# Technology adoption and technical efficiency in maize production in rural Ethiopia

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## Abstract

*Farm efficiency analysis provides significant insights into farms' potential to enhance agricultural productivity. This article reports on an investigation of technology adoption and technical efficiency (TE) in the Ethiopian maize sector. We estimated TE while accounting for the potential technological difference between improved and local maize varieties and addressing self-selection bias resulting from farmers' decisions to adopt new crop varieties. Using comprehensive household-level data collected in 2011 from five major maize-producing regions in Ethiopia, we specified a stochastic frontier model to estimate TE and employ propensity score-matching technique to address self-selection bias. The result confirm that imposing a homogenous technology assumption for improved and local maize varieties biases efficiency estimates and the ranking of farmers based on their efficiency scores. The mean TE of 66.18%, estimated after correcting for technology difference and self-selection bias, indicated that an increase of around 33.82% in maize productivity could be achievable with the current input levels and technology.*

**Key words**: technology adoption; technical efficiency; improved maize; propensity score matching; Ethiopia

## 1. Introduction

Although agriculture remains the primary source of food and livelihood for rural households in many developing countries, its contribution to food security and poverty reduction is minimal. Particularly in sub-Saharan Africa, where the majority of the rural population relies on agriculture for livelihood purposes, the massive gap between food production and consumption has made the region one that is characterised by severe food shortages. Because farm efficiency analysis provides significant insights into farms' potential to enhance agricultural productivity, estimating farm efficiency has been a subject of considerable interest to researchers in the past few decades. There are a growing number of studies examining efficiency in crop production within the context of developing countries (see Coelli *et al*. 2002; Alene & Hassan 2006; Haji 2007; Ndlovu *et al*. 2014). In many of the previous studies, however, the focus has been on estimating efficiency without accounting for potential technological differences in crop production. Such an approach could bias efficiency estimates and potentially could lead to inappropriate policy choices. Tsionas (2002) argues that the failure to adequately account for technology differences may yield biased estimates of technical efficiency (TE). For Mayen *et al*. (2010), this failure may bias the TE modelling and estimations. The focus on estimating efficiency while controlling for the potential technology differences is therefore crucial for implementing effective policies for enhancing crop productivity.

As argued by Alene and Manyong (2007), when farmers have access to different crop technologies that have different output potentials, estimating aggregate production function assumes that the conventional and non-conventional inputs are independent of the farmers' technology adoption decision-making. Despite the presence of considerable differences in the adoption of yield-enhancing crop technologies in smallholder crop production, the approach to analyse farm efficiency has traditionally been to employ an aggregate production function that implicitly assumes homogenous technology. Some exceptions are Alene and Hassan (2006), Aye and Mungatana (2011) and Ndlovu *et al*. (2014), who investigated the impact of agricultural innovation efficiency in smallholder crop production. Although these studies attempted to account for the differences in crop varieties by assuming different production frontiers for adopters and non-adopters, a major limitation is that the studies ignore the self-selection bias resulting from farmers' decisions to adopt new crop varieties. Further, these studies assumed different frontiers for adopters of a given crop technology and local crop growers, without conducting a formal test to discover whether the two varieties are indeed different.

The current article makes two important contributions to the growing body of knowledge on farm efficiency. First, we estimate technical efficiency by correcting for the influence of the potential technological difference between improved maize variety (IMV) and local maize variety (LMV). By identifying adopters and non-adopters of IMV, we examine to what extent efficiency results (the parameter estimates and TE estimates) can be affected by the failure to account for technological differences between crop varieties. Second, we provide new empirical evidence on the link between technology adoption and farm efficiency by correcting for self-selection in the modelling of efficiency using the propensity score-matching (PSM) technique. Previous studies on the efficiency of the maize sector in Ethiopia are scarce and, if available, limited to a specific region or zone (see, for example, Seyoum *et al*. 1998; Alene & Hassan 2006; Haji 2007). A recent meta-analysis of efficiency studies on Ethiopian crop sub-sector (see Geffersa *et al*. 2019) indicates that most of the previous national-level studies focused on estimating household-level efficiency by integrating outputs from multiple crops. To the best of the authors' knowledge, this is the first crop-specific efficiency study at the national level in Ethiopia. We extend and complement the policy implications of previous studies using comprehensive and nationally representative household-level data collected from about 2 000 maize farmers in Ethiopia.

## 2. Methodological approach

### 2.1 Theoretical framework

We employed the non-separable farm-household theoretical model of Singh *et al*. (1986) to understand farmers' decisions to adopt IMV, in combination with a production frontier approach proposed by Farrell (1957). Due to the market imperfections prevalent in developing countries, we assume, following Singh *et al*. (1986), that household $i$'s maize production and consumption decisions are non-separable. The household produces maize for its own consumption and for sale to maximise profit (π):

$$\pi_i = f(p_M, M_i, w_x), \tag{1}$$

where $p$ and $w$ are output and input price vectors respectively. $M_i$ is a maize output, which is a function of farm inputs ($X_i$) and IMV adoption:

$$M\_i = f(X\_i, I\_i). \tag{2}$$

For each maize farm, a decision to grow IMV depends on optimising the expected return, which can be reflected through yield gains. Thus, household $i$ adopts IMV if the expected utility from adopting ($U_I$) is higher than the expected utility from dis-adopting ($U_0$). As the utilities are unobservable, we use a latent variable, $IMV_i^*$, which captures the benefit of adopting:

$$\mathrm{IMV}_i^* = z_i\alpha + e_i \quad for \quad \left\{ \mathrm{IMV}_i = \begin{matrix} 1 \text{ if } z_i\alpha + e_i > 0 \\ 0 \text{ otherwise} \end{matrix} \right., \qquad U_I - U_0 > 0, \tag{3}$$

where $IMV_i$ is a binary variable (= 1 if a farmer adopts IMV; 0 otherwise), which is a function of exogenous variables $(z)$, and $e_i$ is an error term.

To model TE in maize production, we re-specify the production function in a frontier production framework, following Farrell (1957):

$$M_i = f(X_i, IMV_i;\ \beta, \theta) + \varepsilon_i, \tag{4}$$

where $M_i$ denotes the maximum possible maize output,
$X_i$ is an input vector,
$\beta$ denotes a vector of parameters corresponding to production inputs,
$\theta$ captures the productivity gain resulting from the yield-enhancing effect of IMV, and
$\varepsilon_i$ is a composed error term.

To account for the stochastic nature inherent in agricultural production, we adopted a stochastic frontier (SF) approach to estimate TE. Compared with other, alternative frontier methodologies such as the deterministic frontier model and data envelopment analysis, there is a predominance of farm efficiency studies using the SF model because it is capable of disentangling inefficiency from random noise. The non-parametric approaches, on the other hand, ignore random errors, thereby attributing all deviations from the frontier to inefficiencies. This assumption is restrictive in the context of smallholder agriculture, because the sector is susceptible to stochastic factors such as rainfall variability, natural hazards and pests (Battese 1992). The added advantage of the SF approach is that it allows estimating parameters and conducting hypothesis testing. This attractive feature of the SF approach permits directly testing the influence of the technology variable using the parameter estimates by introducing a categorical variable that characterises the production technology (i.e. IMV in our case). The general SF model proposed by Aigner *et al*. (1977) can be specified as:

$$M_i = \mathrm{f}(X_i;\ \beta)\exp(\varepsilon_i), \tag{5}$$

where $\varepsilon_i$ is a composed error term, $= v_i - u_i$; $v_i$ is the disturbance error term that is independently and identically distributed (*i.i.d.*) as $v_i \sim N(0, \sigma_v^2)$ and intended to capture events beyond the control of the farmers; and $u_i$ is a non-negative random variable intended to capture technical inefficiency. Assuming $u_i$ to have a half-normal or exponential distribution, the $TE_i$ score for $i^{th}$ farmer is measured as the ratio of observed output to maximum feasible output: $TE_i = \exp(-u_i)$.

### 2.2 Empirical stochastic frontier (SF) model

#### 2.2.1 Empirical model specification and estimation issues

Our empirical model was specified following the SF specification proposed by Coelli *et al*. (1999) that accommodates 'environmental factors'. This model makes it possible to account for factors that are not directly related to the farm production process but are assumed to affect farmers' production performance in the production frontier. Thus, it allows for incorporating variables such as a soil quality indicator and a technology dummy (IMV) directly into the production frontier. The general empirical model is specified as:

$$M_i = \{f(X_i, IMV_i, LandQuality_i;\ \beta, \theta)\} + v_i - u_i, \tag{6}$$

where $f(.)$ represents the appropriate maize production function and
$LandQuality_i$ denotes an average land quality index for household $i$.

One of the recent extensions to include potential exogenous inefficiency variables in the stochastic frontier framework involves directly parameterising the variance of the inefficiency term by treating the efficiency determinants as heteroscedastic in the inefficiency function (see Kumbhakar & Lovell 2000; Wang 2002; Hadri *et al.* 2003). This approach ensures consistency in the SF parameter estimates and TE estimates because it relaxes the restrictive assumption of homoscedasticity in the variance of the inefficiency term imposed by earlier SF models (Kumbhakar & Lovell 2000; Wang 2002). This extension is analogous to a one-step estimation procedure, which allows the simultaneous estimation of the frontier parameters and the parameters of the inefficiency variables.

As argued by Kumbhakar and Lovell (2000), heteroscedasticity is a serious issue in an SF model because it could occur in both random terms (disturbance term and inefficiency component). We therefore generalised Coelli *et al.*'s (1999) specification in Equation 6 to allow for heteroscedasticity in the variances of both terms ($v_i$ and $u_i$) following a double-heteroscedasticity approach proposed by Hadri *et al.* (2003). Formally, the specification in Equation 6 is extended as:

$$M_i = \{f(X_i, LandQuality_i, IMV_i;\ \beta, \theta)\} + v_i - u_i \tag{7}$$

$$\sigma_{ui}^2 = \exp\,(\delta Z_i') \tag{7a}$$

$$\sigma_{vi}^2 = \exp\,(\eta Z_i'), \tag{7b}$$

where $Z_i'$ is a vector of exogenous variables expected to determine inefficiency,
$\sigma_{ui}^2$ is the variance of the inefficiency term,
$\sigma_{vi}^2$ is the variance of the inefficiency term, and
$\delta$ and $\eta$ are parameters to be estimated.

### 2.2.2 Empirical model parameterisation and variables

There is considerable debate about the selection of an appropriate functional form in SF modelling, with the Cobb-Douglas and translog forms being the most widely used (Abdul-Salam & Phimister 2017). As a result of its computational simplicity, the Cobb-Douglas functional form has been used most commonly. Given its flexibility, a translog functional form can be interpreted as a true representation of any underlying production frontier (Battese 1992). Based on this argument, and a likelihood ratio (LR) test[1] that supported the translog functional form, we specified Equation 7 using a translog specification.

The first specification, which imposes a homogenous technology assumption by assuming an aggregate production function for IMV and LMV, is specified as:

[1] Based on the LR test statistic of 211.96 ($P < 0.01$), with the degrees of freedom equal to the number of parameters, a null hypothesis that the coefficients of all interaction and squared terms in the translog function are equal to zero ($H_0$: $\beta_{jk} = 0$) was rejected.

$$lnM_i = \beta_0 + \sum_{j=1}^{7} \beta_j lnX_{ij} + \sum_{j=1}^{7}\sum_{k=1}^{7} \beta_{jk} \left(lnX_{ij}\right)(lnX_{ik}) + \mu_i lnLandQuality_i + (\mathrm{v_i} - \mathrm{u_i}), \tag{8}$$

where $lnM_i$ denotes the log of the total maize output (in kg) obtained from the $i^{th}$ farmer,
$X_i$ denotes a vector of input variables,
$\left(lnX_{ij}\right)(lnX_{ik})$ denote the squared and interaction terms,
$\beta_0, \beta_j, \beta_{jk}$ and $\mu_i$ are parameters to be estimated,
And all other terms are as defined above.

### 2.3 Accounting for technological heterogeneity and self-selection

The frontier production function can differ for farmers producing IMV and LMV due to the different yield potentials and complementary services associated with the technology package. We account for such a potential technological difference by introducing a technology dummy (IMV) in the SF model, along with its interactions with production inputs, denoted by $(lnX_{ij})(IMV_{ij})$. As such, we extend the SF specification in Equation 8 that imposes a homogenous technology assumption to allow for different technologies for IMV and LMV:

$$\begin{aligned} lnM_i = {} & \beta_0 + \sum_{j=1}^{7} \beta_j lnX_{ij} + \frac{1}{2}\sum_{j=1}^{7}\sum_{k=1}^{7} \beta_{jk} (lnX_{ij})(lnX_{ik}) + \mu_i lnLandQuality_i + \theta_1 IMV_i \\ & + \frac{1}{2}\sum_{j=1}^{7} \theta_j (lnX_{ij})(IMV_{ij}) + (\mathrm{v_i} - \mathrm{u_i}) \end{aligned} \tag{9}$$

$$\sigma_{ui}^2 = \exp\,(\delta Z_i') \tag{9a}$$

$$\sigma_{vi}^2 = \exp\,(\eta Z_i') \tag{9b}$$

The inclusion of a technology adoption variable would present a potential endogeneity problem due to self-selectivity by the farmers, as the two groups of farmers may differ systematically in terms of certain household and farm characteristics. To address this, we employed a propensity score-matching (PSM) technique that accounts for differences in observed covariates between adopters and non-adopters of IMV. The basic idea behind the PSM procedure is estimating the probability or the propensity score (p-score) for the farmers based on their socio-economic characteristics. The empirical process follows a three-step procedure. The first step involves estimating a probability model for producing IMV and estimating p-scores for each farmer growing LMV. Following Imbens and Wooldridge (2009), the p-score is defined as:

$$P(y = 1|X) \equiv Pr\left(Ti = 1\middle|x_1, x_2 \ldots., x_j\right) = E[Ti|Xi], \tag{10}$$

where y is a response variable representing technology adoption, x denotes a set of explanatory variables for a given farm household, and $T$ refers to a technology. The prediction of p-scores follows a non-linear binary (probit or logit) model:

$$\mathrm{IMV_i^*} = \mathrm{Z_i}\alpha + \psi_\mathrm{i} \quad for \quad \left\{ \mathrm{IMV_i} = \begin{array}{l} 1 \text{ if } \mathrm{Z_i}\alpha + \mathrm{u_i} > 0 \\ 0 \text{ otherwise,} \end{array} \right. \tag{11}$$

where $IMV_i$ is a binary variable as defined above,

Z is a vector of factors that may influence farmers' adoption decision, and
$\psi_i$ is an error term assumed to be normally *i.i.d.*, with mean 0 and variance $\sigma^2$.

In the second step, we used the p-scores to compare the outcomes from IMV growers (treated) and LMV growers (untreated) with the most similar characteristics. Finally, we matched the LMV subsample using the predicted p-scores (i.e. the propensity to produce IMV). All other LMV producers were discarded from further analysis. As such, we created an approximation of a condition in which the two groups of farmers could be comparable in terms of observable characteristics. Although PSM eliminates the baseline differences between IMV and LMV farmers, it fails to account for the unobservable variables that may influence the choice of technology. To minimise concerns about possible unobservable heterogeneity that could influence the choice of maize varieties, we included region dummies to control for potential region-level fixed effects.

## 3. Data source and variables

The dataset for this study comes from a survey conducted in Ethiopia by the International Maize and Wheat Improvement Centre (CIMMYT) in collaboration with the Ethiopian Institute of Agricultural Research. CIMMYT conducted the survey in 2011 as part of the project known as the Sustainable Intensification of Maize-Legume Cropping Systems for Food Security in Eastern and Southern Africa. The survey employed a multi-stage sampling technique. The first stage involved a purposive selection of 39 districts from the five major maize-producing regions of Ethiopia (Tigray, Amhara, Oromia, Benshangul-Gumuz and SNNP).[2] The agro-ecological potential for maize production was used as an important criterion to select sample districts. In the second stage, 74 *kebeles*[3] were randomly chosen with a probability proportional to size. In the final stage, 2 454 maize farmers were interviewed. The dataset consists of information on maize production and input use, technology adoption, and socioeconomic and farm characteristics. Out of the total of 2 454 maize-producing farm households, 2 364 households were left after the data-cleaning process. Table 1 presents a description of the variables. Hybrid varieties, improved open-pollinated varieties (OPV), and local open-pollinated varieties (Zeng *et al*. 2015) are the commonly grown maize varieties in Ethiopia. Based on previous studies (e.g. Zeng *et al*. 2015) and consultation with expert maize breeders from CIMMYT, this study differentiates the maize varieties as either *improved* or *local* (recycled or OPV that has been recycled).[4] We used seven conventional inputs for maize production to estimate our SF model.

The descriptive results show that there is a large output difference between farmers who produced IMV and those who produced LMV. The mean output for IMV (mean = 2 821.8 kg) is more than twice that of the mean output from LMV production. This indicates a potential technological difference between the two maize varieties. Aside from the direct inputs of production, we used a land quality index ($LandQuality$) to capture the differences in plot quality characteristics. Following Abro *et al*. (2014), a composite variable was created using both slope and nutrient status indicators reported by the farmers.[5] Potential inefficiency factors included as heteroscedastic variables in the inefficiency function are also described in Table 1.

[2] SNNP stands for the Southern Nations, Nationalities, and People's Region.
[3] *Kebele* refers to the lowest administrative unit in Ethiopia.
[4] OPVs and any hybrid the farmer recycled for more than three cropping seasons is categorised as local (Zeng *et al.* 2015).
[5] Prior to indexing, values of 1 for a flat slope, 2 for a medium slope and 3 for a steep slope were assigned to every plot. Similarly, if the soil fertility was good, we assigned a value of 1; if medium, we assigned a value of 2; and if bad, we assigned a value of 3. Finally, a quality indicator was developed by multiplying the slope and fertility indicators in such a way that a plot with a value of 1 had the best land quality, while a plot with the lowest quality had a value of 9. According to our coding, a higher value indicated lower land quality.

**Table 1: Descriptive statistics of variables used in the efficiency estimations (N = 2 364)**

| Variables | Variable descriptions | Mean |
|---|---|---|
| ***SF production variables*** | | |
| *Output* | Maize output (in kg): Pooled sample | 2 485.20 (19 232.00) |
| | IMV growers | 2 821.80 (21 121.50) |
| | LMV growers | 876.80 (1 634.40) |
| ***Inputs*** | | |
| Labour | The total family and hired labour (in man-equivalent units) | 36.57 (50.33) |
| Land | The total area of land utilised for maize production (in hectares) | 0.86 (0.88) |
| Fertiliser | The total quantity of chemical fertiliser applied for maize production (in kg) | 81.20 (138.96) |
| Seed | The total quantity of maize from its own source and purchased (in kg) | 25.83 (157.16) |
| Chemicals | The total cost of pesticide and herbicide used for maize production (ETB)[a] | 8.88 (53.79) |
| Bullock | Total days of bullock labour used for maize production | 13.12 (27.87) |
| Equipment | A proxy of farm capital, measured as a total value of farm equipment (sickles, hoes and ploughs) used for maize cultivation | 81.29 (233.56) |
| IMV | Improved maize adoption (= 1 for adopters of IMV, 0 for LMV) | 0.83 (0.38) |
| $LandQuality$ | An average land quality index (1 = best, …, 9 = worst) | 2.22 (1.33) |
| ***Inefficiency determinant and heteroscedasticity variables*** | | |
| Age | Age of the household head (in years) | 42 (12) |
| Age_squared | The squared term of the age of the household head | 1 968 (1 206) |
| Gender | Gender of the household-head (1 = Male) | 4.92 (0.27) |
| Education | Education level (formal years of schooling) of the household head | 2.94 (3.32) |
| Family_size | Total size of the household (family members in AEU)[b] | 4.84 (2.08) |
| Farm_size | Total cultivated land in hectares | 8.26 (6.88) |
| Fragmentation | The total number of plots managed by the farmer | 1.65 (1.12) |
| Livestock | Total livestock resources owned by the family (measured in TLU)[c] | 10.98 (11.09) |
| Asset | Total value of household assets (in ETB) | 502.89 (1 127.69) |
| Off-farm_income | Per capita income (in ETB) earned from working outside own farm | 18.86 (148.16) |
| Savings | Total household savings in ETB | 1 679.21 (5 977.00) |
| Farmer_group | Membership in farmers group (= 1 for member of farmer groups) | 0.37 (0.48) |
| Extension | Number of extension contacts | 3.93 (5.41) |

**Notes:** Standard deviations are in parentheses.
All values of the production variables reported here are the actual values before the logarithm transformation.
[a] All monetary values are in Ethiopian Birr (ETB), the local currency, where 1 USD was equivalent to 17.01 ETB in 2011.
[b] AEU: adult-equivalent unit, converted using appropriate conversion factors to account for age and gender differences across family members.
[c] TLU: tropical livestock units

## 4. Results and discussion

The econometric results of this study are divided into two major sections. First, we present the estimations of the SF model using an aggregate production function (i.e. assuming a homogenous production technology for IMV and LMV). The second section reports the results estimated by relaxing the homogenous technology assumption.

### 4.1 Estimates of the SF model using an aggregate production function

Table 2 presents the results of the SF model that assumes homogenous production technology for IMV and LMV (as specified in Equation 8).

#### 4.1.1 SF parameter estimates and TE

The positive signs of the first-order coefficients of the production inputs indicate that all inputs used in maize production have a positive relationship with the output variable. However, only operated area, the quantity of seed, and bullock labour significantly increased the level of maize output in the best practice.[6] The gamma[7] estimate of the model ($\gamma = 0.595$) suggested that about 60% of the deviation of the output from the frontier was due to inefficiency. Of the input variables, the large first-order coefficient *Land* emphasises the role of land in enhancing maize yield. This result supports the theoretical prediction that land, as physical capital, plays a positive role in farm production. The negative influence of land quality on maize output indicates that land with a poor quality decreases maize yield. This could be because land with poor quality reduces the soil responsiveness to chemical fertiliser and applications of improved seeds. The result agrees with the findings of Abro *et al*. (2014). The overall mean TE was 61.22%. This implies that, when adopters and non-adopters of IMV are assumed to be operating under the same technologies, an increase in maize productivity of about 38.78% can be achieved with the current input level and technology. Figure 1 shows the frequency distribution of individual TE scores.

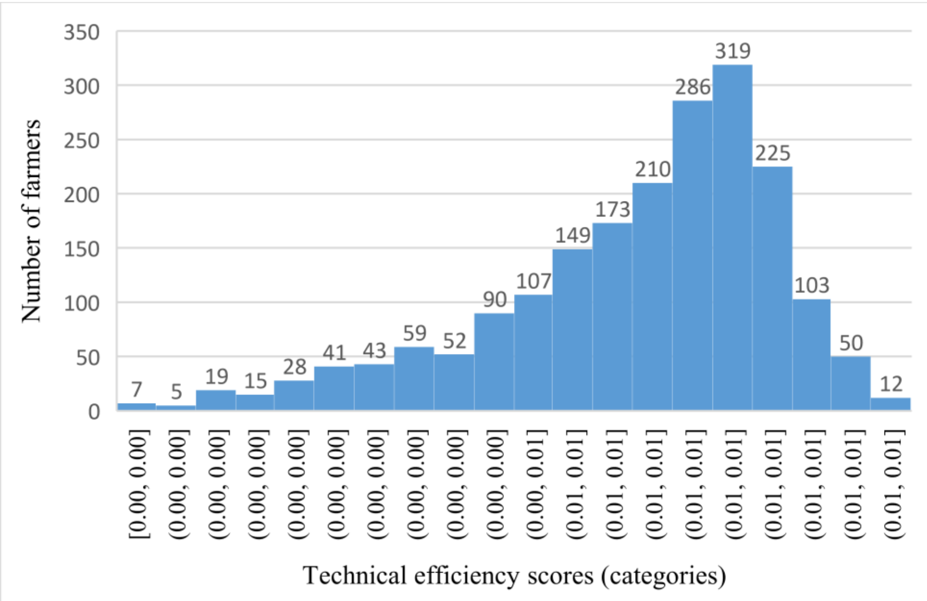


**Figure 1: Frequency distribution of TE scores**

On average, farmers producing IMV have a TE score that is about 6.64% higher than that of LMV farmers. The mean difference in TE between the two groups was statistically significant at a 1% level of significance. Moreover, as Figure 2 shows, the density of the mean TE of IMV producers was higher than that of the LMV producers. This result suggests that – besides the direct yield advantage of IMV shown in the descriptive results – farmers producing IMV also achieved an increase in TE. However, we cannot conclude this result at this stage, for two reasons. First, a potential technology difference was not taken into consideration while estimating the SF model. Second, the two groups may not be comparable directly, as the mean difference could be due to initial differences among farm households that would possibly lead to self-selection into the adoption of IMV. We address these issues in section 4.2.

[6] As part of the robustness check, we estimated the SF model using a Cobb-Douglas form and found that the results are more or less consistent (the results can be obtained upon request).
[7] We conducted a test to detect the presence of inefficiency, because the empirical SF model can be estimated using SF analysis only if the inefficiency effects are stochastic (i.e. the one-sided error term is different from zero). The one-sided generalised LR test (with a test statistic of 33.40 and $P < 0.01$) suggested rejecting the null hypothesis that inefficiency effects are absent in the model ($\sigma2u = 0$).

**Table 2: SF model results estimated assuming homogenous technology for IMV and LMV**

| **Stochastic production frontier estimates** | | **Technical inefficiency estimates** | |
|---|---|---|---|
| *Production variables* | *Coefficient* | *Inefficiency variables* | *Coefficient* |
| Ln(Labour) | 0.051 (0.143) | Age | 0.060*** (0.023) |
| Ln(Land) | 1.064*** (0.343) | Age_squared | -0.001** (0.000) |
| Ln(Seed) | 0.263*** (0.081) | Gender | -0.460*** (0.152) |
| Ln(Fertiliser) | 0.068 (0.046) | Education | -0.028 (0.018) |
| Ln(Chemicals) | 0.024 (0.088) | Family_size | -0.075*** (0.029) |
| Ln(Bullock) | 0.358** (0.140) | Farm_size | -0.058 (0.106) |
| Ln(Equipment) | 0.091 (0.080) | Fragmentation | -0.012 (0.051) |
| Ln(Labour)*Ln(Labour) | 0.026 (0.020) | Livestock | 0.035 (0.073) |
| Ln(Labour)*Ln(Land) | -0.068 (0.099) | Asset | 0.000 (0.001) |
| Ln(Labour)*Ln(Seed) | 0.034 (0.023) | Off-farm_income | -0.039*** (0.014) |
| Ln(Labour)*Ln(Fertiliser) | -0.037*** (0.014) | Savings | -0.113*** (0.041) |
| Ln(Labour)*Ln(Chemicals) | 0.051** (0.023) | Farmer_group | -0.242** (0.102) |
| Ln(Labour)*Ln(Bullock) | -0.071* (0.037) | Extension | -0.014 (0.009) |
| Ln(Labour)*Ln(Equipment) | 0.009 (0.029) | *Region:* | |
| Ln(Land)*Ln(Land) | -0.762*** (0.112) | Region 2: Amhara | -0.789** (0.314) |
| Ln(Land)*Ln(Seed) | -0.026 (0.050) | Region 3: Oromia | -1.233*** (0.313) |
| Ln(Land)*Ln(Fertiliser) | 0.059* (0.032) | Region 4: Benishanguel-Gumuz | -0.781** (0.356) |
| Ln(Land)*Ln(Chemicals) | 0.006 (0.047) | Region 5: SNNP region | -0.942*** (0.318) |
| Ln(Land)*Ln(Bullock) | 0.083 (0.111) | Constant | 2.459** (0.970) |
| Ln(Land)*Ln(Equipment) | 0.247*** (0.078) | **Heteroscedasticity in idiosyncratic error variance**[a] | |
| Ln(Seed)*Ln(Seed) | -0.009 (0.007) | *Variables* | *Coefficient* |
| Ln(Seed)*Ln(Fertiliser) | -0.005 (0.007) | Age | 0.060*** (0.023) |
| Ln(Seed)*Ln(Chemicals) | 0.015 (0.010) | Age_squared | -0.001** (0.000) |
| Ln(Seed)*Ln(Bullock) | 0.025 (0.024) | Gender | -0.460*** (0.152) |
| Ln(Seed)*Ln(Equipment) | -0.074*** (0.015) | Education | -0.028 (0.018) |
| Ln(Fertiliser)*Ln(Fertiliser) | 0.046*** (0.006) | Family_size | -0.075*** (0.029) |
| Ln(Fertiliser)*Ln(Chemicals) | -0.002 (0.006) | Farm_size | -0.058 (0.106) |
| Ln(Fertiliser)*Ln(Bullock) | -0.021 (0.013) | Fragmentation | -0.012 (0.051) |
| Ln(Fertiliser)*Ln(Equipment) | -0.002 (0.008) | Livestock | 0.035 (0.073) |
| Ln(Chemicals)*Ln(Chemicals) | 0.004 (0.011) | Asset | 0.000 (0.001) |
| Ln(Chemicals)*Ln(Bullock) | -0.032 (0.022) | Off-farm_income | -0.039*** (0.014) |
| Ln(Chemicals)*Ln(Equipment) | -0.034** (0.016) | Savings | -0.113*** (0.041) |
| Ln(Bullock)*Ln(Bullock) | 0.003 (0.021) | Farmer_group | -0.242** (0.102) |
| Ln(Bullock)*Ln(Equipment) | -0.012 (0.029) | Extension | -0.014 (0.009) |
| Ln(Equipment)*Ln(Equipment) | 0.010 (0.010) | *Region*[b]*:* | |
| Ln(Land Quality) | -0.047*** (0.011) | Region 2: Amhara | -0.789** (0.314) |
| Constant | 5.113*** (0.257) | Region 3: Oromia | -1.233*** (0.313) |
| Gamma ($\gamma = \sigma^2_u / (\sigma^2_v + \sigma^2_u)$) | 0.595 | Region 4: Benishanguel-Gumuz | -0.781** (0.356) |
| Log-likelihood | -1961.25 | Region 5: SNNP region | -0.942*** (0.318) |
| Observations | 1 993 | Constant | 2.459** (0.970) |
| *Summary of TE estimates (%)* | | | |
| Mean | 61.22 | | |
| Standard deviation | 16.53 | | |
| Minimum | 0.96 | | |
| Maximum | 92.67 | | |

**Notes:** * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[a] Positive estimates of the variance parameters indicate that increased use of the associated variable implies a higher variance in maize yield, and vice versa.

[b] Region 1, Oromia, was arbitrarily chosen as a reference region.

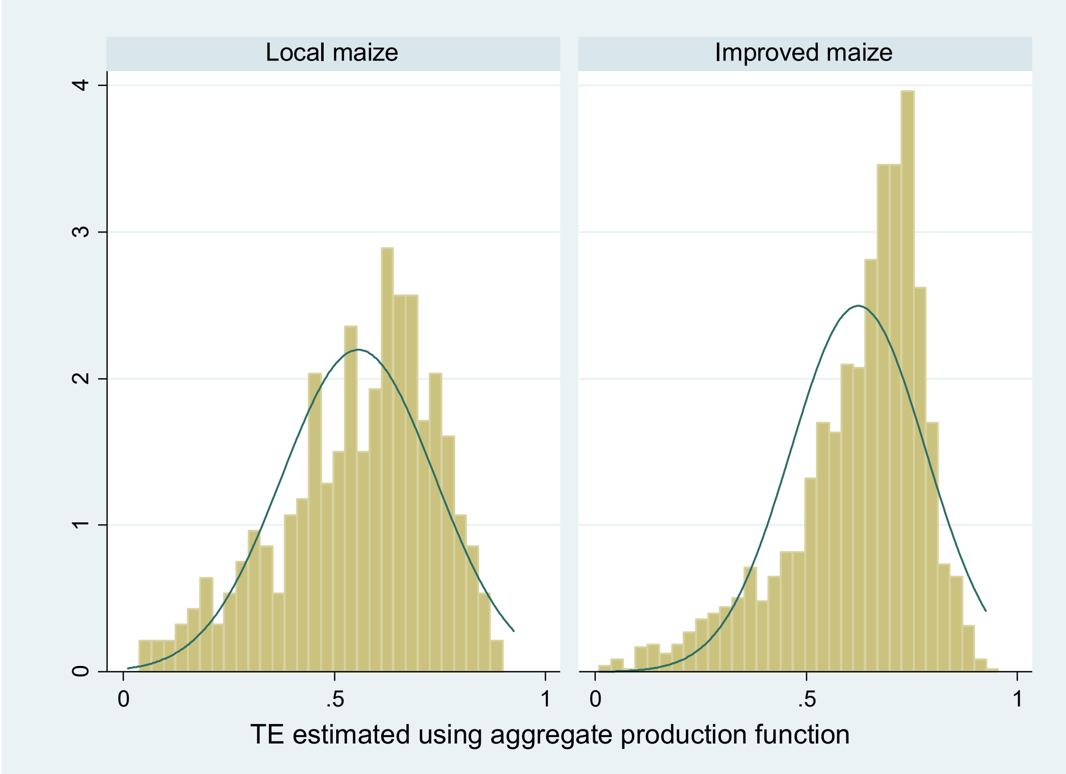


**Figure 2: Frequency distribution of TE scores, by the adoption of IMV**

### 4.1.2 Determinants of technical inefficiency in maize production

The technical inefficiency model estimates that were estimated simultaneously with the SF parameters (presented in the second half of Table 2) show the impact of various exogenous factors on technical inefficiency in maize production. The negative coefficients imply that the associated variable reduces inefficiency in maize production. The positive and statistically significant result for the *Age* of the household head suggests that younger farmers are technically less inefficient. The possible explanation could be that, despite the lack of farming experience, younger farmers might be less conservative in applying new practices that enhance their input allocation skills. This result is consistent with previous studies in developing countries, such as those by Seyoum *et al*. (1998) and Abdul-Salam and Phimister (2017).

The negative effect of *Gender* of the household head on technical inefficiency suggests that male-headed households are less inefficient. This can be because, in the rural areas of most of the developing countries, the households headed by male farmers have better access to resources compared to those headed by female farmers. This result is consistent with previous studies done in Africa (see, for example, Abate *et al*. 2014).

The negative effect of *Family size* on technical inefficiency indicates that maize farms operated by a large household are less inefficient. This finding is consistent with previous findings from developing countries, in which it has been argued that, as a primary source of labour force, a farm family plays a positive role in agricultural production (Coelli *et al*. 2002, Ndlovu *et al*. 2014).

The negative and significant influence of *Household saving* and *Household asset* on technical inefficiency indicates that farm households with a better wealth position are less inefficient. This finding supports the notion that household wealth plays an important role in boosting agricultural productivity by facilitating farming activities through solving liquidity constraints in purchasing the necessary inputs. The finding is also consistent with previous studies on the efficiency of crop production (see, for example, Haji 2007).

The negative effect of involvement in *Famer group* suggests that farmers involved in rural farmer groups are less inefficient. This could be because members of farmer groups are more likely to have access to information on efficiency-enhancing technologies through farmer networks. Previous studies (see Tessema *et al*. 2016) indicate that well-functioning farmer networks enhance technology diffusion among farming communities in Ethiopia. The finding is consistent with previous farm efficiency studies from Ethiopia (see Abate *et al*. 2014).

**4.2 Results of SF model after accounting for technology differences and self-selection**

This section presents the SF model estimated by relaxing the homogenous technology assumption imposed in the previous section and addressing a potential self-selection bias.

**4.2.1 PSM analysis**

We used a probit model to estimate the binary model specified in Equation 11. Following that, we generated propensity scores for each farmer to compare the outcomes of IMV adopters and non-adopters. Table 3 summarises the probit estimates of the propensity to produce IMV. The variables[8] included in the probit estimation have the expected signs, except for the age of the household head.[9] From several matching techniques available for impact assessment, we used the five nearest neighbours matching technique to match each IMV user with the mean of the five non-users of IMV who had very similar p-scores. We used the PSM result to generate a subsample of maize farmers among whom the adoption of IMV was assigned randomly.

Figure 3 shows the density distributions of p-scores for the adoption of IMV to check for the presence of enough overlap between adopters and non-adopters. The p-distributions appear with a sufficient common support region, suggesting an adequate overlap. We also assessed the overall matching quality by using a two-sample t-test.[10] We identified significant mean differences for some variables before matching. After the matching, however, the differences for all variables turned out to be insignificant. This indicates that all the variables were balanced after matching. The matching reduced initial differences, with the bias being less than 5% for all covariates.

[8] Due to the non-normal distribution of the variables, logarithmic transformation was done for Off-farm income, Livestock, Land size and Asset before estimating the adoption equation.
[9] As the aim of using PSM was only to balance the observed distribution of covariates across the adopters and non-adopters, we have not provided a detailed interpretation of the estimates here.
[10] In order to save space, we have not presented the test results for the matching quality assessment here. The results can be obtained from the authors upon request.

**Table 3: Probit estimates of the propensity to produce IMV (N = 1 896)**

| Variable | Coefficient | Standard error |
|---|---|---|
| Age (of the household head in years) | -0.01** | 0.00 |
| Gender (of the household-head: 1 = a male household head) | 0.05 | 0.14 |
| Education (education level of the household head, years of schooling) | 0.00 | 0.01 |
| Family size (total family size in AEU) | 0.04** | 0.02 |
| Asset (total household asset in ETB) | 0.04 | 0.03 |
| Off-farm income (per capita, ETB) | 0.00 | 0.00 |
| Livestock (TLU) | -0.01 | 0.06 |
| Land size (total land holding in hectares) | -0.01 | 0.07 |
| Plot distance (walking minutes) | 0.17*** | 0.04 |
| Fragmentation (number of maize plots) | 0.13*** | 0.04 |
| Soil slope (1 = flat, 2 = medium, 3 = steep) | 0.069 | 0.08 |
| Soil fertility (1 = good, 2 = medium, 3 = poor) | 0.27*** | 0.07 |
| Farmer group (1 = members) | 0.25*** | 0.08 |
| Extension service (1 = yes) | 1.19*** | 0.46 |
| Information on IMV (1 = yes) | 0.03 | 0.11 |
| *Region* [a]*:* Region 2: Amhara | -0.56 | 0.37 |
| Region 3: Oromia | -0.84** | 0.36 |
| Region 4: Benishanguel-Gumuz | -1.55*** | 0.39 |
| Region 5: SNNP | -0.37 | 0.36 |
| Constant | -0.89 | 0.90 |
| *Model summary* | | |
| Pseudo $R^2$ | 11.60% | |
| IMV adopters correctly predicted | 81.00% | |
| IMV non-adopters correctly predicted | 76.50% | |
| Total correctly predicted | 80.00% | |

**Notes:** * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are in parentheses
[a] Region 1, Oromia, was used as a reference

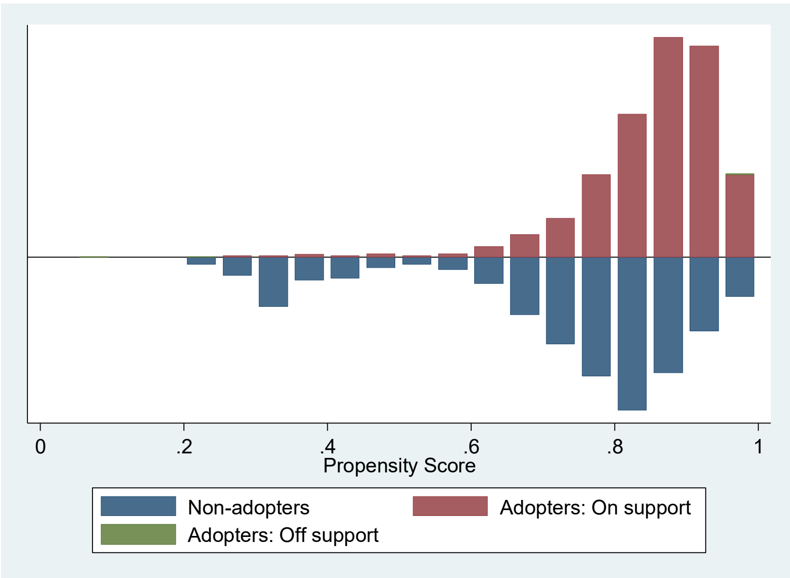


**Figure 3: Propensity score distribution and common support for IMV, after matching**

### 4.2.2 Assessing the influence of technology difference in TE modelling

In this section, we extend the analyses by accounting for a potential technological difference arising from the adoption of IMV, to investigate whether neglecting such a difference in the modelling of efficiency introduces any bias. Table 4 presents the results (estimated using Equation 9).

**Table 4: SF results, estimated by relaxing homogenous technology assumption**

| **Stochastic production frontier estimates** | | **Technical inefficiency estimates** | |
|---|---|---|---|
| *SF production variables* | *Coefficient* | *Inefficiency variables* | *Coefficient* |
| Ln(Labour) | 0.071 (0.143) | Age | 0.068*** (0.023) |
| Ln(Land) | 0.878** (0.344) | Age_squared | -0.001*** (0.000) |
| Ln(Seed) | 0.251*** (0.084) | Gender | -0.459*** (0.152) |
| Ln(Fertiliser) | 0.030 (0.053) | Education | -0.028 (0.018) |
| Ln(Chemicals) | 0.041 (0.092) | Family_size | -0.074*** (0.028) |
| Ln(Bullock) | 0.346** (0.146) | Farm_size | -0.064 (0.105) |
| Ln(Equipment) | 0.110 (0.084) | Fragmentation | -0.002 (0.050) |
| Ln(Labour)*Ln(Labour) | 0.027 (0.021) | Livestock | 0.017 (0.073) |
| Ln(Labour)*Ln(Land) | -0.056 (0.099) | Asset | 0.000 (0.000) |
| Ln(Labour)*Ln(Seed) | 0.038* (0.023) | Off-farm_income | -0.037** (0.015) |
| Ln(Labour)*Ln(Fertiliser) | -0.031** (0.014) | Savings | -0.116*** (0.041) |
| Ln(Labour)*Ln(Chemicals) | 0.055** (0.023) | Farmer_group | -0.231** (0.102) |
| Ln(Labour)*Ln(Bullock) | -0.072* (0.037) | Extension | -0.014 (0.009) |
| Ln(Labour)*Ln(Equipment) | 0.014 (0.030) | *Region:* | |
| Ln(Land)*Ln(Land) | -0.634*** (0.115) | Region 2: Amhara | -0.853*** (0.307) |
| Ln(Land)*Ln(Seed) | -0.043 (0.050) | Region 3: Oromia | -1.338*** (0.306) |
| Ln(Land)*Ln(Fertiliser) | 0.048 (0.032) | Region 4: Benishanguel-Gumuz | -1.057*** (0.362) |
| Ln(Land)*Ln(Chemicals) | 0.006 (0.047) | Region 5: SNNP region | -1.008*** (0.312) |
| Ln(Land)*Ln(Bullock) | 0.021 (0.112) | Constant | 2.391** (0.968) |
| Ln(Land)*Ln(Equipment) | 0.207*** (0.079) | **Heteroscedasticity in idiosyncratic error variance** | |
| Ln(Seed)*Ln(Seed) | -0.010 (0.007) | ***Variables*** | ***Coefficient*** |
| Ln(Seed)*Ln(Fertiliser) | -0.005 (0.007) | Age | -0.003 (0.029) |
| Ln(Seed)*Ln(Chemicals) | 0.014 (0.010) | Age_squared | 0.000 (0.000) |
| Ln(Seed)*Ln(Bullock) | 0.031 (0.023) | Gender | 0.438 (0.339) |
| Ln(Seed)*Ln(Equipment) | -0.069*** (0.015) | Education | 0.037** (0.019) |
| Ln(Fertiliser)*Ln(Fertiliser) | 0.046*** (0.006) | Family_size | -0.009 (0.031) |
| Ln(Fertiliser)*Ln(Chemicals) | -0.001 (0.006) | Farm_size | -0.258* (0.138) |
| Ln(Fertiliser)*Ln(Bullock) | -0.020 (0.013) | Fragmentation | 0.064 (0.050) |
| Ln(Fertiliser)*Ln(Equipment) | 0.001 (0.008) | Livestock | 0.259*** (0.083) |
| Ln(Chemicals)*Ln(Chemicals) | 0.002 (0.011) | Asset | 0.001*** (0.000) |
| Ln(Chemicals)*Ln(Bullock) | -0.033 (0.022) | Off-farm_income | 0.022 (0.015) |
| Ln(Chemicals)*Ln(Equipment) | -0.033** (0.016) | Savings | 0.227*** (0.045) |
| Ln(Bullock)*Ln(Bullock) | 0.004 (0.020) | Farmer_group | -0.173 (0.120) |
| Ln(Bullock)*Ln(Equipment) | -0.005 (0.030) | Extension | -0.010 (0.010) |
| Ln(Equipment)*Ln(Equipment) | 0.008 (0.010) | *Region[a]:* | |
| Ln(Land Quality) | -0.052*** (0.011) | Region 2: Amhara | 0.277 (0.533) |
| ***Technology variables:*** | | Region 3: Oromia | 0.474 (0.513) |
| IMV | 0.592*** (0.219) | Region 4: Benishanguel-Gumuz | 0.003 (0.654) |
| IMV*Ln(Labour) | -0.101 (0.075) | Region 5: SNNP region | 0.237 (0.534) |
| IMV*Ln(Land) | 0.382** (0.190) | Constant | -5.896*** (1.858) |
| IMV*Ln(Seed) | -0.021 (0.044) | | |
| IMV*Ln(Fertiliser) | -0.003 (0.023) | | |
| IMV*Ln(Chemicals) | -0.030 (0.040) | | |
| IMV*Ln(Bullock) | -0.005 (0.078) | | |
| IMV*Ln(Equipment) | -0.042 (0.046) | | |
| Constant | 4.861*** (0.268) | | |
| Gamma ($\gamma = \sigma^2_u / (\sigma^2_v + \sigma^2_u)$) | 0.696 | | |
| Log likelihood | -1942.29 | | |
| Observations | 1 991 | | |
| *Summary of TE estimates (%)* | | | |
| Mean | 61.39 | | |
| Standard deviation | 16.56 | | |
| Minimum | 0.93 | | |
| Maximum | 93.10 | | |

**Notes:** * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. [a] Region 1, Oromia, was used as a reference.

Before estimating the empirical models by relaxing the homogenous technology assumption imposed in the previous section, we statistically tested whether the two technologies were indeed different, following Mayen *et al*. (2010). We employed the Wald testing procedure to test the restrictions that the intercept term and slope shifters are jointly equal to zero. The test result, with a test statistic of 25.43 (p-value < 0.01 and eight degrees of freedom), suggested a rejection of the null hypothesis that the intercept and slope shifters corresponding to the technology dummy are jointly zero. This indicates that the homogenous technology assumption for the two crop varieties (IMV and LMV) was not appropriate.

As the results presented in Table 4 show, the parameter estimates for the SF model and the inefficiency part are consistent with the results estimated with a model imposing a homogenous technology assumption (see Table 2). Although the magnitudes of the estimates varied slightly across the two models, the statistical significance and the signs of the parameter estimates were consistent. This indicates that the parameter estimates are not sensitive to the assumption imposed on the production technology. The positive and statistically significant result for the IMV dummy variable indicates that farmers growing a yield-enhancing maize variety have indeed achieved a yield gain. This result corroborates our descriptive result reported in section 4.1, namely that farmers producing IMV had a higher maize yield than did farmers producing LMV.

Following this, we estimated TE under different assumptions about production technology to examine the effects on TE estimates. Table 5 summarises the results. The overall mean TE estimates, with and without imposing a homogenous technology assumption for the two groups of farmers, are quite similar. This indicates that accounting for the potential technological difference between IMV and LMV did not significantly influence the overall TE estimate. This holds for the results estimated both before and after correcting for self-selection bias. However, the result reveal that the imposition of a homogenous technology assumption biased the estimated TE for the two groups of farmers.

**Table 5: Summary of TE scores for maize farmers, estimated under different technology assumptions**

| Assumptions on production technology | Mean technical efficiency (%)[a] | | | |
|---|---|---|---|---|
| | Pooled sample | Farmers using improved maize | Farmers using local maize | Difference in means[b] |
| ***All farms*** | | | | |
| Aggregate production function<br>(*homogenous technology assumed*) | 61.22<br>(0.37) | 62.31<br>(0.39) | 55.66<br>(1.01) | 6.64***<br>(0.99) |
| | | | | |
| Different technology<br>*(homogenous technology assumption relaxed)* | 61.39<br>(0.37) | 61.67<br>(0.40) | 59.94<br>(0.98) | 1.73**<br>(0.97) |
| ***PSM subsample*** | | | | |
| Aggregate production function<br>(*homogenous technology assumed*) | 65.69<br>(0.76) | 67.87<br>(1.16) | 64.53<br>(0.98) | 3.34**<br>(1.58) |
| Different technology<br>*(homogenous technology assumption relaxed)* | 66.18<br>(0.80) | 65.52<br>(1.25) | 66.54<br>(1.03) | 1.02<br>(1.68) |

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01

[a] Standard errors are in parentheses; [b] The mean difference refers to the mean difference in TE scores between farmers using improved maize and those using local maize (t-test).

Both results – prior to and after correcting for self-selection bias – indicate that imposing a homogenous technology assumption on the two crop varieties biased the TE scores for both adopters and non-adopters of IMV, in two ways. First, it led to an upward bias in the estimate of TE for IMV farmers, while it resulted in a downward bias in TE estimate for LMV farmers. Second, the results estimated both before and after correcting for self-selection bias indicate that the mean difference between adopters and non-adopters of IMV was statistically significant under the assumption of homogenous technology. This suggests that imposing a wrong homogenous technology assumption on the two varieties has biased the ranking of maize farmers based on their level of efficiency. In contrast, the results estimated after relaxing the homogenous technology assumption for the PSM subsample confirm that the mean difference of TE between the two groups is statistically insignificant. This suggests that, when measured against the appropriate frontier – where no homogenous technology is assumed and self-selection bias is corrected – there is no statistically significant TE difference between IMV farmers and LMV farmers.

Overall, the result suggest that an incorrect homogenous technology assumption for crop varieties with different yield potential is inappropriate. This finding supports the finding of Mayen *et al*. (2010), who argue that failure to account for technology differences in the modelling of farm efficiency biases efficiency estimates.

### 4.3 Robustness check

We undertook a supplementary analysis to investigate whether the results of the regular SF model are consistent with an alternative model specification, in order to check the robustness of the results presented in the main sections. Using the classical SF approach might not provide a complete picture of the differences in TE between the adopters and non-adopters of IMV if IMV is a distinctive technology among maize farmers. To correct for the technological difference in comparing TE in situations where groups of firms may differ in production technology, some recent literature suggests using a metafrontier framework developed by Battese *et al*. (2004) and O'Donnell *et al*. (2008). Although the metafrontier framework is capable of correcting for the technological difference by disentangling the technology gap from the efficiency gaps, the empirical relevance of this approach depends considerably on the accessibility of the available production technology. This is because the estimation of a meta-production function is "... based on the idea that all producers in the various production groups have potential access to an array of production technologies, but each may choose a particular technology, depending on specific circumstances ..." (Huang *et al*. 2014:241). In the context of our study, it was restrictive for us to assume that all maize farmers had unconstrained access to IMV, because the diffusion process of maize technologies is constrained by access to improved varieties (Abate *et al*. 2015). Therefore, we estimated the stochastic metafrontier (SMF) model as an alternative model specification to check the robustness of our main results (i.e. the SF results). Overall, the SMF results are similar to those of the SF and hence are not reported here, but are available from the authors on request.

## 5. Summary and conclusions

Previous farm studies paid little attention to potential technological differences in crop varieties. This could bias efficiency estimates and potentially lead to inappropriate policy choices. Focusing on the Ethiopian maize sector, we estimated technical efficiency (TE) and examined the impact of technological differences on efficiency estimation. Using comprehensive household-level data collected in 2011, we specified a stochastic frontier analytical framework and employed a propensity score-matching procedure to address a potential self-selection bias in the estimation of efficiency.

We were comforted to find that accounting for a potential technological difference between the improved maize variety (IMV) and the local maize variety (LMV) did not affect the overall mean TE of maize farmers, or the parameter estimates of the stochastic frontier (SF) model and the inefficiency model. However, the results confirmed that imposing a homogenous technology assumption for IMV and LMV biases the mean efficiency estimates for adopters and non-adopters. Our findings reveal that the homogenous technology assumption biased efficiency scores upward for adopters of IMV, while it led to a downward bias in the TE estimate for non-adopters. Further, the efficiency results estimated after correcting for self-selection bias confirmed that imposing an incorrect homogenous technology assumption for the two maize varieties misleads the ranking of farmers based on their efficiency scores. This suggests that it is inappropriate to make an incorrect homogenous technology assumption for crop varieties with different yield potential. Therefore, we argue that, when farmers have access to different technologies that have different output potentials, failure to account for differences in crop variety in the modelling of farm efficiency biases the efficiency estimates. This consequently could lead to a biased ranking of farmers based on their efficiency scores, followed by potentially inappropriate policy choices.

The overall mean TE estimate of 66.18%, which was estimated after controlling for technological heterogeneity and potential self-selection bias, implies that, measured against the appropriate frontier, an increase in maize productivity of around 33.82% could be achievable with the current input levels and technology. The results from modelling the inefficiency imply that the factors associated with technical inefficiency in maize production are: being an old farmer, being a female household head, a small family size, little household savings, a low level of asset ownership, less involvement in farmer groups, and less frequent extension contact. The findings indicate that the first possible policy direction that could reduce inefficiency in the Ethiopian maize sector, and in other, comparable developing countries, could be to empower young farmers through field-based training and crop-specific extension services. The second policy option could be enhancing household cash savings by creating alternative income-generating sources that could facilitate the operation of maize farms by solving short-term liquidity constraints on purchasing the necessary inputs. Promoting formal farm groupings could also enhance efficiency through well-functioning farmer networks that potentially would provide access to basic inputs and information on efficiency-enhancing technologies. Moreover, increased maize productivity requires the effort of local and regional government bodies to enhance the use of improved land-management practices to maintain or restore land quality.

Finally, there are three important points worth noting in this study. First, our production frontier estimations may be influenced by other crops in cases where maize plots were intercropped with other minor crops. It was difficult to treat the output from the other crops in the production function because it was difficult to allocate the total inputs for each crop separately. Second, efficiency estimates might be influenced by other sources of technological heterogeneity. One source of heterogeneity could be the adoption of other complementary innovations. Third, as the study is limited to one country and cross-sectional data, the findings might be influenced by geographical variations and time patterns. Thus, future research taking such issues into account might ensure the generalisability of our empirical findings.

**References**

Abate GT, Francesconi GN & Getnet K, 2014. Impact of agricultural cooperatives on smallholders' technical efficiency: Empirical evidence from Ethiopia. Annals of Public and Cooperative Economics 85(2): 257-86.

Abate T, Shiferaw B, Menkir A, Wegary D, Kebede Y, Tesfaye K, Kassie M, Bogale G, Tadesse B & Keno T, 2015. Factors that transformed maize productivity in Ethiopia. Food Security 7(5): 965–81.

Abdul-Salam Y & Phimister E, 2017. Efficiency effects of access to information on small-scale agriculture: Empirical evidence from Uganda using stochastic frontier and IRT models. Journal of Agricultural Economics 68(2): 494–517.

Abro ZA, Alemu BA & Hanjra MA, 2014. Policies for agricultural productivity growth and poverty reduction in rural Ethiopia. World Development 59: 461–74.

Aigner D, Lovell CK & Schmidt P, 1977. Formulation and estimation of stochastic frontier production function models. Journal of Econometrics 6(1): 21–37.

Alene A & Hassan RM, 2006. Erratum: The efficiency of traditional and hybrid maize production in Eastern Ethiopia: An extended efficiency decomposition approach. Journal of African Economies 15(2): 91–116.

Alene A & Manyong V, 2007. The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: An endogenous switching regression analysis. Empirical Economics 32(1): 141–59.

Aye GC & Mungatana ED, 2011. Technological innovation and efficiency in the Nigerian maize sector: Parametric stochastic and non-parametric distance function approaches. Agrekon 50(4): 1–24.

Battese GE, 1992. Frontier production functions and technical efficiency: A survey of empirical applications in agricultural economics. Agricultural Economics 7(3): 185–208.

Battese GE, Rao PDS & O'Donnell CJ, 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. Journal of Productivity Analysis 21(1): 91–103.

Coelli T, Perelman S & Romano E, 1999. Accounting for environmental influences in stochastic frontier models: With application to international airlines. Journal of Productivity Analysis 11(3): 251–73.

Coelli T, Rahman S & Thirtle C, 2002. Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: A non-parametric approach. Journal of Agricultural Economics 53(3): 607–26.

Farrell MJ, 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society 120(3): 253–90.

Geffersa AG, Agbola FW & Mahmood A, 2019. Technical efficiency in crop production across agro-ecological zones in Ethiopia: A meta-analysis of frontier studies. Outlook on Agriculture 48(1): 5–15.

Hadri K, Guermat C & Whittaker J, 2003. Estimation of technical inefficiency effects using panel data and doubly heteroscedastic stochastic production frontiers. Empirical Economics 28(1): 203–22.

Haji J, 2007. Production efficiency of smallholders' vegetable-dominated mixed farming system in eastern Ethiopia: A non-parametric approach. Journal of African Economies 16(1): 1–27.

Huang CJ, Huang T-H & Liu N-H, 2014. A new approach to estimating the metafrontier production function based on a stochastic frontier framework. Journal of Productivity Analysis 42(3): 241–54.

Imbens GW & Wooldridge JM, 2009. Recent developments in the econometrics of program evaluation. Journal of Economic Literature 47(1): 5–86.

Kumbhakar SC & Lovell CK, 2000. Stochastic frontier analysis. Cambridge: Cambridge University Press.

Mayen CD, Balagtas JV & Alexander CE, 2010. Technology adoption and technical efficiency: Organic and conventional dairy farms in the United States. American Journal of Agricultural Economics 92(1): 181–95.

Ndlovu PV, Mazvimavi K, An H & Murendo C, 2014. Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. Agricultural Systems 124(3): 21–31.

O'Donnell CJ, Rao DSP & Battese GE, 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empirical Economics 34(2): 231–55.

Seyoum E, Battese GE & Fleming E, 1998. Technical efficiency and productivity of maize producers in eastern Ethiopia: A study of farmers within and outside the Sasakawa-Global 2000 project. Agricultural Economics 19(3): 341–8.

Singh I, Squire L & Strauss J, 1986. The basic model: Theory, empirical results, and policy conclusions. In Singh I, Squire L & Strauss J (eds.), Agricultural household models: Extensions, applications, and policy. Baltimore MD: The Johns Hopkins University Press.

Tessema YM, Asafu-Adjaye J, Kassie M & Mallawaarachchi T, 2016. Do neighbours matter in technology adoption? The case of conservation tillage in northwest Ethiopia. African Journal of Agricultural and Resource Economics 11(3): 211–25.

Tsionas EG, 2002. Stochastic frontier models with random coefficients. Journal of Applied Econometrics 17(2): 127–47.

Wang H-J, 2002. Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. Journal of Productivity Analysis 18(3): 241–53.

Zeng D, Alwang J, Norton GW, Shiferaw B, Jaleta M & Yirga C, 2015. Ex post impacts of improved maize varieties on poverty in rural Ethiopia. Agricultural Economics 46(4): 515–26.