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Research Paper

Endogeneity, Heterogeneity and Determinants of Inefficiencies in Grain Crops-Producing Farmers: Evidences from Central Highlands of Ethiopia

Oumer Berisso*

Department of Economics, School of Humanities and Social Sciences, Adama Science and Technology University, P.O. Box 1888, Adama, Ethiopia

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Abstract

Agricultural sector is crucial for Ethiopia's overall economic growth and has notable spillover effects. Hence, it is essential to conduct recurrent analysis of production performance, investigating efficiency level and inefficiency differentials, which are key indicators of productivity growth and informative for policymakers. This paper estimated transient and persistent inefficiencies distinguished from farm-heterogeneity and endogeneity for Ethiopian grain crop-producing farmers for the period of 2004 – 2015. The study used Mundlak-adjusted random effect – four error component stochastic frontier model by extending earlier version of the model to distinguish endogeneity and farm-heterogeneity from time-invariant inefficiency and to explain inefficiencies. The adjusted model was then estimated using multi-step estimation. The mean estimates of persistent, transient and overall efficiencies were 79, 73 and 58%, respectively. Result from inefficiency effect model revealed sex, family-size, number of plots, owing-oxen, soil-fertility and rainfall influenced transient inefficiency negatively; while, age, education, and temperature variation had positive effect. Persistent inefficiency was influenced negatively by owing-oxen, soil-fertility, farm-size, population pressure, rainfall, and market proximity; whereas, age and education affected it positively. Generally, the overall technical efficiency is low, mainly due to the transient part. In conclusion, the findings are vital to initiate government policy options to reduce inefficiency, focusing on factors affecting the long-run and short-run inefficiencies distinctly. The low level of efficiency can be addressed by facilitating farmers' access to more arable-land and modern farming tools and machinery, creating targeted support programs for female farmers, improving technologies that promote soil-fertility and reduce weather adverse effects in central highlands of Ethiopia.

1. Introduction

Within the analysis of crop production performance, studying the sources of increased production and examining the extent and identifying the sources of inefficiencies are important indicators for productivity growth and they are relevant instrument for informing agricultural policymakers. The agricultural sector, particularly that of crop-farming sub-sector, plays the central role in Ethiopia though the sector's performance in terms of technical efficiency and productivity growth is sub-optimal when compared with performances in the Sub-Saharan Africa (SSA). In SSA, where most countries derive over 60% of their livelihoods from agriculture and related economic activities (Maurice et al. 2015), knowing the level of efficiency of smallholder farms has important implications for the choice of development strategy. Agriculture sector plays important role in overall economic growth of Ethiopia, and it has significant spillover effects on the other

*Corresponding author, e-mail: oumer.beriso@astu.edu.et

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sectors of the economy as well (Anbes, 2020). According to the World Bank (2022), agriculture accounted 37.6 and 33.3% to national GDP in 2021 and 2022, respectively. The sector provides livelihood to more than 75% of the population and 80% of foreign earnings (NBE, 2019).

Ethiopia's grain production is prodigiously of a subsistence nature and it is dominated by smallholders mainly for basic self-consumption, most of who work on less than a hectare of land. The principal grain crops include cereal such as barley, corn, maize, sorghum, teff and wheat, accounting to 71% of the 2020/21 production. These crops represent nearly 80% of the cultivated land and they employ 60% of the rural workforce (CSA, 2021). However, the state of the grain crop sub-sector is progressively declining in Ethiopia; as the result, its productivity remains low due to numerous challenges - limited private investment, fragmented markets, environmental degradation and recurrent shocks (Neglo et al., 2021). Moreover, the sector is characterized by inefficiencies and low productivity in which cereal crops have shown a steady low-growth rate in the last two decades (Abebayehu, 2023; Merihun et al., 2022). Hence, being an agriculture dependent country with limited capacity for developing and adopting new technologies, increasing production and enhancing farming efficiencies with the existing technologies is not a matter of choice but is instead a must for Ethiopia. Recent Ethiopian government plan - the 10 years development plan - notes that the anticipated productivity and efficiency enhancement in the crop farming sector is only possible through efficient utilization of resources, proper management and dissemination of available technologies and tackling the challenges which have constrained the achievement of farmers' full potential (PDCE, 2020). Hence it is significant to study farm production performance, in particular the grain crop sub-sector.

A numbers of researchers have analyzed farm technical efficiency and their determinants of smallholder farmers in Ethiopian agriculture using different methodologies. Bamlak et al. (2009) and Endrias et al. (2013) assessed the level of technical efficiency and determinants of crop farming. Most studies pay relatively little attention to assessing the influence of agro-eco-climatic factors and adaptation strategies on farm efficiency in the country. These studies typically employed cross-sectional data, specific geographical areas, and specific crops (Getachew, 2018; Talie et al., 2019; Assefa et al., 2019) and they used inefficiency effects model (Battese and Coelli, 1995) that fails to separate inefficiency from unobserved heterogeneity. The existing studies are almost exclusively based on overall inefficiency measures that do not distinguish between transient and persistent inefficiency. More importantly, though few studies (Abebayehu, 2023; Merihun et al., 2022; Oumer et al., 2022) have been emerging differentiating between transient and persistent inefficiency components in Ethiopian farming context, none of them have applied to account for endogeneity and heterogeneity for grain crop-producing farms.

The study considered the most recent Generalized True Random Effects - Four error Component Stochastic Frontier (GTRE-4eCSF) panel data model that disentangles farm-heterogeneity and endogeneity from inefficiency while estimating persistent and transient with their determinants for Ethiopia's major grain crop-producing farmers using a household-level panel dataset. The researcher extended the earlier 4eCSF model to address heterogeneity, endogeneity and determinants of transient and persistent inefficiency. The model was extended in three ways: firstly, Mundlak-adjustment was made to the random effects specification to account for unobserved time-invariant farm-heterogeneity which is correlated to the random error; secondly, factors explaining inefficiencies were included in the Mundlak-adjusted in GTRE-4eCSF model to accommodate the determinants of persistent and transient inefficiencies; thirdly, the potential endogeneity from different sources were addressed by applying a multi-step estimation of non-linear Generalized Method of Moments (GMM) estimator. Hence, it supposed to provide consistent estimates by accounting for three sources of potential endogeneity: endogeneity due to unobserved heterogeneity, simultaneity of input use with both types of technical efficiency and potential correlation of the noise term with the regressors. Thus, the extended model produced estimates of both inefficiency and their determinants thereof, while controlling farm-heterogeneity and endogeneity. Consequently, it provided a more thorough analysis, compared to earlier models applied to this field in Ethiopia. This study is one of the first applications of the recent methodological advances in augmented GTRE–4eCSF model.

Thus, the objective of this study is to estimate long-run (persistent) and short-run (transient) inefficiencies separated from farm-heterogeneity and endogeneity and also to assess inefficiency differentials for major grain crop-producing farmers in central highlands of Ethiopia. From a policy outlook, the study may contribute to a better understanding of the efficiency of crop-farming households and the impact of its different components on overall farm performance. Moreover, the paper has an important policy implication for the developing nations to make clear factors of agricultural inefficiency and possibly to help them devise strategies that can contribute to the betterment of their national agricultural production.

2. Materials and Methods

2.1. Description of the model used

The 4eCSF model distinguishes between time-invariant firm heterogeneity, the time-invariant efficiency, the time-varying efficiency and the stochastic error-term (Kumbhakar et al., 2014; Colombi et al. (2014).

The 4eCSF model is given as:

$$y_{it} = \alpha_0 + f(x_{it};\beta) + x_i + v_{it} - \eta_i - u_{it} \quad \ldots (1)$$

where y_{it} denotes the natural logarithm of output for farm-household i at time t; $i = 1, \ldots, n$ denotes production units (farm-household), and $t = 1, \ldots, T$ indicates the time period at which each unit is observed, x_{it} is a vector of inputs (expressed in logs); $f(x_{it};\beta)$ stands for the production technology governing the input – output relationship; β is a vector of parameters to be estimated; α_0 is a common intercept.

The remainder parts of Eq. (1) incorporate four-components of the composite random terms which can be expressed in two groups as: $\psi_i = \chi_i - \eta_i$ *and* $\varepsilon_{it} = v_{it} - u_{it}$. ψ_i depicts time-invariant component where χ_i capturing unobserved farm-heterogeneity while η_i captures persistent inefficiency. ε_{it} is a time-varying component where $-\upsilon_{it}$ is the random/stochastic error term that accounts for measurement and functional form errors, and u_{it} captures transient inefficiency.

In this model, v_{it} and u_{it} are independently and identically distributed (i.i.d). variables following $N(0,\sigma_v^2)$ and $N^+(0,\sigma_u^2)$, respectively; χ_i is assumed to be i.i.d. $N(0,\sigma_\chi^2)$ and η_i is i.i.d. $N^+(0,\sigma_\eta^2)$. The farm-heterogeneity χ_i in the above model can be modeled as either fixed effects (FE) or Random effects (RE) model. FE has the advantage of allowing for correlation between heterogeneity and the explanatory variables and hence provides unbiased estimates of the parameter vector β. RE model may result in biased estimates of technology parameters when the unobserved factors are correlated with the explanatory variables. Karagiannis (2014) argues that random effects SF models may be more appropriate for agricultural production given the time-lag between input decisions and output realization and the uncertainty regarding production conditions. Hence, one can assume that the correlation between the weather affected stochastic error term and the predator mined input variables is zero or very small. However, even if this was not the case, the FE estimator does not allow the inclusion of any time-invariant variables (e.g. variables accounting for the production environment) of the farm unit in the estimation because of perfect multicollinearity with χ_i.

As a solution to the problem, Addo and Salhofer (2022) assumed farm-heterogeneity to be random, but applyed Mundlak's (1978) adjustment to reduce potential biases in the parameters; this study applied the augmented GTRE–4eCSF model. Accordingly, to control correlation between farm-specific effects and explanatory variables, and to reduce the potential biases in the slope parameters and inefficiency term, as proposed by Farsi et al. (2005), in this study farm-heterogeneity was assumed to be random and modeled as: $\chi_i = \phi'\bar{x}_i + \xi_i$, where; $\bar{x}_i$ is the vector of farm level arithmetic mean of each input variable in the model; ϕ, is the corresponding parameters to be estimated, and ξ_i is pure time-invariant heterogeneity. All the other parameters are defined in the same way as in Eq. (1).

Hence augmenting Eq. (1) by this auxiliary equation and rewriting it gives Eq. (2):

$$y_{it} = \alpha_0 + f(x_{it};\beta) + (\phi'\bar{x}_i + \xi_i) + V_{it} - \eta_i - u_{it} \quad \text{...} (2)$$

The augmented GTRE–4CSF model in Eq. (2) controls time-invariant farm effects by distinguishing farm-heterogeneity from persistent inefficiency. In addition, it controls for endogeneity due to the correlation between χ_i and x_{it}. Nevertheless, it doesn't control for the endogeneity that can arise due to correlation between u_{it} and x_{it} as well as v_{it} and x_{it}; and also it doesn't account for potential heteroscedasticity in any stochastic component. Consequently, to account for potential heteroscedasticity, in line with Addo and Salhofer (2022) and Badunenko and Kumbhakar (2017), the augmented GTRE – 4eCSF model in Eq. (2) was extended to include determinants of persistent and transient inefficiency components, so that η_i and u_{it} are heteroscedastic. Accordingly, to explain differences in inefficiency, the variances of time-invariant (persistent) and time-variant (transient) inefficiency were assumed conditioned by a set of determinants ***z*** (the combination of w_i and z_{it}) variables, making the variance parameters (η_i and u_{it}) functions of the determinants.

Thus, it was assumed $\eta_i(w_i) \sim N^+(0, \sigma_\eta^{\,2}(w_i))$ and $u_{it}(z_{it}) \sim N^+(0, \sigma_u^{\,2}(z_{it}))$, where both η_i and u_{it} follow half normal distribution. Assuming means of both transient and persistent inefficiency are non-linear functions of contextual variables z_{it} and w_i, respectively, (Badunenko and Kumbhakar 2017; Lien et al., 2018), Eq. (2) will become the form of Eq. (3):

$$y_{it} = \alpha_0 + f(x_{it};\beta) + \phi'\bar{x}_i + \xi_i + V_{it} - \eta_i(w_i) - u_{it}(Z_{it}) \quad \text{..} (3)$$

The GTRE–4CSF model can be estimated using a single-step maximum likelihood procedure (Colombi et al. 2014); however, the multi-step estimation procedure is more straightforward to implement (Kumbhakar et al., 2014), especially when explanatory variables are included in the inefficiency terms, enabling investigating factors that cause farms to deviate from frontier technologies (Lien et al., 2018). Hence, in line with Addo and Salhofer (2022) and Lien et al. (2018), relying on a modified version of Kumbhakar et al.'s (2014) GTRE model, the multi-step procedure introduced by Bokusheva et al., (2023) was applied. The latter approach has the advantage of providing consistent estimates by accounting for the three sources of potential endogeneity. Accordingly, to implement this procedure, it was assumed that the farm-effects ξ_i to be random and *i.i.d.* with mean zero and also the random shock v_{it} to have zero mean and constant variance.

Moreover, it was assumed that the expected values to $E(\eta_i(w_i)) = g_1(w_i)$ *and* $E(u_{it}(z_{it})) = g_2(z_{it})$ by assuming $g_1(\cdot)$ and $g_2(\cdot)$ to have a parametric functional form so that $E(\eta_i(w_i))$ *and* $E(u_{it}(z_{it}))$ are non-negative. As a result the persistent inefficiency, $\eta_i(w_i)$ is non-negative such that $E(\eta_i(w_i)) = g_1(w_i) \geq 0$ and the transient inefficiency $u_{it}(z_{it})$ is non-negative such that $E(u_{it}(z_{it})) = g_2(z_{it}) \geq 0$.

To instrument the multi-step estimation procedure, Eq. (3) was rewritten again as:

$$y_{it} = \alpha_0^{\,*} + f(x_{it};\beta) + \phi'\bar{x}_i + \lambda_i + \varepsilon_{it} \quad \text{.........} (4)$$

Where, $\alpha_0^{\,*} = \alpha_0 - g_1(w_i) - g_2(z_{it})$;

$$\lambda_i = \xi_i - \eta_i(w_i) + g_1(w_i);$$
$$\varepsilon_{it} = V_{it} - u_{it}(z_{it}) + g_2(z_{it})$$

Here the expected value $E(u_{it}(z_{it})) = \sqrt{2/\pi}\,\sigma_u^{\,2}(z_{it}) \equiv g_2(z_{it})$, which is estimated as a function of time-varying exogenous parameters $\sigma_u^{\,2} = \exp\left(\frac{1}{2}(\kappa_0 + \kappa' z_{it})\right)$, where $\sigma_u^{\,2}$ is the variance of the transient inefficiency, and κ the vector of unknown parameters to be estimated (Battese and Coelli 1995); and the expected value $E(\eta_i(w_i)) = \sqrt{2/\pi}\,\sigma_\eta^{\,2}(w_i) \equiv g_1(z_i)$ is parameterized as $\sigma_\eta^{\,2} = \exp\left(\frac{1}{2}(\delta_0 + \delta' w_i)\right)$, where $\sigma_\eta^{\,2}$ is the variance of the persistent inefficiency and δ is a vector of unknown parameters to be estimated (Addo and Salhofer, 2022; Lien et al., 2018).

Thus, expected values can be expressed as:

$$E\big(u_{it}(z_{it})\big) = \sqrt{\tfrac{2}{\pi}}\exp\left(\tfrac{1}{2}(K_0 + K' Z_{it})\right) \text{ and}$$

$$E\big(\eta_i(w_i)\big) = \sqrt{\tfrac{2}{\pi}}\exp\left(\tfrac{1}{2}(\delta_0 + \delta' w_i)\right) \quad \text{..........} (5)$$

Hence, from Eq. (2) – Eq. (5), the GTRE-4eCSF model with heteroscedasticity in both persistent and transient technical efficiency can be rewritten as:

$$y_{it} = \alpha_0 - \sqrt{\frac{2}{\pi}} \exp\left(\frac{1}{2}(K_0 + K' z_{it})\right) - \sqrt{\frac{2}{\pi}} \exp\left(\frac{1}{2}(\delta_0 + \delta' w_i)\right) + f(x_{it};\beta) + \phi' \overline{x}_i + \lambda_i + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots (6)$$

Overall, a non-linear GMM estimator was applied to estimate production technology parameters for the model in Eq. (6), assuming that z_{it} and w_i are exogenous and they are uncorrelated with v_{it}.

The estimation procedure consists of four steps.

Step 1: GMM estimator is used to account for the three sources of potential endogeneity and to estimate the production technology parameter β for the model in Eq. (6). It estimates the model both in levels and in differences and it uses two types of instruments: the lagged values of the level variables for the differenced equations and the lagged values of the differenced variables for the equations in levels. Additional variables related to farm-heterogeneity, such as credit access, farmer's age, irrigated land size, as well as regional dummies and more variables can be used as instruments if available. The non-linear GMM consistently estimates the technology parameters estimates of β, δ *and* κ directly from the moment conditions, without imposing any conditions on the distribution of the error term.

Step 2: The residuals from Eq. (6), namely $\hat{r}_{it}$, derived using the GMM estimates of β, δ and κ were used. Barring the difference between the true and estimated parameters, these residuals can be written as $\hat{r}_{it} = \lambda_i + \varepsilon_{it}$. This Eq. can be estimated as a random effects model, which will give the predicted values of the time-invariant λ_i and time-varying ε_{it}. Note that these are zero-mean random variables, *i.e.* $E(\lambda_i) = 0$, $E(\varepsilon_{it}) = 0$ and there are no regressors.

Step3: The predicted value for λ_i from the second step and $E(\eta_i)$ estimated in the first step, are used to estimate the persistent technical efficiency and its determinants using a SF model in which the dependent variable is r_{1it}. For this, given that $E(\eta_i(\mathrm{w_i})) = \sqrt{2/\pi}\sigma_\eta^{\ 2}(w_i) \equiv g_1(z_i)$, the residuals for $\lambda_i = \xi_i - \eta_i(w_i) + m_i(w_i)$ can be rewritten λ_i as: $r_{1t} = \lambda_i - E(\eta_i(\mathrm{w_i})) = \xi_i - \eta_i(w_i)$, then the distributional assumptions about η_i and ξ_i were made in such a way as: $\xi_i \sim N(0, \sigma_\xi^{\ 2})$ and the persistent inefficiency term η_i is assumed to follow a half-normal distribution with $\eta_i(\mathrm{w_i}) \sim N^+(0, \sigma_\eta^{\ 2}(w_i))$, *where* $\sigma_\eta^{\ 2} = \exp\left(\frac{1}{2}(\delta_0 + \delta' w_i)\right)$.

Consequently, $r_{1t} = \lambda_i - E(\eta_i(\mathrm{w_i})) = \xi_i - \eta_i(w_i)$ was estimated using the standard cross-sectional SF technique and the predicted values of η_i was obtained using Jondrow et al. (1982) procedure, and estimated values of persistent technical efficiency (PTE) as $PTE = \exp(-\hat{\eta}_i)$ was also determined.

Step 4: In a similar way, in the final step, predicted values for ε_{it} from the second step, and E (u_{it}) estimated in the first step, are used to estimate the transient technical efficiency and its determinants using a SF model in which the dependent variable is r_{2it}. Indeed, given that $E(u_{it}(\mathrm{z_{it}})) = \sqrt{2/\pi}\sigma_u^{\ 2}(z_{it}) \equiv g_2(z_{it})$, the residuals for $\varepsilon_{it} = v_{it} - u_{it}(z_{it}) + g_2(z_{it})$ from the second step can be rewritten as: $r_{2it} = \varepsilon_{it} - E(u_{it}(z_{it})) = v_{it} - u_{it}(z_{it})$. Here, $v_{it} \sim N(0, \sigma_v^{\ 2})$; and the transient term u_{it} is assumed to follow a half-normal distribution with $u_{it}(\mathrm{z_{it}}) \sim N^+(0, \sigma_u^{\ 2}(\mathrm{z_{it}}))$; so that $\sigma_u^{\ 2} = \exp\left(\frac{1}{2}(\kappa_0 + \kappa' z_{it})\right)$. Hence, the predictions, $\hat{u}_{it}$ for the inefficiency values of u_{it} (z_{it}), as well as the marginal effects of the z_{it} variables on transient inefficiency were obtained and transient efficiency (TTE) as $TTE = \exp(-\hat{u}_{it})$ was estimated. Note that the determinants of transient inefficiency are modeled in the pre-truncated variance of u_{it}. This specification allows not only for heteroscedasticity but also for variations in the mean of u_{it}. Indeed, since u_{it} is assumed to follow a half-normal distribution, then $E(u_{it}(z_{it})) = \sqrt{2/\pi}\sigma_u^{\ 2}(z_{it}) = \sqrt{2/\pi}\exp\left(\frac{1}{2}(\kappa_0 + \kappa' z_{it})\right)$ (Badunenko & Kumbhakar 2017). This implies that, given the half-normal assumption, the parameterization of $\sigma_{u_{it}}^{2}$ allows the z_{it} variables to affect the expected value of the transient inefficiency and that the sign of κ reveals the direction of the effect of z_{it} on E (u_{it}). Finally, the overall technical efficiency (OTE) was simply the product of PTE and TTE.

For empirical model, the most commonly used functional forms in efficiency analysis are the Cobb-Douglas (CD) and the trans-log (TL) specifications. In the present paper, to estimate the parameters of the production function in the first step, the TL functional form, which has proven standard as it has the advantage of being more flexible than and superior to simpler forms such as the CD, was utilized (Lien et al., 2018) as it captures both first and second order effects and accommodates non-linearity within the input variables.

Hence the empirical specification is given by:

$$\ln y_{it} = \alpha_0 + \sum_{j=1}^{J} \beta_j \ln x_{j,it} + \beta_t t + \frac{1}{2}\left(\sum_{j=1}^{J} \sum_{h=1}^{J} \beta_{jh} \ln x_{j,it} \ln x_{h,it} + \beta_{tt} t^2\right) + \sum_{j-1}^{J} \beta_{ji} \ln x_{j,it}\, t + \sum_{j=1}^{J} \phi_j \ln \bar{x}_{it} + \lambda_i + \varepsilon_{it} \quad \text{.....} (7)$$

where all variables are as previously defined.

The Mundlak adjustment, as well as an interaction time term for inputs were included. Moreover, the time trend variable (t) and its squared term were involved in order to separate exogenous technical change from inefficiency and to capture the shift in crop production over time. The trend captures the direction of the change, while the squared term captures the non-linear shift in the production function over time.

2.2. Data sources

The data source for the study is the fraction of Ethiopian rural household survey (ERHS) dataset. This dataset is farm-level panel data, conducted in collaboration by the department of economics, Addis Ababa University and international food policy research institute (IFPRI). The dataset includes farm production and economic data collected in 5 rounds (in years 1994, 1999, 2004, 2009 and 2015) from randomly selected farm-households at local farmers associations (FAs) level in rural Ethiopia, which was selected to represent the country's diverse farming systems. The farms included in this dataset are a stratified sample representing the Ethiopian agricultural sector in terms of standard output, production orientation and altitude, found in five agro-ecological zones (AEZs) in the country (Dercon, 2004). One of these AEZs is the central highland AEZ, represented in study by the FAs from Amhara and Oromia regions. Accordingly data for the current study covers seven FAs in five districts in these two major grain crop-producing regions in the central highlands of Ethiopia.

The database provides information on physical quantities, such as area, production and yields for each crop and socio-economic characteristics of farmers and their households, such as age, educational level and gender of manager. For this paper, the data collected in last three rounds, in 2004, 2009 and 2015 years, covering seven FAs, forming a partially balanced 367 panel farm-households from 1043 observations, was used. These three rounds include more FAs than the earlier from the two major grain crop-producing regions (Amhara and Oromia). Moreover, additional secondary data such as FAs' altitude and metrological data were obtained from the Ethiopian Meteorology Authority (EMA). The meteorological data includes monthly average observations of rainfall and maximum and minimum temperature (from which their annual mean values and their variability were computed), from 2004 to 2015 collected in stations close to the study villages.

2.3. Variables of the study

2.3.1 Input-output variables used in the stochastic frontier function

The dependent variable for the stochastic frontier function, the production output (*Y*), is total revenue from sales of cereals produced by the farm, which combines aggregate cereal crop output market value measured in thousands of Ethiopian birr (ETB). Six different conventional production input variables were included in the estimated frontier model. Inorganic-fertilizers (X_1) measured in kilogram; agro-chemicals (X_2) measured in ETB, these include the sum of costs on pesticides, herbicides, fungicides and insecticides used by the farmers; agricultural machinery-implement (X_3) measured in ETB, which is the sum of costs on tractor, combiners and related machinery and equipment;

livestock-ownership (X_4) measured in tropical livestock units (TLUs) as a proxy for wealth and asset endowments; Farm-labour (X_5) measured in man-day-units (MDUs) and it includes both family and hired workers disaggregated by gender and age; and lastly cereal sown farmland-area (X_6) measured in hectares, it captures the total crop planted farmland-area. All values are aggregated per/at farm-household level; and monetary values are deflated using the appropriate price indices from official statistics, with 2004 the base year.

2.3.2 Variables used to explain inefficiency

Following Addo and Salhofer (2022) and Lien et al. (2018) approaches, for this paper two different set of variables were considered to assess inefficiency effects. The first set of variables include, time-varying (z_{it}-variables) which are likely to change over the observed period; in addition to dummy variables which were used to explain transient inefficiency. These include farmer-specific characteristics, adaptation technologies, agro-ecological and climatic factors.

Next, to maintain the time-invariant features for factors explaining persistent inefficiency, the researcher took the means over time of time-varying variables (from the first set of determinants) and used with other dummy variables so that all factors are time-invariant. Hence, the second set of variables includes the time-invariant (wi- variables) that are relatively stable over time factors and they were used to explain persistent inefficiency.

2.3.3 Descriptive statistics of the study variables

The statistical summary of the data used in the study are provided in Table 1 and Table 2. The output and input variables reveal that production and input usage had positive trends over time in the study area (Table 1). As is evident from the table, there was relatively little use of cultivated farmland which is typical of smallholders farming and considerable variations in the amount of fertilizers, agrochemicals, machinery and farm-labor usage pattern. For such production, the farmers have used on average 1.9 ha for grain crops cultivation. They used an average of 234 MDUs of labor, reflecting the fact that grain crop-farming is labor-intensive in Ethiopia. Their inorganic fertilizers application was minimal with an average of 113.3 ETB per farm-household. Livestock-ownership, which is a proxy for wealth and asset endowments and used as a source of draft power, food, income, and energy for rural farm-households in Ethiopia, averaged to 7 TLUs.

The variables used in the inefficiency effect model are given in Table 2. The statistics shows that majority of the farm-households were male-headed (71.4%). The number of plots cultivated by the farmers which is also used as a proxy to measure land-fragmentation among subsistent smallholders averaged 3.7 with a maximum of 21 plots. The two interaction variables: total farm-size (interaction between area-cultivated and number of plots) and population pressure (the ratio of the size of productive household members to the cultivated land-size) averaged 3.9 and 5.1, respectively.

Education plays an important role in enhancing e utilization of farm inputs and in the willingness to adopt new technologies, hence it has a potential to improve farming efficiency. The data for this study shows that the farm head's educational level varied over the years. 59.25% had not attended any formal education; 42.5% of these had not attained informal school either, 3.64% had some religious learning and 13.1% had participated in adult literacy programs.

Table 1: Summary statistics of variables used in the frontier function

Stochastic Frontier Variables	2004		2009		2015		All-waves			
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Min	Max
Output value	2,225	2,711	12,457	12,492	27,498	22,278	14,718	18,355	107	133,127
Inorganic-fertilizers	88.2	141.1	95.2	108.0	152.5	110.0	113.3	122.8	0.1	1400.0
Agro-chemicals	23.7	77.2	126.7	506.0	324.8	682.3	165.9	520.2	0.0	8,560.0
Farm-labor	263.0	285.6	176.2	227.8	266.5	251.3	233.7	257.5	30.0	2,546.0
Machinery	41.9	301.8	873.9	3160.5	429.6	929.8	471.1	1,987.9	0.5	36,540.0
Livestock units	4.5	4.0	7.8	6.5	8.3	7.8	7.0	6.6	0.0	58.8
Planted-area	1.9	1.1	2.1	1.4	1.6	1.3	1.9	1.3	0.1	11.0

Table 2: Summary statistics of variables in inefficiency effect model

Continuous Variables	Mean	SD	Min	Max	Dummy Variables	%
Total farm size	3.90	5.00	0.10	61.00	Own an ox (at least one)	78.80
Farm head's age	51.60	15.20	17.00	103.00	Credit access	55.10
Family-size	5.60	2.50	1.00	16.00	Farm head's sex	71.40
Farm head's schooling	5.20	6.50	-	30.00	Soil-conservation	52.40
Number of plots cultivated	3.70	2.60	1.00	21.00	Water-harvesting	20.50
Distance to closest market center	9.40	7.00	0.30	24.00	Irrigation	29.20
Population pressure	5.10	6.10	0.20	61.50	Off/non-farm activity	39.60
Soil quality (index)	2.18	4.11	1.00	8.00	Agri. Ext. advisory service	34.80
Annual average rainfall	72.10	16.00	47.50	120.00	Remittance	27.10
Annual average temperature	18.30	3.60	13.20	24.00	Lowland AEZ	26.70
Rainfall coefficient of variation	0.01	0.01	0.01	0.03	Midland AEZ	37.70
Temperature Coeff. of variation	5.80	1.70	3.20	8.40	Highland AEZ	35.60

AEZ is for agro-ecological zone

The remaining 41% had attended formal schooling ranging from primary to tertiary level; out of which 33 % had completed primary school, 7% had completed secondary school and only 1% had completed tertiary school.

Soil quality was proxies by an index as an indicator for the land-fertility using information on slope type and fertility of the plot cultivated by the farmers. The index was computed as combination of the values of the quality indicators of the slope type and fertility of the plots. The average soil quality index was 2.1, ranging from one to eight. As to the computational orientation of these indices, the closer the index to one, the higher the soil quality of the plot, while the closer the index to eight, the lower the soil quality.

Extension participation was represented by extension visits per week/month in which the farmers reported contact with extension agents. However, a dummy variable was used, in which a value of 1 was assigned if the farmer got agricultural advisory services. Accordingly, a total of 34.8% of the farmers reported contact with extension agents seeking agricultural advisory service. Agricultural credit plays a crucial role in rural crop farming, as it enhances production efficiency and productivity if used appropriately, by filling the financial gaps of smallholder farmers. In this study, 55% of the sampled farmers had access to credit from different sources.

3. Results and Discussion

3.1. Stochastic production frontier parameters estimates

The stochastic production frontier parameters were estimated, relying on a trans-log (TL) functional form with time trend. The input and output variables were scaled by their arithmetic means prior to transformation into logarithm values. The estimates of the production frontier and the bootstrap standard errors computed from the model specification are presented in Table 3. The result shows that all first-order parameters are significant at 1% level. Hence, an increase in the use of these inputs enhanced cereal production. The estimation has a strong fit with first-order parameters, all positive and values less than one, which satisfies monotonicity and diminishing marginal product conditions. Moreover, the log-likelihood and wald-χ^2 estimates showed the results were significant. A number of second-order parameters are also significant. For example, the second-order parameter estimates are positively significant for the inorganic-fertilizer and agro-chemicals inputs.

Table 3: Parameters from the trans-log production frontier

Variable	Parameter	Estimate	Bootstrap Std. Err.	Variable	Parameter	Estimate	Bootstrap Std. Err.
Constant	β_0	0.847**	0.838	ln(IF)∗ln(PA)	β_{16}	0.011	0.015
ln(IF)	β_1	0.098*	0.071	ln(AC)∗ln(FL)	β_{23}	-0.002	0.006
ln(AC)	β_2	0.043***	0.039	ln(AC)∗ln(MI)	β_{24}	-0.007**	0.003
ln(FL)	β_3	0.15	0.174	ln(AC)∗ln(LH)	β_{25}	0.002	0.005
ln(MI)	β_4	0.008***	0.070	ln(AC)∗ln(PA)	β_{26}	-0.011	0.009
ln(LH)	β_5	0.15***	0.113	ln(FL)∗ln(MI)	β_{34}	0.011*	0.007
ln(PA)	β_6	0.925***	0.222	ln(FL)∗ln(LH)	β_{35}	0.026**	0.014
Mean_{IF}	δ_1	0.002***	0.001	ln(FL)∗ln(PA)	β_{36}	-0.099***	0.034
Mean_{AC}	δ_2	0.013***	0.011	ln(MI)∗ln(LH)	β_{45}	0.005	0.008
Mean_{FL}	δ_3	0.001	0.001	ln(MI)∗ln(SA)	β_{46}	0.010	0.013
Mean_{MI}	δ_4	0.001	0.001	ln(LH)∗ln(PA)	β_{x56}	-0.002	0.018
Mean_{LH}	δ_5	0.005	0.009	Time∗ln(IF)	β_{1t}	0.031*	0.019
Mean_{PA}	δ_6	-0.038***	0.038	Time∗ln(AC)	β_{2t}	-0.002	0.009
$\ln^2$(IF)	β_{11}	0.023**	0.012	Time∗ln(FL)	β_{3t}	-0.049	0.038
$\ln^2$(AC)	β_{22}	0.017***	0.007	Time∗ln(MI)	β_{4t}	-0.019*	0.013
$\ln^2$(FL)	β_{33}	-0.003	0.030	Time∗ln(LH)	β_{5t}	0.02	0.021
$\ln^2$(MI)	β_{44}	0.008	0.012	Time∗ln(PA)	β_{6t}	0.009	0.054
$\ln^2$(LH)	β_{55}	0.001	0.011	Time	β_t	3.558***	0.417
$\ln^2$(PA)	β_{66}	-0.11**	0.083	Time*Time	β_{tt}	-0.766***	0.125
ln(IF)∗ln(AC)	β_{12}	0.001	0.003	Sigma_u	σ_u	0.124	0.069
ln(IF)∗ln(FL)	β_{13}	0.005	0.010	Sigma_v	σ_v	0.683	0.032
ln(IF)∗ln(MI)	β_{14}	-0.002	0.005				
ln(IF)∗ln(LH)	β_{15}	0.001	0.005	Log likelihood	-1081.85	Wald χ^2 (41)	3410.32***

, ** and * indicate significance at the 0.10, 0.05 and 0.001 levels, respectively. Subscripts on β coefficients refer to inputs: where, 1 stands for inorganic-fertilizers (IF); 2 for agro-chemicals (AC); 3 for farm-labor (FL); 4 for machinery-implement (MI); 5 for livestock-holding (LH); and 6 for planted-area (PA).*

Estimates of the time-trend and its squared term were significant at 1% level. The time-trend is positive, showing that the grain crop-farmers experienced technical progress for their grain crop production over the period, meaning that technology shifted outward. Elasticity with respect to cultivated land-area is found to be the largest, followed by that of inorganic-fertilizers; indicating that grain crop production in central highlands of Ethiopia is largely driven by productivity of land. This result is consistent with the findings of Addo and Salhofer (2022), Oumer et al. (2022) and Lien et al. (2018), which were similar studies on crop farms.

The mean estimate of return to scale (RTS) is 0.64, suggesting the grain crop-farmers in the sample exhibited decreasing RTS. The 1.08 mean estimate of technical change (TC) reveals steady acceleration of TC which is progressive at an increasing rate. This may be a result of an increase in farming skills, improved input quality and skills in the use of modern inputs. These findings are quite similar to the TC estimates by Kumbhakar et al. (2014) and somewhat lower than those found by Lien et al. (2018) in Norwegian crop-producing farms.

3.2. Technical efficiency

The technical efficiency score is presented in Table 4. The model provides estimates of the persistent and transient efficiency components; from which the overall technical efficiency was obtained as their product for major grain crop-producing farmers in central highlands of Ethiopia. The distributions of both types of efficiency scores are close. Overall technical efficiency followed a similar pattern as transient efficiency in terms of dispersion, suggesting that efficiency gains are still possible for grain crop farms in the study area. Moreover, variability between persistent and transient efficiency scores clearly demonstrated the existence of significant unobserved-heterogeneity in the sample and it should be considered in efficiency modeling and its specifications. Hence, it seems reasonable since the Mundlak specification accounts for unobserved farm-heterogeneity, which is otherwise interpreted as persistent inefficiency. The efficiency estimation results of Table 4 shows that the persistent efficiency is relatively dense around the mean, while the transient efficiency scores are more dispersed, suggesting that transient inefficiency poses a greater problem for Ethiopian crop-producing farmers than the persistent component, suggesting priorities should be given to the interventions that reduce transient inefficiency. The efficiency result shows that significant number of farm-household have scored a technical efficiency below the mean technical efficiency scores, which indicates that there was a lot of room for improvement using the present state of technology.

Table 4: Distribution of efficiency scores

Technical efficiency	Mean	Std. Dev.	Min	Max
Transient	0.729	0.121	0.048	0.948
Persistent	0.788	0.071	0.471	0.921
Overall	0.575	0.110	0.030	0.832

3.3. Inefficiency effect

The result concerning the sources of transient and persistent inefficiency are presented in Table 5. The data was checked for the existence of multicollinearity in the hypothesized explanatory variables before estimation and the results confirmed that there was no multicollinearity problem. Regarding the effect of the explanatory variables, a negative sign implies decreases in the variance of the inefficiency function and, thus, it reveals a positive relationship with efficiency and vice versa. That is, a positive coefficient suggests, an increase in inefficiency if the corresponding variable increases and by contrast, a negative coefficient implies that an increase in the factor is in favorable for efficiency. From Table 5**,** transient inefficiency was negatively and significantly influenced by the farm head’s sex, family size, owing oxen, number of plots, land fertility and rainfall, indicating that the variables lead to increase in transient efficiency. However, transient inefficiency was positively and significantly related to age and educational level of the farm-head, and annual temperature variations. Hence, an increase in the factors reduced transient efficiency ceteris paribus.

The result on persistent inefficiency shows that factors such as having oxen, land quality and mean of time-variant factors, such as total farm-size, population pressure, average annual rainfall and distance to the market center, influenced negatively and significantly persistent inefficiency. Hence, an increase in these factors raises persistent efficiency ceteris paribus. On the other hand, the opposite is true for the age and educational level of the farm-head as these variables were positively and significantly related to persistent inefficiency. Most of the farmer-specific variables have significantly affected technical efficiency.

More specifically, age of farm-head is the proxy for the experience of the head in farming is expected to affect efficiency positively; however, an adverse effect is plausible if older farmers are unable to adapt to new and improved production technologies, or make less effort in the years before they retire (Madau, 2011).

Considering the possible tradeoffs between the two contrasting effects, literature accounts for the possibility of mixed results, for instance negative by Wadud and White (2000), but positive by Assefa et al. (2019). For this study, age of the farm-head found to have a positive significant effect on both persistent and transient inefficiency. This indicates that as farmers get older, the more they become inefficient both persistently and transiently than their younger counterparts in grain crop-farming. That is, young farmers are becoming relatively more efficient over time by improving learning-by-doing, but this would continue until the relationship levelled off and it is expected to decline as the farmer gets older. This supports the argument that farmers become less efficient as they get much older; older farmers are less willing to adopt new practices and modern inputs, and they are more risk averse than young farmers. This result is supported by the result of the descriptive summary, as age of the farmers was between 17 and 103 years, with a mean of 52 years, indicating that the farm-heads were relatively old during the study period, a condition that might affect both inefficiency components negatively. The finding is consistent with results of similar studies (Talie et al., 2019; Anbes, 2020).

Table 5: Parameters of inefficiency factors

Transient inefficiency factor	*Coef.*	*Std. Err.*	*Persistent inefficiency factor*	*Coef.*	*Std. Err.*
Farm head's sex	-0.304*	0.201	Farm head's sex	-0.018	0.179
Farm head's age	0.014**	0.006	Farm head's age, mean	0.020***	0.007
Family size	-0.077**	0.041	Family size, mean	-0.039	0.054
Farm head's Educ.	0.032**	0.013	Farm head's educ., mean	0.066***	0.018
Marital status	-0.053	0.056	Marital status	0.055	0.046
Number of plots	-0.094*	0.060	Number of plots, mean	0.045	0.065
Total farm size	-0.009	0.036	Total farm size, mean	-0.063*	0.035
Population pressure	0.001	0.017	Population pressure, mean	-0.206***	0.042
Soil quality index	-172***	0.043	Soil quality index	-.232***	0.045
Credit use	-0.166	0.181	Credit use	-0.151	0.160
Own ox	-0.574***	0.210	Own ox	-0.303*	0.196
Soil-conservation	-0.126	0.174	Soil-conservation	-0.009	0.157
Water-harvesting	-0.237	0.212	Water-harvesting	-0.251	0.197
Irrigation	-0.120	0.252	Irrigation	-0.299	0.213
Remittance	-0.289	0.229	Remittance	0.216	0.165
Off-farm work	0.257	0.188	Off-farm work	0.026	0.160
Advisory services	-0.058	0.183	Advisory services	-0.064	0.155
Distance to market center	-0.025	0.021	Distance to market center	-0.041**	0.020
Time	-0.009	0.124	Time, mean	0.509	0.947
Av. annual rainfall	-0.014**	0.006	Av. annual rainfall, mean	-0.025***	0.008
Av. annual temp	0.001	0.024	Av. annual temperature, mean	-0.014	0.034
RF coef. of variations	-16.593	21.746	RF coef. of variations, mean	-7.915	55.846
Temp. coef. of variations	0.221***	0.081	Temp. coef. of variations, mean	0.108	0.476
Midland AEZ	-0.618	0.476	Midland AEZ	-0.308	0.239
Highland AEZ	-1.058	0.848	Highland AEZ	-	-
Constant	-1.638***	0.090	Constant	-1.837***	0.132
Log likelihood = -804.96731	Wald χ^2	62.31***	Log likelihood = -461.50518	Wald χ^2	208.29***

, ** and * are at $p < 0.05$, $p < 0.01$ and $p < 0.001$, respectively.*
AEZ, Av., coef., RF and temp., refer to agro-ecological zone, average, coefficient, rainfall, temperature, respectively.

On the other hand, the farm-head's education is one of the factors that studies frequently relates to farming efficiency, despite the empirical evidence reveals mixed results. Some of the studies, such as Bamlaku et al. (2009) argued that education is associated with efficient management of production systems and hence higher farming efficiency levels. In contrast, others argued that when a farmer gets access to better education, he or she may get better opportunities outside the farm sector to pursue other income earning activities, hence resulted in negative effect to farming efficiency (Ogada et al., 2014). Contrarily, Temesgen and Ayalneh (2005) argued that in developing countries education do not has clear effect on performance of the agricultural production. For this study, the empirical result shows the level of education of the farm-head to have a positive significant effect on both transient and persistent inefficiency. It shows that higher levels education has adverse effect on farming efficiency, showing farmers who have higher levels of education tend to be less efficient in grain crop production. This likely reflects that farming might be seen a secondary occupation for those with higher level of education. Education increases the likelihood of non-farm employments as some level of education gives the skill to create and better manage some small businesses (Ogada et al., 2014).

With respect to the effect of household's family-size on crop farming efficiency, the result shows household's family-size has showed negative and significant effect on transient inefficiency. This implies that the more the number of economically active members in the household's family the more the transient efficiency in crop-farming. Consequently, households with less family-size are less efficient compared with larger sized households. The possible reason for this may be that large household's size enhances the availability of labor which may guarantee increased efficiency. The result confirms the importance of family labor as a critical input in rural farming, specifically, at the peak farming cycle such as preparation, planting and harvesting time during which the farmer faces the labor bottlenecks. Assefa et al. (2019) reported similar result; whereas Essa et al. (2012) and Anbes (2020) stated the opposite.

The variable number of plots cultivated by the farmers (included as a proxy to access effect of farmland-fragmentation on farm inefficiency) was negatively and significantly associated with transient inefficiency, suggesting that farmers cultivating on more number of plots are technically efficient as compared to those cultivating on less number of plots. For a given area of cultivated land, the more the number of plots is the greater the farm load and resource constraint to disbursed all the plots, thus increasing technical inefficiency. This positive productivity effect may represent the reduced risk that different plots provide if the plots are sufficiently far apart and disbursed, such that farmers face different degrees of weather-induced output variations (production loss due to risks related to weather, pests and diseases) and soil fertility on the different plots. Moreover, the result can be explained in terms of access to farm-land and that farmers with more plots are likely to adopt innovations because they may be willing and able to bear more risks than their counterparts and may have preferential access to farm inputs and this will enable them to improve the level of their transient efficiency. Anbes (2020) and Assefa et al. (2019) reported similar results.

Considering the variable total farm-size under grain crop cultivation - created by multiplying the number of plots that farmers cultivate with cultivated farmland-area - encompassed as a proxy to access the effect of farm-size (scale) on farm efficiency, there is a negative effect of total farm-size on both inefficiency components. This reflects the positive effects of economies of scale on efficiency, implying large farms are more technically efficient than small farms. In particular, the result shows positive influence of total farm-size on persistent efficiency. Large scale farms decrease persistent inefficiency relative to small scale farms. This is in line with the findings of Addo and Salhofer (2022) and Anbes (2020).

Another interaction variable, population pressure, which is the ratio of number of economically active family members (older than 14 years) in the household to the cultivated farmland area, was used to investigate the claim overcrowded agricultural land holdings favorably affect efficiency. In this study, it is found that population pressure is influenced persistent inefficiency negatively and significantly, implying a desirable effect on persistent efficiency. The result implies that for a given amount of family farm-labor, increase in the size of cultivated-land leads to increase in persistent efficiency; households that have lesser land per household member are less efficient. Considering the small average farm size of Ethiopian farms, one would expect that increasing farm size would improve technical efficiency through reduced management costs and increased flexibility in the use of other inputs (Endrias et al., 2013; Tipi et al., 2009).

The result indicates that an average land quality index proxy used to control soil fertility of the plots had a negative significant impact on both transient and persistent inefficiency. Farmers operating on more fertile plots perform significantly better than their counterparts, thereby strengthening the fact that improvement in soil fertility is a decisive element in increasing farm efficiency (Anbes, 2020; Zhang et al., 2016). Thus, improving soil quality of arable land through improved farm-land management technologies is necessary. Not only the quantity of land but also its quality is crucial to increasing productivity and efficiency. The result also showed that possessing an ox or oxen, which is used as animal draft power for farming activity, has a positive and significant effect on both transient and persistent inefficiency. It reveals oxen are important factor as the major source of traction power in Ethiopia crop farming and indicating lack of it as a major constraint to crop-farming efficiency (Bamlak et al., 2009 and Oumer et al., 2022).

The amount of average annual rainfall also affect both transient and persistent inefficiencies significantly and negatively. Rainfall enhances crop production as it improves the soil moisture content and enables it to use the fertilizers and other inputs effectively, hence enhancing both transient and persistent efficiencies. The result indicates the extent to which subsistence farmers relies on rainfall and it explains why crop production in Ethiopia is sensitive to variation in the amount of rainfall. Similar results were reported by Addo and Salhofer (2022) and the result is also in line with studies that examined farm efficiency based on classical inefficiency effects models, without distinguishing between transient and persistent efficiency (Bamlak et al., 2009; Madau, 2011).

On the other hand, a considerable deviation from the optimal average value of the extreme quantity, that is, its variability, as represented by temperature coefficient of variation has significant positive effect on crop-farming transient inefficiency. When temperature diverged from its average value, both upward and downward, the level of transient efficiency significantly diminished (Ogada et al., 2014). On the other hand, the result reveled that distance to market centers has negative significant effect on persistent inefficiency. The farmers who are closer to the market centers may increase the non-farm employment opportunities with higher returns than from farming, leading them to reallocate their labor and time from farm to non-farm activities, tends to be less efficient. Thus, proximity to market places diverts farmers from crop-farming activity, due to better access to alternative employment opportunities. Similar results were reported by Agerie et al. (2019) and Tamirat et al. (2020); while, the result of the study by Mesfin et al. (2021) was opposite.

4. Conclusion and Recommendations

This study estimates persistent and transient inefficiencies separated from farm-heterogeneity and endogeneity for major grain crop-producing farmers in central highlands of Ethiopia. Mundlak–adjusted generalized true random effect – four error components stochastic frontier panel data model was used to disentangle farm-heterogeneity and endogeneity from farm inefficiency while estimating persistent and transient inefficiencies and also their determinants. The study applied modified multi-step procedure in estimating the Mundlak-adjusted GTRE–4eCSF model using an unbalanced panel data of 1,043 observations from 367 farm-households in two major grain crop-producing regions in central highlands of Ethiopia observed over the period 2004 – 2015.

The study extended the earlier version of 4eCSF model to address farm-heterogeneity problem and to explain technical inefficiencies. The model was extended in three ways: (1) Mundlak–adjustment was made to the random effects specification to account for unobserved time-invariant farm-heterogeneity which is correlated to the random error; (2) factors explaining inefficiencies in the Mundlak–adjusted were included in GTRE–4eCSF model to accommodate the determinants of persistent and transient inefficiencies, assuming the variances of time-invariant and time-variant inefficiencies are conditioned by a set of determinants and (3) the potential endogeneity from different sources applying a multi-step estimation were addressed by applying non-linear GMM estimator.

The estimated mean transient, persistent and overall efficiency scores were 73, 79 and 58 %, respectively. The efficiency result shows that significant number of farm-household have scored a technical efficiency below the mean scores, which indicates that there was a lot of room for improvement using the present state of technology. Empirical result from the inefficiency effect model shows that transient inefficiency was negatively significantly affected by the household's family size, farm head's sex, number of plots, owing oxen, land fertility and average annual rainfall, indicating a unit enhancement in these factors raises the transient efficiency, ceteris paribus. The transient inefficiency was influenced positively and significantly by age and educational level of the farm head, and annual temperature variations. On the other hand, the empirical results show that factors such as having oxen and total farm size, population pressure, land fertility, average annual rainfall and distance to the market center influenced negatively and significantly persistent inefficiency; which means that a unit increase in these variables could increase the persistent efficiency level by the same unit. The opposite is true for age and mean educational level of the farm head as these variables were influenced positively and significantly persistent inefficiency. The findings exhibit a low overall technical efficiency of Ethiopian grain crop-farmers is mainly due to the transient part; however, the persistent inefficiency is still substantial.

Hence, these findings are important to initiate government policy options to reduce inefficiency focusing on factors affecting the long-run and short-run inefficiencies distinctly. The current low level of efficiency can be addressed by facilitating farmers' access to more arable-land, and modern farming tools and machinery, creating targeted support programs for female farmers, improving technologies that promote soil-fertility and reduce weather adverse effects in central highlands of Ethiopia. Hence, with food security implications, the study recommends policies that could advance improved technologies for soil and land management, by investing in research and development of technologies that enhance them. It is important to implement targeted initiatives that provide support for female farmers to enhance their participation in agricultural decision-making and production, and to encourage the adoption of agro-ecological practices that are resilient to climate change impacts while promoting the use of climate-smart agriculture practices that mitigate adverse weather effects. By focusing on these interconnected strategies, Ethiopia can significantly enhance the efficiency of its crop-farming sector, leading to improved livelihoods for farmers, better food security, and greater economic growth. Generally, the outputs of this study may also have policy implication for the other developing nations, to make clear the factors of crop-farming technical inefficiencies and possibly help them devise strategies that can contribute to the betterment of their national agricultural production efficiency.

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