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HETEROGENEITY, TRANSIENT AND PERSISTENT PRODUCTION EFFICIENCIES OF MAJOR CROPS IN SOUTHERN ETHIOPIA

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ABSTRACT

Agricultural productivity is a cornerstone for the economy of Ethiopia to ensure rural transformation. However, the increment of productivity of crops has slow progress. Hence, this study undertook to separate farm heterogeneity, short-run and long-run inefficiencies of productivity in southern Ethiopia. The study used the models of decomposing technical efficiency through various techniques like 4-random error components of stochastic frontier panel data models to distinguish between time-invariant farm-heterogeneity, persistence, and short-run inefficiencies. Thus, models used for the analysis have shown different estimates of overall efficiency levels. Fixed-effect and Kumbhakar-Heshmati models did not separate unobserved persistent efficiency from farm-heterogeneity efficiency. The estimated efficiency by the Kumbhakar-Lien-Hardaker model (0.4449) is significantly higher than the mean of the fixed-effect model with much lower variations. Mean transient efficiencies gleaned from true-fixed-effect, consistent true-fixed-effect, and Kumbhakar-Lien-Hardaker models become nearly equal except, the Kumbhakar-Heshmati model indicated that farmers faced severe persistent productivity inefficiency problems. Average technical change in 2011/12 was 20.67% and declined much more to 9.44% and 5.82% in 2013/14 and 2015/16, sequentially. According to the estimation of overall technical efficiency, it is possible to capture about 39% to 99% of the untapped production in the crop subsector of Southern Ethiopia. Therefore, there was a decline in the growth rate of fertilizer used and land size covered by considered crops in the area. Land covered was declined by 3.06% for the considered crops from 2013/14 to 2015/16 production period. In the mean summary of technical efficiency at the zonal level, the aggregate persistent efficiency is lower than the transient one for all the zones. It confirmed that inefficiency varies from zone to zone between zones and household to household within the zone during the survey years. Thus, the policymaker should pinpoint the causes of inefficiencies separated in the time factors to improve the productivity of considered crops in the study area. A policy point that treats the persistent, transient, and farm-specific inefficiency enhancing conditions has to be set separately in each zona of Southern Ethiopia. Moreover, the greater focus of the policy is to alleviate the persistent inefficiency increasing factors in the study area.

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INTRODUCTION

Among the dominant sources for improving agricultural output; agricultural input use, climate conditions, and other location-specific constituents; technologies of farms and best agronomic practices are determinants. As acknowledged by Antwi David (2020), the classical definition of productivity is a measure of how efficiently inputs are combined to produce maximum outputs. However, productivity growth is sub-optimal in Africa compared with performances in Asia, America, and Europe. Thus, agricultural productivity growth in Sub-Saharan Africa (SSA) remains slowly moving up, albeit some studies had predicted some degree of recovery in productivity growth after the mid-eighties (Pisulewski, 2019). Though the Ethiopian agricultural sector averagely accounts for 36.3% of GDP in 2015/16, it has ample arable land, an abundant workforce, and diverse agro-ecological zones. However, growth depends on resource use technical efficiency (TE), and technological change. Conceptually, TE describes how a producer can produce maximum feasible output using available inputs (Goshu *et al.,* 2019; Tenaye, 2020).

Chiona *et al.,* (2014) indicated that long-run inefficiency varies across farms due to institutional and statutory environmental facts. While, short-run inefficiency changes because of shocks associated with TC, human capital, and learning-by-doing. Evaluation of long-run and short-run components of inefficiency and their separation from unobserved heterogeneity effects have the reverse orientation on promoting efficiency (Colombi *et al*., 2014; Kumbhakar *et al.,* 2015; Adom *et al.,* 2020).

Above all, on average, 79% of land and 85% of grain crop production was covered by cereal crops in a slight improvement in the TE in Ethiopia for the last decade (Hvits and Christine, 2016). There are also conditions in which inefficiency never changes over time: the existing quality of soil, farm water sources for irrigation, the managerial ability of farms, and no shift in the farming system stand amongst many. However, conditions in which inefficiency can change as time change: inefficiency caused by the natural hazard, insufficiency of technologies, ignorance for TC. Moreover, the distinction between the persistent and residual components of inefficiency is because they have different policy implications (Heshmati et al., 2018; Agasisti *et al.,* 2019).

On the other hand, panel data in the SPF models have several potential advantages over simple cross-sectional data. Panel data can offer consistent estimators of farm inefficiency and make specific distributional assumptions regarding one-sided error terms associated with inefficiencies (Kathuria, 2011; Colombi *et al.,* 2017; Lai *et al*., 2018).

Against the above discussion, the pivotal research question of this study is distinguishing sources of inefficiency that is elucidated by the objectives of ensuring the practical application of recently developed models on the selected crops in SE: Teff[1] (*Eragrostis*), wheat (*Triticum*)**,** maize (*Zea Mays*), barley (*Hordeum Vulgare*), and sorghum (*Sorghum Bicolor*). Therefore, the objectives of the article are presented as follows: first, describing the empirical and theoretical concepts of the issues. Next, the study shows the data sources and the models adopted for analysis. Then, the results of the

[1]Teff is the staple-small size local cereal that originated from Ethiopia.

study followed by a nuanced discussion presented. Finally, the study concluded by providing plausible recommendations for practitioners and policymakers.

Limitations of the Study

Though this study is done based on strongly balanced panel data, data is within the short-term panel. The FE model has a limitation of creating bias when the data is characterized by a small number of panels but, the degree of bias was lessened by increasing the number of households across the survey years (Treiman, 2014). Moreover, as suggested by (Longhi and Nandi, 2014), systematic measurement errors are expected limitations across the season. However, the power of panel data depends on the reliability and validity of the information it contains (Hill et al., 2020).

TIME-INVARIANT AND VARIANT INEFFICIENCY: CONCEPTS AND MEASUREMENT

The panel data controls the individual heterogeneity, high variability, less collinearity between variables with more degrees of freedom and efficiency. Therefore, there are factors in which inefficiency never changes over time: the existing quality of soil, farm water sources for irrigation, no shift in the farming system is called persistent inefficiency. However, factors of transient inefficiency are natural hazards, inaccessibility/insufficiency of technologies, and ignorance of TC (Alemu and Bishaw, 2015; Agasisti et al., 2017).

Furthermore, applying a single-stage SF is appropriate in separating the inefficiency effects as an explicit function of the vector of firm/farm-specific variables plus random error can overcome the problems of inconsistencies. Therefore, this model allows inefficiency parameters and TE to vary across time in a potentially different manner and has high predictability across farms. However, interpretations of both terms are commonly time-related (Colombi et al., 2014; Lai *et al*., 2018).

RESEARCH DESIGN AND METHODOLOGY

Data Sources and Collection Methods

The specific collection of primary data was executed by employing semi-structured interviews, focus group discussions (FGDs), and key informant interviews (KII). The regional, three Zonal, and three districts Agriculture office heads were selected as KII, purposively. Two FGD from each of the enumeration areas (EAs) were selected, holding ten households purposively. The reason was to supplement the quantitative data for triangulation. Inclusive questionnaires of household demographic and agricultural information from Ethiopian Socioeconomic Survey (ESS) datasets were used for the study.

In the data cleaning process, strongly balanced panel data consisting of 2,187 households were created for SE as the secondary data. The data set included an aggregated number of major crops (barley, maize, teff, wheat, and sorghum) produced

and valued in three steps. First, the quantity of product measured in different local units is converted into a standard measure (kilogram).

Following the findings of Bachewe (2015), conversion factors (CF) were prepared by the Central Statistic Authority (CSA) used at the village level. In the second step, the quantity of production in kilograms converted into monetary values in Ethiopian Birr using average *Kebele*[2] level unit prices collected. Finally, the value of output is generated by multiplying the average unit price at *the Kebele* level by the total quantities produced in kilograms. Land size owned by households measured by local units is also converted into standard measure (hectare) using the CF of CSA and aggregated into the household level.

One of the inherent limitations of this study was the use of family labor as a proxy indicator for the labor force used in crop production. As aforementioned, it is due to inconsistency in the duration of labor use data across different years. The labor force included from land preparation up to the harvesting period is calculated as follows: firstly, we calculated the adult equivalent by sorting the age of each household member by using the standards. Secondly, days in a week and to annual were found converted. Thirdly, the man-days appeared by multiplying them by their respective category (men, women, and children).

The number of farm capital was the sum of the number of sickles, hoes, *Mofer*[3], *Kenber*[4], water storage pit, water pump, traditional plow, and modern plow converted for cultivation. However, the differences in the quality of farm capitals owned and homogeneity assumption is expected to increase the risk of measurement errors in the data analysis.

Sampling Techniques and Sampling Size Determination

The Ethiopian Central Statistic Authority's (CSA) Agricultural Sample Survey (AgSS) Enumeration Areas (EAs), which are 74 in total were applied to select households based on probability proportional to the sizes of the total EAs in SE. A total of 888 house heads were selected from a randomly selected 30 AgSS EAs of CSA. In all the years (2011, 2013, and 2015), the selected EAs and households per EA have remained the same for quantitative data.

Method of Data Analysis and Model Specification

While Heshmati *et al.*, (2018) acknowledged four alternative SPF panel data models for estimating and analyzing persistent and transient efficiencies disentangling them from time-invariant farm effects. The first model is the FE one assumes inefficiency effects to be time-invariant and individual-specific that can offer estimates of long-run inefficiencies.

The second model is the true-fixed effects (TFE) model proposed by Greene (2005a) that could separate inefficiencies into transient from persistent effects. The third

[2]*Kebele* is the smallest administrative structure next to the district
[3]*Mofer* is one of the farm capital which could be tied with kenber and pulled by the oxen
[4]*Kenber* is also the farm capital used to plowing land putting on the heads of oxen to be connected with mofer

model is the 3-components random errors that estimate long-run and short-run inefficiencies without accounting for heterogeneity (Kumbhakar and Heshmati, 1995). The fourth model is the recently developed 4-component error that measures persistent and transient inefficiency by separating them from time-invariant farm effects and noise (Kumbhakar *et al.*, 2015; Colombi *et al*., 2017).

The Stochastic Production Frontier Model Specification

Model 1: Fixed-Effect Model treated as long-run inefficiencies

To specify a model with time-invariant inefficiency effect, we treat a time-invariant term to represent long-run inefficiency to obtain:

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \varepsilon_{it} - u_i \quad (1)$$

This model utilizes the panel feature of the data via, plus it can be estimated when the inefficiency component u_i is a fixed parameter by the FE-model. However, this model has been criticized for its assumption about inefficiency, individual instinctive ability, and other persistent farm-heterogeneities that seems to be unrealistic, especially for a long panel dataset (Lai *et al*., 2018).

Model 2: True Fixed-Effects Model treated as heterogeneity

The TFE-model by Greene (2005) separately treats time-invariant farm-heterogeneity and transient inefficiency effects.

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \mu_i + V_{it} - \alpha_{it} \quad (2)$$

Where μ_i are random-effects to capture any time-invariant farm-heterogeneity, not inefficiency α_{it} represents transient inefficiency and V_{it} is a random shock with the following distribution:

$$\alpha_{it} \sim N^{+}(0, \beta_{\alpha}^{2}),\ V_{it} \sim N^{+}(0, \beta_{v}^{2}), \text{ and } \mu_i \sim N^{+}(0, \beta_{\mu}^{2}) \quad (3)$$

If μ_i is handled as a fixed parameter that cannot capture inefficiency, the model is considered as a TFE-model. The TFE-model allows inefficiency to be time-variant and controls for farm-heterogeneity to capture by a farm-specific intercept and assumes that inefficiency terms are always transient. Thus, it fails to capture persistent inefficiency (Kumbhakar and Heshmati, 1995).

Model 3: Individual effects treated as persistent inefficiencies

To overcome the downward bias of inefficiency estimation of the TFE-model and its ignorance about the steadfast inefficiency component, Kumbhakar and Heshmati (1995) proposed a model that treats individual effects as steadfast inefficiency decomposing inefficiencies into persistence and transient segments.

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \pi_{it} \text{ Or}$$
$$y_{it} = \sigma_0 + f(X_{it};\theta) + \varepsilon_{it} - \omega_i - \varphi_{it} \quad (4)$$

Then, this Kumbhakar and Heshmati-model (KH-model) split the error term into three components where ε_{it} captures a random shock; ω_i captures individual-effects as steadfast inefficiency; φ_{it} captures the transient inefficiency component (Lai *et al.*, 2018).

Model 4: Separation of individual heterogeneity from persistent inefficiencies

Finally, the KLH-model decomposes the error term in the production function into four components: the first captured sectors' latent-heterogeneity across farms (μ_i); the second captured transient inefficiency (φ_{it}); the next captured persistent inefficiency (ω_i) while the last ingredient captured random shocks/noise affecting the farm (V_{it}). Consider the following panel data SPF model based on distributional assumptions:

$$y_{it} = \sigma_0 + f(X_{it};\theta) + \mu_i + V_{it} - \omega_i - \varphi_{it} \quad (5)$$

This model has four components: two of which, $\omega_i>0$ and $\varphi_{it}>0$ are inefficiencies, and the other two are sectorial effects and noise μ_i and $V_{it,}$ respectively.
Thus, multistep procedure:

$$y_{it} = \sigma^*_0 + f(X_{it};\theta) + \sigma_i + \varepsilon_{it} \quad (6)$$

This model was disaggregated as follow:

$$\sigma^*_0 = \sigma_0 - E(\omega_i) - E(\varphi_{it}) \quad (7)$$
$$\sigma_i = \mu_i - \omega_i + E(\omega_i) \quad (8)$$
$$\varepsilon_{it} = V_{it} - \varphi_{it} + E(\varphi_{it}) \quad (9)$$

Therefore, σ_i and ε_{it} in Equations 8 and 9 would have zero mean and constant variance, which is evaluated in three steps: Step 1: Since equation (9) is the standard random-effect panel regression used to estimate θ hat. This procedure also gives predicted values of σ_i and ε_{it}, which we denote by σ hat and ε_{it} hat. Step 2: The time-varying inefficiency, $\varphi_{it,}$ was estimated. The predicted values ε_{it} were used from Step 1. Equation (9) assumes V_{it} was distributed across the producers and time (i.i.d) N (0, $\alpha 2_v$) and φ_{it} is N^+ (0, $\alpha 2_\varphi$), which means E (φ_{it}) = ($\sqrt{2}/ \pi\alpha 2_\varphi$), and ignoring the difference between the true and predicted values of ε_{it}. This procedure gives a prediction of the residual inefficiency components φ_{it} hat. Step 3: The final step, ω_i were estimated in the same fashion to step 2 and step 1 as the best linear predictor. Equation (8) assumes μ_i and ω_i were distributed across the producers (i.i.d), N (0, $\alpha 2_\mu$) and N+ (0, $\alpha 2_\varphi$), respectively. Besides that, by using E (φ_{it})=($\sqrt{2}/ \pi\alpha 2_\varphi$), the standard normal-half-normal SPF model crosses the producers and obtained estimates of the persistent inefficiency components, ω_i. Persistent TE estimated from = exp(-ω_i). The variables included in the model and their expected signs are presented in Table 1. The aggregate output of major crops is the

dependent variable that was assembled from the works of literature discussed in the first portion of the study.

TABLE 1. VARIABLES USED FOR THE ESTIMATION OF THE AGGREGATED OUTPUTS OF MAJOR CROPS

Description	Expected Sign
Amount of seeds consumed	+
Amount of fertilizer consumed	+
Landholding's by the households	+
The labor force at household	+
The number of plowing oxen	+
Age of the household's head	-
Access for Credit service	+
Sex of the head of the household	+

Source: Developed Based on Review of Literature.

RESULTS AND DISCUSSIONS

Descriptive Statistics of Stochastic Production Frontier

The major crops grown in SNNPR are Teff **(***Eragrostis*), wheat **(***Triticum*)**,** maize (*Zea Mays*), barley (*Hordeum Vulgare*) and, sorghum (*Sorghum Bicolor*) (Hvits and Christine, 2016). The bulk of production increased due to an increment in the factors of production, except for sorghum. Variation of the output to the variation in the utilization of inputs is attributed (Table 2).

TABLE 2. THE AVERAGE GROWTH RATE OF VOLUME OF PRODUCTION OF MAJOR CROPS

Major Crops	The average Growth rate of crops is %	
	2013/14	2015/16
Barley	53.61	37.41
Maize	9.79	11.17
Sorghum	-26.24	-31.97
Teff	41.28	30.23
Wheat	29.79	25.08

Source: Authors' estimation.

There was also a slight decline in fertilizer consumption in the 2013/14 survey year compared to that of 2011/12. About 15.22% increment of land coverage from 2011/12 to 2013/14 declined by 10.38% in 2015/16. Therefore, it is possible to argue

increment in the volume of production of considered crops mainly comes from the area expansion in the study area (Table 3). According to the qualitative data, the needs for the fertilizer were fluctuated due to the repayment problems and mismatch between the demands and supply of smallholder households in the study area. It contradicts the findings (Goshu *et al.,* 2019). However, it is consistent with the study of (Taffesse *et al.,* 2012).

There was a decline in the growth rate of fertilizer used and land size covered by considered crops. There was a decline of land coverage by 3.06% for the considered crops from the 2013/14 to 2015/16 production period (Table 3).

TABLE 3. MEAN VALUES AND AVERAGE GROWTH RATE OF HOUSEHOLDS INPUT-OUTPUT DATA USED IN STOCHASTIC PRODUCTION FRONTIER (2011-2016)

Variables	2011/12	2013/14	2015/16	AGR in %
Amount of fertilizer used	71.56	61.64	66.8	-0.52
Households' seed used	2.90	14.99	19.69	57.14
Number of farm-capital	4.31	4.92	5.04	5.88
Labor force	319.55	388.62	412.37	10.4
Area cultivated	0.92	1.07	0.95	-3.06
Number of plowing oxen	0.82	1.15	1.14	9.62
Real value of output produced	1,035.09	1,092.4	1,240.78	10.51

Source: Authors' calculation.

Hypothesis tests on the Estimation of Stochastic Production Frontier

Inputs and aggregated crop output transformed to their corresponding logarithmic values in estimating the SPF function. However, there were some variables with the logarithmic value of zero that could become undefined. Following Wassie (2014), the variables with zero values in the dataset changed to nearly zero (0.0001) values before transforming the data to logarithmic form. Various statistical tests were performed for the parameter estimates of the production frontier and the factors that are presumed to affect the efficiency of producers of major crops as well as the validity of the model before the analysis.

Wald tests are the commonly used parametric test for testing the null hypothesis (H_0) of either no or constant inefficiency. It means, the variance of the one-sided process is not zero, and the explanatory variables are jointly significant in explaining the dependent variable. Thus, inefficiency effects are present in the model. Since γ took the value between 0 and 1, the H_0 is rejected at $p<0.001$. Besides, the eta (η) is different from zero, H_0 is rejected at $p<0.001$. Alternatively, this is to test whether the SPF function is more appropriate than the conventional one. However, if the H_0 is not rejected, the SPF function could be equivalent to the conventional one.

Moreover, restrictions for no unobserved heterogeneity, no observed heterogeneity, and the assumption of constant inefficiency over term for technical

inefficiency are rejected at the 1% level of significance. Therefore, unconstrained TE, a time-varying, time in-varying, and half-normal distribution for inefficiency were estimated (Table 4).

TABLE 4. PROPERTIES OF WALD TEST STATISTIC

Hypotheses	**LL H_0**	**LL H_1**	**Wald Test Statistic**	**p-Value**
No unobserved heterogeneity	H_0: Var (u_{it})=0	H_1 :Var (u_{it})≠0	578.55	0.000
No observed heterogeneity	H_0: $\alpha_1 = \alpha_3 = \cdots \alpha_6 =$	H_1 :$\alpha_n \neq 0$	1020.70	0.000
Constant inefficiency	H_0 : eta(η)=0	H_1 : eta(η)≠0	637.87	0.000

Source: Author's calculation.

Furthermore, the robustness checks under alternative specifications of the models were performed. The robustness checks showed how regression coefficient estimates behaved when the regression specification changed in some way, usually by adding or removing explanatory variables. Based on the estimation results presented in Table 5, the Ho is rejected at p<0.001. It was also confirmed that there is half-normal distribution. Thus, the Ho for the test of no half-normal distribution is rejected at p<0.001.

The likelihood-ratio test statistic λ = -2{log [Likelihood (Ho)]–log [Likelihood (H_1)]} has approximately a chi-square distribution ($\chi 2$), distribution with q equal to the number of parameters assumed to be zero in the H_0; it is compared with the critical values of ($\chi 2$) and decided between the two models (Table 5) (Chiona *et al.*, 2014).

TABLE 5. GENERALIZED LIKELIHOOD RATIO TESTS FOR THE PARAMETERS OF STOCHASTIC PRODUCTION FRONTIER AND INEFFICIENCY FACTORS

Hypotheses	**LL H_0**	**LL H_1**	**Test Statistics***	**Critical Value**	**Decision**
Constant return-to-scale Ho: $\beta 1 = \beta 2 = \beta 3 = \beta 4 = \cdots = \beta 6 = 0$	-3421.55	-3411.38	20.51	20.34	Reject H_0
μ is not half − normal distribution (H_0: $\mu = 0$)	-3421.01	-3403.62	34.78	22.46	Reject H_0
No inefficiency (H_0: $\gamma = 0$)	-3436.92	-3403.62	66.6	13.82	Reject H_0

Note LL stands for log-likelihood
Source: Authors' estimation.

Estimates of Technical Efficiency

Consistent with the findings of Adom *et al.,* (2020) study, according to KLH-model, about 27.4% of TE is possibly used to produce maximum aggregate crops in SE. Comparatively; the estimated overall TE in the KLH-model is higher than the values obtained under the KH and TFE models. Moreover, results from the KLH-model provided time-varying TE that reflects the overall/transient efficiencies. Thus, the other model's results illustrated significant variations from KLH-model estimations across models and that the efficiency scores are sensitive to the model's specifications (Table 6).

Consistent with the findings of (Berisso and Heshmati, 2020), the estimation of the KLH-model for mean persistent efficiency was 0.4449 but FE and KH-models were underestimated. However, the mean transient efficiency values obtained from TFE, CTFE, KLH, and KH-models 0.6100091, 0.6159822, 0.428353, and 0.6160639, respectively, indicated that producers faced severe persistent productive inefficiency problems in SE. The average persistent productive inefficiency is 79.04%, designating that the study area stayed in long-lasting challenges in inefficiency. Therefore, it is possible to argue that mediocre, there was 43.24% of un-captured household's time-varying TE in the production processes (Table 6). It is consistent with (Heshmati *et al*., 2018) findings.

TABLE 6. ESTIMATE OF TECHNICAL EFFICIENCY

TE	Mean	Std. Dev.	Minimum	Maximum
Overall TE				
FEM_TFEM	0.0679536	0.0442676	0.00000105	0.9999991
FEM-CTFEM	0.068619	0.0740559	0.0000009	0.9999991
K-L-H	0.2741433	0.0646918	0.0000419	0.7867339
K-H	0.0309569	0.0132422	0.0003802	0.8250605
Persistent TE				
FEM	0.1113977	0.1202241	0.0010558	1
K-L-H	0.4449917	0.1766847	0.0483087	0.7867345
K-H	0.0722698	0.0708844	0.0215765	1
Transient TE				
TFEM	0.6100091	0.3682091	0.0009933	0.9999989
CTFEM	0.6159822	0.3658393	0.0008563	0.9999991
K-L-H	0.6160639	0.3661426	0.0008673	0.9999992
K-H	0.428353	0.1868145	0.0176221	0.8250605

Note: CTFEM (consistent TFE-Model)
Source: Authors estimation.

Estimated Marginal Elasticity

Consistent with the findings (Adom *et al.,* 2020; Tenaye, 2020), estimates of production elasticity indicated that each input contributed significantly to the considered crop production. However, the magnitude of the elasticity varies across models. Therefore, as land coverage increases by 1%, the estimated increment in the outputs of considered crops were by 0.31% and 0.17% in both the FE and TFE models, respectively (Table 7).

In the same fashion, 1% increment of land coverage of major crops, the KH and KLH-models estimations of outputs are by 0.12% and 0.21%, respectively, in the study area. Increase in the labor force by 1%, increased production of considered major crops by 0.03% in the FE-model but 0.04% in TFE, KH, and KLH-models. Moreover, a 1% increase in fertilizer utilization has an estimation of 0.03% improvements of considered crop output in both FE and TFE-models yet, the magnitude and effect on those crops was the same (0.04%) in both KH and KLH-models during the survey years (Table 7).

The marginal effects of the number of oxen have the same magnitude in the products of considered crops in FE and TFE models in the study area. In other words, a 1% increase in the number of oxen increased the aggregate major crops by 0.07% in both FE and TFE models during the survey years. However, a 1% increase in the number of oxen is estimated to improve 0.06% and 0.12% outputs of major crops in KH and KLH-models, respectively. However, the magnitude of marginal elasticity in both FE and KH-models is lesser than TFE and KLH-models in the analysis. An increase of 1% in the utilization of seed was estimated to increase the production of considered crop outputs by 0.04% and 0.03% in FE and KH-models, respectively (Table 7).

TABLE 7. ESTIMATED MARGINAL ELASTICITY OF COBB-DOUGLAS STOCHASTIC FRONTIER ANALYSIS

Variables	FEM Estimate	TFEM Estimate	KH Estimate	KLH Estimate
Logarithmic value of land_size	0.31*** (0.063474)	0.17*** (0.00173)	0.12*** (0.0356)	0.21*** (0.035646)
Logarithmic value of labor force	0.03*** (0.008048)	0.04*** (0.0003)	0.04*** (0.0064)	0.04*** (0.065953)
Logarithmic value of oxen	0.07*** (0.008139)	0.07*** (0.0006)	0.06*** (0.00695)	0.12*** (0.072786)
Logarithmic value of fertilizer used	0.03*** (0.006448)	0.03*** (0.0004)	0.04*** (0.005029)	0.04*** (0.04149)
Logarithmic value of seed used	0.04*** (0.007281)	0.05*** (0.0005)	0.03*** (0.005986)	0.05*** (0.05155)

*Denote: Coefficient) standard errors under parentheses. ***, ** and * denote 1%, 5% and 10% statistical significance level.*
Source: Author's Estimation.

Estimates of Technical Efficiencies across Zone in Southern Ethiopia

In comparison, the aggregate persistent TE is lower than the transient one in SE, confirming that inefficiency varies from zone to zone between zones and household to household within the zone during the survey years (Table 8). As the qualitative data indicated that the variability in the determinant factors of efficiency, some of the central zones: Gurage, Sidama, Hadiya, Kambata Tamibaro, Gedeo, Wolayita, Gamo Gofa, and Silti zones have better performance of producing those crops than others. However, based on the quantitative data estimation, the periphery zones like Derashe and Burji Special were better than those in the centers.

A comparison of TE between zones within SE revealed some extent of heterogeneities. Following the findings of Berisso and Heshmati (2020), based on TFE and KLH-models, the top-five good performing zones were Derashe (0.687 and 0.689), Burji Special (0.683 and 0.667), Gurage (0.656 and 0.651), Sidama (0.645 and 0.645), and Woliata (0.638 and 0.645). It is consistent with the findings of Hvits and Christine (2016). Therefore, Derashe emerged as the best performer followed by Burji Special, Gurage, Sidama, and Woliata (Table 8).

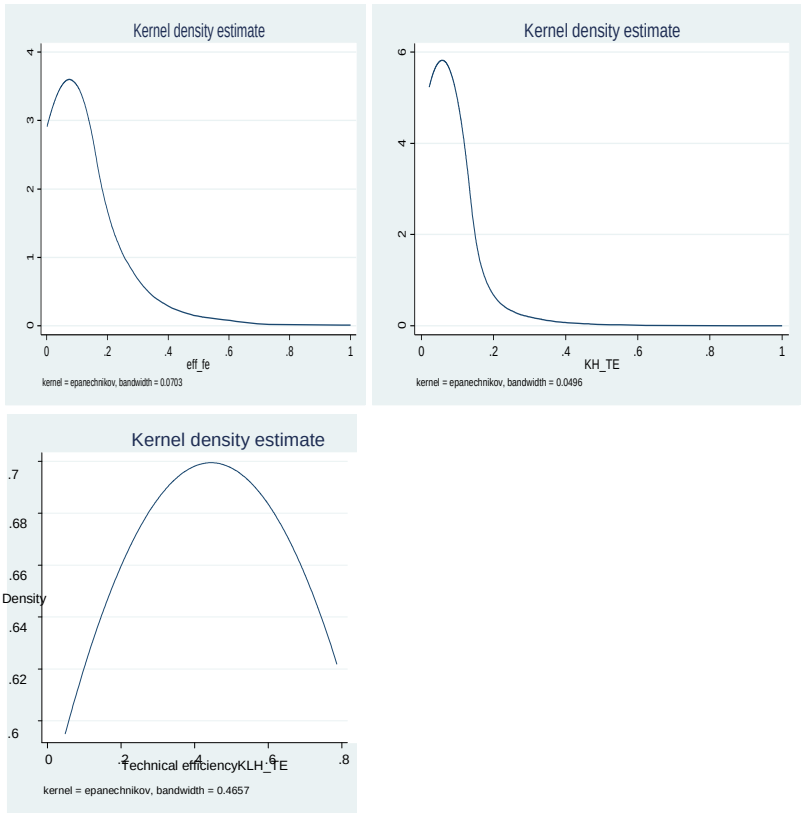
TABLE 8. MEAN SUMMARY OF EFFICIENCY MEASURES IN ALL MODELS BY ZONES

	PTE			TTE			
Zones/Areas of SE	**FEM**	**KH**	**KLH**	**TFEM**	**CTFEM**	**KH**	**KLH**
Gurage	0.120	0.053	0.504	0.656	0.651	0.487	0.651
Hadiya	0.082	0.068	0.422	0.606	0.616	0.418	0.615
Kambata Tamibaro	0.058	0.074	0.376	0.601	0.606	0.363	0.605
Sidama	0.263	0.036	0.624	0.645	0.645	0.611	0.645
Gedeo	0.216	0.044	0.569	0.633	0.630	0.546	0.632
Wolayita	0.076	0.068	0.408	0.638	0.644	0.398	0.634
South Omo	0.038	0.097	0.310	0.553	0.649	0.310	0.650
Sheka	0.242	0.055	0.550	0.635	0.637	0.539	0.638
Kefa	0.033	0.103	0.326	0.611	0.608	0.290	0.609
Gamu Gofa	0.046	0.100	0.355	0.607	0.608	0.332	0.610
Bench Maji	0.129	0.263	0.520	0.611	0.621	0.510	0.621
Yem	0.024	0.216	0.248	0.529	0.531	0.212	0.531
Amaro Special	0.110	0.051	0.511	0.578	0.587	0.472	0.587
Burji Special	0.028	0.169	0.272	0.683	0.666	0.216	0.667
Konso Special	0.069	0.081	0.468	0.581	0.577	0.379	0.577
Derashe	0.137	0.062	0.523	0.687	0.688	0.457	0.689
Dauro	0.034	0.097	0.321	0.601	0.605	0.299	0.606
Basketo	0.177	0.048	0.552	0.592	0.617	0.546	0.615
Konta	0.048	0.104	0.350	0.602	0.581	0.334	0.581
Silti	0.084	0.062	0.438	0.573	0.583	0.441	0.583
Alaba	0.089	0.061	0.427	0.532	0.549	0.445	0.549

Denote: PTE (persistent technical efficiency), TTE (transient technical efficiency)
Source: Author's computation.

Furthermore, to get a better picture of efficiency components in different models, we used density plots for each of the models in the analysis. These density plots show that the distribution of persistent efficiencies in the FE and KH-models was identical and except for some values in the upper tail. In the persistent TE, most households had low efficiency in SE. However, in the KLH-model, there are the highest steadfast efficiency scores with a mean value of more than 44% (Figure 1).

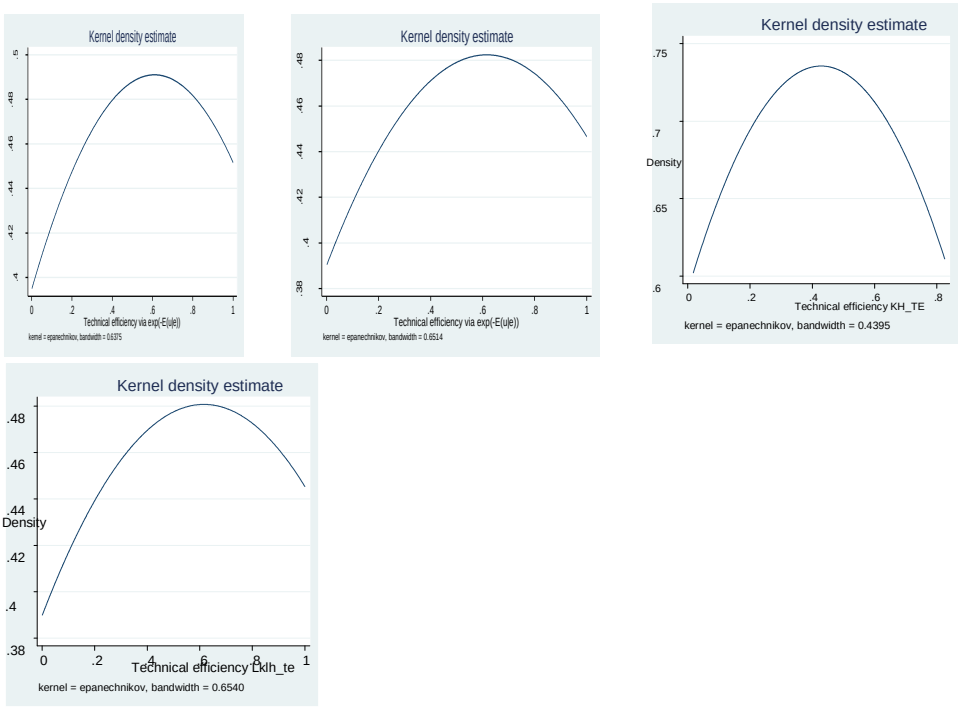
FIGURE 1. DISTRIBUTION OF PERSISTENT EFFICIENCIES ACROSS MODELS



Source: Author's computation.

As the parts of overall efficiency, the spread of the transient efficiency was significantly higher than that of the persistent component. Therefore, persistent inefficiency is a challenge compared to the other inefficiency in SE (Figure 2).

FIGURE 2. DISTRIBUTION OF TRANSIENT EFFICIENCIES ACROSS MODELS



Source: Author's computation.

Total Factor Productivity, Returns to scale and Technical Changes by Preferred True Fixed Effect Model

Consistent with the studies of (Colombi *et al.*, 2017; Keith *et al.*,2017), the TFE-model found unobserved household/farm-specific heterogeneity in producing values of overall/transient efficiencies that were preferred to separate inefficiencies across individual and time. Therefore, in TFE-model, TE increased from 63.82% to 72.72% from 2011 to 2013, while it declined to 56.62% in 2015. The diminishing return to scale was from 87.05% to 77.53% in 2011/12 to 2013/14 and declined more to 62.8% in 2015/16.

Moreover, the average TC in 2011 was 20.67% and declined much more to 9.44% and 5.82% in 2013 and 2015, respectively, indicated that households were less sensitive to the newly invented technologies. Thus, uptake of technological practices for the production of considered crops through intensification has decreased in SE (Table 9).

TABLE 9. MEAN SUMMARY OF COMPONENTS OF PRODUCTIVITY SCORES

Variables	2011		2013		2015	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Technical Efficiency	0.6382	0.3502	0.7272	0.3276	0.5662	0.3538
Return to Scale	0.8705	0.2287	0.7753	0.2278	0.6280	0.2280
Technical Change	0.2067	0.1415	0.0944	0.1485	0.0582	0.1246
Total Factor of Productivity	5.6167	1.3370	6.1813	1.1799	5.9368	1.2409

Source: Author's Computation.

CONCLUSION AND IMPLICATIONS FOR POLICY

The efficiency estimated in KLH-model is higher than the values obtained under the other models. Thus, the results from the KLH-models provided time-varying TE that reflects the overall efficiencies indicating the sensitivity of the model's specified. Moreover, it is possible to argue that mediocre, there is 43.24% of un-captured households' time-varying TE in the production processes of those considered crops in SE.

The results show differences in inefficiency at the zone level during the survey years, confirmed that Derashe performed well followed by Burji Special, Gurage, Sidama, and Woliata. The estimation of total efficiency implied that by improving efficiency in the agricultural sector, Southern Ethiopia can capture about 39% to 99% of the uncaptured or untapped maximum considered crop production. Finally, this study pinpoints the policy implication of having a separate national plan on the sources of inefficiencies based on time. The local government has to work on the persistent inefficiency sources of the region.

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