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Farm-Heterogeneity and Persistent and Transient Productive Efficiencies in Ethiopia's Smallholder Cereal Farming

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Preface

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Abstract

This paper investigates persistent and transient productive efficiencies of Ethiopian cereal farmers for the period 1999-2015. It uses a 4-random error component stochastic frontier panel data model to distinguish between time-invariant farm heterogeneity and persistence and transient inefficiencies. It compares this model with three other stochastic frontier panel data models in which one of the four components is missing. The models allow the estimation of persistent and transient efficiencies for each farmer and each time period. The first-order estimates of the parameters indicate that agrochemicals, livestock, machinery and labor significantly enhanced cereal production. The results of the efficiency estimation indicate that the mean and dispersion of efficiencies among farmers differed by the model's specifications and their agro-ecological zones and sub-zones. The results also show that cereal farming was technologically regressed at an increasing rate and exhibited increasing returns to scale. The results confirm that in general farmers were unable to achieve full productive efficiency and efficiency estimates consistently declined over time. The results further show that cereal growing farmers' experienced much more persistent inefficiency problems as compared to transient inefficiencies. These findings are important and can be used to initiate agricultural policy options which are tailored at enhancing improvements in farming efficiency. The study therefore recommends policies that will improve measures that can reduce persistent inefficiencies, improve the supply of agricultural inputs and also policies that can meet the needs of farmers and which suit their agro-ecological zones.

Keywords: Farm-heterogeneity, persistent and transient efficiencies, cereal farming, agro-ecological zones, panel data and Ethiopia.

JEL Classification: C23, D21, D23, D24, O13, Q12.

1. INTRODUCTION

Studying the sources of growth in agricultural production and analyzing farm performance is an important step in assessing the developmental role that agriculture plays in developing countries. Knowing the levels of efficiency of smallholder farmers has important implications in the choice of development strategies, particularly in Sub-Saharan Africa (SSA) where most countries derive over 60 per cent of their livelihoods from agriculture and related economic activities (Maurice et al., 2014). Agriculture in Ethiopia contributes 40 per cent to its GDP, provides employment and livelihood to more than 83 per cent of the population, contribute 85 per cent to the country's total export earnings and supplies 73 per cent of the raw materials to domestic industries (AfDB, 2011). However, the sector is characterized by rain-fed agriculture, frequent droughts, high population pressures and severe land degradation; it is also vulnerable to climate change. The sector is compounded by one of the lowest productivity levels in the world and is dominated by subsistence smallholders who usually cultivate areas which on average are less than 1.5 hectares (FAO, 2009).

Cereals are the most vital crop in Ethiopia. As a major food crop they comprise about two-third of the agricultural share of GDP and one-third of the national GDP. Cereals have a line share in the country's crop farming in terms of production volumes, farm land and farm households. According to ECSA (2015) cereals comprised about 79 per cent of the total cropped area, 85 per cent of the grain crop production and engaged 81 per cent private farmers for the Meher season in the 2014-15 production year. Cereal production was marked by remarkable growth in Ethiopian crop farming during the last decade. Several of ECSA's yearly publications indicate that cereal production grew consistently from an average of 16 million metric tons (MMTs) in 2004-08 to 21.6 MMTs in 2009-14, averaging 18.8 MMTs for a decade with a growth rate of 2.74 per cent per annum. However, despite the widely-believed view that agriculture plays a central role in Ethiopia's economic transformation, others maintain that the sector did not perform as per expectations. According to Kassahun (2011) the sector is characterized with inefficiencies and poor productivity and cereal production showed a steady low-growth rate in the last two decades. These observations underline the importance of knowing the performance/efficiency levels of cereal farmers in Ethiopia. This information will help enhance food security which is an important issue for policymakers in agrarian countries like Ethiopia.

Since the pioneering work of Farrell (1957) various studies have been conducted in efficiency literature to examine efficiency in crop farming in different countries using different methodologies. Most studies are based on Farrell-type measures of efficiency. However, over the years various methods of estimating production frontiers have also been developed so as to be able to come up with reliable efficiency measures. These frontier methods vary from econometric (a stochastic frontier analysis-SFA) to non-econometric (data envelopment analysis-DEA) methods. The stochastic production frontier (SPF) model which was introduced by Aigner et al. (1977) accommodates different circumstances (Battese and Coelli, 1992, 1995; Jondrow et al., 1982; Kumbhakar, 1991; Pitt and Lee, 1981; Schmidt and Sickles, 1984). SFA has been extensively used for estimating technical efficiencies. In particular, the SPF model is a better fit for an analysis of agricultural efficiencies because of the higher noise as a result of the stochastic nature of the production process and yield variability usually experienced in agricultural data.

However, efficiency results from such models are sensitive to the way in which they are modeled and interpreted and to the assumptions underlying the model mainly when panel data is used (Kumbhakar et al., 2014, 2015). The main reason for the different assumptions is that when panel data is available, the productive efficiency of a farm is composed of persistent and transient components of efficiency that cannot be captured distinctively by the earlier SPF models. In addition, these models do not treat explicitly unobservable individual/farm effects in inefficiencies thus generating a mis-specification bias. Further, the effects of these factors may be captured by the term 'inefficiency' thereby producing biased efficiency results. Nevertheless, when panel data started being available, panel data models were developed (Colombi et al., 2014; Filippini and Greene, 2016; Kumbhakar et al., 2014; Tsionas and Kumbhakar, 2014) which allow separating the two components of inefficiency along with disentangled heterogeneity effects.

Several empirical works have been undertaken to investigate the efficiency of Ethiopia's crop farming using different methodologies. However, thus far there have only been limited attempts at studying farming efficiency applying panel data SFP models. Most of the studies use simpler model specifications of the type used by Battese and Coelli (1992, 1995). These models have inherited the problems raised earlier. Moreover, to the best of the author's knowledge, no study provides separate estimates of the two inefficiency components and these studies have also not disentangled heterogeneity effects from inefficiencies. However, estimates of persistent inefficiencies provide useful information about farmers because high persistent inefficiency scores are indicators of non-competitiveness. This inefficiency may be due to the presence of structural problems in the organization of a farm's production process or the presence of systematic shortfalls in managerial capabilities or lasting habits of farmers of wasting inputs. The transient part of inefficiency on the other hand may stem from temporal behavioral aspects of the management, for example, from a non-optimal use of some inputs due to the presence of non-systematic management problems that can be solved in the short term. Further, as discussed by Kumbhakar et al. (2015), knowing estimates and information about the two components of inefficiency, especially in long panels and their separation from heterogeneity effects, are important as they allow farmers to elicit their resource/cost saving potential both in the short run and in the long run. Each component provides different information with different policy implications for promoting efficiency in the production of scarce resources.

Accordingly, the present study applies a recently proposed 4-component random error panel data SPF model following Kumbhakar et al., (2014) to estimate persistent and transient efficiencies by disentangling them from unobserved farm-heterogeneity effects for smallholder cereal farmers in Ethiopia using a partially balanced panel dataset. It also compares the results from this model with the other three SPF models in which one of the four components is missing. This study contributes to existing literature as it provides one of the first empirical analyses to show the presence of persistent and transient inefficiencies using a novel econometric approach -- a 4-component random-error panel data SPF model -- for Ethiopia's smallholder cereal farmers. Second, to the best of the author's knowledge, this is the first panel data analysis which addresses the problems of individual and farm heterogeneities in measuring production efficiencies in Ethiopia's crop farming that disentangles farm heterogeneity from inefficiency effects. Thus, it provides valuable information on persistence and transient inefficiencies and farm heterogeneity effects. Third, it has an analysis based on agro-ecological zones (AEZs) which considers cereal farming at the farm-household level and thus it also considers output. Therefore, it is replicable elsewhere in the country, between regions and within AEZs.

The rest of the paper is organized as follows. Section 2 presents the method and data used; it also gives the specifications of the panel data stochastic frontier models, the estimation procedure and the dataset used in the analysis. Section 3 gives estimations and results and discusses the empirical findings**.** Section 4 gives a summary, conclusions and policy recommendations.

2. METHOD AND DATA for THE STUDY

2.1. A partial review of panel data stochastic frontier models

Since their inception SPF models have been used for measuring and comparing the performance of individual production units within a geographic location, an industry or in the agricultural sector. Extensive research in this field has resulted in the rapid development of econometric techniques concerning specifications, estimations and testing issues of the models. These techniques have developed rapidly and have been implemented in many areas mostly using cross-sectional and panel data. The use of a panel data model in estimating producers' efficiencies helps avoid some of the problems related to distributional assumptions encountered in a cross-section approach. According to Schmidt and Sickles (1984) when inefficiency is time-invariant, panel data enables one to estimate inefficiency consistently without distributional assumptions. Panels also have the advantage of separating individual and time-specific effects from the combined effect (Heshmati et al., 1995). Further, panel data enables one to control individual heterogeneity effects, it has greater variability, less collinearity between variables, a higher degree of freedom and more efficiency; panel data is also more capable of identifying and measuring the effects that are not detected in cross-sectional or time-series data.

A panel data SPF model that was introduced in the early 1980s assumed inefficiencies to be individual-specific and time-invariant. That is, inefficiency levels may be different for different producers but they did not change over time. This means that an inefficient producer does not learn how to improve his performance over time. This might be the case in some situations where, for example, the soil quality is poor and a farm lacks water sources for irrigation, or inefficiencies are associated with managerial abilities and there is no change in management and production technology for a farm during the period of the study (Kumbhakar et al., 2014, 2015). This seems unrealistic particularly when production competition is considered.

Another drawback of this approach is that farm heterogeneity cannot be distinguished from inefficiencies; all time-invariant heterogeneity is confounded by inefficiencies. This raises key questions on whether inefficiency has been persistent over time or is it in time-varying units? And whether time-invariant individual effects represent persistent inefficiencies, or the effects are independent of inefficiencies and capture persistent farm heterogeneity. Related to these questions and as discussed in Colombi et al. (2014) and Kumbhakar et al. (2014, 2015), several panel data SPF models were developed to include both time-invariant and time-varying inefficiency effects. Some of these models were developed based on the assumption that all the time-invariant (fixed or random) effects were persistent inefficiencies (for example, Pitt and Lee, 1981; Schmidt and Sickles, 1984). Others were developed based on the assumption that the time-variant effects were transient inefficiencies without considering farm effects (for example, Battese and Coelli, 1992; Lee and Schmidt, 1993) and some others separated farm effects from transient inefficiencies without considering the possibility of persistent inefficiencies (for example, Greene, 2005a, 2005b). The models proposed by Kumbhakar (1991) and Kumbhakar and Heshmati (1995) are in between. These models treat farm effects as persistent inefficiencies and include another component to capture transient inefficiencies.

Some recently developed panel models provide information on whether a farm is characterized by the presence of both types of inefficiencies and are concerned with the separation of inefficiencies from heterogeneity effects (Colombi et al., 2014; Filippini and Greene, 2016; Kumbhakar et al., 2014; Tsionas and Kumbhakar, 2014) that may overcome some of the limitations of the earlier approaches. These recently developed models have been proposed with an error structure that is decomposed into four elements thus making it possible to account separately for the usual noise in the data, farmer/farm unobserved time-invariant heterogeneity and transient/short-run and persistent/long-run inefficiency components. Herein, transient inefficiency is interpreted as short-term production inefficiency associated with changes in managerial skills or disruptions resulting from the adoption of new technologies. By contrast, persistent inefficiencies are long-run production inefficiencies due to structural or institutional factors which evolve slowly over time. While long-run inefficiencies and farmer/farm unobserved-heterogeneity are both time-invariant effects, a major difference between them is that the latter is always beyond the control of the farmers (for example, geological/locational make-up of a farmer/farm and other physical features). Thus, having estimates and information about persistence and transient components of inefficiency and separating them from heterogeneity effects are important. Each component provides different information and has different policy implications.

In line with Heshmati et al. (2016) and Rashidghalam et al*.,* (2016) this paper uses 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 basic version of panel data models: the fixed-effects model by Schmidt and Sickles (1984) which assumes inefficiency effects to be time-invariant and individual specific. It thus offers estimates of persistent/long-run inefficiencies. The second model is a true fixed-effects panel data model proposed by Greene (2005a). This separates transient/short-run inefficiencies from persistent individual effects. The third model is a 3-component random error panel data model (Kumbhakar and Heshmati, 1995) that gives estimates of persistent and transient inefficiencies without accounting for farm heterogeneity. The fourth model is a recently developed 4-component error panel data model by Kumbhakar et al. (2014) that provides estimates of persistent and transient inefficiencies separating them from time-invariant farm effects and noise.

2.2 Model specifications and the estimation procedure

Consider the traditional panel data SPF model:

$$
\begin{aligned}
(1)\qquad y_{it} &= \alpha_0 + x'_{it}\beta + \varepsilon_{it} - \tau_{it} \\
&= \alpha_0 + x'_{it}\beta + \varphi_{it}
\end{aligned}
$$

where, $i = 1,2,...,N$ is an index for farmer i and $t = 1, 2,...,T$, represent time. The variable y_{it} represents the output of a farmer; x_{it} is row vector of input variables of a farmer plus other exogenous/control variables such as time trend (and depending on the specification of the production technology, squares of the inputs and their cross-product terms). The parameter α_0 is a common intercept; β is a vector of unknown parameters to be estimated; ε_{it} *and* τ_{it} are the idiosyncratic and inefficiency components of the 'composed error term', φ_{it} and $\tau_{it} \geq 0$ is a transient inefficiency term of individual *i* which is assumed to be *identically independently distributed (i.i.d.)* as half normal, that is, $\tau_{it} = |\mathrm{T}_{it}|,\ where\ \mathrm{T}_{it} \sim i.i.d.\ N^{+}(0, \sigma_{\mathrm{T}}^{2})$ .Similarly, ε_{it} is a random noise assumed to be $\varepsilon_{it} \sim i.i.d.\ N(0, \sigma_{\varepsilon}^{2})$.

2.2.1 Model specification

In this section, we present the specifications of the four SPF panel data models used in this study. The specification of all models is based on the formulation of the model given in Eqn.

1. Karagiannis and Tzouvelekas (2009) and Rashidghalam et al. (2016) provide a comparison of alternative specifications of inefficiency based on the same data. In this study, we focus on four main ones.

Model 1: Individual effects treated as long-run inefficiencies

To specify a model with time-invariant inefficiency effects we treat the term τ_{it} in Eqn. 1 as a time-invariant term u_i to represent long-run inefficiency to obtain:

(2) $$y_{it} = \alpha_0 + f(x_{it};\beta) + \varepsilon_{it} - u_i \quad ; \qquad u_i \geq 0$$

This model utilizes the panel feature of the data via u_i and it can be estimated when the inefficiency component u_i is a fixed parameter by the fixed-effect model (FE-model) or when u_i is treated as a random variable by the random-effect model, assuming ε_{it} *and* u_i are homoscedastic. This model has been criticized for its assumption about inefficiency as time-invariance inefficiency seems to be unrealistic, especially for a long panel dataset because this inefficiency term may capture some time-invariant farm attributes such as individual instinctive abilities and other persistent farm heterogeneities that are unrelated to the production process but which affect the output. Thus, these factors may be confounded with inefficiency and the model is miss-specified and tends to over-estimate inefficiency levels.

Model 2: Individual effects treated as heterogeneity

To overcome the drawbacks of the FE-model, Greene (2005a) proposed an extension of this model called the 'true' fixed-effects (TFE) model. The purpose of this model is to treat time-invariant farm heterogeneity and transient inefficiency effects separately. Hence, treating the inefficiency term τ_{it} as a time-varying term in Eqn. 1 but splitting the error term as: $\varepsilon_{it} = \mu_i + \upsilon_{it}$; we obtain:

(3) $$y_{it} = \alpha_0 + f(x_{it};\beta) + \mu_i + \nu_{it} - \tau_{it}$$

where μ_i is random-effects to capture any time-invariant farm heterogeneity, not inefficiency; τ_{it} represents transient inefficiency and v_{it} is a random shock with the following distribution:

(4) $$\tau_{it} \sim N^+(0,\sigma_\tau^{\ 2}),\ v_{it} \sim N(0,\sigma_v^{\ 2}),\ and\ \mu_i \sim N^+(0,\sigma_\mu^2)$$

If in this model if we treat μi as a fixed-parameter that does not capture inefficiency then the model becomes a true fixed-effects model (TFE-model).

The TFE-model allows inefficiency to be time-variant and controls for farm heterogeneity for it to be captured by a farm specific intercept. However, the model views individual effects as being different from inefficiency and assumes that inefficiency terms are always transient. Thus, it fails to capture persistent inefficiencies. Therefore, the individual effects cannot be distinguished from transient inefficiencies and the persistent component of inefficiency is completely absorbed in a farm's constant term. Hence, all time-invariant effects that are not necessarily inefficient are included as inefficiencies and therefore $\hat{\tau}_{it}$ might be picking up farm heterogeneity in addition to or even instead of inefficiencies (Kumbhakar and Heshmati, 1995). Consequently, the model is miss-specified and tends to under-estimate transient inefficiency levels and can hence over-estimate efficiency scores.

Model 3: Individual effects treated as persistent inefficiencies

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

To formalize this model we split the inefficiency term, τ_{it} in Eqn. 1 as: $\tau_{it} = \eta_i + u_{it}$ to obtain:

$$
\begin{aligned}
(5) \qquad & y_{it} = \alpha_0 + f(x_{it};\beta) + \varphi_{it} \\
& \varphi_{it} = \varepsilon_{it} - \tau_{it} \quad ; \quad \tau_{it} = \eta_i + u_{it} \quad \textit{so that} \\
& y_{it} = \alpha_0 + f(x_{it};\beta) + \varepsilon_{it} - \eta_i - u_{it}
\end{aligned}
$$

This model (KH-model) split the error term into three components where ε_{it} captures a random shock; $\eta_i \geq 0$ captures individual effects as persistent inefficiency; and $u_{it} \geq 0$ captures the transient inefficiency component. Unlike the TFE-model, the KH-model does not consider any time-invariant farm effects and hence confounds these effects in an individual's persistent inefficiencies. Consequently, the model is again miss-specified and is likely to produce persistent inefficiency estimates with an upward bias.

Model 4: Separation of individual heterogeneity from persistent inefficiencies

To overcome the limitations of these three models, Colombi et al. (2014), Kumbhakar et al., (2014) and Tsionas and Kumbhakar (2014) proposed a model that split the error term into four components -- persistent and transient inefficiencies, random farm effects and noise. Hence, we specify a model that distinguishes between persistent and transient inefficiencies and time-invariant inefficiencies from farm effects (Kumbhakar et al., 2014) using the decompositions $\tau_{it} = \eta_i + u_{it}$ *and* $\varepsilon_{it} = \mu_i + \upsilon_{it}$ in Eqn. 1 to obtain:

$$(6) \qquad y_{it} = \alpha_0 + f(x_{it};\beta) + \mu_i + v_{it} - \eta_i - u_{it}$$

This model (KLH-model) decomposes the error term, φ_{it} into four components as: $\varphi_{it} = \mu_i + v_{it} - \eta_i - u_{it}$; where μ_i is a random farm effect that captures time-invariant farm's heterogeneity (for example, oil quality) which has to be disentangled from persistent individual effects (for example, a farmer's skills); υ_{it} is the idiosyncratic random component; $\eta_i \geq 0$ captures persistent inefficiencies; and $u_{it} \geq 0$ captures transient inefficiency effects. Without μ_i the Eqn. 6 is reduced to the KH-model and without η_i it is the same as the TFE-model.

2.2.2 Models' estimation procedures

To estimate the FE-model we reformulate Eqn. 2 to obtain the following estimable model:

$$
\begin{aligned}
& y_{it} = \alpha_0 + f(x_{it};\beta) + \varepsilon_{it} - u_i = (\alpha_0 - u_i) + f(x_{it};\beta) + \varepsilon_{it} \\
(7) \qquad & \quad = \alpha_i + f(x_{it};\beta) + \varepsilon_{it}
\end{aligned}
$$

Eqn. 7 is like a standard fixed-effects panel data model (Schmidt and Sickles, 1984), where $\alpha_i = \alpha_0 - u_i$ is farm specific intercepts. Here u_i *and* α_i are individual effects and are assumed to be fixed-parameters to be estimated along with the parameter vector β. One can apply the standard fixed-effect panel data estimation method to obtain $\hat{\alpha}_i$ and the following transformation to obtain an estimate for u_i :

(8) $$\hat{u}_i = \max_i(\hat{\alpha}_i) - \hat{\alpha}_i \geq 0, \qquad i = 1,..., N$$

and obtain farm specific technical efficiency estimate $TE_i = Exp(-\hat{u}_i)$. This formulation implicitly assumes that the most efficient unit in the sample is 100 per cent efficient so that inefficiencies for other farmers are relative to the best farmer.

We estimate the TFE-model by making a distributional assumption on the random error. Different estimation methods have been proposed for estimating the KH and KLH-models. Colombi et al. (2014) used a single stage maximum likelihood estimation (MLE) method based on the distributional assumptions of the 4-error components; Kumbhakar and Heshmati (1995) and Kumbhakar et al. (2014) used a multi-step procedure; and Filippini and Greene (2016) used the simulated ML approach. However, due to its simplicity we used the multi-step estimation procedure suggested by Kumbhakar et al. (2014) for the KH and KLH-models. The multi-step procedure has the advantage of avoiding strong distributional assumptions by estimating the model using the ML method. In what follows we present the multi-step approach for the two models.

The KH-model can be estimated in four steps. The steps are described in Kumbhakar et al. (2015). For this we rewrite the model in Eqn. 5 as:

(9) $$y_{it} = \alpha_i + f(x_{it}; \beta) + \omega_{it} ,$$
$$\alpha_i = \alpha_0 - \eta_i - E(u_{it}) \; and \; \omega_{it} = \varepsilon_{it} - (u_{it} - E(u_{it}))$$

In this case the error component ω_{it} has zero mean and constant variance. Thus, the model in Eqn. 9 which fits the standard panel data model with individual effects can be estimated either by the least squares dummy variable (LSDV) or by the generalized least squares method. Under the LSDV framework, using a multi-step procedure, the model can be estimated in four steps as: In step 1, we estimate Eqn. 9 using the standard within fixed-effects panel data model to obtain consistent estimates of β. In step 2, we estimate persistent inefficiencies, in which we obtain their components $\hat{\eta}_i$ which can be used to estimate persistent technical efficiency $PTE = \exp(-\hat{\eta}_i)$. In step 3, using the standard half-normal SF model we estimate α_0 and the parameter associated with ε_{it} *and* u_{it}. Finally, in step 4, we use the JLMS technique to estimate the residual inefficiency u_{it}. This procedure predicts the residual inefficiency component $\hat{u}_{it}$ which can be used for estimating residual technical efficiency $RTE_{it} = \exp(-\hat{u}_{it})$. Finally the overall technical efficiency (OTE) is obtained from the product of persistent and residual efficiencies, that is, $OTE_{it} = PTE_i \times RTE_{it}$

To estimate the KLH-model, we reformulate Eqn. 6 as:

(10) $$y_{it} = \alpha_0^* + f(x_{it}; \beta) + \alpha_i + \omega_{it}$$

where $\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it}); and \; \alpha_i = \mu_i - \eta_i - E(\eta_i) ; and \; \varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$

With this specification α_i *and* ω_{it} have zero mean and constant variance since Eqn. 10 is a familiar panel data model. Like in the previous case we use the 4-step approach to estimate the KLH-model. In the first step, the standard fixed-effect panel regression is used to estimate $\hat{\beta}$. This procedure also gives predicted values of α_i *and* ε_{it}, denoted by $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}^*$. In step 2, the time-varying technical efficiency is estimated using the predicted value of ε_{it}^{*} from the previous step using the standard stochastic frontier technique. This procedure predicts the time-varying residual technical inefficiency which can be used to estimate $RTE_{it} = \exp(-u_{it} | \varepsilon_{it}^{*})$. In step 3 we estimate η_i, following a procedure similar to the one in step 2. For this we use the standard pooled half-normal stochastic frontier model to obtain estimates of the persistent inefficiency component η_i . Then PTE can be estimated using the formulae $PTE_i = \exp(-\hat{\eta}_i)$ and $OTE_{it} = PTE_i \times RTE_{it}$ (see Table 1).

Table 1. Summary of main characteristics and assumptions of the four models applied

	FE-model	***TFE-model***	***KH-model***	***KLH-model***
Farm-specific effects α_i	Fixed	Fixed	Fixed	Fixed
Full composed error term $\varphi_{it} = \varepsilon_{it} - \tau_{it}$	$\varphi_{it} = \varepsilon_{it} - u_i$	$\varphi_{it} = \mu_i + v_{it} - \tau_{it}$	$\varphi_{it} = \varepsilon_{it} - \eta_i - u_{it}$	$\varphi_{it} = \mu_i + v_{it} - \eta_i - u_{it}$
	$\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^{2})$ $u_i \sim N^{+}(0, \sigma_u^{2})$	$\tau_{it} \sim N^{+}(0, \sigma_{\tau}^{2})$, $v_{it} \sim N(0, \sigma_v^{2})$, $and \, \mu_i \sim N(0, \sigma_{\mu}^{2})$	$u_{it} \sim N^{+}(0, \sigma_u^{2})$, $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^{2})$, $and \; \eta_i \sim N^{+}(0, \sigma_{\eta}^{2})$	$u_{it} \sim N^{+}(0, \sigma_u^{2})$, $v_{it} \sim N(0, \sigma_v^{2})$, $\mu_i \sim N(0, \sigma_{\mu}^{2}) \; and$ $\eta_i \sim N^{+}(0, \sigma_{\eta}^{2})$
Persistent inefficiency estimator	$E(u_i \| \varphi_{it})$	None	$E(\eta_i \| \varphi_{it})$	$E(\eta_i \| \varphi_{it})$
Transient inefficiency estimator	None	$E(\tau_{it} \| \varphi_{it})$	$E(\tau_{it} \| \varphi_{it})$	$E(\tau_{it} \| \varphi_{it})$
Estimation Method	COLS	ML	ML	ML

Note: FE-the Fixed Effect Model, TFE-the True-Fixed Effect Model, KH-the Kumbhakar and Heshmati (1995) Model, KLH- the Kumbhakar, Lien and Hardaker (2014) model; Corrected Ordinary Least Squares (COLS); ML-Maximum Likelihood.

2.3 The Empirical Model

The production function $f(x_{it};\beta)$ in models 1 to 4 is specified using a translog (TL) functional form because of its flexibility (Christensen et al., 1973). Hence, assuming a TL with the time-trend representation we estimate a stochastic frontier panel data model using the following specification:

(11)
$$\ln y_{it} = \alpha_0 + \sum_{j=1}^{J} \beta_j \ln X_{jit} + \beta_t T_t + \frac{1}{2}\left(\sum_{j=1}^{J}\sum_{k=1}^{J} \beta_{jk} \ln X_{jit} \ln X_{kit} + \beta_{tt} T_t^{2} \right) + \sum_{j=1}^{J} \beta_{jt} \ln X_{jit} T_t + \varepsilon_{it} - \tau_{it}$$

where $\ln y_{it}$ is the natural logarithm of output measure of farmer *i; $i = 1,2,...,N$*; in time period *t, $t = 1,2,...,T$*; and $\ln X_{it}$ is a vector of natural logarithm of *j, $j = 1,2,...,J$* inputs. The explanatory variable T is a time trend and is a proxy for the exogenous rate of technical change, while all other variables ($\alpha, \beta, \varepsilon$ *and* τ) maintain their previous definitions as in Eqn. 1.

Elasticities (E), technical changes (TC) and returns to scale (RTS)

Since the coefficients of the TL production function do not have direct interpretations, we computed elasticities of output with respect to each input. As all the variables are expressed in their logarithms their elasticities can be simply obtained from a partial differentiation of the production function with respect to appropriate inputs based on:

$$E_{jit} = \frac{\partial \ln y_{it}}{\partial \ln X_{jit}} = \beta_j + \beta_{jj} \ln X_{jit} + \beta_{jt} T_t \quad , \tag{12}$$

the rate of TC and RTS is obtained from:

$$TC_{it} = \frac{\partial \ln y_{it}}{\partial \ln T_t} = \beta_t + \beta_{tt} T_t + \sum_{j=1}^{J} \beta_{jt} \ln X_{jit} \quad and \; RTS_{it} = \sum_{j=1}^{J} E_{jit} \; . \tag{13}$$

Elasticity measures the responsiveness of output to a 1 per cent change in the j^{th} input used by farmer i at time t. TC is the percentage change in output due to an increment of time measured in years for unchanged input use. RTS measures the percentage change in output in response to a proportional 1 per cent increase in all inputs simultaneously. Technology exhibits increasing, constant or decreasing RTS respectively if RTS is greater than, equal to or less than one. All input elasticities, RTS and TC are computed at every data point.

2.4. Data and Variables in the Study

The data source for our study was the Ethiopian Rural Household Survey collected from randomly selected farm households in rural Ethiopia in 1994-2015. It includes farm production and economic data collected at 5 years' intervals from local Farmers Associations (FAs) that were selected to represent the country's diverse farming systems. Originally, the first four waves of the survey were conducted in collaboration with the Department of Economics, Addis Ababa University (AAU) and the International Food Policy Research Institute (IFPRI). The last round was extended forming a sub-sample from the original respondents covering eight FAs following a similar strategy. This comprised of 503 farm households compiled by the researcher in 2015 in collaboration with AAU and the Environment for Development (EfD) at the University of Gothenburg, Sweden. Consequently, this study employs data from the last four rounds (1999, 2004, 2009 and 2015) covering eight Fas thus forming a partially balanced panel of 446 households and 1,648 observations. These four rounds were selected to allow for even time spacing and covering approximately similar time frames. The 1994 survey was excluded as it misses most of the important variables for the analysis.

We used aggregated cereal output measured in Ethiopian birr (ETB) as a dependent variable using the following explanatory variables: labor employed measured in man-day units (MDUs); cereal sown farmlands in hectares; amount of fertilizers used in kilograms; agricultural machinery implements in ETB; and livestock ownership in tropical livestock units (TLUs) as a proxy for wealth and livestock asset endowments. Agrochemicals in ETB including pesticides, herbicides and insecticides and oxen as animal draft power in number of the oxen owned as these are mainly used in traditional farming during land preparation and harvesting periods. It also uses a time trend and its square. The time trend captures the shift in production over time representing technical changes, while the squared trend captures the non-linear shift in the production function over time. All monetarily measured variables are transformed to fixed ETB prices obtained by deflating to 1999 prices. The input variable seeds was excluded from the analysis due to lack of information on it.

2.5 Descriptive Summary

Table 2 presents the summary statistics of the data (mean and dispersion) and the evolution of cereal production output and input variables over time. As shown in the table, mean cereal production was about 1,952 kg ranging between 34 kg and 51,100 kg per farm household during the study period. Evolution of cereal production over time reveals that production increased over the period as the mean of production was about 1,260 kg in 1999 which rose steadily to 3,020 kg in the 2015 production year. For this production the farmers cultivated cereals on average on about 1.8 hectares and used 342.6 MDUs of labor. Fertilizer application was minimal with an average of 116.1 kg per farm household while the expenses on agrochemicals were on average 133.9 ETB. The farmers spent 336.27 ETB for agricultural machinery used per farm household. Average livestock ownership was 6.5tropical livestock units (TLUs) and average oxen ownership was around 1.8 oxen meaning that farms on average owned two oxen ranging from no ox to nine oxen per farm household.

Table 2. Summary statistics of input and output variables (NT=1,648)

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Output(kg)	1952.25	2681.81	34.00	51100.00
Fertilizers(kg)	116.09	138.86	0.00	1400.00
Agrochemicals(ETB)	133.90	447.17	0.00	8560.00
Labor(DMU)	342.62	714.21	3.00	8333.88
Machinery(ETB)	336.27	1775.88	0.00	36540.00
Livestock(TLUs)	6.49	5.93	0.00	58.80
Number of oxen	1.75	1.35	0.00	9.00
Planted-area (Hec.)	1.75	1.28	0.02	11.00

Source: Author's computation.

3. EMPIRICAL RESULTS AND DISCUSSION

3. 1. An Analysis of the results of production frontier estimates and elasticities

Table 3 presents estimates of the translog production frontier parameters obtained from the econometric estimation of each of the alternative models. As shown in the table most of the parameter estimates from the models were significantly different from zero at the 5 per cent level or lower. For all the models the estimated first-order parameters (β_i) had the anticipated (positive) sign and magnitude (between zero and one), whereas the bordered Hessian matrix of the first and second-order partial derivatives was negative and semi-definite indicating that all regularity conditions of the production economic theory which require that the partial output elasticities be non-negative and less than one (that is, positive and diminishing marginal products) were valid at the point of approximation. Thus, the results of all the four models behaved well in a production frontier function. The estimates of the first-order parameters with respect to agrochemicals, labor, machinery, oxen and livestock were all statistically significant. This suggests that cereal production in the study area was most responsive to these inputs. Hence, an increase in agrochemicals, machinery, labor use and more livestock units that may include plowing oxen enhanced cereal production.

Estimates of the time-trend and its squared term were significantly positive at the 1 per cent level showing that cereal farmers experienced technical changes (TC) which regressed with an increasing rate over the sample period. Estimates of time interacted with farmland area were positive implying that TC was land using. The coefficients of time interactions with other inputs were negative and significant implying factor using TC for these inputs and suggesting input saving TC. Estimates of time interaction with agrochemicals were not significant implying technical neutrality with respect to this input. However, the overall TC was not neutral because some production factors significantly changed over time.

Production elasticities, returns to scale and technical **changes**

Average estimates of production input elasticities estimated at the mean of the data, computed from Eqn. 12, returns to scale and technical changes are presented in Table 4. Estimates of production elasticities with respect to all inputs evaluated at the mean of the data were significantly different from zero. All point elasticity estimates across models were positive, indicating positive marginal products of inputs. The positive sign of the elasticities further indicates that lack of these inputs hampered agricultural activities and hence output levels. Estimates of production elasticities indicate that each input contributed significantly to cereal production, however, the magnitude of the elasticities differed across models. For instance, if a farmer increased the number of the oxen by 1 per cent, keeping other inputs constant this increased cereal production by 0.450 per cent (FE, KH and KLH-models) and 0.465 per cent (TFE-model). Similarly, an increase in livestock rearing by 1 per cent increased production by 0.274 per cent in the TFE-model and 0.240 per cent in the other models. An increase in agrochemicals by 1 per cent increased production by 0.064 per cent for the TFE-model and 0.068 per cent in the other models and increasing cultivated land area by 1 per cent increased production by 0.276 per cent in the TFE-model and 0.333 per cent in the other models. Moreover, as can be observed from Table 4, in almost all the models for all productive inputs, the elasticities with respect to oxen were the highest, elasticities with respect to cultivated land size were the second highest and those for fertilizers were the least. These indicate that more oxen contributed the most to cereal production, followed by land. The least contribution was of fertilizers. The results suggest that traction animal power contributes to higher levels in cereal farming but this may be because animal traction power is a dominant form of land preparation under conventional farming. Our results are similar to what other studies have found in Ethiopia (Gebreegziabher et al., 2005).

Table 3. Estimates of the parameters using the TL production frontier across models (NT=1,648)

		FE Model		***TFE Model***		***KH & KLH Models***	
Variables		***Estimate***	***S. E***	***Estimate***	***S. E***	***Estimate***	***S. E***
Fertilizer	β_{x1}	0.063	0.080	0.089	0.067	0.063	0.080
Agrochemicals	β_{x2}	0.108^{*}	0.059	0.098^{**}	0.050	0.108^{*}	0.059
Labor	β_{x3}	0.350^{***}	0.114	0.341^{***}	0.095	0.350^{***}	0.114
Machinery	β_{x4}	0.289^{***}	0.077	0.287^{***}	0.064	0.289^{***}	0.077
Livestock	β_{x5}	0.194	0.126	0.223^{**}	0.106	0.194	0.126

Oxen	β_{x6}	0.382	0.292	0.391*	0.244	0.382	0.292
Area	β_{x7}	0.069	0.133	0.014	0.112	0.069	0.133
Fertilizer*Fertilizer	β_{x11}	-0.002	0.018	0.003	0.015	-0.002	0.018
Agrochemicals*Agrochemicals	β_{x22}	-0.005	0.014	-0.002	0.012	-0.005	0.014
Labor*Labor	β_{x33}	0.035	0.023	0.030	0.019	0.035	0.023
Machinery*Machinery	β_{x44}	0.058***	0.016	0.061***	0.013	0.058***	0.016
Livestock*Livestock	β_{x55}	0.121***	0.028	0.125	0.024	0.121***	0.028
Oxen*Oxen	β_{x66}	-0.224	0.223	-0.214	0.186	-0.224	0.223
Area*Area	β_{x77}	-0.118***	0.026	-0.125***	0.022	-0.118***	0.026
Fertilizer*Agrochemicals	β_{x12}	-0.004	0.013	-0.008	0.011	-0.004	0.013
Fertilizer*Labor	β_{x13}	0.019	0.025	0.013	0.021	0.019	0.025
Fertilizer*Machinery	β_{x14}	-0.002	0.015	-0.003	0.012	-0.002	0.015
Fertilizer*Livestock	β_{x15}	-0.093***	0.029	-0.099***	0.025	-0.093***	0.029
Fertilizer*Oxen	β_{x16}	0.102	0.066	0.111**	0.056	0.102	0.066
Fertilizer*Area	β_{x17}	0.111***	0.035	0.126***	0.029	0.111***	0.035
Agrochemicals*Labor	β_{x23}	-0.012	0.02	-0.007	0.016	-0.012	0.02
Agrochemicals*Machinery	β_{x24}	0.000	0.013	0.001	0.011	0.000	0.013
Agrochemicals*Livestock	β_{x25}	0.068***	0.028	0.071***	0.024	0.068***	0.028
Agrochemicals*Oxen	β_{x26}	-0.108**	0.054	-0.110**	0.045	-0.108**	0.054
Agrochemicals*Area	β_{x27}	-0.007	0.028	-0.002	0.023	-0.007	0.028
Labor*Machinery	β_{x34}	0.068***	0.019	0.070***	0.016	0.068***	0.019
Labor*Livestock	β_{x35}	0.051	0.046	0.045	0.038	0.051	0.046
Labor*Oxen	β_{x36}	-0.103	0.096	-0.098	0.08	-0.103	0.096
Labor*Area	β_{x37}	-0.043	0.043	-0.036	0.036	-0.043	0.043
Machinery*Livestock	β_{x45}	-0.003	0.028	0.002	0.024	-0.003	0.028
Machinery*Oxen	β_{x46}	0.021	0.054	0.018	0.045	0.021	0.054
Machinery*Area	β_{x47}	-0.042	0.027	-0.042*	0.023	-0.042	0.027
Livestock*Oxen	β_{x56}	-0.190	0.129	-0.206**	0.108	-0.190	0.129
Livestock*Area	β_{x57}	-0.193***	0.07	-0.194***	0.058	-0.193***	0.07
Oxen*Area	β_{x67}	0.333***	0.144	0.329***	0.12	0.333***	0.144
Time*Fertilizer	β_{x1t}	-0.024*	0.014	-0.026**	0.012	-0.024*	0.014
Time*Agrochemicals	β_{x2t}	-0.010	0.011	-0.011	0.009	-0.010	0.011
Time*Lobar	β_{x3t}	-0.115***	0.022	-0.119***	0.018	-0.115***	0.022
Time*Machinery	β_{x4t}	-0.029*	0.018	-0.037**	0.015	-0.029*	0.018
Time*Livestock	β_{x5t}	-0.049*	0.026	-0.051**	0.022	-0.049*	0.026
Time*Oxen	β_{x6t}	0.086*	0.052	0.073*	0.044	0.086*	0.052
Time*Area	β_{x7t}	0.114***	0.031	0.118***	0.026	0.114***	0.031
Time(1=1999,…,4=2015)	β_{t}	0.688***	0.163	0.666***	0.139	0.688***	0.163
Time*Time	β_{tt}	0.355***	0.052	0.394***	0.047	0.355***	0.052
Constant	β_{0}	4.683***	0.396	4.155***	0.457	4.683***	0.396
σ_u		0.512		5.503**	2.933	0.512	
σ_v		0.748		-0.954***	0.038	0.748	
γ		0.319		0.385***	0.015	0.319	
R^2		0.758				0.758	
LogL				-1564.860		-1563.252	

Notes: *: p<0.05; **: p<0.01; ***: p<0.001.

Subscripts on β_x coefficients refer to inputs: 1 = Fertilizers; 2 = Agrochemicals; 3 = Labor; 4 = Machinery; 5 = Livestock; 6 = Number of oxen; and 7 = Planted area.

We also calculated returns to scale (RTS) and technical changes (TC), computed from Eqn. 13 in all the four models and used the results for a robustness check. Accordingly, as can be seen from Table 4 estimates of returns to scale (RTS) evaluated at the mean data point were similar across models; however, their magnitudes are model specific. Specifically, RTS was 1.538 in the TFE-model and 1.572 in other models. Hence, in general the results suggest that cereal growing farmers in the sample exhibited increasing returns to scale in all the models. Our empirical results indicate that all models predicted similar patterns of technical changes. All alternative estimators revealed positive TC estimates which are progressive at an increasing rate with the time pattern being model specific. In particular, TC estimates clearly indicate technical regression at an increasing rate of 0.901 in the TFE-model and 0.880 in the other models. This is a result of an increase in farming skills, improved seed quality and skills in the use of machinery and fertilizers.

Table 4. Mean Input Elasticities, Returns to Scale (RTS) and technical Changes (TC) across Models

Input	***FE Model***	***TFE Model***	***KH & KLH Models***
Fertilizer	0.004	0.012	0.004
Agrochemicals	0.068	0.064	0.068
Labor	0.224	0.191	0.224
Machinery	0.254	0.256	0.254
Livestock	0.240	0.274	0.240
Oxen	0.450	0.465	0.450
Planted-area	0.333	0.276	0.333
RTS	1.572	1.538	1.572
TC	0.876	0.902	0.876

Source: Author's computation.

3.2. **T**echnical **efficiency**

Table 5 gives the distribution of persistent and transient efficiency scores obtained from alternative models. The FE-model produces values of technical efficiency that are time-invariant and therefore should reflect persistent efficiencies. Results from the KH and KLH-models provide persistent as well as transient technical efficiency components. The TFE-model, which does not include persistent efficiencies, produces values that are time-variant and therefore reflects the overall (transient) efficiencies. In general, the results illustrate significant variations in efficiency estimations across models and that the efficiency scores are sensitive to the model's specifications.

3.2.1 **Time-invariant/persistent** technical **efficiencies**

As shown in Table 5, mean persistent technical efficiencies in the FE and KH-models were 0.30 with larger dispersions. Contrarily, mean persistent efficiency captured by the KLH-model was 0.79 which is significantly higher than the mean of FE and KH-models with much lower efficiency variations. Hence, comparing efficiency estimates across models the results obtained by the FE and KH-models do not provide precise information on the level of persistent efficiencies. The reason for this is that these models do not separate unobserved persistent farm-heterogeneity from inefficiencies and parts of time-invariant farm effects can be confounded in persistent inefficiencies. Thus, the models tend to over-estimate inefficiency scores, hence generating lower estimates of persistent efficiencies.

Distribution of persistent efficiencies further shows that almost 58 per cent of the farmers were operating below the mean score in the KH-model, as against 44 per cent in the KLH-model. In the KLH measure, 94 per cent of the farmers had persistent efficiency scores between 0.71 and 0.90. On the other hand, in FE and KH estimates more farmers had efficiency scores between 0.21and 0.30 implying that most cereal farmers faced severe persistent productive inefficiency problems in the study area.

Table 5. Distribution of persistent and transient efficiencies

	PTE (%)		***TTE (%)***			
TE-Interval (%)	***FE and KH-models***	***KLH-model***	***TFE-model***	***OTE_KH-model***	***OTE_KLH-model***	***RTE_(KH & KLH) models***
0-10	2.91	0	0	13.41	0	0
11-20	25.34	0	0	42.72	0.36	0.12
21-30	29.15	0	0	25.55	0.91	0.42
31-40	19.28	0	0	12.50	4.13	0.73
41-50	10.76	0	0.12	3.58	19.54	2.97
51-60	6.50	0.22	0.00	1.40	50.24	10.38
61-70	3.36	5.38	0.18	0.67	23.97	32.83
71-80	1.12	47.09	7.40	0.12	0.85	45.33
81-90	1.35	47.31	2.61	0.06	0	7.04
91-100	0.22	0	89.68	0	0	0.18
Mean	0.304	0.791	0.944	0.210	0.545	0.690
Sta. dev.	0.155	0.053	0.065	0.111	0.082	0.094
Minimum	0.054	0.567	0.427	0.020	0.105	0.141
Maximum	1.000	0.889	1.000	0.840	0.783	0.927
Yearly mean of the transient efficiency						
1999			0.964	0.213	0.550	0.695
2004			0.958	0.195	0.523	0.661
2009			0.941	0.215	0.559	0.707
2015			0.918	0.210	0.541	0.684

Source: Author's computation.

3.2.2 Time-variant/transient technical **efficiencies**

The mean transient technical efficiencies obtained from the KH, KLH and TFE models is 0.21, 0.55 and 0.94 respectively. The result shows that there were fewer farmers with transient efficiency scores below 90 per cent in the TFE-model than there were in the other two models. The variations in transient efficiency estimates by these models are due to their underlying assumptions. The TFE-model assumes that inefficiency is always time-varying and controls for unobserved farm heterogeneity to be constant over time without considering individual effects. However, if a farm household is characterized by persistent individual effects, this becomes part of farmer-specific constant terms. Consequently, the model under-estimates transient inefficiency levels which result in transient efficiency scores inflating upwards.

Unlike the TFE-model, the KH-model does not consider any time-invariant effects; it is associated with a farm and treats all time-invariant farm effects as inefficiencies. Hence, it confounds farm effects with individual persistent inefficiencies. Thus, the part of inefficiency persistence captured by this model is over-estimated. Consequently, the model is likely to produce over-estimated persistent inefficiency scores and therefore generate lower estimates of persistent efficiencies. But we know that OTE (which is time-variant) is a product of persistent and residual efficiencies. Thus, transient efficiencies in the KH-model are lower due to low persistent efficiency estimates. These characteristics of the KH-model, together with those of the TFE-model, suggest that latent farm and individual effects as unobserved in heterogeneity are significant in the sample and require us to reconsider our modeling to obtain more accurate efficiency estimates.

Thus, believing that the true measure of efficiency may be somewhere between these extremes we considered a recently developed more flexible efficiency model called the GTFEM or KLH-model which might come closer to capturing true efficiency. This model overcomes some of the limitations of the earlier models by decomposing overall inefficiencies into persistent and residual components; it also distinguishes time-invariant farm effects from persistent inefficiencies. Like the KH-model, the KLH-model decomposes efficiencies into persistent and transient components. However, the separation of persistent inefficiencies from time-invariant farm effects results in higher estimates of persistent inefficiencies as compared to the estimates in the KH model with low variations. Thus, mean transient efficiency results in the KLH-model are higher as compared to the KH-model and less as compared to the TFE-model. The frequency distribution of transient efficiencies also shows that 46 per cent of the farmers were operating below the mean score in the KLH-model as opposed to 60 per cent in the KH-model.

In general, the variability in efficiency scores across the models that we considered clearly demonstrates the existence of significant unobserved farm/individual heterogeneity in the sample and should be considered in efficiency modeling and specifications. This is in line with the findings of Heshmati et al., (2016) and Kumbhakar et al., (2014). Besides our results also show that efficiency estimates vary over time. Transient efficiencies varied across years; these decreased during the study period; 2009 was the most efficient year and 2015 was the least efficient year. Concerning the patterns of efficiency ratings through time the results show that the level of transient efficiencies was quite low and was mostly concentrated between 0.11and 0.20 in the KH-model and it was quite moderate and concentrated between 0.51 and 0.60 in the KLH-model in all the years.

Further, to get a better picture of efficiency components in different models, we used density plots for them. These density plots show that the distribution of persistent efficiencies in the FE and KH-models was identical (Figure 1) and except for some values in the upper tail, most of the farmers had low levels of efficiency in so far as their persistent efficiencies are concerned. This was, however, not the case in the KLH-model as it provided the highest persistent efficiency scores, having a mean that was 50 per cent higher as compared to the FE and KH-models with the least dispersion.

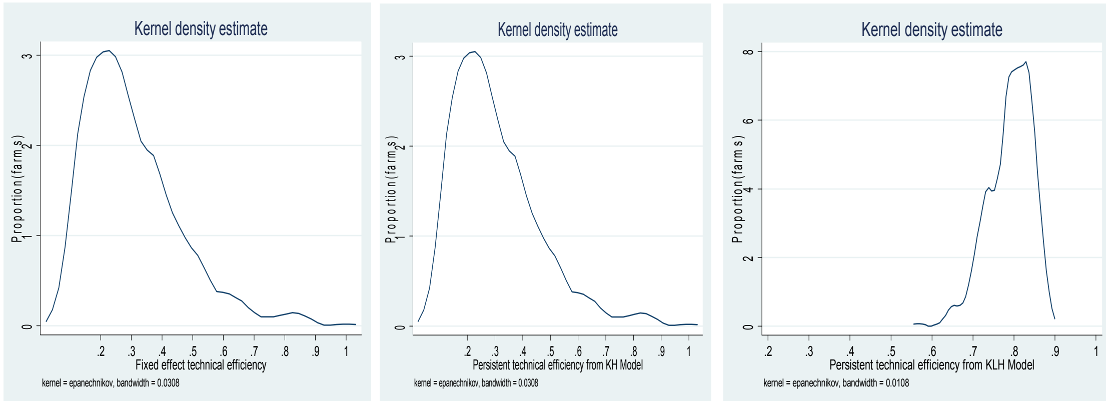

Figure 1. Distribution of persistent technical efficiencies across models

Regarding the distribution of transient efficiencies since the individual-effects are not considered to be inefficiencies in the TFE-model this leads to high efficiency scores (Figure 2) with low dispersion (Figure 3) as compared to the other two models.

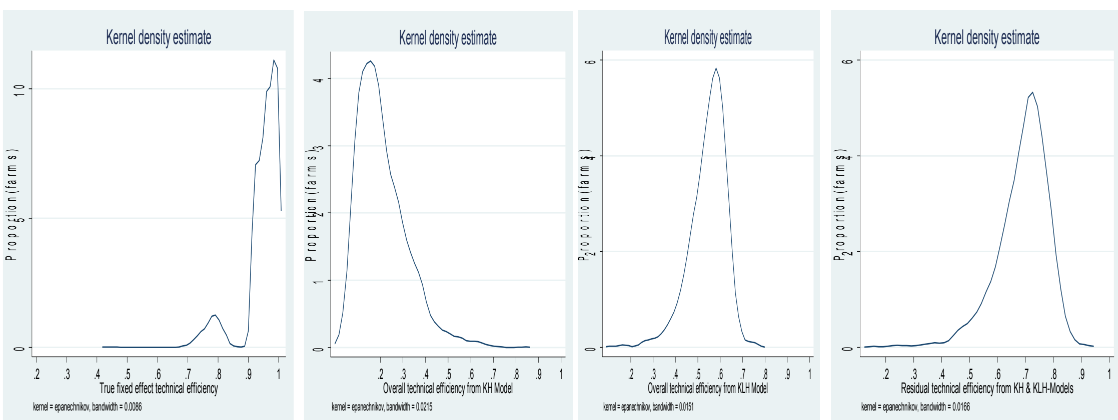

Figure 2. Distribution of transient technical efficiencies across models

The distribution of transient efficiencies in the KH-model is similar to its persistent component but its mean is pushed back by about 10 per cent. Whereas in the KLH-model most of the farmers were found to have moderate levels of transient efficiency scores, lying between those in the TFE and KH-models (Figure 2); the scores were spread between those in the TFE-model (low spread) and the KH-model (high spread) (lower part of Figure 3). Similar results were found by Heshmati et al. (2016) and Kumbhakar et al. (2014).

The spread of the residual efficiency component in the KH and KLH-models as a main element of overall efficiency was significantly higher for the persistent component as compared to the residual component in both the models (Figure 2). Thus, the results suggest that persistent inefficiencies were a bigger problem as compared residual/transient inefficiencies in the sampled cereal farmers.

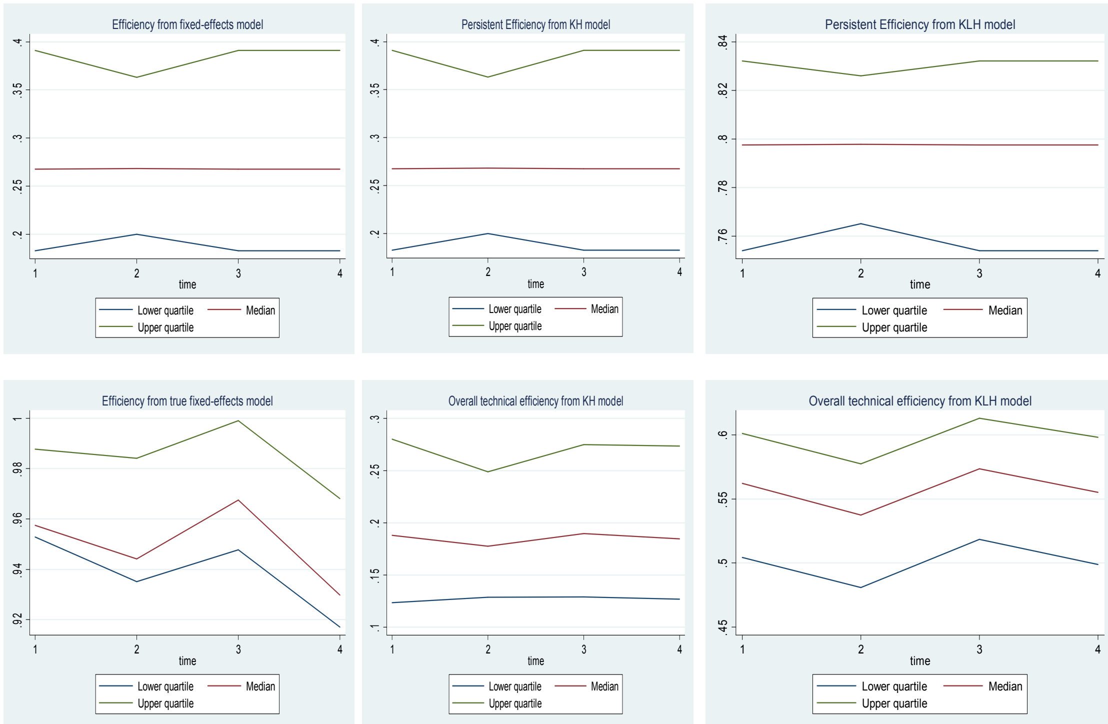

Figure 3. The median, first and third quartiles (middle, bottom and top lines) of technical efficiencies

Finally, to compare across models and explore the effects of the estimated models on the ranking order of farmers' technical efficiencies, we estimated Kendall's rank correlation coefficient between efficiency scores (Table 6). The correlation coefficients for persistent efficiencies between FE, KH and KLH-models were positive and high, implying that the models were consistent in generating similar results. Further, correlation coefficients between transient efficiency estimates obtained from all the models were positive, except for the KH and TFE-models. The KH and TFE-models had high ranking disagreements. This result is not surprising given the assumptions with respect to time-invariant effects. Transient efficiency estimates from the KLH and TFE-models, however, had a low positive correlation while the results from the KH and KLH-models were independent and had a positive correlation.

Table 6. Kendall's rank order correlation across models

	TE_FE	PTE _KH	PTE _KLH	TE_TFE	OTE_KH	OTE_KLH
TE_FE	0.998					
PTE _KH	0.998	0.998				
PTE _KLH	0.998	0.998	0.998			
TE_TFE	-0.024	-0.024	-0.024	1.000		
OTE_KH	0.845	0.845	0.845	-0.013	1.000	
OTE_KLH	0.322	0.322	0.322	0.043	0.477	1.000

Source: Author's computation.

3.2.3 Estimates of technical efficiencies across agro-ecological zones

For an investigation of farmers' performance across AEZs and their position compared to a zone with better efficiency scores, we also give efficiency estimates by AEZs in Table 7. Efficiency measures in the alternative models reveal that there were systematic differences between AEZs and agro-ecological sub-zones (AESZs), which show the effects of geographical/climatic conditions on efficiencies.

Table 7. Mean efficiency measures in all models by AEZs and AESZs

		PTE		*TTE*			
AEZs	***AESZs***	***FE & KH-models***	***KLH-model***	***TFE-model***	***OTE_KH-model***	***OTE_KLH-model***	***RTE_(KH & KLH) models***
Lowland(mean)	Hot to warm, sub-moist lowland	0.220	0.763	0.897	0.151	0.525	0.688
	Wet-moist cool midland	0.201	0.750	0.990	0.139	0.516	0.689
	Sub-moist cool midland	0.412	0.829	0.984	0.285	0.572	0.690
	Dry-warm midland	0.319	0.804	0.901	0.221	0.557	0.693
Midland(mean)		0.311	0.794	0.794	0.215	0.548	0.691
	Cool highland	0.496	0.839	0.948	0.344	0.581	0.692
	Wet-cool highland	0.278	0.786	0.971	0.190	0.539	0.685
Highland(mean)		0.387	0.813	0.960	0.267	0.560	0.689

Source: Author's computation.

As one moves from a highland to lowland AEZ, the mean of technical efficiency decreases. This suggests that more productive efficiency is associated with an area at a higher altitude where the rainfall and temperature are favorable for cereal production. The low mean score noted in lowland areas can be attributed to several factors that act as constrains in cereal production notably irregularity in rainfall, high temperatures and poor soil characteristics. Further, when we look at the situation across AESZs or through surveyed Farmers' Associations, estimates of technical efficiencies are the highest in cool highland AESZs and the lowest in wet-moist cool midland AESZs.

4. SUMMARY, CONCLUSION and recommendations

This paper investigated persistent and transient production efficiencies among Ethiopian cereal farmers in the period 1999-2015. It used a 4-error component panel data SF model (KLH-model) to distinguish between time-invariant farm heterogeneity and persistent and transient inefficiency components. The results of this model were compared to the other three panel data SF-models in which one of the four components is missing. The models differed in their underlying assumptions of time-variant/invariant efficiencies and their decomposition as well as the separation of technical inefficiencies and farm heterogeneity effects. The TFE-model disentangled time-varying inefficiencies from time-invariant heterogeneity. The KLH and KH-models distinguished between persistent and transient inefficiencies and the FE-model was used for estimating time-invariant efficiencies for comparison purposes.

The first-order parameter estimates indicate that agrochemicals, labor, machinery, oxen and livestock significantly enhanced output, suggesting that cereal production in the study area was most responsive to these inputs. Coefficient of time interacted with farmland-area was positive and significant implying that TC was land using. Estimates of time interactions with other inputs were significantly negative, implying factor using TCs for these inputs. This consequently suggested input saving TCs. However, the overall TC was not neutral because some production factors significantly changed over time. Estimates of production elasticities indicate that each input contributed significantly in enhancing cereal production levels. The results further show that cereal farming was technologically regressed at an increasing rate and this was exhibited in an increasing returns to scale. Estimated efficiency results across the models in general, illustrate significant variations in efficiency estimates across the models showing that efficiency estimations were sensitive to a model's specifications. The results also confirm the assumption of significant farm heterogeneity in the sample which was demonstrated by the significant over-estimates of efficiency in the TFE-model and under-estimates of efficiency in the KH-model. The KLH-model overcame these problems by splitting time-persistent noise into farm-specific and persistent inefficiency effects in addition to its efficiency decomposition into persistent and transient components. Consequently, this model provided a very dissimilar estimate of overall efficiency levels in the TFE and KH-models reducing downward and upward biases.

Kendall's rank correlation coefficients showed that the FE, KH and KLH-models were generating similar and consistent persistent efficiency measures. Further, the correlation between estimates of transient efficiencies obtained from all the models was positive, except for KH and TFE-models. The transient technical efficiency estimates obtained from the KLH and TFE-models had low positive ranks, while the results based on the KH and KLH-models had large positive ranks. The results also show differences in efficiency levels in AEZs and AESZs. This shows the impact of geographical/climatic conditions on efficiency. As one moves from highland to lowland AEZs technical efficiencies decrease. Further, considering the situation across AESZs or through surveyed PAs, efficiency estimates were found to be the highest in cool highland and sub-moist, cool midland AESZs and the lowest in hot to warm, sub-moist lowland and wet-moist cool midland AESZs. The results confirm that in general the farmers were unable to achieve full production efficiency. The wide variations in estimates of technical efficiencies across farmers and over time gives an indication that most of the farmers were still using their resources inefficiently in the production process and there still existed wide room for improving cereal production by improving the current levels of efficiency.

These findings are important and can be used to initiate government policy options when planning agricultural policies tailored at supporting various AEZs across the country. The study therefore recommends policies that improve measures that reduce persistent inefficiencies, improve the supply of agricultural inputs and policies that meet the needs of farmers and suit the peculiarities of agro-ecological zones.

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