Annual and cropping season environmental production conditions effects on smallholder technical efficiency in sub-Saharan Africa: Evidence from Ethiopia

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Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1.

1 Introduction

In sub-Saharan Africa, agriculture is an important activity which serves as the engine of economic growth by contributing substantially to GDP and employing a large proportion of the rural population. Rural households often engage in subsistence farming to feed their families and if possible sell the remaining of their stock. Governments tend to assist subsistence agriculture by providing technical knowledge in the form of extension services to enhance productivity and efficiency. Studies have shown that unless urgent efforts are made to raise crop yields and increase technical efficiency,[1] subsistence farmers are likely to reap meager harvests (Fleshman 2006).

Agriculture in most developing countries is rain-fed and depends highly on environmental conditions. Farming decisions are based on the availability of rainfall during the growing season or previous rainfall history (Hoanh et al. 2015). Though irrigation reduces the dependency on rainfall and variability in yields, inaccessible credit and very low incomes in developing countries coupled with risk preferences affect farmers' decisions to engage in irrigation farming. The irrigated share of Africa's cropland is estimated to be less than a quarter of the world's average (Svenden, Ewing and Msangi 2009; Moyo, BAH and Verdier-Chouchane 2015). Regarding the sub-region, only 4 percent of croplands are irrigated in sub-Saharan Africa (World Bank 2008). The clear message is that without any intervention, agricultural production in sub-Saharan Africa may continue to wither under extreme weather conditions.

As world leaders seek to find solutions to reduce greenhouse gas emissions and their possible consequences, there is a keen interest in how changes in the environment will affect agricultural activities especially in developing countries where adoption of farm technologies is still low and prohibits farmers to cope with environmental changes. In seasons with unfavorable environmental conditions, farmers are not able to increase productivity and

[1]To be technically efficient means farmers need to minimize waste by using production techniques that use the least amount of inputs to achieve maximum output.

utilize inputs efficiently. To decrease the impact of adverse environmental conditions and smoothen their income which depends highly on yields, farmers often engage in off-farm activities to supplement household income and shift to more drought tolerant crops.

The impact of increased weather variability on farming activities, especially in rural or vulnerable communities, has become a major concern as scientist continue to predict more extreme weather conditions. Recent studies show that the adverse effects of climate change have already begun to affect the planet, with the global economy firmly on track to produce levels of emissions that could generate rising sea levels, intense droughts and food shortages, destructive storms and floods, and other catastrophic effects[2] (Davenport and Harris 2015). Therefore, there is a need to examine the effect of environmental conditions on farm technical efficiency in developing countries and find adaptation measures that ensure and increase the productivity of smallholder farmers.

There are numerous studies on farm technical efficiency in developing countries. Most of these studies concentrate on efficiency in maize and rice farming (Kibirige et al. 2014; Abdulai and Eberlin 2001; Sherlund et al. 2002; Dalton 1999). However, expect Sherlund et al. (2002) that introduced and stressed the importance of including environmental variables in technical efficiency studies for smallholder productivity fifteen years ago and applied it to rice farming, very few studies have done so. To our knowledge, no studies have included environmental variables in technical efficiency analysis for maize, wheat and sorghum, which are the most important crops for smallholders in sub-Saharan Africa. This study contributes to the literature on technical efficiency in two ways. First, we estimate the level of technical efficiency in wheat, maize, and sorghum for subsistence farmers in Ethiopia and show how technical efficiency estimates are affected when controlling for environmental production conditions. Second, given that daily environmental production condition data is available we also estimate a model that includes annual environmental production conditions for the exact cropping season (planting to harvest) and find significant differences. Given increased climate

[2]Evidence of changes in climate extremes is already emerging in Southern and West Africa (New et al. 2006).

variability more accurate efficiency estimates will be useful to stakeholders in agriculture.

The rest of this paper is organized as follows. Section 2 reviews the literature on farm technical efficiency and the relationship between agriculture and climate. Section 3 outlines the theoretical and empirical models used for the estimation and section 4 provides descriptive statistics of the variables used in the model. Section 5 discusses the results and its implications, and section 6 concludes.

2 Literature Review

2.1 *Technical Efficiency*

Farm technical efficiency has been subject to numerous studies. The literature on technical efficiency, especially in developing countries, shows that inefficiencies exist in the agricultural sector. The level of technical efficiency in most developing countries is below optimal. For example, Bravo-Ureta and Evenson (1994) estimated farm technical efficiency in eastern Paraguay and found the level of efficiency for cotton and cassava to be 40.1% and 52.3%, respectively, which is significantly below the maximum possible level attainable. In eastern Ethiopia, the level of technical efficiency is estimated to be between 74.8% to 93.7% for maize farming when extension services are upgraded to smallholder farmers while efficiency for farmers who did not receive the upgrade range from 55.7% to 96.5% (Seyoum et al. 1998).

In sub-Saharan Africa, the average level of technical efficiency for maize cultivation estimated is 82% for West Africa countries, 57% for East Africa countries and 72% for Southern Africa countries (Kibirige et al. 2014). In Central American countries, such as Nicaragua, the average technical efficiency is estimated to be 69.8% for maize farming (Abdulai and Eberlin 2001). Solis et al. (2008) found that the average level of farm technical efficiency among peasant farmers who participated in natural resource management programs in El-Salvador and Honduras was 78%, on average. This percentage is similar to Latin America countries according to Bravo-Ureta et al. (2007). Therefore, sub-Saharan Africa and Central

America countries can boost agricultural productivity and increase economic growth through a more efficient use of inputs. However, these countries have not been able to achieve high productivity due to the extensive use of more primitive technology (Seyoum et al. 1998) and climate uncertainty.

For developed countries like the United Sates, the average technical efficiency of dairy farms is 83% (Bravo-Ureta and Rieger 1991) and 85% for crops (Bagi 1987). Liu and Zhuang (2000) also estimated the level of farm efficiencies using rural household data and found that farmers in Sichuan and Jiangsu district of China are 85% and 88% efficient, respectively. Most countries in Europe have a relatively high average level of efficiency, ranging from 72% to 92% for both field crops and dairy farms (Bakucs et al. 2011).

Factors that determine farmers level of efficiency include access to credit, access to extension services, farmer education, farm size, and availability of migrant workers. Some of these factors have a positive relationship with farmers' level of efficiency, especially in developing countries. Efficiency may increase with an increase in farmers education, farm size, access to credit and extension services. However, there are controversies about the relationship between efficiency and some of these factors (Bravo-Ureta and Evenson 1994). For instance, Tadesse and Krishnamoorthy (1997) show that there is significant variation in the average level of technical efficiency among rice farmers operating on small, medium and large farms. The most efficient farmers are those who work on small farms with an efficiency level of about 85%, followed by medium scale farmers with 83% efficiency while efficiency on large farms averages around 80%. Their findings are consistent with the results obtained by Bozoglu and Ceyhan (2007) who found that small farm size vegetable farmers are more technically efficient than their larger counterparts.

As mentioned, Sherlund et al. (2002) is the first study to stress the importance of controlling for environmental conditions in technical efficiency studies in rain-fed agriculture. Using panel household data for rice smallholders from Cote d'Ivoire they estimated technical efficiency with and without controlling for environmental conditions and found that when controlling for environmental conditions estimates of technical efficiency are significantly lower stressing the importance of including environmental conditions in farm efficiency studies.

2.2 *Agriculture and Climate*

It is well known that climate variability causes fluctuations in crop production. While seasonal rainfall totals and season-to-season variability are important, the pattern of within-season variability can also have a major effect on crop production. Agriculture as a whole has always been highly dependent on climate variations (Climate Institute 2007). Solar radiation, temperature, and precipitation are the main factors that affect crop and livestock growth. In recent years, there have been great concerns about how changes in these factors will affect agricultural production and hence the future food supply.[3] Experts predict that climate change will result in more frequent disruption of food production and increased food prices in many parts of the world, with developing nations facing the greatest risk. Further, high temperatures will make many agricultural lands less productive and unsuitable for cultivation (Mendelsohn and Dinar, 1999). On the other hand, climate change may hurt agriculture less in developed nations such as the United States and Europe since adaptation by farmers in these countries would reduce some of the damages from climate change (Mendelsohn and Dinar 1999). Therefore, developing nations are expected to be affected the most by the changes in weather conditions.[4]

As mentioned, the use of low-performing technologies coupled with inaccessible credit still characterizes farming activities in developing countries and makes it difficult to adapt to climate variability. However, these countries have the potential to improve productivity if the appropriate technologies and innovations are adopted (IAAST 2009). The adoption of

[3] More frequent and extreme weather events, such as droughts and floods, are expected to make local crop production even more challenging. Climate change is projected to put an estimated 49 million more people at risk of hunger by 2020 (IFAD 2009).

[4] The inevitable changes to climatic patterns which are likely to exacerbate existing rainfall variability in SSA and further increase the frequency of climatic extremes (IPCC 2007).

new technologies will help support the natural life cycles, that is, nutrients of soil and water and conserve sufficient biological conditions for future production regarding improvements in crop quality, productivity (Linham and Nicholls 2010) and efficient use of available resources. Frequent and severe droughts are also becoming a major challenge to agriculture production in many parts of the world (Esikuri 2005), and it is believed that these droughts are likely to continue if global temperatures continue to rise (Williams and Funk 2011).

Even though efficient irrigation methods and the use of genetically modified crops have been developed to solve some of these problems, agricultural production in developing countries is entirely sustained through rainwater, with only 6% of the total cultivated area equipped for irrigation (You et al. 2011). Because of this, governments and non-governmental agencies are substantially increasing investments in irrigation, and studies have shown that 58% of the rural population in Sub-Saharan Africa can benefit from investments in irrigation and consequently increase the world food production (Faures and Santini 2008).

Climate variability and change have also become a major determinants of welfare in rural areas because of the dependence on agriculture for subsistence consumption and livelihoods (Alem and Colmer 2013). Existing literature shows that climate variability would have an effect on welfare through the monetary and psychological impact of risk and uncertainty (Porcellie and Delgado 2009; Doherty and Clayton 2011). For instance, households who depend heavily on agricultural income may have to alter their consumption or send their children to work instead of school to supplement income (Jacoby and Skoufias 1997). Also, farmers may adjust fertilizer and pesticide use depending on the climatic conditions and diversify geographically by having plots of land in different locations (Skoufias and Vinha 2013). In countries where there are fewer adaptation practices, climate variability or increases in diurnal (within-day temperature) variation can generate significant economic losses (Dixon and Segerson 1999).

In developing nations like Ethiopia, which is where the data for this study came from, where much of the rural population relies on subsistence farming the impact of extreme weather has been very drastic over the years. During the last years, Ethiopia has experienced countless localized drought events and seven major droughts, five of which resulted in famines. Climate variability is likely to worsen these conditions especially in the southern, southwestern and northern parts of the country (GFDRR 2011). Migration in search of relief and lack of adequate shelter is increasing in areas where drought is impacting animals and crops. In recent years, the government of Ethiopia has made efforts to reduce the impacts of climate variability and change on its citizens by improving irrigation and educating farmers on the climate variability and change. In addition, the government of Ethiopia has also initiated the Climate Resilient Green Economy (CRGE) to help protect citizens against the impacts of climate variability and change. Notwithstanding these efforts, agriculture production remains low in most parts of the country.

3 Methodology

3.1 *Theoretical Model*

Farm technical efficiency is usually measured by a non-parametric approach using Data Envelopment Analysis (DEA) or a parametric approach, which is the Stochastic Frontier Approach (SFA). The most common method used to measure farm technical efficiency is the Stochastic Frontier Approach developed by Aginer, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). The general specification of the model which is also used in this study is given as:

$$Y_{it} = f(X_{it}; \beta) + V_{it} - U_{it} \tag{1}$$

Where Y_{it} is output for the ith farm in tth time, X_{it} is a vector of inputs that the ith farm uses in production at time t, and β is a vector of parameters in the model. The model consists of a composite error term $(V_{it} - U_{it})$, where V_{it} measures the unobservable factors that affect the ith farm's production in time t while U_{it} is non-negative and captures the inefficiencies from production. The first error term V_{it} is identically and independently distributed $N(0, \sigma_v^2)$ and U_{it} is independently distributed as truncation at zero of the normal distribution $N(\mu, \sigma_u^2)$. This model relies on farm input information to estimate the production frontier, that is, the amount of capital, land, labor, fertilizer, pesticide, etc., used by the farmer in the growing season. However, in practice, a farmer's production also depends on existing environmental conditions (Sherlund et al. 2002). The quality of soil, the slope of the land, temperature and availability of rainfall often determines output levels in countries where farming activity is relies more on environmental conditions. Based on this practice a good estimate of the stochastic frontier is to incorporate these factors to avoid the problem of omitted variable bias.

To measure farm inefficiencies Battese and Coelli (1995) proposed that the technical inefficiency of each farmer at a given point in time can be estimated as:

$$U_{it} = \sum \delta_k Z_k \tag{2}$$

where δ_k is a vector of parameters and Z_k is a vector of observable factors associated with technical inefficiencies in the production process. The observable factors include socio-demographic factors such as farmers age, gender, education and other household specific factors. The model is estimated in terms of the variance parameters, that is,

$$\sigma = \sigma_v^2 + \sigma_u^2 \tag{3}$$

and

$$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)} \tag{4}$$

the parameter γ has a value between zero and one, such that the value of zero is associated with the absence of technical inefficiency from the model (Battese and Tessema 1993). The efficiency of an individual farmer, on the other hand, can be defined as the ratio of the observed output to the maximum possible outcome attainable in the situation where no inefficiencies exist. Hence, technical efficiency (TE) can be expressed as:

$$TE_i = \frac{\mathbb{E}(Y \mid U_{it}, X_{it})}{\mathbb{E}(Y \mid U_{it} = 0, X_{it})} \tag{5}$$

Given that the production function is expressed in logarithmic form then the technical efficiency (TE_i) for each farm conditional on their U_{it} is:

$$TE_i = exp(-U_{it}) \tag{6}$$

TE_i lies between 0 and 1, where 0 means the farm is technically inefficient and 1 means the farm is technically efficient, that is, the farm uses the optimal combinations of inputs to attain maximum level of output. The output that can be achieved depends on the farmer's access to an appropriate amount of inputs, however, the number of inputs used within a given season is also determined by the environmental conditions that the farmer face. For example, the amount of labor required for weeding depends on the volume and timing of rainfall (Mochebelele et al. 2000). Therefore, the omission of environmental variables from the data may introduce some biased in the estimation of the stochastic frontier (Mochebelele et al. 2000). Further, if the estimates of the stochastic frontier are bias then the technical efficiency measure U_{it}, generated from equation (1) are also likely to be biased and result in inconsistent estimates of the parameters in equation (2). In sum, the omission of environmental production conditions affects both output and inputs thereby leading to biased estimates of the parameters of the production frontier and technical efficiency.[5]

[5] The relationship between output and inputs is normally estimated in the literature as $\ln Y_i = f(X_i, W_i^*) + V_i - U_i$ where $W_i^* \subseteq W_i$, omits some of the variables in W_i; call this omitted variable $\tilde{W}_i$. This omitted variable lead to biased and inconsistent estimates of the parameters of $f(.)$ if $\tilde{W}_i$ is correlated with both X and Y (Sherlund et al. 2002).

3.2 *Empirical Model*

The stochastic frontier is used to estimate the technical efficiency for each farm in this study. The frontier represents an efficient technology, and any deviation from the boundary is considered inefficient (Okon et al. 2010). We estimate a Cobb-Douglas stochastic production frontier where the function is given by:

$$\ln Q_i = \beta_i \ln X_i + V_i - U_i \tag{7}$$

Where lnQ_i is the logarithm of total crop produced by the ith household in each year, lnX_i is the logarithm of inputs used to produce the crop such land size, labor days, capital, and the number of oxen used to plow. β is a vector of parameters that will be estimated by the model, V_i is a vector of random terms that are unobservable to the household which affects the production process. To account for how variation in environmental conditions affect the household production frontier, we estimate equation (7) with and without environmental production conditions. In our first model, we estimate the conventional production frontier by considering only inputs used by the household farmer and ignore any effects of the environment. However, in practice, smallholder farmers rely on the environment, they adjust inputs in response to changes in the environment (Sherlund et al. 2002). Therefore, in our second model, we consider this practice by including environmental variables such as rainfall, temperature, soil fertility, the slope of the land and topographic location in the production frontier. Because the prevailing weather conditions during the growing season have a greater impact on farmers production decisions, we also use growing season average rainfall and temperatures for each crop in the second model.

To analyze how the yearly weather pattern affects small household farmers production, we also estimate the production frontier using the annual climate averages instead of growing season averages, that is, annual average rainfall and temperature, both minimum and maximum. In addition to the production frontier, we estimate the technical efficiency of small household farmers for each crop in relation to the three different specifications. The inefficiency model is estimated by:

$$U_i = \sum \delta_k Z_k \tag{8}$$

Where Z_k are variables associated with technical inefficiencies such as the age of the farmer, level of education, the number of times visited by an extension officer, the size of the household and the location of the farmland, δ_k is the parameter to be estimated in the inefficiency model. From the production function, we measure the technical efficiency of each farm by the exponential of the negative U_i, which is defined above as the conditional expectation of each farm's observable output to the maximum possible output under the condition of no inefficiencies on the farm. We used the maximum likelihood estimator to estimate the production frontier with and without controlling for environmental production conditions to see any differences in the significance and magnitude of the estimates.

4 Data

This study relies on household survey data from the Ethiopian Rural Household Surveys (ERHS)[6] and climate data from the African Flood and Drought Monitor (AFDM).[7] A total of 1,259 households from the same villages were surveyed in 2004 and 2009. The villages and households were randomly selected, and they account for diversity in the farming systems in Ethiopia. To ensure that families who do not have access to land are adequately represented, the sample within each village was stratified. The survey data contain information on the socio-demographic characteristic such as age, household size, education and other factors. In addition, the survey data provides some information on the environmental production

[6]Data is made available by Addis Ababa University, Centre for the study of African Economies and the International Food Policy Research Institute.

[7]The AFDM was developed by the Prince University and uses available satellite remote sensing and in-situ information, a hydrological modeling platform and a web-based interface for Operational and research use in Africa (Gao and Mills 2016).

conditions of each household, such as soil quality and slope of the land. Our climate data contains minimum temperature (degrees Celsius), maximum temperature (degrees Celsius) and precipitation (mm) measured daily. We incorporate these three primary variables into the household survey data to determine the effects of environment and climate on household production and efficiency. More specifically we include the daily average minimum temperature during the main growing seasons for wheat, maize, and sorghum cultivation, the daily average maximum temperature during the main growing seasons for wheat, maize and sorghum cultivation, and the daily average precipitation during the main growing seasons for wheat, maize, and sorghum farming. As mentioned, in an additional specification we also include the same environmental production conditions data, but we use annual averages of the climate variables instead of the cropping season average. We present the summary statistics of each variable in Table 1. The variables that determine household production in these villages include farm size, labor inputs, capital (which includes the value of farming equipment and household off-farm income) and the number of oxen used for plowing. As shown in Table 1, the average farm size cultivated for the three crops ranges between 0.5 hectares to 1.2 hectares, which suggests that most of the farmers in our sample are smallholders. The average household consists of about five persons, husband and wife with three children. On average, household heads are about 52 years and mostly without formal education. As evident in Table 1, 54% of the households in our sample have no education, 27% with primary education, 8% have completed secondary school education and 0.3% hold a college degree. Family heads who enroll in adult education or some other form of education (e.g., Islamic education) represent 19% of the total sample. Further, the descriptive statistics show that extension agents visit farmers at least once during the growing season.

The daily average of minimum temperature within the main meher[8] growing season for maize and sorghum farming is 13^0C (55.4^0F) while the daily average maximum temperature is about 26^0C (78.8^0F) in the same growing season. For wheat farming the temperature

[8]Meher is the main rainy season in Ethiopia which comes between the month of May and October. The shorter rainy season is the Belg which occurs between February and April.

decreases just by 1^0C (33.8^0F) compared to what is observed in the maize and sorghum growing seasons. On the other hand, daily average rainfall is quite high during the wheat growing season compared to maize and sorghum growing seasons. Daily average rainfall is about 4mm per day when households grow their wheat and 3.5mm per day for maize and sorghum meher growing seasons. In contrast, annual daily rainfall is about 2.4mm, and the annual maximum temperature is 26^0C (78.8^0F) while the annual daily minimum temperature is around 12^0C (53.6^0F).

5 Results and Discussions

The maximum likelihood estimates of the Cobb-Douglas stochastic frontier production for wheat, maize, and sorghum production are presented in Tables 2, 3 and 4, respectively. The tables provide the stochastic production frontier estimates for three models, that is; without environmental conditions (Model 1), the environmental conditions within the growing season (Model 2) and the annual environmental conditions (Model 3). Parameter estimates for wheat production without accounting for the environmental production conditions show that the level of inputs (land, labor, capital, and oxen) are positively related to wheat production and statistically significant at the one percent level. However, when we account for environmental conditions with the growing seasons, wheat become less responsive to variation in inputs (land, labor, and the number of oxen) compared to the first specification (without environmental variables). Wheat output responses to land and labor decrease by 14% and 8%, respectively, for our model with season averages of environmental conditions compared to without environmental conditions (model 1). Intuitively, the marginal product of land and labor falls when environmental conditions are not favorable during the growing season. These results are similar to Sherlund et al. (2002) for rice farming, who reported that the elasticity of output to labor falls when environmental production conditions are accounted for. Capital, on the other hand, becomes statistically insignificant to wheat output once we control for within season environmental production conditions. Interestingly, wheat continues to be less responsive to land when we specify the production frontier with annual averages of environmental variables. The level of responsiveness decreases further to 23% while for labor it remains the same at 8%. This shows that farmer's output is not only impacted by conditions within the growing season but also environmental conditions in the whole year.

For maize farming, labor becomes statistically significant to output at the 0.1 level when environmental conditions within the season are controlled. Maize output is likely to increase by 13% if farmers increase the number of labor days by 1%. Our observation on maize output response to land is similar to what we found on wheat farming; output is less responsive to any changes in labor when growing season environmental conditions are controlled for. The level of responsiveness decreases from 0.392 in the no environmental conditions case (Model 1) to 0.333 in the controlled case (Model 2). This represents a 15% reduction in the level of responsiveness. Although capital relates positively with maize output and is statistically significant at 0.1 level with the no environmental conditions specification, it remains statistically insignificant when we consider environmental conditions. It is somewhat a reflection that if the environment is not conducive for cultivation, then capital inputs cannot be put to productive use by the farmer. When we further consider the annual daily averages of the climate factors, the results tend to vary more from the within the growing season case for maize than what we observed for wheat farming. Here, we see that the rate of responsiveness of labor drops in maize production while it is almost unchanged in wheat production. This is to be expected as maize needs a lot more water than wheat to achieve good yields. Capital remains statistically insignificant when we include the annual daily averages. The effect of the number of oxen on maize production is significant for both within growing season and annual environmental production conditions.

The estimates for sorghum farming show a similar pattern when we compare to wheat and maize farming; the only observable difference is how the number of oxen contribution to output increases for the season and annual environmental conditions case. Output elasticity to oxen increases as we move from the no environmental conditions specification to the season and annual models which incorporate environmental production conditions. Even though the percentage increase in responsiveness is just about 2% between the season and annual environmental conditions case, sorghum is the only crop among all the three crops which shows a consistent increase in responsiveness to the number of oxen. This result is not surprising since sorghum is widely grown in the highlands where farmers use more animal power for seedbed preparation and planting. Studies have shown that animal power contributes to more than 1000 hr/farm/year to seedbed preparation and planting in Ethiopian highlands (Gryseels et al. 1984).

Our findings on farm level of efficiency raise a series of questions about the importance of environmental variables in the first-step estimation. Unlike previous studies on maize, wheat, and sorghum that do not control for environmental production conditions in the first-step, our estimates show that including environmental variables in the first step is critical in determining the source of inefficiency. The results for technical efficiency estimates are presented in Tables 5, 6 and 7 for wheat, maize, and sorghum, respectively. Results in Table 5 for technical efficiency in wheat production suggest that there is no difference with respect to the contribution of age, extension visits and levels of education when we control for environmental production conditions. However, differences in technical efficiency in wheat farming across years and some regions (Amhara and Oromia) change significantly when we control for environmental variables.

Table 6 which presents the results for technical efficiency in maize production paints a different picture. It reveals that age has a negative and statistically significant effect on the efficiency of maize farming in all three specifications, even though this effect is subtle. Referring to the average age in our sample, we could explain this by asserting that older people tend to be less active and influential in mobilizing farming activities. Hence the level of farm efficiency tends to decrease as age increases. The effects of extension visits tend to be relatively stable across all three specifications for maize. Additionally, geographical location affects technical efficiency in maize production when environmental production factors are ignored. Estimates for sorghum technical efficiency in Table 7 do not vary much across the three specifications for age and extension variables. However, when we control for environmental variables, primary education appears to contribute more to technical efficiency. Also, differences in technical efficiency across the different regions (Amhara, Oromia, and SNNPR) become insignificant for technical efficiency in sorghum production.

6 Conclusion

In this study, we examine the impacts of controlling for environmental production conditions on small-scale farmers' technical efficiency in Ethiopia for maize, sorghum and wheat production. We can derive three key findings conclusions from this study. First, our results show that accounting for environmental production conditions in the stochastic frontier helps to determine the sources of inefficiencies which may otherwise be ignored or overestimated. Second, results do not differ for maize and sorghum, when controlling for environmental production conditions during the cropping season and annually but they differ slightly for wheat suggesting that more research needs to be conducted with respect to the period that describes environmental production condition variables. Finally, results vary across the three crops and regions in Ethiopia.

The differences in results across crops and regions in Ethiopia suggest that more studies should be conducted in other countries in sub-Saharan Africa given the high climate variability across and within sub-Saharan African countries. These types of studies provide additional information to policy makers to assess how changes in environmental production conditions affect farmers efficiency especially in developing countries where production depends heavily on the environment and is facing increased climate variability. The lesson from this study is similar to what Sherlund et al. (2002) observed for rice farming, that is, controlling for environmental production conditions does not only affect the parameter estimates of the production frontier or reduce estimated technical inefficiencies, rather it helps to examine the sources of inefficiencies better. Given that environmental data is becoming more readily available, technical efficiency studies may utilize them more easy.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Wheat output (kg)	436.125	477.223	0	4000
Maize output (kg)	507.498	722.986	0	7800
Sorghum output (kg)	522.792	488.889	0	3300
Wheat land (ha)	0.538	1.463	0	20.25
Maize land (ha)	1.106	7.325	0	161.125
Sorghum land (ha.)	1.029	6.728	0	121
Labor (days)	18.583	18.676	0	243
Number of oxen	0.904	1.134	0	11
Capital (birr)	374.129	1521.856	0	60030
Household size	4.691	2.266	1	15
Age (Years)	51.775	14.963	15	120
No education (1=yes, 0= no)	0.539	0.499	0	1
Primary education (1=yes, 0= no)	0.27	0.444	0	1
Secondary education (1=yes, 0= no)	0.079	0.269	0	1
College education (1=yes, 0= no)	0.003	0.059	0	1
Other education (1=yes, 0= no)	0.188	0.391	0	1
Extension visit	1.216	3.384	0	100
Soil fertility(indexed[a])	1.609	0.623	1	3
Land slope (indexed[a])	1.291	0.433	1	3
Tigray Region (1=yes, 0= no)	0.112	0.315	0	1
Amhara Region (1=yes, 0= no)	0.314	0.464	0	1
Oromia Region (1=yes, 0= no)	0.261	0.44	0	1
SNNPR[b]Region (1=yes, 0= no)	0.313	0.464	0	1
Year 2004 (1=yes, 0= no)	0.495	0.5	0	1
Year 2009 (1=yes, 0= no)	0.505	0.5	0	1
Minimum temperature wheat season (celsius)	12.644	2.705	6.939	16.873
Minimum temperature maize season (celsius)	13.166	2.675	7.714	17.003
Minimum temperature sorghum season (celsius)	13.166	2.675	7.714	17.003
Maximum temperature wheat season (celsius)	25.796	2.704	20.572	30.365
Maximum temperature maize season (celsius)	26.597	2.67	21.844	31.193
Maximum temperature sorghum season (celsius)	26.597	2.67	21.844	31.193
Rainfall wheat season (mm per day)	3.964	1.076	0.929	6.384
Rainfall maize season (mm per day)	3.516	1.085	0.911	5.509
Rainfall sorghum season (mm per day)	3.516	1.085	0.911	5.509
Rainfall wheat season lagged one year (mm per day)	4.922	2.248	1.097	9.995
Rainfall maize season lagged one year (mm per day)	5.041	2.102	1.237	9.800
Rainfall sorghum season lagged one year (mm per day)	5.041	2.102	1.237	9.800
Rainfall wheat season lagged two years (mm per day)	4.509	1.909	0.391	6.879
Rainfall maize season lagged two years (mm per day)	4.618	2.06	0.395	7.142
Rainfall sorghum season lagged two years (mm per day)	4.618	2.06	0.395	7.142
Annual rainfall (mm per day)	2.414	0.746	0.542	3.755
Annual maximum temperature (celsius per day)	26.51	2.498	21.162	29.743
Annual minimum temperature (celsius per day)	11.718	2.632	5.729	15.6

[a] 1=Good, 2=Average, 3=poor [b] Southern Nations, Nationalities, and Peoples

Table 2: Stochastic Frontier Production: Wheat

Variable	**Model 1**	**Model 2**	**Model 3**
Wheat land	0.484***	0.418***	0.375***
	(0.0419)	(0.0384)	(0.0379)
Labor	0.197***	0.182***	0.182***
	(0.0500)	(0.0445)	(0.0436)
Number of oxen	0.290***	0.187**	0.229**
	(0.0756)	(0.0699)	(0.0701)
Capital	0.0822***	0.0267	0.0231
	(0.0241)	(0.0236)	(0.0237)
Soil fertility		-0.0415	-0.0652
		(0.0659)	(0.0650)
Land slope		-0.00921	-0.000967
		(0.106)	(0.105)
Amhara Region		0.807*	2.228***
		(0.329)	(0.316)
Oromia Region		1.203***	2.941***
		(0.248)	(0.305)
SNNPR Region		0.192	2.921***
		(0.301)	(0.493)
Year 2009		-0.628**	-0.775***
		(0.236)	(0.126)
Wheat season min. temperature		0.465***	
		(0.0833)	
Wheat season max. temperature		-0.610***	
		(0.0951)	
Wheat season rainfall		-0.375***	
		(0.0832)	
Wheat season rainfall lagged one year		0.0456	
		(0.0312)	
Wheat season rainfall lagged two years		0.209***	
		(0.0468)	
Annual rainfall			-0.289**
			(0.0932)
Annual max. temperature			-1.228***
			(0.158)
Annual min. temperature			1.073***
			(0.141)
Constant	5.730***	15.43***	24.31***
	(0.194)	(1.667)	(2.582)
σ^2	459.0885	226.4106	228.8249
	(1383.531)	(398.8891)	(389.8677)
γ	0.999	0.998	0.999
	(0.0028)	(0.0027)	(0.0025)
Log-likelihood	-661.1631	-565.6518	-563.6243
Observations	538	538	538

Standard errors in parentheses $^{***}p < 0.01$, $^{**}\ p < 0.05$, $^{*}p < 0.1$

Table 3: Stochastic Frontier Production: Maize

Variable	**Model 1**	**Model 2**	**Model 3**
Maize land	0.392***	0.333***	0.339***
	(0.0318)	(0.0281)	(0.0266)
labor	0.0329	0.125*	0.0891
	(0.0679)	(0.0585)	(0.0571)
Number of oxen	0.310***	0.183*	0.280***
	(0.0887)	(0.0794)	(0.0785)
Capital	0.0669*	-0.0511	-0.0426
	(0.0309)	(0.0276)	(0.0278)
Soil fertility		-0.0738	-0.129
		(0.0746)	(0.0758)
Land slope		-0.138	-0.179
		(0.111)	(0.113)
Amhara Region		-0.458	1.489**
		(0.388)	(0.497)
Oromia Region		1.313***	2.476***
		(0.326)	(0.422)
SNNPR Region		0.775*	3.497***
		(0.372)	(0.693)
Year 2009		-0.331	-0.430*
		(0.245)	(0.212)
Maize season min. temperature		-0.316*	
		(0.146)	
Maize season max. temperature		0.363**	
		(0.130)	
Maize season rainfall		-0.0539	
		(0.0593)	
Maize season rainfall lagged one year		0.00561	
		(0.0348)	
Maize season rainfall lagged two years		0.166**	
		(0.0610)	
Annual rainfall			-0.210*
			(0.0982)
Annual max. temperature			-0.959***
			(0.259)
Annual min. temperature			1.135***
			(0.276)
Constant	6.489***	0.0425	17.11***
	(0.264)	(1.686)	(3.529)
σ^2	4.906	407.090	266.178
	(4.58)	(808.140)	(1848.335)
γ	0.872	0.999	0.998
	(0.117)	(0.002)	(0.014)
Log-likelihood	-863.095	-754.9675	-756.6670
Observations	595	595	595

Standard errors in parentheses ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 4: Stochastic Frontier Production: Sorghum

Variable	**Model 1**	**Model 2**	**Model 3**
Sorghum land	0.189***	0.142***	0.155***
	(0.0431)	(0.0338)	(0.0335)
Labor	0.332**	0.253**	0.236**
	(0.103)	(0.0823)	(0.0813)
Number of oxen	0.221	0.413**	0.422**
	(0.152)	(0.127)	(0.128)
Capital	-0.00469	0.0337	0.0723
	(0.0458)	(0.0442)	(0.0405)
Soil fertility		-0.127	-0.115
		(0.0914)	(0.0923)
Land slope		-0.133	-0.0975
		(0.156)	(0.156)
Amhara region		3.943***	-1.213
		(1.058)	(0.936)
Oromia region		4.539***	0.0857
		(0.899)	(0.938)
SNNPR region		1.900	-4.605**
		(1.109)	(1.525)
Year 2009		1.857***	1.436***
		(0.521)	(0.346)
Sorghum season min. temperature		-0.877*	
		(0.344)	
Sorghum season max. temperature		0.551*	
		(0.276)	
Sorghum season rainfall		-0.195*	
		(0.0842)	
Sorghum season rainfall lagged one year		-0.227***	
		(0.0620)	
Sorghum season rainfall lagged two years		-0.594***	
		(0.153)	
Annual rainfall			-0.413***
			(0.115)
Annual max. temperature			2.568***
			(0.465)
Annual min. temperature			-2.912***
			(0.593)
Constant	6.895***	2.614	-26.77***
	(1.262)	(3.348)	(5.183)
σ^2	0.698	0.732	0.611
	(.076)	(0.798)	(0.526)
γ	0.435	0.586	0.491
	(0.133)	(0.442)	(0.439)
Log-likelihood	-232.7891	-184.3451	-184.8702
Observations	192	192	192

Standard errors in parentheses ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 5: Technical efficiency: Wheat

Variable	Model 1	Model 2	Model 3
Household size	0.00587	0.00465	0.00490
	(0.00303)	(0.00307)	(0.00302)
Age	-0.000149	0.00000268	0.000116
	(0.000527)	(0.000532)	(0.000523)
Primary education	0.00912	0.00237	0.0122
	(0.0194)	(0.0196)	(0.0193)
Secondary education	0.0624*	0.0252	0.0266
	(0.0258)	(0.0260)	(0.0256)
College education	-0.0421	-0.0620	-0.0531
	(0.0983)	(0.0994)	(0.0977)
Other education	0.00855	-0.0110	-0.0128
	(0.0174)	(0.0176)	(0.0173)
Extension	-0.00134	0.00304	0.00314
	(0.00262)	(0.00265)	(0.00260)
Year 2009	-0.0926***	0.0180	-0.0218
	(0.0142)	(0.0144)	(0.0141)
Amhara region	0.281***	0.0186	0.0487
	(0.0251)	(0.0254)	(0.0250)
Oromia region	0.381***	0.0357	0.0526*
	(0.0264)	(0.0267)	(0.0263)
SNNPR region	0.0307	0.00998	0.0114
	(0.0385)	(0.0389)	(0.0383)
Constant	0.368***	0.637***	0.636***
	(0.0394)	(0.0398)	(0.0392)

Standard errors in parentheses ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 6: Technical efficiency: Maize

Variable	**Model 1**	**Model 2**	**Model 3**
Household size	0.000493	0.00535	0.00383
	(0.00298)	(0.00309)	(0.00259)
Age	-0.00137**	-0.00149**	-0.00144**
	(0.000524)	(0.000543)	(0.000455)
Primary education	0.00520	0.00714	0.00503
	(0.0188)	(0.0194)	(0.0163)
Secondary education	-0.0136	0.0209	-0.00155
	(0.0244)	(0.0253)	(0.0212)
College education	0.0147	0.0582	0.0152
	(0.0765)	(0.0792)	(0.0664)
Other education	0.0149	0.0278	0.0163
	(0.0186)	(0.0192)	(0.0161)
Extension	0.00551**	0.00495**	0.00501***
	(0.00174)	(0.00180)	(0.00151)
Year 2009	-0.0600***	-0.0974***	-0.0921***
	(0.0136)	(0.0140)	(0.0118)
Amhara region	0.0797	0.0388	-0.00245
	(0.0525)	(0.0544)	(0.0456)
Oromia region	0.373***	0.0530	0.0222
	(0.0511)	(0.0529)	(0.0443)
SNNPR region	0.294***	0.0434	-0.000920
	(0.0515)	(0.0534)	(0.0447)
Constant	0.328***	0.681***	0.772***
	(0.0592)	(0.0613)	(0.0514)

Standard errors in parentheses ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 7: Technical efficiency: Sorghum

Variable	**Model 1**	**Model 2**	**Model 3**
Household size	-0.00207	0.00120	0.00171
	(0.00237)	(0.00450)	(0.00419)
Age	-0.000112	-0.000208	-0.0000531
	(0.000378)	(0.000719)	(0.000670)
Primary education	0.00935	0.0819**	0.0721**
	(0.0134)	(0.0255)	(0.0237)
Secondary education	-0.0451	0.0663	0.0663
	(0.0262)	(0.0498)	(0.0464)
College education	-0.116	-0.0480	0.0265
	(0.0634)	(0.121)	(0.112)
Other education	0.0145	0.0437	0.0381
	(0.0123)	(0.0234)	(0.0218)
Extension	0.0000619	0.00186	0.00133
	(0.00211)	(0.00401)	(0.00373)
Year 2009	-0.00882	-0.0411*	-0.0510**
	(0.0101)	(0.0192)	(0.0179)
Amhara region	0.0937	0.0147	0.0315
	(0.0620)	(0.118)	(0.110)
Oromia region	0.162*	-0.00996	-0.00161
	(0.0632)	(0.120)	(0.112)
SNNPR region	0.0469	-0.0471	-0.0248
	(0.0720)	(0.137)	(0.128)
Constant	0.0747	0.675***	0.659***
	(0.0679)	(0.129)	(0.120)

Standard errors in parentheses ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$

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