# Climate change adaptation and productive efficiency of subsistence farming: A bias-corrected panel data stochastic frontier approach

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## Abstract

We explore the impact of climate change adaptation on the technical efficiency of Ethiopian farmers using panel data collected from 6,820 farm plots. We employ Green's (2010) stochastic frontier approach and propensity score matching to address selection bias. Our results reveal that climate change adaptation improves the efficiency of maize, wheat, and barley production. We also show that failure to account for selection bias underestimates the average efficiency level. Our findings imply that the expansion of climate change adaptation at larger scales will provide a double benefit by curbing climate-related risks and increasing the efficiency of farmers. Moreover, increasing credit access and introducing mechanisms that allow farmers to get enough amount of water during the main growing season will enhance the efficiency of subsistence farmers.

**Keywords:** agriculture; climate change; climate change adaptation; selection bias; technical efficiency

**JEL codes:** Q12, Q52, Q54

## 1. Introduction

Climate change continues to be seen as a serious threat to the natural and human systems of the world. These effects range from ecosystem shifts and species extinctions to disruption of food production and water supply, and endangering food security and welfare (IPCC, 2014). Many studies show that effects of climate change are paramount in the agriculture sector, which, on the one hand, is the most vulnerable sector to climate-related shocks and, on the other hand, is the main source of economic growth, particularly, among smallholder farmers in Sub-Saharan Africa, including Ethiopia (Deressa and Hassan, 2009; Di Falco et al., 2012; Zhang et al., 2017; Crost et al., 2018).

Agriculture is the pillar of the Ethiopian economy in terms of employment, exports, and national income. It employs 80 percent of the country's labour force and contributes 75 percent to the merchandise export earnings and nearly 40 percent to the GDP (NBE, 2016). Ethiopia's economy is highly vulnerable to climate change for two main reasons. First, the agriculture sector in Ethiopia is characterized by being mainly subsistence, rain-fed, dominated by cereal crops, where smallholder farmers produce about 90-95 percent of the total agricultural output. Second, Ethiopia remains one of the least developed countries with a per-capita annual income of $660. Thus, the risk of food insecurity and poverty are highly likely to increase in the country, unless proper measures are taken to mitigate the impact of climate change.

It is widely recommended that implementing adaptation strategies will help reduce the effect of climate change (Bradshaw et al., 2004; Di Falco et al., 2011; Lin, 2011; Teklewold et al., 2013; Huang and Sim, 2021). Increasing production efficiency is one way of improving sustainability and resilience (Wassie, 2014; Lokina and Lwiza, 2018). First, climate adaptation strategies abate the effect of climate change through increasing resilience capacity. Second, climate adaptation strategies increase farmers' productivity by introducing new or improved agricultural practices, improving technical efficiency (TE). This will directly contribute to an increase in crop yield and farm income, which in turn will improve farm households' welfare and then will enhance farms' adaptive capacity.

Addressing this issue is more critical in countries like Ethiopia, where reconciling food production and environmental sustainability is very difficult, partly due to the alarming growth in population and lower agricultural technology adoption rates, coupled with persisting traditional agricultural practices. In response to this, we explore the effect of climate change adaptation on the TE of farmers operating under subsistence agriculture in the Nile basin of Ethiopia. Although there is extensive literature on climate adaptation effects on subsistence farming, there are fewer studies on efficiency that account for selection bias and exploit panel data. We employ a selection bias corrected model under a stochastic production frontier (SPF) framework. Our approach jointly implements propensity score matching (PSM) to address selection bias due to observed farmers' heterogeneity and Greene's (2010) approach to deal with selection bias due to unobserved farmers' heterogeneity in a panel data setting.

Previous studies mainly investigate the effects of climate adaptation strategies from three interrelated perspectives. The first strand focuses on yield and income effects of climate adaptation (see, e.g., studies by Di Falco and Veronesi, 2013; Teklewold et al., 2013; Arslan et al., 2015; Tambo and Mockshell, 2018; Suresh et al., 2021). The other two strands base their analyses on effects of climate adaptation strategies on poverty and risk exposure (see, e.g., Di Falco et al., 2011; Di Falco and Veronesi, 2014; Kassie et al., 2015; Farris et al., 2017; Khanal et al., 2021) and welfare implications (see, e.g., Asfaw and Shiferaw, 2010; Khonje et al., 2015; Asmare et al., 2019). However, none of these studies use panel data, and hence do not capture dynamic aspects of adaptation to climate change.

Vijayasarathy and Ashok (2015) for India and Khanal et al. (2018) for Nepal find that various climate adaptation measures are associated with higher farmers' TE. On the contrary, Otitoju and Enete (2014) report that multiple planting dates – one climate adaptation practice – in Nigeria have a negative effect on farmers' TE. These studies, however, fail to account for selection bias: the fact that farmers who employ climate adaptation measures are different in many ways from farmers who do not. Furthermore, to the best of our knowledge, there is no study that examines the efficiency effect of climate change adaptation in the context of Ethiopian subsistence agriculture.[1]

We explore the impact of climate change adaptation on TE under subsistence farming by using a plot-level panel dataset from rural smallholder farmers of Ethiopia. Furthermore, we examine the importance of accounting for weather and soil factors when estimating farmer' plot-specific productive efficiency for specific crops.

[1] The only studies we are aware of that relate to our analysis are by Di Falco et al. (2012) and Di Falco and Veronesi (2013), who explore the effect of climate change adaptation on Ethiopian households' income. However, these studies do not analyze the efficiency effect of climate change adaptation.

The remainder of this study is organized as follows. In Section 2, we provide some background information on climate change adaptation together with our data. Section 3 presents the empirical strategy. The results are presented and discussed in Section 4. We conclude in Section 5.

## 2. Data and background information on the study area

### 2.1 Study area and data

The study uses a panel data collected using a survey from 929 farm households and 6,820 plots within the Nile basin of Ethiopia. The survey was conducted by the Environment and Climate Research Center (ECRC) at the Ethiopian Development Research Institute in 2015, 2016 and 2017.[2]

The Nile basin in Ethiopia covers around 34 percent of the area of the country and 40 percent of the country's population. In the study area, the average size of a farm per household is rather small – less than one hectare, traditionally farmed with animal draught power, and relaying heavily on labour. The employment of other inputs is rather limited, Deressa et al. (2009).

The dataset comprises of various surveyed households' and associated land plot characteristics, households' perceptions of climate change and climate change adaptation practices. The study also incorporates two climate variables – the average annual temperature (measured in ºC) and average rainfall of Belg and Meher seasons[3] (measured in mm) for the period from 1983 to 2015. Considering long-term averages of climatic variables as indicators of climate change is a common approach (see, e.g., Mendelsohn et al., 2007; Di Falco and Veronesi, 2013).

The precipitation and temperature data were gathered from every single meteorological station in the nation. The Thin Plate Spline approach for a spatial interpolation was utilized to attribute the plot-explicit precipitation and temperature values using the geographic location data of each plot.[4] Its advantages are that it is accessible, easy to apply, and it accounts for spatially varying geographical relationships (Di Falco et al., 2011).

[2] A sample of households was selected in 2015 and continuously surveyed for the years 2016 and 2017.

[3] Meher is the main cropping season ranging from April to December. Belg covers the time from February to September.

[4] This approach is the common and widely used method to produce spatial climate data sets. See, for example, Wahba (1990) for more information.

The variables used in this study together with their definitions and main summary statistics are presented in Appendix Table A1. A detailed explanation about the sampling frame and sample selection procedure can be found in (Asmare et al., 2019).

## 2.2 Background information on climate and climate change adaptation practices in the study area

*Dynamics of average rainfall and temperature*

Identifying whether farmers notice climate change is the first step in any climate change adaptation impact evaluation study. Therefore, we look at the dynamics of the geo-referenced rainfall and temperature data specific to our study area for the last 32 years. Then, we analyze surveyed farmers' personal perceptions about climate change, their observed climate related shocks and their actually implemented climate change adaptation strategies.

The dynamics of rainfall and temperature are presented in Figure A1, on-line appendix. It is evident that surveyed plots have been significantly affected by rainfall and temperature variability. We can identify at least three extreme periods when there is an acute shortage of rainfall: 1984, 2002, and especially, 2011–2012. The three main drought events Ethiopia experienced after the 1970s followed these extreme weather events (Gebremeskel et al., 2019). The 1985 drought was mainly caused by a lower level of rainfall in 1984. Low precipitation in 2002 also led to the second drought in 2003. The third and the most disastrous drought not only in Ethiopia but also in the Horn of Africa was in 2011. In 2011, two consecutive (Belg and Meher seasons) rain failures in Ethiopia resulted in a devastating drought impacting the southern, eastern, and north-eastern parts of the country (Somali, Afar, East and Southern Tigray, Southern Oromia and SNNPR affecting 4.5 million individuals, the worst drought in 60 years.

*Farmers' perceptions of climate change and implemented climate adaptation measures*

One section in the questionnaire collected information about farmers' climate change perceptions together with their implemented climate adaptation measures. Specifically, the ECRC asked the following questions: Have you noticed any changes in climate over your lifetime? If you have noticed changes in climate over your lifetime, do you practice the following climate adaptation practices? About 95 percent of surveyed farm households in the study area indicated that they had noticed some changing climatic conditions. From Table 1 it is evident that most observed changing climate conditions are related to rainfall, such as erratic nature of rains, late rains, and decreasing rainfall. About 60 percent of surveyed farm households stated that these changing climatic conditions had affected the productivity of their farm plots.

**Table 1: Notice of climatic change and implemented climate adaptation strategies, pooled plot level data**

| Noticed climatic change | No. of obsv. | Percent | Climate related shocks | No. of obsv. | Percent | Implemented climate adaptation strategies | No. of obsv. | Percent |
|---|---|---|---|---|---|---|---|---|
| More hot days | 317 | 4.65 | Drought | 853 | 13.57 | Improved crop variety | 2,636 | 38.68 |
| More cold days | 43 | 0.63 | Flood | 267 | 4.25 | Agroforestry | 964 | 14.15 |
| Rainfall increasing | 414 | 6.07 | Erratic rainfall | 1,658 | 26.38 | Minimum tillage | 229 | 3.36 |
| Rainfall decreasing | 1,351 | 19.81 | Animal attack | 216 | 3.44 | Soil conservation | 1,489 | 21.86 |
| Rains are more erratic | 2,200 | 32.26 | Land slide | 17 | 0.27 | Intercropping | 266 | 3.90 |
| Rains come earlier | 527 | 7.73 | Hailstorms | 543 | 8.64 | Irrigation | 288 | 4.23 |
| Rains come later | 1,428 | 20.94 | No shocks | 2,542 | 40.44 | Crop rotation | 4,579 | 67.21 |
| Others | 187 | 2.74 | Others | 190 | 3.02 | Crop residue | 1,943 | 28.52 |
| No change | 353 | 5.17 | **Total** | **6,286** | **100** | Row planting | 1,620 | 23.78 |
| **Total** | **6,820** | **100** | | | | | | |

*Source*: Authors' calculations based on survey data.

As one can see from Table 1, crop rotation (reported by 67.2% of surveyed farm households), improved crop varieties (38.7%), crop residue (28.5%), row planting (23.8%), and soil conservation activities (21.9%) were the main climate change adaptation practices used by these farmers.

## 3. Empirical strategy

### 3.1 Identification of causal effects

The main challenge to infer causal effects in impact evaluation studies is addressing selection biases arising from observed and unobserved heterogeneities. For this reason, we measure the impact of climate change adaptation on surveyed farmers' TE following the recent works of Bravo-Ureta et al. (2011) and Villano et al. (2015) who combined PSM to correct for selection bias arising from observable factors with Greene (2010) proposed SPF model with a correction for unobserved sample selection. We exploit a similar approach in the panel data setting.

To deal with selection bias from unobservable variables (e.g., farmer's innate and managerial ability, risk preferences and motivation) within SPF formulations, we employ the approach introduced by (Greene, 2010).[5] It assumes that the unobserved characteristics in the sample selection equation (i.e., the error term, $w$, in Eq. 1) are correlated with the noise in the stochastic frontier model (i.e., the part of the noise term, $v$, in Eq. 2). Sample selection bias due to unobserved heterogeneity arises, if the error term in the production function, v, is correlated with unobservable factors in the sample selection equation, $w$, that is if $\rho = corr\ (w,v) \neq 0$. The sample selection and SPF models, together with their error structures, can be specified as follows:

Sample selection: $d^* = \boldsymbol{\alpha}'z + \mathrm{w},\ d = 1(d^* > 0)$ (1)

SPF: $\mathrm{y} = \boldsymbol{\beta}'\mathrm{x} + v - u$ (2)

where y and x are only observed when $d$ = 1.

Error structure: $u = |\mathrm{U}|$ with $\mathrm{U} \sim N(0, \sigma_u^2)$ (3)

$(v, w) \sim$ bivariate normal with $[(0,0), (\sigma_v^2, \rho\sigma_v, 1)]$

For the panel data specification, it is assumed that the 'selection' takes place only once, before the production model operates. In the specification of the model, $d$ and $w$ do not change from period to period. Thus, the selection model used here is a random-effects selection model (Greene, 2016).[6]

$d$ in the sample selection equation is a binary variable equal to one for plots that implemented adaptation strategies in the first wave of the survey period (2015) and zero for plots of non-adopters,

[5] Heckman (1979) sample selection model, which uses the inverse mills ratio as a bias correction factor, has been used by many studies for around three decades. However, this approach is inappropriate for non-linear models such as SPF (Greene, 2010). Recently, alternative approaches have been introduced to deal with this problem. The first two attempts are made by Kumbhakar et al. (2009) and Lai et al. (2009). The model developed by Kumbhakar et al. (2009) assumes that the selection mechanism carries on through the one-sided noise term in the production function. They used this model to assess the efficiency of dairy farming in Finland. On the other hand, Lai et al. (2009) developed a model that assumed that the selection is correlated with the composed error in the frontier. They implemented their model to explore wage determination. However, the log-likelihood of these two models is computationally cumbersome.

[6] For details on model specification see LIMDEP 11 econometric modelling guide page 1500-1505.

$z$ is a vector of explanatory variables included in the sample selection model, and $w$ is an unobservable error term. In the SPF model, y is plot level output, $x$ is a vector of plot level farming inputs in the production frontier. In the same model $v$ and $u$ represents the stochastic error term and the inefficiency term respectively. The vectors of coefficients $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the parameters to be estimated, while the characters in the error structure are the components of the errors parallel to those usually included in the stochastic frontier specification. It is important to highlight that a statistically significant $\rho$ parameter is evidence that selectivity bias in unobservable is present.

### 3.2 Estimation procedure

Even though several methods can be employed to estimate propensity scores, we base our analysis on a "1-to-1" nearest neighborhood matching technique with replacement (Caliendo and Kopeinig, 2008) where every plot adopter is matched with a plot non-adopter imposing the common support condition.[7] We conduct a plot level analysis for the following reasons. First, in our dataset adaptation strategies are recorded at the level of the farming plot. Second, there are many plot-level characteristics, such as fertility of the plot, slope, distance from home stead, plot-level rainfall, and temperature values, that are important in explaining plot-level agricultural efficiency and output. Failure to control for these plot-specific varying factors might lead to misleading results. Other studies also follow the similar approach (see, e.g., Di Falco et al., 2011; Kassie et al., 2015).

In our modelling framework, a plot is considered as a climate adopter; if one or two specific climate adaptation strategies (i.e., improved crop varieties and / or soil conservation activities) are practiced on that plot. To choose among the practiced adaptation strategies, listed in Table 1, we follow two approaches. First, we consider the correlations between farmer perceptions of climate change and the adaptation practices. Table A2, on-line Appendix shows that two adaptation strategies – improved crop variety and soil conservation – have the highest correlation with the climate notice variable. Second, we assume that the likelihood of implementing a given adaptation strategy should be positively and significantly affected by climate variables like temperature and rainfall. Indeed, the results from a probit model reported in Table A3 in the Appendix show that the probability of implementing improved crop variety and soil conservation strategies are positively correlated with average temperature and negatively correlated with the standard deviation of rainfall. Hence, we

[7] As a robustness test, we also used the radius matching technique to show that our main results do not depend on the choice of the matching approach. The result of this exercise is presented in Table A13 in the online appendix.

select these two adaptation strategies – improved crop varieties and soil conservation activities[8] –for our analysis. [9]

To facilitate the selection of matching variables, we rely on results of previous studies that analyzed climate change adaptation decisions by subsistence farmers (Di Falco and Veronesi, 2013; Kassie et al., 2013; Teklewold et al., 2013; Khanal et al., 2018; Teklewold et al., 2019; Ojo and Baiyegunhi, 2020). The matching variables are (1) various socio-economic factors, such as age, income, gender, education, marital status, household size, off-farm employment; (2) credit and institutional factors, including extension service, food aid, farmers perception whether to relay on government during bad harvest season, land ownership, land certification, market distance, and farm support; (3) various farming plot characteristics, such as slope, soil fertility, soil depth, and plot distance to the home stead; and (4) climatic variables, such as monthly average growing season rainfall and its square, annual average temperature and its square, standard deviation of growing season rainfall, standard deviation of temperature, and farmers' perception about whether the growing season rainfall was enough.

The matching procedure generates a total of 6,588 matched observations, of which 2,997 are adopters and 3,591 are non-adopters. Table A4 (on-line) presents the descriptive statistics of the variables used in the selection model across the matched and unmatched samples and the *t* test of whether the means

[8] Improved crop varieties include higher yield crop varieties and draught-resistant crop varieties. Soil conservation activities include stone bunds and soil bunds.

[9] One question that may arise here is why we do not consider all climate adaptation strategies that farmers implemented. We are constrained to choose only two climate adaptation strategies because of the methodology we use. Greene's (2010) sample selection correction approach developed for the SPF framework is designed only for the binary selection equation. As we believe that, by using a more appropriate methodology that allows us to address selection bias, we get more robust results than, by using methodologies considering many adaptation strategies without addressing selection bias, we focus only on the two of them. In addition, there are some adaptation strategies that farmers practice habitually regardless of changing climate conditions. For instance, it is a common practice to rotate crop type from year to year. Hence, we want to disentangle these types of practices from adaptation practices that are driven by climate change. Thus, in this study, when we refer to adopters, we mean climate adopters and when we refer to non-adopters – climate non-adopters.

of plot adopters and plot non-adopters are equal. It is evident that before matching, for most variables this hypothesis is rejected, while after matching, for all variables this hypothesis is accepted, at least at the five percent level of significance. In addition, we provide the distribution of the estimated propensity scores in Figure A2 in the on-line Appendix. The majority of propensity scores for adopters and non-adopters are found under the region of common support, therefore, the overlap assumption is fulfilled.

We estimate the SPF model with this matched sample corrected for sample selection. This requires a probit model, which is assumed to be associated with a number of plot-specific variables of the adoption of climate adaptation practices on a plot, household characteristics and exogenous climate characteristics.

The SPF model is estimated using a log-linear Cobb-Douglas[10] specification as follows:

$$ln(OUTPUT_{it}) = \beta_0 + \beta_1 ln\ (LAND_{it}) + \beta_2 ln\ (LABOUR_{it}) + \beta_3 ln\ (ASSET_{it}) + \beta_4 ln\ (SEED_{it}) + \beta_5 ln\ (UREA_{it}) + \beta_6 ln\ (DAP_{it}) + \beta_7 ln\ (TLU_{it}) + v_{it} - u_{it}, \quad (4)$$

where $v_{it}$ and $u_i$ are as defined in Eq. 3. The dependent variable, $OUTPUT_{it}$, is the total weight of harvested crops (wheat, teff, maize, and barley) from the $i^{\text{th}}$ plot measured in kilograms in production period *t*. The choice of these particular four crops is based on the importance of these crops in Ethiopian agriculture. They account for about three-fourths of the total cultivated area and 70 percent of the total agricultural production (Taffesse et al., 2011). The explanatory variables include: plot land size measured in hectares; total amount of labour in the plot measured in person days; total value of productive farm assets measured in Ethiopian Birr; total amount of seed used in the plot measured in kilograms; total amount of UREA and DAP fertilizers used in the plot measured in kilograms; and total amount of livestock owned by the household measured in tropical livestock units (TLU).

The average log values of output and input variables used in the SPF models for the matched sample are presented in Table 2. It is evident that, on average, output is significantly higher for adopters than for non-adopters. Furthermore, adopters consume significantly more labour, use a lower amount of seeds, and possess higher assets than non-adopters.

[10] The likelihood ratio test suggest that the Cobb-Douglas functional form is preferred over the translog counterpart. LR $chi^2$ =34.67, Prob>$chi^2$ =0.1795.

**Table 2: Descriptive statistics of output and input variables used in the SPF models for the matched sample**

| | Adopters | | Non-Adopters | | |
|---|---|---|---|---|---|
| | Mean | S. D. | Mean | S. D. | Difference in means ‡ |
| OUTPUT (ln) | 5.66 | 1.05 | 5.35 | 1.06 | -0.31*** |
| LAND (ln) | 0.25 | 0.17 | 0.24 | 0.16 | -0.01* |
| LABOUR (ln) | 5.62 | 1.05 | 5.39 | 1.14 | -0.23*** |
| ASSET (ln) | 9.69 | 1.30 | 9.60 | 1.31 | -0.09*** |
| DAP (ln) | 2.34 | 1.52 | 1.57 | 1.62 | -0.77*** |
| UREA (ln) | 2.11 | 1.51 | 1.29 | 1.55 | -0.82*** |
| SEED (ln) | 2.47 | 1.16 | 2.67 | 1.09 | 0.20*** |
| TLU (ln) | 1.60 | 0.61 | 1.59 | 0.62 | -0.01 |
| **No. of obsv.** | **2,997** | | **3,591** | | |

Notes: ‡t tests are performed to determine if the sample means are significantly different between adopters and non-adopters.

Before presenting and discussing the estimation results, following Bravo-Ureta et al. (2011), we summarize the main estimation steps we perform to obtain the selection bias corrected average TE scores for adopters and non-adopters.

1. First, we estimate a pooled unmatched SPF model (*Pooled-U*), which includes the dummy variable *Adaptation* (zero for non-adopters, one for adopters) as an explanatory variable of the climate change adaptation decision. Hence, this model does not control for any type of biases.
2. Next, two separate SPF models are estimated with the unmatched dataset, again ignoring any biases, one for adopters (*Adopters-U*) and the other for non-adopters (*Non-Adopters-U*).
3. The impact of correcting for self-selection is analyzed next. Using all the available data, we conduct PSM to address the bias from observed factors by matching adopters with non-adopters. Then, the selection Probit model for the matched sample is estimated.
4. The fourth step is to estimate two separate SPF models by using the unmatched data and by correcting for selection bias following Greene (2010), one for adopters (*Adopters-U-S*) and the other for non-adopters (*Non-Adopters-U-S*).
5. The pooled SPF model is re-estimated with the matched sample. It includes *Adaptation* dummy variable (zero for non-adopters, one for adopters) as an explanatory variable to represent the climate change adaptation decision.

6. Without addressing selection bias from unobserved factors, two distinct conventional SPF models are estimated using the matched subsamples, one for adopters (*Adopters-M*) and the other for the non-adopters (*Non-Adopters-M*). At this stage, the model addresses only biases from observed heterogeneities.
7. Finally, two separate SPFs are estimated using the matched subsamples, one for adopters (*Adopters-M-S*) and the other for the non-adopters (*Non-Adopters-M-S*), correcting for selectivity bias. Thus, these models take care of both types of selection biases (from observed and unobserved variables).

Next to the baseline model (Eq. 4), we estimate several additional SPF models for the matched sample. First, we estimate a separate SPF model and evaluate the effect of climate adaptation for each type of crop (wheat, teff, maize, and barley) as we expect that climate adaptation strategies might be crop specific. By estimating a separate SPF model for each crop, we will check whether the production of these crops is based on the same technology or not.

Second, we expand the baseline SPF model (Eq. 4) by including weather and soil related factors that can potentially affect output of harvested crops. Sherlund et al. (2002) claim that failure to account for these factors will underestimate efficiency and overestimate inefficiency, which could mislead policy makers. This SPF model includes climate and soil variables, such as average Meher season rainfall and average temperature for 32 years (1983-2015), fertility of the soil, depth of the soil, and slope of the plot. The inclusion of these important factors enables us to compare the discrepancy in input elasticities and level of efficiency (if any) with and without weather and soil variables.

## 4. Results and discussion

### 4.1 Main results from the baseline model

The maximum likelihood estimation results from the conventional SPF model and SPF model adjusted for sample selection are presented in Table 3 for the matched sample and in on-line appendix Table A5 for the unmatched sample. In line with our expectations, the estimates imply the positive partial elasticities for all production inputs, except DAP. However, the elasticities vary in terms of magnitude and statistical significance across different models. In all models reported in Table 3 and on-line appendix Table A5, plot size (*LAND*) and labour contribute most to the total output of both plot adopters and plot non-adopters.

**Table 3: Parameter estimates of the conventional and sample selection SPF models, the matched sample**

| | Conventional SPF | | | Sample selection SPF | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Pooled-M | Adopters-M | Non-Adopters-M | Adopters-M-S | Non-Adopters-M-S |
| LAND (ln) | 2.13*** | 2.08*** | 2.17*** | 2.29*** | 1.87*** |
| | (28.88) | (20.17) | (21.29) | (0.06) | (0.11) |
| LABOUR (ln) | 0.07*** | 0.07*** | 0.06*** | 0.06*** | 0.07*** |
| | (7.04) | (4.90) | (4.88) | (0.02) | (0.01) |
| ASSET (ln) | 0.04*** | 0.01 | 0.05*** | -0.00 | 0.06*** |
| | (5.14) | (1.10) | (5.24) | (0.01) | (0.01) |
| DAP (ln) | -0.001 | 0.05 | -0.02 | -0.01 | 0.00 |
| | (-0.75) | (0.33) | (-1.52) | (0.01) | (0.01) |
| UREA (ln) | 0.09*** | 0.11*** | 0.07*** | 0.13*** | 0.05*** |
| | (9.08) | (7.96) | (5.38) | (0.01) | (0.02) |
| SEED (ln) | 0.061*** | 0.02* | 0.09*** | 0.07*** | 0.10*** |
| | (6.84) | (1.91) | (7.57) | (0.02) | (0.01) |
| TLU (ln) | 0.03* | 0.04* | 0.02 | 0.05* | 0.03 |
| | (1.86) | (1.67) | (0.85) | (0.03) | (0.03) |
| Adaptation | 0.19***(9.29) | - | - | - | - |
| Constant | 4.76***(59.15) | 5.20***(44.03) | 4.60***(42.88) | 5.61***(0.15) | 4.86***(0.12) |
| $\sigma$ *(u)* | 1.13***(0.02) | 1.26***(0.02) | 1.29***(0.02) | 0.874***(0.06) | 1.10***(0.04) |
| $\sigma$ *(v)* | 0.32***(0.02) | 0.28***(0.03) | 0.31***(0.03) | 0.97***(0.03) | 0.85***(0.02) |
| $\Lambda$ | 3.98 | 5.81 | 4.09 | 0.89 | 1.13 |
| Log-likelihood | -8,156 | -3,630 | -4,502 | -5,980 | -6,740 |
| Selectivity correction term ($\rho$) | - | - | - | 0.92***(0.12) | -0.86***(0.02) |
| No. of obsv. | 6,588 | 2,997 | 3,591 | 2,997 | 3,591 |

Standard errors in the parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

From the conventional pooled SPF models for the unmatched (*Pooled-U*) and matched (*Pooled-M*) samples, we find that the effect of climate change adaptation on agricultural output is positive and significant (see columns 1 in on-line appendix Table A5 and Table 3, respectively). This result might suggest that plot adopters and plot non-adopters use different agricultural production technologies. We perform the LR test to check if there is a difference in the production technology among the two groups. The test result shows a test statistic of 32.77 ($p$ = 0.00), implying that the null hypothesis, which claims adopters and non-adopters having the same production technology, is rejected. Hence, our test results confirm the appropriateness of fitting two distinct SPF models – one for adopters and the other one for non-adopters.

Next, we analyze the impact of correcting for self-selection. First, we look at the results from the Probit model that estimates the determinants of a farmer's decision to implement climate change adaptation measures in their specific plot using the matched sample. The estimates summarized in Table 4 indicate that the likelihood of implementing climate change adaptation is influenced by many factors, including farm household characteristics, plot specific covariates, institutional factors as well as climatic variables. For instance, we find that extension service about climate change adaptation, farm support, and farmers' education increase the likelihood of implementing climate change adaptation measures. Furthermore, farmers are more likely to practice climate change adaptation on plots that are owned and managed by themselves than on shared plots, which implies that tenure security is a factor for sustainable land management.

Also, we find that the effect of temperature is U-shaped, that is at lower temperature levels, the likelihood of climate change adaptation is lower. However, this inverse relationship will cease after a certain temperature as implied by the estimated coefficient of the squared term of temperature. A higher temperature beyond this threshold increases the likelihood to implement a climate change adaptation measure. This might be due to the fact that a higher temperature beyond the optimal level required for crop production will cause a water shortage and other disasters, including drought and crop loss.

**Table 4: Parameter estimates of climate change adaptation decision using the matched sample**

| Variable | Coefficient | Variable | Coefficient |
|---|---|---|---|
| AGE | 0.02** | SHALDEPT | -0.023 |
| | (2.23) | | (-0.36) |
| AGE2 | -0.01** | PLOTDIST | 0.01 |
| | (-2.23) | | (0.04) |
| GENDER | 0.21** | FARMSUPPO | 0.22*** |
| | (2.55) | | (3.04) |
| MARRIED | -0.10 | HHSIZE | 0.01 |
| | (-1.43) | | (0.81) |
| OFFEMP | 0.01 | LANDOWNER | 0.14*** |
| | (0.02) | | (2.66) |
| CREDIT | -0.08** | AVMRF | 0.04*** |
| | (-2.15) | | (5.09) |
| AID | -0.28*** | SDMRF | -0.02*** |
| | (-3.86) | | (0.02) |
| RELGOV | -0.03 | AVMRFSQ | -0.01*** |
| | (-0.87) | | (-2.99) |
| CERTIFICAT | 0.01 | AVTMPSQ | 0.02*** |
| | (0.40) | | (4.32) |
| EDUC | 0.02** | AVTEMP | -0.80*** |
| | (2.52) | | (-4.03) |
| FLATSLOP | -0.07 | SDTEMP | 0.11** |
| | (-0.86) | | (2.41) |
| MEDMSLOP | 0.03 (0.38) | ENOURAIN | 0.02 (0.54) |
| MEDMDEPT | -0.03 (-0.84) | MKTDIST | -0.01 (-1.55) |
| MEDMSOIL | 0.22*** (3.80) | CLIMEEXTE | 0.08**(2.20) |
| | | Location dummies | Yes |
| GOODSOIL | 0.22*** | Log pseudo-likelihood | -4, 207 |
| | (3.49) | Prob > chi2 | 0.00 |
| Constant | 2.68 (1.35) | No. of obsv. | 6,588 |

*Notes*: Robust standard errors clustered at plot level in the parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.

We use the growing season plot-specific rainfall (Meher season) and its variability to estimate the effect of rainfall on climate adaptation decisions. Considering season-specific rainfall rather than the total amount of annual rainfall is appropriate, as it will show the real response of farmers to changing climatic conditions. Unlike temperature, the effect of rainfall is an inverted U-shape. Initially, at lower levels of rainfall, the likelihood of adaptation increases with an increase in rainfall. But after some level of rainfall, higher rainfall is associated with a lower chance of practicing a climate adaptation strategy. Our results are in line with the results of Deressa et al. (2009) and Deressa et al. (2011), who showed that weather variables like precipitation and temperature significantly determine the decision to implement climate adaptation strategies.

The estimates of the sample selection SPF models show that the sample selection correction term ($\rho$) is statistically different from zero for both adopters and non-adopters in the matched and unmatched samples. This result implies the existence of selection bias from unobservable factors. Hence, estimating the separate selection bias-corrected SPF models for adopters and non-adopters is justified. Even though the main objective of this study is to measure the impact of implemented climate change adaptation strategies on TE of plot adopters, we also aim to understand how addressing selection bias from observed and unobserved heterogeneities affect the estimated TE scores. In Table 5 we present the average TE scores for adopters and non-adopters estimated by using the conventional SPF and selection bias-corrected SPF models for the unmatched and matched samples. In addition, Table 5 presents the differential, in percentage terms, between the TE for adopters and the TE for non-adopters.

The average TE scores reveal that plot adopters are more efficient than plot non-adopters and that this difference is statistically significant after addressing selection bias in both the matched and unmatched samples. After addressing both types of biases, the TE differential between adopters and non-adopters is 12.37 percent, which is significantly larger than the conventional counterpart (4.21%). This suggests that by implementing climate change adaptation strategies, plots are becoming more efficient. Furthermore, our results reveal that the conventional SPF models underestimate the impact of climate change adaptation on average TE.

**Table 5: Average TE levels across different models**

| | **Conventional SPF** | | | | **Selectivity-corrected SPF** | | |
|---|---|---|---|---|---|---|---|
| | Unmatched sample | | | | | | |
| | Pooled-U | Adopters-U | Non-Adopters-U | *t* test of means‡ | Adopters-U-S | Non-Adopters-U-S | *t* test of means‡ |
| TE | 41.33 | 42.26 | 40.55 | 1.71*** | 48.88 | 40.23 | 8.65*** |
| TE Differential | 4.21% | | | | 21.50% | | |
| | Matched sample | | | | | | |
| | Pooled-M | Adopters-M | Non-Adopters-M | t test of means‡ | Adopters-M-S | Non-Adopters-M-S | t test of means‡ |
| TE | 44.6 | 45.10 | 44.19 | 0.91* | 53.03 | 47.19 | 5.84*** |
| TE Differential | 2.059% | | | | 12.37% | | |

*Notes*: ‡*t* tests are performed to determine if the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

In line with the findings of Villano et al. (2015) and Azumah et al. (2019), our results show that failure to correct for selection bias from observed and unobserved factors overestimates inefficiency, while it underestimates the TE gap between adopters and non-adopters. However, the results of Bravo-Ureta et al. (2011) are in contrary to this, where the TE gap between treated and control groups reduced as the correction for bias was implemented.

Even though plots in which climate change adaptation practices are implemented are more efficient, there is still a huge potential to increase production and the overall efficiency of these plots. For the matched sample, after accounting for selection bias, the average TE of plot adopters is 53 percent, the average TE of plot non-adopters, corrected for selection bias, is estimated to be 47 percent indicating that farmers lose 52.81 percent of their total output because of technical inefficiency.

Addressing selection bias from both observables and unobservables not only reduces the proportion of plots operating at the lower level of efficiency, but also increases the proportion of plots operating at higher efficiency levels. For instance, when we compare the proportion of plots operating with 51-60 percent TE without accounting for any type of biases (Fig. A3A, on-line) to its counterpart when accounting for biases (Fig. A3D, on-line), the proportion of plots increases from 6 percent to 11.63 percent for adopters and from 6.83 percent to 10.84 percent for non-adopters. The effect of controlling for selection bias is larger for adopters.

We also look at which of the two groups (plot adopters or plot non-adopters) have a higher level of output after addressing selection bias from both observed and unobserved heterogeneities. Towards this end, we compare the average predicted frontier output for adopters and non-adopters generated from the selection bias-corrected SFP models. On average, plot adopters not only attain higher TE, but also show statistically significant higher predicted outputs, Table 6.

**Table 6: Predicted frontier output in kg after bias correction**

| Sample | Adopters | Non-adopters | *t* test in means‡ |
|---|---|---|---|
| Average | 724.46 | 608.76 | 115. 7*** |
| Min | 6.63 | 12.47 | |
| Max | 4,918.62 | 5,130.82 | |

*Notes*: ‡*t* tests are performed to determine if the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Finally, we repeat the previous analysis using the balanced sample only. As we explicitly pointed out in section 3.1, it is assumed that once plot adopters are selected as adopters in the first wave of the survey period, they will remain adopters for the next two survey years. To address this, we constructed the balanced sample, where a plot adopter is considered as an adopter if it adopts in all the three years and a plot non-adopter as a non-adopter if it does not adopt in all the three survey years. The results from the analysis of the balanced data sample (see Table A6, on-line) are consistent with the main findings discussed above.

### 4.2 Determinants of technical inefficiency

Identifying the determinants of technical efficiency (inefficiency) could enhance policy making by indicating the potential directions of agricultural policy. Table 7 presents the determinants of TE estimated from a selectivity corrected maximum simulated loglikelihood SPF and inefficiency models. For comparison, Table 7 provides the results for the pooled sample (Column 1), the sample of farming plots adopters (Column 2), and the sample of farming plots non-adopters (Column 3). In our estimation, we include different covariates that could explain TE, including socio-demographic factors, plot characteristics, institutional and climate related factors. A positive significant estimated coefficient indicates a positive (negative) effect on inefficiency (efficiency).

**Table 7: Determinants of technical inefficiency**

| | 1 | 2 | 3 |
|---|---|---|---|
| | Pooled | Adopter | Non-adopter |
| Age | -0.003*** | -0.002 | -0.004*** |
| | (0.001) | (0.001) | (0.001) |
| Gender | 0.106* | 0.015 | 0.067 |
| | (0.055) | (0.088) | (0.081) |
| Education | 0.005 | 0.003 | -0.002 |
| | (0.004) | (0.007) | (0.006) |
| HH size | -0.015*** | -0.025*** | -0.010 |
| | (0.005) | (0.008) | (0.007) |
| MARRIED | -0.080* | -0.071 | -0.058 |
| | (0.047) | (0.070) | (0.070) |
| CREDIT | -0.068*** | -0.053 | -0.067** |
| | (0.023) | (0.037) | (0.033) |
| RELGOV | -0.061** | -0.072* | -0.029 |
| | (0.025) | (0.041) | (0.036) |
| PLOTDIST | 0.001 | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.000) |
| SHALDEPT | 0.070* | 0.073 | 0.022 |
| | (0.041) | (0.069) | (0.057) |
| MEDMDEPT | 0.040 | 0.062 | 0.025 |
| | (0.028) | (0.042) | (0.040) |
| MEDMSLOP | -0.007 | -0.016 | 0.016 |
| | (0.069) | (0.097) | (0.097) |
| FLATSLOP | 0.044 | 0.160* | 0.003 |
| | (0.068) | (0.095) | (0.095) |
| GOODSOIL | 0.287*** | 0.139** | 0.203*** |
| | (0.040) | (0.067) | (0.056) |
| MEDMSOIL | 0.192*** | 0.050 | 0.173*** |
| | (0.037) | (0.061) | (0.053) |
| AVMRF | 0.014*** | 0.020*** | 0.018*** |
| | (0.002) | (0.003) | (0.003) |
| SDMRF | -0.001 | -0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| AVTEMP | -0.027*** | -0.018 | -0.031** |
| | (0.010) | (0.016) | (0.014) |
| SDTEMP | -0.005 | -0.038 | -0.020 |
| | (0.027) | (0.047) | (0.035) |
| AVMRFSQ | -0.000*** | -0.000*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) |
| Location dummy | Yes | Yes | Yes |
| Constant | 3.734*** (0.308) | 4.409*** (0.470) | 3.462*** (0.452) |
| Log-likelihood | -12,786 | -5,837 | -6,768 |
| No. of obsv. | 6,588 | 2,997 | 3,591 |

*Notes*: Standard errors in the parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results reveal that the determinants of the TE are similar for plots adopters and plots non-adopters. However, the size and statistical significance of the effects are different. For instance, the technical inefficiency of adopters is significantly influenced by family size, reliance on government, and climatic factors. For adopters, larger family size reduces inefficiency. As implementing climate change adaptation measures require both monetary and non-monetary outlay including labour, large families could facilitate the effectiveness of the implemented adaptation strategy by providing the required labour. On the other hand, large family size could also serve as a source of diversified farming knowledge, information, and non-farm income.

We also find that farmers perception of being able to rely on government during bad cropping season significantly enhance TE of plots adopters. This could be due to the fact that government support during bad harvest season serves as a partial source of insurance against crop failure. This might encourage farmers to implement new and improved agricultural technologies that spur efficiency. Looking at climatic factors, the amount of rainfall during the main harvesting season has a nonlinear effect on the efficiency of both adopter and non-adopter plots. A lower amount of rainfall during this season reduces TE while a higher rainfall beyond some threshold level improves efficiency. As farmers in the study area are characterized by rainfed subsistence farming, lack of enough rainfall during the main harvesting season will inhibit production efficiency by causing crop failure, asset depletion and welfare loss in general. This result is in line with the findings of Auci and Coromaldi (2021). Unlike rainfall, temperature appears to significantly improve efficiency of plots non-adopters only. Beyond climate related factors, non-adopter plots' TE is significantly affected by plot characteristics, age of the household head, and access to credit. Compared with young farmers, old farmers are more efficient indicating the role of farm experience in boosting productive efficiency. On the other hand, access to additional financial resources could assist farmers to smooth their consumption during bad harvesting seasons and also could serve as a source of finance to purchase improved agricultural inputs and technologies. Similar results are found by Abdulai and Abdulai (2016) for Zambia and Azumah et al. (2019) for Ghana.

### 4.3 Additional results

Even though the results from our basic model estimation show the general efficiency effect of climate adaptation and the problem of failure to account for selection bias, it has two caveats. First, the estimated SPF model does not account for weather and soil factors, which might be important. Second, we do not estimate a separate production function for each crop by accounting for technological differences of each crop.

To understand whether our main production function estimates are sensitive to climatic and soil factors, we estimate the SPF models adjusted for sample selection for the matched samples with weather and soil variables. We report the results from this estimation in Table A7, on-line (columns 3-4) next to the results from the baseline model (columns 1-2). It is evident that all models deliver similar partial elasticities for all main production inputs. The input elasticities of climate and soil variables are in line with our expectation. A higher rainfall and a higher fertility of the soil positively contribute to the total output, while a higher plot slope and temperature are associated with a decreasing level of output.

The availability of plot-specific data for each crop allows us to estimate a separate production function for each crop. The results from the estimated crop-specific SPF models adjusted for sample selection for the matched samples can be found in the on-line appendix Table A8. We also measure the effects of climate adaptation strategies on each crop's TE, which are summarized in Table 8. The results reveal that climate adaptation strategies have a crop-specific effect. From the considered crops, climate adopters achieve a higher level of efficiency in maize, wheat, and barley. On the other hand, climate adaptation measures seem to reduce efficiency for teff. This implies that the assumption of climate adaptation strategies being equally effective could be misleading. In the case of our study, climate adaptation in the form of improved varieties and soil and water conservation activities can spur productive efficiency for maize, wheat, and barley crops.

**Table 8: Crop specific TE estimation after accounting for weather and soil factors for the matched sample under different models**

| | **Conventional SPF** | | | | **Selectivity-corrected SPF** | | |
|---|---|---|---|---|---|---|---|
| | Pooled-M | Adopters-M | Non-Adopters-M | *t*-test of means‡ | Adopters-M-S | Non-Adopters-M-S | *t*-test of means‡ |
| **Maize** | | | | | | | |
| TE | 43.65 | 45.78 | 40.85 | 4.93*** | 59.01 | 38.24 | 20.77*** |
| TE Differential | 12.06% | - | - | - | 54.31% | | |
| Number of obsv. | 2,006 | 1,150 | 856 | | 1,150 | 856 | |
| **Wheat** | | | | | | | |
| TE | 47.72 | 47.64 | 47.82 | -0.18 | 49.80 | 48.05 | 1.75** |
| TE Differential | -0.37% | - | - | - | 3.642% | | |
| Number of obsv. | 1,501 | 778 | 723 | | 778 | 723 | |
| **Teff** | | | | | | | |
| TE | 52.21 | 52.91 | 51.78 | 1.13 | 57.52 | 60.19 | -2.67*** |
| TE Differential | 2.18% | - | - | - | -4.43% | | |
| Number of obsv. | 1,877 | 721 | 1,156 | | 721 | 1,156 | |
| **Barley** | | | | | | | |
| TE | 45.03 | 44.73 | 45.15 | -0.42 | 46.48 | 44.40 | 2.08* |
| TE Differential | -0.93% | - | - | - | 4.68% | - | - |
| Number of obsv. | 1,204 | 348 | 856 | | 348 | 856 | |

*Notes*: ‡ *t* tests are performed to determine if the sample means are significantly different between adopters and non-adopters; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.00$.

### 4.4 Robustness tests

We perform four robustness checks. First, we would like to check whether our main results on adaptation hold once the analysis is performed at the household level by considering the same adaptation strategies. This is important as the decision to implement particular climate change adaptation measures is made by farm households. Second, we check whether the results differ once we consider other climate adaptation strategies. Third, we look at the results performed for each wave of survey data. Finally, we modify our definition of adaptation. As we discussed in the empirical strategy section, the selection bias correction model developed by Greene (2010) assumes that the selection takes place only once – in our case, in the first year when our survey data was collected. But farmers' climate change adaptation decision might be different from year to year, meaning that a farm plot might be considered as a plot non-adopter in the first survey year, but as a plot adopter in the second and or third survey periods. To account for this, as a robustness test, we modify our definition of adaptation in a way that a farm plot is considered as an adopter if the considered climate adaptation strategies are implemented in that specific plot at least in one of the three survey years.

The results from the different SPF models with the household level data are reported in the on-line appendix Table A9. We can see that household adopters have higher TE levels than household non-adopters across all models. The results from the SPF models based on plot level data and using different adaptation strategies – crop diversification and agro-forestry – are summarized in the on-line appendix Table A10. The selection of these two adaptation strategies is based on the work of Deressa et al. (2011) and Di Falco et al. (2011), which showed that these two strategies are commonly used to curb climate related shocks in their study areas. Our results show that plot adopters are more efficient than plots non-adopters. The efficiency difference becomes larger when we control for both types of biases. Moreover, the year-by-year TE estimates also reveal the same result, except for the year 2016 (see on-line appendix Table A11). Finally, we reestimate our model using the modified definition of adaptation and find that, as in the main analysis, adopters attain a higher level of TE than non-adopters. The average TE difference between adopter plots and non-adopter plots is statistically significant (see on-line appendix Table A12).

## 5. Concluding remarks

In this study, we investigate the impact of climate change adaptation measures on farmers' TE. For this purpose, we estimate the selectivity bias-corrected stochastic frontier models with the plot-level panel data collected by surveying rural farm households in the Nile basin of Ethiopia. We address selection bias from observed and unobserved heterogeneities by jointly implementing the PSM method with Greene (2010) sample selection model developed for the stochastic frontier framework under panel data setting.

Our results show that the presence of selection bias, arising from unobserved factors like motivation, risk attitude and innate farmers' ability, affects farmers' climate change adaptation practices. Furthermore, we find that climate change adaptation significantly improves TE. That is, farming plots with climate change adaptation are more efficient than farming plots without climate change adaptation. The impact of adaptation becomes larger once we account for selection bias from observed and unobserved covariates, suggesting that failure to address selection bias under non-random assignment of an intervention significantly underestimates the level of TE. All these results are robust to the analysis performed with the data at the household level, to the inclusion of different climate change adaptation strategies and to the year-by-year plot level analysis. Furthermore, we show the importance of accounting for weather and soil factors when estimating farmer' plot-specific productive efficiency, and that the impact of climate adaptation is crop specific. In the case of our study, climate adaptation in the form of improved varieties and soil conservation activities spur TE of barley, wheat, and maize crops.

We also find that different factors, including socio-economic characteristics, institutional factors, plot and climate related factors impact TE of adopters and non-adopters differently. While TE of adopters is significantly and positively affected by family size, perception of government support during bad harvest season, TE of non-adopters appears to be positively and significantly associated with age of the farm household head and access to credit. Regarding climate related factors, average growing season rainfall has a U-shaped effect on the efficiency of both adopter and non-adopter plots. Lower rainfall in the growing season inhibits efficiency while a higher level of rainfall which is enough for the crop boosts efficiency of subsistence farmers.  But temperature positively and significantly affects the efficiency of plots non-adopters only.

Moreover, we show that farmers' decision to implement climate change adaptation measures in their plots is significantly affected by both socio-economic, institutional and climate related variables. Extension service about climate change adaptation, education level of the household head and farm support significantly increase the likelihood of implementing climate change adaptation. Climate variables affect adaptation decisions non-linearly. While the effect of plot-specific average temperature is U-shaped, the effect of the growing season's rainfall is an inverted U-shape.

From the results of this study the following policy implications are drawn. First, subsistence farmers are, on average, operating below their full potential, which needs a special policy intervention that would unleash the existing farmers' productive potential. Second, as climate change adaptation measures have a positive and significant effect on farmers' productive efficiency, policy makers need to increase awareness among farmers not only about the fact that climate change adaptation measures lessen climate related shocks, but also about the fact that these measures can increase farmers' productivity. Hence, a robust and well-endorsed adaptation package could improve productivity and, consequently, improve food security of the country. Third, the efficiency effect of climate adaptation is crop specific. Hence, agricultural policy makers should identify specific climate adaptation strategies suitable for each crop type rather than promoting climate adaptation as a general tool to curb climate related shocks.

Fourth, we show that failure to address selection bias in the measurement of farmers' productive efficiency will lead to biased results and will mislead the decision making of policy makers. Hence, policies aiming to increase farming's productive efficiency and to reduce the impacts of climate change on agriculture should follow studies that use appropriate empirical techniques.

Fifth, there are different factors that serve as a sources of subsistence farmers' inefficiency, and these factors differ between plots adopters and plots non-adopters. In particular, policy makers aiming at improving subsistence farmers' efficiency should focus on expanding credit access and ensuring water supply during the growing season.

Finally, policies seeking to create a climate-resilient agricultural sector should promote and expand tenure security, extension service about climate change adaptation and financial farm support, as these "ingredients" appeared to be important in explaining farmers' decision to implement climate change adaptation strategies.

Even though our study brought an important contribution to the literature, it is not without limitations. The selection bias correction model developed by Greene (2010) under stochastic frontier analysis framework and used in our study is for binary selection only. To the best of our knowledge, there is no other method that would allow estimating a multinomial selection model to address selection bias under stochastic frontier analysis framework. But climate adaptation decision is multinomial as farmers usually implement a combination of different adaptation strategies. Greene (2010) selection model further assumes that the selection takes place only once (in our case, in the first survey year). Thus, future studies could focus on relaxing the selection model to account for selection at different periods.

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