.497         |
| Credit constraint         | 0.372         | 0.484         | 0.265             | 0.443         | 0.528             | 0.501         |
| Distance to market        | 34.64         | 21.716        | 30.456            | 18.877        | 40.772            | 24.093        |
| Distance to FTC           | 19.293        | 12.125        | 16.023            | 9.874         | 24.084            | 13.486        |
| Land per AE               | 0.576         | 0.434         | 0.598             | 0.415         | 0.544             | 0.46          |
| Livestock (TLU per AE)    | 0.582         | 0.409         | 0.556             | 0.362         | 0.621             | 0.469         |
| Family size               | 6.808         | 2.173         | 6.9               | 2.126         | 6.674             | 2.24          |
| Ln(annualconAE)           | 8.426         | 0.449         | 8.468             | 0.439         | 8.365             | 0.457         |
| Maize_yield               | 679.127       | 479.951       | 668.104           | 459.520       | 695.278           | 509.617       |
| Maize_area                | 2.055         | 1.432         | 1.950             | 1.360         | 2.208             | 1.523         |
| Maize_Fertilizer          | 32.069        | 29.828        | 36.301            | 29.170        | 25.868            | 29.796        |
| Maize_seed                | 6.533         | 4.608         | 6.177             | 4.305         | 7.053             | 4.988         |
| Maize_labour              | 27.476        | 16.683        | 26.582            | 15.771        | 28.785            | 17.911        |

Source: Authors’ calculation using the survey data.

| Districts | Kebele | Number | Percent |
|-----------|--------|--------|---------|
| Girawa    | Jiru Gemechu | 35    | 9.86    |
| Girawa    | Hula Jeneta   | 67    | 18.87   |
| Girawa    | Lencha        | 58    | 16.34   |
| Girawa    | Rasu Jeneta   | 40    | 11.27   |
| Haramaya  | Danno         | 48    | 13.52   |
| Haramaya  | Gobe Salma    | 46    | 12.96   |
| Haramaya  | Addele Waltaha| 21    | 5.92    |
| Haramaya  | Tuji Gebisa   | 40    | 11.27   |
| Total     |          | 355    | 100     |
and unobserved factors influence the decision to adopt modern agricultural technology and welfare outcome given the adoption decision.

The result of the selection equation reveals that the size of owned land is positively and significantly related to the adoption of improved maize varieties. This is justifiable because land indicates the capacity to purchase external inputs such as improved maize varieties as land is a proxy for wealth in rural area. This result is in line with the research of Wainaina, Tongruksa-wattana, and Qaim (2016).

Similar to the work of Khonje et al. (2015), our study also indicated that family size has a positive affect on the adoption of improved maize varieties. Credit constraints negatively influence the adoption of improved seed varieties, suggesting that liquidity-constrained households are less likely to adopt agricultural technologies that require cash outlays. This is plausible as timely availability of a production loan is essential for acquiring required inputs. This is also consistent with Feleke and Zegeye (2006). The other institutional variable which significantly determines the adoption of improved maize varieties is distance to farmers training centers. Access to market information also affects the adoption of improved seed varieties positively. This is again conceivable because the availability of market information will reduce transaction costs to farmers in the search to find markets for farm produce and inputs. A similar result is found in the work of Khonje et al. (2015).

The predicted values of the consumption expenditure per adult equivalent from ESR model are used to examine the impact of the adoption of improved maize varieties. Table 4 presents the ESR-based ATU and ATT of the adoption of improved maize varieties on consumption expenditure. Results show that the adoption of improved maize varieties increases consumption expenditure significantly. As shown in the Table, households that did not adopt, would also have benefited significantly had they adopted improved maize varieties.

To check the robustness of our ESR findings, we also adopted the PSM technique. The predicted scores used to match adopters with non-adopters ranges from 0.0972706 to 0.9179284. The propensity scores for non-members vary between 0.0972706 and 0.89544 and for adopters it varies between 0.2310169 and 0.9179284. Thus, the common support region, where the values of propensity scores of both treatment and comparison groups found is between 0.2310169 and 0.89544. This region of common support for the propensity scores is also clear from the density distribution for the two groups of adopters and non-adopters (Figure 1).

Table 3. Estimates of the ESR.

| Variables                  | Coef (Non-adaptors) | Coef (adopters) | Selection | Marginal effect |
|----------------------------|---------------------|-----------------|-----------|-----------------|
| Age_HH                     | -0.007              | -0.013**        | -0.008    | -0.003          |
| Sex_HH                     | 0.109               | 0.007           | 0.244     | 0.076           |
| Education HH               | 0.019               | 0.001           | 0.026     | 0.008           |
| Education of spouse        | 0.086               | -0.033          | 0.048     | 0.015           |
| Agri Cooperative           | 0.123               | 0.181*          | 0.233     | 0.072           |
| Social Responsibility      | -0.038              | -0.066          | -0.214    | -0.066          |
| Maize Experience           | -0.003              | 0.001           | -0.003    | -0.001          |
| Extension contact          | 0                   | 0.001           | 0.001     | 0.000           |
| Access to Market info      | 0.130*              | 0.11            | 0.029***  | 0.198           |
| Training                   | 0.166**             | 0.121           | 0.209     | 0.065           |
| Credit constraint          | -0.136*             | -0.098          | -0.459*** | -0.142          |
| Distance to market         | -0.001              | 0               | -0.006    | -0.002          |
| Land per AE                | 0.363***            | 0.285***        | 0.945**   | 0.293           |
| Square of Age_HH           | 0.116               | 0.296***        | -0.168    | -0.052          |
| Family size                | 0                   | 0               | 0.198     | 0.045           |
| Confidence on Extension    | 0.105               | 0.121           | 0.209     | 0.065           |
| Distance to FTC            | -0.019***           | 0.006           | -0.006    | 0.002           |
| Square of Land per AE      | -0.217              | 0.141           | -0.067    | 0.043           |
| Square of Livestock (TLU)  | -0.083              | 0.249           | -0.026    | 0.077           |
| Cons                       | 8.013***            | 8.703***        | 7.895***  | 0.557           |
| Sigma                      | -0.725***           | -0.795***       | -1.055    | 0.799           |
| Rho                        | 1.313***            | 1.019***        | 0.246     |                 |

Source: Authors’ calculation using the survey data.
Note: ***, ** and * significant at 1%, 5% and 10% probability level, respectively.

Table 4. ESR-based average treatment effects of adoption of improved maize varieties.

| Farm households’ type and treatment effects | To adopt | Not to adopt | ATT |
|--------------------------------------------|----------|--------------|-----|
| Farm households that adopted (ATT)         | 8.917    | 8.482        | 0.435*** |
| Farm households that did not adopt (ATU)   | 8.356    | 7.799        | 0.557*** |

Source: Authors’ calculation using the survey data.
***significant at 1% probability level.
As emphasized by Rosenbaum and Rubin (1983) and DiPrete and Gangl (2004), ensuring the balancing condition is a crucial issue in PSM as it reduces the influence of confounding variables. Hence, we conducted a covariate balancing tests and the result is presented in Table 5. The result shows that the standardized mean difference for overall covariates used in the estimation process reduced from 32.40% before matching to a range of 3.5–6.1% after matching. The total bias also reduced significantly via the matching process. Moreover, the p-values of the LR tests show the joint significance of all covariates in the probit model after matching, which was insignificant before matching. The pseudo-$R^2$ was also reduced significantly from 12.9% before matching to a range of 0.5–0.8% after matching and was fairly low, indicating that after matching there were no systematic differences in the distribution of covariates between the two studied groups. Hence specification of the propensity score estimation process is successful regarding balancing the distribution of covariates between adopters and non-adopters.

After ensuring the common support area and verifying the matching quality of our PSM model, we then analyzed the impact of the adoption of improved maize varieties on consumption per adult equivalent using three different algorithm techniques. All the analyses were based on the implementation of common support, so that the distributions of adopter and non-adopter units were located in the same domain. Bootstrap standard errors based on 100 replications are reported. As presented in Table 6, the adoption of improved maize varieties positively and significantly increases consumption expenditure per adult equivalent. The increase in consumption expenditure per adult equivalent ranges from 14.4% to 19.2%. Other studies also indicated similar links between the adoption of improved seed varieties and welfare improvement in different parts of the world (Mendola (2007) in

![Figure 1. Common support for propensity score. Treated on support indicates the individuals in the adoption group who find a suitable match, whereas treated off support indicates the individuals in the adoption group who did not find a suitable match and Untreated indicates non-adopters.](image)

### Table 5. Matching quality indicators before and after matching.

| Matching algorithm      | Pseudo-$R^2$ | LR chi$^2$ | $p >$ chi$^2$ | Mean standardized bias |
|-------------------------|--------------|------------|---------------|------------------------|
|                         | Before       | After      | Before        | After                  | Before         | After     | Total % bias reduction |
| Nearest neighbor        | 0.129        | 0.005      | 61.84         | 2.69                   | 0.00           | 0.975     | 32.4                 | 3.5       | 98.7                  |
| Radius matching         | 0.129        | 0.008      | 61.84         | 4.57                   | 0.00           | 0.87      | 32.4                 | 6.1       | 99.8                  |
| Kernel matching         | 0.129        | 0.006      | 61.84         | 3.14                   | 0.00           | 0.958     | 32.4                 | 3.7       | 96.7                  |

Source: Authors’ calculations using the survey data.
Bangladesh, Khonje et al. (2015) in Zambia and Asfaw et al. (2012) in Tanzania and Ethiopia).

4.2.2. Estimation of the SPF and measuring TE

We started by examining whether a single conventional SPF could represent the two groups (adopters and non-adopters) or whether a separate SPF should be used for each of them. To determine this, we conducted a LR test based on the following specification:

\[
LR = -2 \times (\ln L_P - (\ln L_A + \ln L_N)),
\]

where \(\ln L_P\), \(\ln L_A\) and \(\ln L_N\) represent the log-likelihood function values obtained from the pooled data set, the adopters and the non-adopters subsamples, respectively.

Hence, we first estimated a SPF with pooled data by including a binary variable, \(\text{Improvedseed}\), as a regressor, which indicates whether the household adopted improved maize varieties or not and then two separate SPF models, one for adopters and a second one for non-adopters, are estimated. The result of the LR test rejected the assumption of a single SPF in favor of separate frontiers for each groups indicating that the two groups have different production functions [\(\chi^2 = 27.26\) (\(p = .000\)). Then, to correct for the possible bias from observable heterogeneities, we re-estimated the above three frontiers (pooled, adopters and non-adopters) using the matched data set. However, results of the LR test again supported separate frontiers for each group. Finally, to correct for the possible bias from unobservables, two separate SPF models were re-estimated using Greene’s (2010) selection correction framework. The results of the SPF models are presented in Table 7 for the unmatched samples and in Table 8 for the matched samples.

The estimated value of sigma is significant at less than one percent probability level for all frontier functions indicating the conventional average production function is not an adequate representation of the data. The coefficient of Rho, which indicates the presence of selection bias, is also significant for the non-adopters in the case of the unmatched data, which suggests the presence of selection bias, which supports the use of a sample

| Table 6. PSM -based average treatment effects of the adoption of improved maize varieties. |
|----------------|----------------|----------------|----------------|
|                | Treated        | Controls       | Difference     | S.E.          |
| Nearest neighbor | 8.466          | 8.322          | 0.144**        | 0.058         |
| Radius matching  | 8.468          | 8.276          | 0.192**        | 0.065         |
| Kernel matching  | 8.466          | 8.32           | 0.146**        | 0.057         |

Note: ** significant at 5% probability level.

| Table 7. Conventional and selection SPF based on unmatched observation. |
|----------------|----------------|----------------|----------------|
| Variables      | Pooled         | Adopter        | Non-adopter    |
|                | coef se        | coef se        | coef se        |
| Cons           | 5.393***       | 0.202          | 5.095***       | 0.362         |
| Ln(Maize_seed) | 0.524***       | 0.175          | 0.760**        | 0.322         |
| Ln(Maize_area) | 0.456***       | 0.176          | 0.201          | 0.321         |
| Ln(Maize_labour)| 0.001          | 0.023          | 0.018          | 0.029         |
| Ln(Maize_Fertilizer)| 0.003*** | 0.001          | 0.004***       | 0.001         |
| Improvedseed   | 0.026*         | 0.014          |                |               |
| Sigma²         | 0.090***       | 0.007          | 0.065***       | 0.007         |
| Sigma(u)| 0.127***       | 0.016          |                |               |

| Table 8. Conventional and selection SPF based on matched observations. |
|----------------|----------------|----------------|----------------|
| Variables      | Pooled         | Adopter        | Non-adopter    |
|                | coef se        | coef se        | coef se        |
| Cons           | 5.375***       | 0.226          | 5.095***       | 0.362         |
| Ln(Maize_seed) | 0.498***       | 0.187          | 0.760**        | 0.322         |
| Ln(Maize_area) | 0.467***       | 0.192          | 0.201          | 0.321         |
| Ln(Maize_labour)| 0.017          | 0.026          | 0.018          | 0.029         |
| Ln(Maize_Fertilizer)| 0.002*** | 0.001          | 0.004***       | 0.001         |
| Improvedseed   | 0.028**        | 0.014          |                |               |
| Sigma²         | 0.083***       | 0.007          | 0.065***       | 0.007         |
| Sigma(u)| 0.134***       | 0.017          |                |               |

| Source: Authors’ calculation using the survey data. Note: ***, ** and * significant at 1%, 5% and 10% probability level, respectively.
selection framework to estimate separate SPF s for the adopters and control groups.

After estimating the SPF corrected for both observed and unobserved heterogeneities, we predicted the TE score of each sample respondent. Table 9 summarizes the distribution of TE scores for both adopters and non-adopters. Accordingly, the TE score ranges between 39.77% and 99.21% with the mean value of 82.34%. The corresponding figure for non-adopters ranges between 39.41% and 97.80% with a mean score of 79.54%. The result also indicates a significant mean difference between the two studied groups. Specifically, the result reveals farmers who adopt improved maize varieties have 4.42% of TE gain compared with their non-adopter counterparts.

Table 9. TE scores after bias correction.

| Groups    | Mean   | Std. Dev. | Min   | Max   |
|-----------|--------|-----------|-------|-------|
| Adopters  | 0.8396 | 0.1258    | 0.3977| 0.9921|
| Non-adopters | 0.7954 | 0.1535    | 0.3941| 0.9780|
| Mean difference | 0.0442*** |

Source: Authors’ calculation using the survey data.
Note: ***significant at 1% probability level.

5. Conclusion

This paper analyzed the impact of improved maize varieties on the productivity and wellbeing of smallholder farmers using a primary data collected from the eastern part of Ethiopia. We combined parametric and semi-parametric estimation techniques to control for selection bias that could arise either from observable or non-observable variables so that we can find the true impact of improved maize varieties. Accordingly, we combined PSM method with ESR to estimate the impact on the welfare of farmers, measured as consumption per adult equivalent, and we adopted a sample selection corrected stochastic frontier developed by Greene (2010) to measure the impact on farm productivity.

The result obtained from both PSM and ESR models shows that the adoption of improved maize varieties leads to significant gains of consumption expenditure per adult equivalent. More importantly, the results showed that non-adopters would have gained from the adoption of improved maize varieties. The study also indicated that those farmers who adopt improved maize varieties have a significant TE gain compared with their non-adopter counterparts.

This significant impact of improved maize varieties is an interesting result for two reasons: firstly, maize is among the main cereal crop produced by smallholder farmers in Ethiopia as it accounts for the largest share of production by volume and it is produced by more farmers than any other crop in the country. The number of households who grew maize increased by 3.5% each year between 2004 and 2013 (Abate et al. 2015). Hence, it can significantly contribute to the economic and social development of smallholder farmers. Secondly, the eastern Hararghe zone, where this study was conducted, is known for its high population density and sustainable intensification using modern inputs is the only option available to increase food production.

The findings of the study stress the need for appropriate policy formulation and implementation which improves the adoption of productivity enhancing technologies in general and improved maize varieties in particular since it has multiplier effects ranging from farm productivity growth to economic growth and poverty reduction.

Notes

1. Following Byerlee et al. (1994), both hybrids and open pollinated varieties whose traits have been enhanced for selected characteristics including drought tolerance, disease resistance, early maturing, increased productivity are considered for this study as improved seed varieties.
2. Besides, we also followed the step-wise approach where each new instrument is added one at a time to see if it adds any new information. We thank an anonymous reviewer for bringing this issue to our attention.
3. Kebele is the smallest administrative hierarchy in Ethiopia.
4. Every kebele administration has a full list of households living in the area. We used this list as a sample frame. When the randomly selected farmer does not produce maize s/he was replaced by the farmer next to him/her on the list.
5. List and definition of variables used for this study is presented under Table: A1
6. quxi is a local measurement unit equivalent with 1/8 of a hectare
7. To see how adult equivalent and TLU are computed, refer to Table A2 and Table A3, respectively.
8. Ethiopian currency; One USD was equivalent with 21.21 ETB in the time of data collection.

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Appendix

Table A1. List and definition of variables used for this study.

| Variable          | Unit    | Definition                                                                 |
|-------------------|---------|-----------------------------------------------------------------------------|
| Improved seed     | Dummy   | 1 if the farmers adopted improved maize varieties; 0 otherwise.             |
| Age_HH            | Years   | Number of years the household head lived                                   |
| Sex_HH            | Dummy   | 1 if the household is male; 0 otherwise                                    |
| Education HH      | Dummy   | 1 if the household head is literate; 0 otherwise                           |
| Education of spouse| Dummy | 1 if the spouse of the head is literate; 0 otherwise.                     |
| Maize Experience  | Years   | Number of years the household head cultivated maize                       |
| Agri Cooperative  | Dummy   | 1 if the household is member of agricultural cooperatives; 0 otherwise    |
| Confidence on Extension | Dummy | 1 if the household has confidence on the skill of the extension agents; 0 otherwise |
| Social Responsibility | Dummy | 1 if the household social responsibilities; 0 otherwise                    |
| Extension contact | Days    | Number of contacts with the extension agent per year                       |
| Access to Market info | Dummy | 1 if the household has access to market information; 0 otherwise         |
| Training          | Dummy   | 1 if the household gets training regarding maize production; 0 otherwise  |
| Credit constraint | Dummy   | 1 if the household faces credit constraints; 0 otherwise                  |
| Distance to market| Minute  | Walking distance between the house of the respondent and the nearest market |
| Distance to FTC   | Minute  | Walking distance between the house of the respondent and farmers training center |
| Land per AE       | quxi    | Size of land owned per adult equivalent                                     |
| Livestock (TLU) per AE | TLU | Size of livestock owned per adult equivalent                               |
| Family size       | Number  | Number of family members                                                   |
| Ln(anualconAE)    | birr⁷   | Annual consumption expenditure per adult equivalent                         |
| Maize_yield       | Kg      | Physical amount of maize produced                                           |
| Maize_area        | quxi    | Size of land that allocated to maize production                             |
| Maize_Fertilizer  | kg      | Amount of fertilizer used for maize production                              |
| Maize_seed        | kg      | The quantity of maize seed that used                                       |
| Maize labour      | Man-equivalent | Both family and hired labor used for different agronomic practices of maize production |

Table A2. Conversion factor for computation of adult equivalent.

| Age group (years) | Male | Female |
|-------------------|------|--------|
| <10               | 0.6  | 0.6    |
| 11–13             | 0.9  | 0.8    |
| 14–16             | 1    | 0.75   |
| 17–50             | 1    | 0.75   |
| >50               | 1    | 0.7    |

Source: Storck et al. (1991).

Table A3. Conversion factors used to estimate tropical livestock unit (TLU) equivalents.

| Animal category    | TLU  |
|--------------------|------|
| Calf               | 0.25 |
| Donkey (young)     | 0.35 |
| Weaned calf        | 0.34 |
| Camel              | 1.25 |
| Heifer             | 0.75 |
| Sheep and goat (adult) | 0.13 |
| Cow and ox         | 1    |
| Sheep and goat (young) | 0.06 |
| Horse              | 1.1  |
| Chicken            | 0.013|
| Donkey (adult)     | 0.7  |

Source: Storck et al. (1991).