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Transient and Persistent Technical Efficiencies in Rice Farming: A Generalized True Random-Effects Model Approach

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Abstract: This study estimates transient and persistent technical efficiencies (TEs) using a generalized true random-effects (GTRE) model. We estimate the GTRE model using maximum likelihood and Bayesian estimation methods, then compare it to three simpler models nested within it to evaluate the robustness of our estimates. We use a panel data set of 945 observations collected from 344 rice farming households in Vietnam's Mekong River Delta. The results indicate that the GTRE model is more appropriate than the restricted models for understanding heterogeneity and inefficiency in rice production. The mean estimate of overall technical efficiency is 0.71 on average, with transient rather than persistent inefficiency being the dominant component. This suggests that rice farmers could increase output substantially and would benefit from policies that pay more attention to addressing short-term inefficiency issues.

Keywords: transient and persistent efficiencies; stochastic frontier; generalized true random-effects model; Bayesian estimation; rice farming; Mekong River Delta

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1. Introduction

Rice is a staple crop with a key role in ensuring national food security and economic development in Vietnam. According to national statistics, in 2022, rice was planted on 7.11 million hectares, accounting for 79.51% of the total annual cropped area, and paddy production was 42.66 million tons, accounting for 60.79% of total crop production (GSO 2023b). Rice is the main food source for more than 99 million Vietnamese people (GSO 2023a), and rice farming is the main livelihood source for about 9 million households (Thang and Phuc 2016). In 2022, the rice sector exported 7.11 million tons of milled rice, adding about $3.45 billion to the nation's GDP (GSO 2023c). Production mainly occurs in two large deltas—the Red River Delta in the north and the Mekong River Delta (MRD) in the south. The MRD accounts for more than 50% of the rice area and production and more than 90% of the rice export volume (Anh et al. 2020; GSO 2023b).

The rice sector has achieved continuous growth since the adoption of the renovation policy ('Doi Moi' policy) in 1986, which helped Vietnam transform from a chronic food importer to a self-sufficient food country and become a leading rice exporter in the last two decades (Linh 2012; Nguyen et al. 2012; Nielsen 2003; Van Long and Yabe 2011). In recent years, paddy production has declined due to reductions in area planted and rice yield (Figure A1), reducing export earnings, among other things. To maintain rice production and export levels, the government needs supportive policies that are well-tailored to improving efficiency, given that the cultivation area is limited and under increasing pressure from urbanization and climate change.

The productive efficiency of rice production in Vietnam has been the subject of a small but growing body of literature (Hien et al. 2003; Huy 2009; Khai and Yabe 2011; Linh et al.

2015; Linh 2012; Tung 2013). While these studies used different methods and data types to examine technical efficiency (TE), no study has analyzed whether the observed TE is due to short-term (transient) or long-term (persistent) factors, a distinction that is important for policy purposes. In addition, the effects of farm heterogeneity, cropping seasons, and rice varieties have been ignored in most of these studies.

To overcome these shortcomings, we estimate the TE of rice farming in Vietnam using the generalized true random-effects (GTRE) model, first introduced by Colombi et al. (2014), Kumbhakar et al. (2014), and Tsionas and Kumbhakar (2014). This model can distinguish between transient and persistent inefficiencies and separate farm heterogeneity from time-invariant inefficiency. The model generalizes earlier stochastic frontier panel models that accounted for some but not all of these effects. Different estimation methods have been developed to estimate this model. For example, Colombi et al. (2014) introduced a full maximum likelihood (ML) estimation method; Kumbhakar et al. (2014) developed a multi-step approach; Tsionas and Kumbhakar (2014) used a Bayesian approach; and, more recently, Filippini and Greene (2016) proposed a maximum simulated likelihood estimation (MSLE) approach. Here, we apply the MSLE approach of Filippini and Greene (2016) to estimate the transient and persistent efficiencies of rice farmers. The results are also compared with those estimated using Bayesian methods, which can allow us to impose monotonicity and concavity conditions to obtain theoretically consistent empirical estimates. These conditions have seemingly been ignored in previous empirical TE studies, which could lead to biased estimates. van den Broeck et al. (1994) indicated that the Bayesian approach has particular advantages in efficiency measurement, including exact (small-sample) inference on efficiencies, easy incorporation of prior ideas and restrictions such as regularity conditions, and formal treatment of parameter and model uncertainty. Bayesian methods are now commonplace in this literature (Griffin and Steel 2007).

This research makes two key contributions to the literature: (1) it is the first study to apply the GTRE model and use both MSLE and Bayesian estimation methods to examine the productive efficiency of rice farming, and (2) it disentangles productive efficiency into transient (short-term) and persistent (long-term) efficiencies while allowing for farm heterogeneity effects. The findings offer detailed and relevant information on Vietnamese rice farming performance for policymakers to design well-tailored policies that will help rice farmers increase efficiency and income.

The rest of the paper is organized as follows: The next section presents a brief review of the methods used in the literature for measuring TE and the empirical applications of the GTRE model. Section 3 describes the data and the methodology used in this study, including the stochastic frontier analysis method, the GTRE model, and further details on empirical implementation. The empirical results from the analysis are presented and discussed in Section 4. Section 5 concludes the paper by drawing some conclusions and policy implications.

2. Literature Review

The concept of productive efficiency began in the early 1950s with the works of Koopmans (1951), Debreu (1951), and Shephard (1953), with the basic definition that "*A producer is technical efficiency if, and only if, it is impossible to produce more of any output without producing less of some other output or using more of some input*" (Kumbhakar and Lovell 2003). Farrell (1957) was the first to measure productive efficiency empirically by defining and breaking down cost efficiency into technical and allocative efficiency using linear programming techniques applied to U.S. agriculture. Since then, different methods for measuring TE have been developed, with two broad approaches widely used in empirical studies: (i) the nonparametric technique, or data envelopment analysis (DEA) (Charnes et al. 1978); and (ii) the parametric approach, or stochastic frontier analysis (SFA) (Aigner et al. 1977; Battese and Corra 1977; Meeusen and van den Broeck 1977).

The SFA models for panel data sets have evolved over the last four decades, with one of the key concerns being whether inefficiency should be treated as a time-variant or time-varying component and whether time-invariant random effects should be treated as firm heterogeneity in production or persistent inefficiency. These developments are summarized into four modeling approaches (Colombi et al. 2014). The first group considered the inefficiency term as time-invariant (Battese and Coelli 1988; Kumbhakar 1987; Pitt and Lee 1981; Schmidt and Sickles 1984). The second group relaxed the assumption and modeled inefficiency as time-variant (Battese and Coelli 1992; Cornwell et al. 1990; Kumbhakar 1990; Lee and Schmidt 1993). However, these two approaches have the same shortcomings in that unobserved individual effects are not considered or separated from inefficiency, which became the target of the third and fourth approaches. The third approach considered random firm effects as long-term (persistent) inefficiency and added a second component to capture this time-variant technical inefficiency (Kumbhakar and Hjalmarsson 1993; Kumbhakar and Heshmati 1995; Kumbhakar and Hjalmarsson 1995). However, in these models, firm heterogeneity is not identified and separated from persistent inefficiency. The fourth approach considered random firm effects (firm heterogeneity, fixed or random) as something different from inefficiency but treated inefficiency as always time-variant or transient (Greene 2005a, 2005b; Kumbhakar and Wang 2005; Wang and Ho 2010). These models fail to capture persistent inefficiency, which is lumped with firm heterogeneity. The fourth approach is likely to produce a downward bias in estimating overall inefficiency, especially if persistent inefficiency exists or is significant. Similarly, the third approach might produce an upward bias in estimating overall inefficiency by treating time-invariant firm effects as inefficiency. The GTRE model, recently introduced by Colombi et al. (2014), Kumbhakar et al. (2014), and Tsionas and Kumbhakar (2014), has four error components and allows us to distinguish between unobserved firm heterogeneity, transient and persistent inefficiencies, and classical noise. Thus, the GTRE model can handle the limitations of the previous panel SFA models.

The parameters of the GTRE model can be estimated in several ways. Colombi et al. (2014) introduced the single-step full ML procedure, which was extended by Badunenko and Kumbhakar (2017) and Lai and Kumbhakar (2018) to accommodate heteroscedasticity in some or all of the error components. The model is simultaneously estimated using a single-step full ML method. However, the approach of Colombi et al. (2014) is difficult to implement in practice due to the complexity of the log-likelihood function and computation demand (Filippini and Greene 2016; Lien et al. 2018). Kumbhakar et al. (2014) developed a multi-step procedure to estimate the four-component model; however, this approach is not as efficient as the one-step ML method, despite being simpler (Lien et al. 2018). Tsionas and Kumbhakar (2014) proposed a partial Bayesian solution. Recently, Filippini and Greene (2016) provided an MSLE approach for estimating the GTRE model that circumvented most of the challenges associated with the classical full information ML procedure proposed by Colombi et al. (2014) by exploiting the Butler and Moffitt (1982) formulation (Lien et al. 2018).

Empirical analysis of transient and persistent efficiency has been applied to many areas, such as energy (Adom et al. 2018; Alberini and Filippini 2018; Filippini and Hunt 2015; Filippini et al. 2018a, 2018b), education (Agasisti and Gralka 2019; Gralka 2018; Salas-Velasco 2020; Titus et al. 2017), health care (Colombi et al. 2014; Colombi et al. 2017), transportation (Albalate and Rosell 2019; Badunenko and Kumbhakar 2016; Colombi et al. 2014; Heshmati et al. 2018), banking (Badunenko and Kumbhakar 2017; Fungáčová et al. 2020; Tsionas and Kumbhakar 2014), tourism (Assaf et al. 2017), and agriculture (Badunenko and Kumbhakar 2016; Colombi et al. 2014; Kumbhakar et al. 2014; Lien et al. 2018; Njuki and Bravo-Ureta 2015; Pisulewski and Marzec 2019). However, the GTRE model has not been applied to rice farming despite numerous empirical studies on efficiency measurement in rice production in the past few decades (see the reviews in Thiam et al. (2001) and Bravo-Ureta et al. (2007)). This study fills this gap by using the GTRE model to estimate transient and persistent TEs in rice farming using a data set collected from Vietnam's MRD. The models are estimated using both MSLE and Bayesian methods to reinforce the robustness of the estimates.

3. Materials and Methods

To examine the sensitivity of estimated results and evaluate the benefits of using the GTRE model, we also estimate and compare results from three traditional models, all of which are nested within the GTRE model. This estimation strategy has been used by Filippini and Hunt (2015) and Alberini and Filippini (2018). The first model we estimated is a cross-sectional (Pooled) model that ignores the panel nature of the data (i.e., ignoring farm heterogeneity and persistent inefficiency). The Pooled model only identifies and estimates transient inefficiency. The second model is the standard panel random-effects (RE) model proposed by Pitt and Lee (1981), which estimates persistent inefficiency and ignores farm heterogeneity and transient inefficiency. The third model is the true random-effects (TRE) model proposed by Greene (2005a, 2005b) as an extension of the panel data version of the Aigner et al. (1977) half-normal model by adding time-invariant individual effects. This model distinguishes unobserved time-invariant individual effects from time-variant inefficiency estimates and treats inefficiency as a time-varying error component (transient inefficiency), while persistent inefficiency is attributed to the time-invariant farm heterogeneity. The final model is the GTRE model, which simultaneously allows for both transient and persistent inefficiencies and farm heterogeneity. The specific econometric specifications of these SFA models are presented in Table 1, showing the differences in error components across models. The first four rows in the table describe the restrictions on each of the error components, with 'Yes' indicating a free variance parameter and 'No' indicating the parameter being restricted to zero. The last row of the table provides the full specifications of the error components with corresponding error variances for the four models.

Table 1. Specifications of the error components in the SFA models.

Disturbance	Pooled	RE	TRE	GTRE
Firm heterogeneity (w_i)	No	No	Yes	Yes
Persistent inefficiency (h_i)	No	Yes	No	Yes
Transient inefficiency (u_{it})	Yes	No	Yes	Yes
Classical noise (v_{it})	Yes	Yes	Yes	Yes
Full random error (ε_{it})	$\varepsilon_{it} = v_{it} - u_{it}$ $v_{it} \sim \mathrm{N}(0, \sigma_v^2)$ $u_{it} \sim \mathrm{N}^+(0, \sigma_u^2)$	$\varepsilon_{it} = v_{it} - h_i$ $v_{it} \sim \mathrm{N}(0, \sigma_v^2)$ $h_i \sim \mathrm{N}^+(0, \sigma_h^2)$	$\varepsilon_{it} = w_i + v_{it} - u_{it}$ $w_i \sim \mathrm{N}(0, \sigma_w^2)$ $v_{it} \sim \mathrm{N}(0, \sigma_v^2)$ $u_{it} \sim \mathrm{N}^+(0, \sigma_u^2)$	$\varepsilon_{it} = w_i - h_i + v_{it} - u_{it}$ $w_i \sim \mathrm{N}(0, \sigma_w^2)$ $v_{it} \sim \mathrm{N}(0, \sigma_v^2)$ $h_i \sim \mathrm{N}^+(0, \sigma_h^2)$ $u_{it} \sim \mathrm{N}^+(0, \sigma_u^2)$

As the Pooled, RE, and TRE models are all nested within the GTRE model, we employ Wald tests to identify if restrictions across models are accepted. The null hypothesis for all three tests is that the restricted model is the 'true' model. Specifically, the Pooled model is tested against the GTRE model with the null hypothesis that there is no farm heterogeneity and persistent inefficiency (i.e., H_0: $\sigma_w = 0$ and $\sigma_h = 0$; H_1: $\sigma_w \neq 0$ and/or $\sigma_h \neq 0$). Second, we test the RE model against the GTRE model with the null hypothesis that there is no farm heterogeneity and transient inefficiency (i.e., H_0: $\sigma_w = 0$ and $\sigma_u = 0$; H_1: $\sigma_w \neq 0$ and/or $\sigma_u \neq 0$). Similarly, we test the TRE model against the GTRE model with the null hypothesis that there is no persistent inefficiency (i.e., H_0: $\sigma_h = 0$; H_1: $\sigma_h \neq 0$).

In addition to formal tests, Badunenko and Kumbhakar (2016) concluded that the reliability of transient and persistent inefficiency estimates depends on three estimated parameter ratios: (1) the ratio of the variance parameter of persistent technical inefficiency to the variance parameter of random heterogeneity ($\lambda_0 = \sigma_h / \sigma_w$), (2) the ratio of the variance parameter of transient technical inefficiency to the variance parameter of classical noise ($\lambda = \sigma_u / \sigma_v$), and (3) the ratio of the variance parameter of persistent technical inefficiency to the variance parameter of transient technical inefficiency ($\Lambda = \sigma_h / \sigma_u$). A large value for the first and/or second ratios (λ_{0i} and/or λ should be >5 and >1, respectively) indicates that the estimates of transient and persistent inefficiencies are accurate and reliable. The third ratio plays a role in identifying the degree to which one can be confident in the accuracy of the estimates. Therefore, to be sure of the reliability of the transient and persistent estimates, we compute and compare these variance ratios. The specifications of these SFA models and associated log-likelihood functions are described in the next subsection.

3.1. Stochastic Frontier Analysis

The standard specification of the stochastic production frontier function (Pooled model) (Aigner et al. 1977) is:

$$y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{it} + v_{it} - u_{it} \tag{1}$$

where the subscript i = 1,. . ., N denotes farms and t = 1, . . ., T_i denotes time period. y_{it} is the output (in log); $\mathbf{X}_{it}$ is a vector of the input variables (in logs); $\boldsymbol{\beta}$ is the associated vector of unknown parameters that will be estimated; v_{it} is a random variable, assumed to be identically independently distributed (*iid*) with zero mean and variance σ_v^2 ($v_{it} \sim \mathrm{N}(0, \sigma_v^2)$) (it is assumed to capture the effect of random noise); and u_{it} is the time-varying non-negative inefficiency random variable, which is assumed to be *iid* with zero mean and variance σ_u^2 ($u_{it} \sim \mathrm{N}^+(0, \sigma_u^2)$). The composite error term $\varepsilon_{it} = v_{it} - u_{it}$ has a two-parameter skew-normal distribution with parameters $\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$. The log-likelihood function for the Pooled model is:

$$\log L(\alpha,\ \boldsymbol{\beta},\ \lambda,\ \sigma) = \sum_{i=1}^{N} \begin{bmatrix} \log\frac{2}{\sigma} + \log\phi\left(\frac{y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}}{\sigma}\right) \\ +\log\Phi\left(\frac{-(y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it})\lambda}{\sigma}\right) \end{bmatrix} = \sum_{i=1}^{N}\left[\log\left\{\frac{2}{\sigma}\phi\left(\frac{\varepsilon_{it}}{\sigma}\right)\Phi\left(\frac{-\varepsilon_{it}\lambda}{\sigma}\right)\right\}\right] \tag{2}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal density and standard normal cumulative distribution function (cdf), respectively.

The standard panel RE model (Pitt and Lee 1981) is the limiting case of Equation (1), where the u_{it} term is replaced by u_i; that is, the inefficiency term remains constant for each farm over time. Thus, this model only estimates persistent inefficiency and ignores farm heterogeneity and transient inefficiency. The log-likelihood function for the RE model is provided by Pitt and Lee (1981).

The TRE model (Greene 2005a, 2005b) extends the standard SFA model by adding an error component, w_i, to capture the time-invariant unobserved effects and treats these effects as random farm heterogeneity:

$$y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{it} + w_i + v_{it} - u_{it} \tag{3}$$

where y_{it}, α, $\boldsymbol{\beta}$, $\mathbf{X}_{it}$, v_{it}, and u_{it} are as defined above. The added farm heterogeneity term w_i is assumed to be normally distributed with a zero mean and variance σ_w^2. The log-likelihood function for the TRE model is:

$$\log L(\alpha, \boldsymbol{\beta}, \lambda,\ \sigma,\ \sigma_w) = \sum_{i=1}^{N} \log \int_{-\infty}^{\infty} \left\{ \prod_{t=1}^{T} \begin{bmatrix} \frac{2}{\sigma}\phi\left(\frac{y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-\sigma_w W_i}{\sigma}\right) \times \\ \Phi\left(\frac{-(y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-\sigma_w W_i)\lambda}{\sigma}\right) \end{bmatrix} \right\} \phi(W_i)dW_i \tag{4}$$

where $w_i = \sigma_w W_i$ and W_i is normally distributed with a mean of 0 and a variance of 1. The integral in Equation (4) does not have a closed form but can be evaluated by simulation (Filippini and Greene 2016). The simulated log-likelihood function is:

$$\log L_S(\alpha, \boldsymbol{\beta}, \lambda,\ \sigma,\ \sigma_w) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \left\{ \prod_{t=1}^{T} \begin{bmatrix} \frac{2}{\sigma}\phi\left(\frac{y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-\sigma_w W_{ir}}{\sigma}\right) \times \\ \Phi\left(\frac{-(y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-\sigma_w W_{ir})\lambda}{\sigma}\right) \end{bmatrix} \right\} \tag{5}$$

where W_{ir} is R simulated draws from the standard normal distribution. Derivatives for gradient-based optimization and computing the estimator of the asymptotic covariance matrix are also simulated.

We now consider the GTRE model (Colombi et al. 2014; Kumbhakar et al. 2014; Tsionas and Kumbhakar 2014), expressed as:

$$y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{X}_{it} + w_i - h_i + v_{it} - u_{it} \tag{6}$$

where y_{it}, α, $\boldsymbol{\beta}$, $\mathbf{X}_{it}$, w_i, v_{it}, and u_{it} are as defined above, and $h_i = |H_i|$ has a half-normal distribution with a zero mean and variance σ_h^2. Thus, in the GTRE model, the disturbance is split into four components. The first component (w_i) captures unobserved farm heterogeneity (Greene 2005a, 2005b), which is now disentangled from the long-term (persistent or time-invariant) inefficiency effects (h_i) in Kumbhakar and Hjalmarsson (1993), Kumbhakar and Hjalmarsson (1995), and Kumbhakar and Heshmati (1995). The third component (v_{it}) captures random shocks, and the last component (u_{it}) captures short-term (transient or time-varying) inefficiency. These four-part disturbances can be grouped into two groups: two time-variant components and two time-invariant components. Filippini and Greene (2016) therefore argued that these could be viewed as a two-part disturbance, one time-variant and one time-invariant, each with its own skew-normal rather than normal distribution. Specifically, $\varepsilon_{it} = (v_{it} - u_{it})$ has a skew-normal distribution with parameters σ and λ described above, while $\varepsilon_{0i} = (w_i - h_i)$ also has a skew-normal distribution with parameters $\lambda_0 = \sigma_h/\sigma_w$ and $\sigma_0 = \sqrt{\sigma_w^2 + \sigma_h^2}$. The GTRE is thus an RE model with skew-normal error components. The full unconditional log-likelihood function for this model based on the joint distribution of $(\varepsilon_{i1}, \ldots, \varepsilon_{iT}, \varepsilon_{0i})$ is derived by Colombi (2010) and Colombi et al. (2011). The log-likelihood function for the GTRE model (Filippini and Greene 2016) is:

$$\log L(\alpha, \boldsymbol{\beta}, \lambda, \sigma, \lambda_0, \sigma_0) = \sum_{i=1}^{N} \log \int_{-\infty}^{\infty} \left\{ \prod_{t=1}^{T} \left[\begin{array}{l} \frac{2}{\sigma}\phi\left(\frac{y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-\varepsilon_{0i}}{\sigma}\right) \times \\ \Phi\left(\frac{-(y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-\varepsilon_{0i})\lambda}{\sigma}\right) \end{array} \right] \right\} \frac{2}{\sigma_0}\phi\left(\frac{\varepsilon_{0i}}{\sigma_0}\right)\Phi\left(\frac{-\varepsilon_{0i}\lambda_0}{\sigma_0}\right) d\varepsilon_{0i} \tag{7}$$

For practical purposes, it is more convenient to use the original parameterization. Recall that $\varepsilon_{0i} = \sigma_w W_i - \sigma_h |H_i|$, where W_i and H_i are both normally distributed with a mean of 0 and a variance of 1. Similarly, the integral in Equation (7) can be simulated, and the simulated log-likelihood function for the GTRE model is:

$$\log L_S(\alpha, \boldsymbol{\beta}, \lambda, \sigma, \sigma_w, \sigma_h) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \left\{ \prod_{t=1}^{T} \left[\begin{array}{l} \frac{2}{\sigma}\phi\left(\frac{y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-(\sigma_w W_{ir}-\sigma_h|H_{ir}|)}{\sigma}\right) \times \\ \Phi\left(\frac{-(y_{it}-\alpha-\boldsymbol{\beta}'\mathbf{X}_{it}-(\sigma_w W_{ir}-\sigma_h|H_{ir}|))\lambda}{\sigma}\right) \end{array} \right] \right\} \tag{8}$$

where H_{ir} is R simulated draws from the standard normal distribution.

The estimation problem is only slightly more difficult than that for the TRE model as it involves an extra parameter, σ_h. The simulation itself involves pairs of dependent random draws from two standard normal distributions. But the optimization problem is essentially the same as the TRE model. After the parameters of all models are estimated, the efficiency scores are predicted using the procedure in Jondrow et al. (1982). The transient TE is computed as $\exp(-u_{it})$, the persistent TE is computed as $\exp(-h_i)$, and the overall TE is the product of transient TE and persistent TE (see Colombi et al. (2014) for details).

3.2. Bayesian Estimation

The Bayesian analysis of an SFA model, originally introduced by van den Broeck et al. (1994) and extended to panel data by Koop et al. (1997), was recently developed and applied in empirical studies as an attractive alternative to the traditional ML approach to the inference of efficiencies because of some advantages highlighted in Koop (1994), van den Broeck et al. (1994), Coelli et al. (2005), and Griffin and Steel (2007). First, in the Bayesian framework, estimators are chosen based on their ability to minimize the loss associated with an estimation error. Second, results are usually presented in terms of probability density functions. Thus, it is possible and convenient to make probability statements about unknown parameters, hypotheses, and models. Third, exact finite-sample results can be obtained for most estimation problems. Fourth, there is a formal mechanism for incorporating non-sample information into the estimation process. Thus, the Bayesian estimation method makes it easy to incorporate restrictions, such as regularity conditions, and allows for a formal treatment of parameter and model uncertainty.

Let $\theta = (\theta_1, \ldots, \theta_k)$ denote the unknown parameters of the GTRE model to be estimated, $p(\theta) \equiv p(\boldsymbol{\beta}, \sigma_w, \sigma_h, \sigma_v, \sigma_u)$ denotes the probability density function (pdf) of prior information for parameters (e.g., information from economic theory or previous empirical studies), and $L(y, \mathbf{X}| \theta)$ is the likelihood function (sample information or the information contained in the data). The posterior distribution follows from Bayes's theorem as:

$$p(\theta| y, \mathbf{X}) \propto L(y, \mathbf{X}| \theta)\, p(\theta) \tag{9}$$

where $p(\theta| y, \mathbf{X})$ is the posterior pdf and $\propto$ denotes 'is proportional to.' In other words, the posterior pdf is proportional to the likelihood function multiplied by the prior pdf. Thus, the posterior distribution includes all the information on the parameters contained in the prior and the data. The prior pdf $p(\theta)$ can be *non-informative* (i.e., ignorance of parameters) or *informative*. For complex models that do not allow inference by analytical methods, implementing the Bayesian approach requires the use of an iterative Markov Chain Monte Carlo (MCMC) algorithm, using either general algorithms such as *Metropolis–Hastings* or *Gibbs Sampling,* which focus on sampling from conditional distributions for blocks of the parameter vector. The Gibbs Sampling algorithm proposed by Koop et al. (1995) is particularly useful for problems involving latent variables, such as SFA models (Coelli et al. 2005), and is commonly used in the literature (Griffin and Steel 2007; Huang 2004; Kumbhakar and Tsionas 2005; Tsionas 2002). The researcher can write their own MCMC algorithms or just specify the model but use BUGS (Bayesian inference Using Gibbs Sampling) software such as WinBUGS or JAGS to handle the MCMC sampling. Once the prior distributions and likelihood function are specified, it is possible to take samples from the posterior distributions and use those samples to make inferences about production frontier parameter values and efficiency levels. Tsionas and Kumbhakar (2014) estimated the GTRE model using Bayesian methods. Further information on the priors used in the specification of our Bayesian model is provided in Appendix A (Table A1) to this paper. The simulation uses two chains of 50,000 iterations with a burn-in phase of 50,000 iterations to remove the influence of the initial values. Since the Gibbs Sampling algorithm can generate highly correlated draws, every tenth draw was retained to reduce autocorrelation in the samples. Hence, every chain contributes a sample of 5000 draws.

3.3. Empirical Models

To estimate the SFA models, we need to assume a functional form for the stochastic frontier function. Empirical studies have used the Cobb–Douglas (CD) production function (Cobb and Douglas 1928) and the flexible translog (TL) production function (Christensen et al. 1971) to represent the stochastic frontier function. Here, we estimate the stochastic frontier model using TL and CD functional forms. As the CD is nested within the TL, we use the likelihood ratio (LR) test to select the more appropriate functional form. The translog GTRE model is shown in Equation (10). The CD form can be obtained as a special case by restricting β_{jk} parameters to zero, while other nested models are estimated by restricting error structures.

$$\ln y_{it} = \alpha + \sum_{j=1}^{6} \beta_j \ln x_{jt} + \frac{1}{2}\sum_{j=1}^{6}\sum_{k=1}^{6} \beta_{jk} \ln x_{jt} \ln x_{kt} + \sum_{l=1}^{3} \beta_l D_l + w_i - h_i + v_{it} - u_{it} \tag{10}$$

where i = 1, . . ., N denotes the i-th farm and t = 1, . . ., T_i denotes the cropping season. y_{it} is the total revenue of the paddy, normalized by its mean. x_{jt} is a vector of j-th used inputs normalized by the means. The six main inputs used in rice production in the MRD are land, seed, fertilizer, labor, chemicals, and capital. D_l $(l = 1,\ 2,\ 3)$ are dummy variables, denoting cropping season effects (D_S2 and D_S3) and a rice variety effect (D_HQRV). α and β are unknown parameters to be estimated. w_i is the normally distributed random component capturing unobserved farm heterogeneity. u_{it} and h_i are non-negative, half-normal *iid* components capturing transient and persistent inefficiencies, respectively. v_{it} is *iid* symmetric random noise.

Output elasticity and returns to scale

The partial output elasticities with respect to inputs are computed to examine the sensitivity of output change when a change in inputs occurs. The partial output elasticity with respect to input j (E_j) is computed as:

$$E_j = \frac{\partial lny_{it}}{\partial lnx_{jt}} = \hat{\beta}_j + \hat{\beta}_{jj} lnx_{jt} + \sum_{k=1}^{5} \hat{\beta}_{jk} lnx_{kt} \quad (11)$$

where $\hat{\beta}_j$, $\hat{\beta}_{jj}$, and $\hat{\beta}_{jk}$ are the parameters of the GTRE model estimated in Equation (10). Returns to scale (RTS) is equal to the sum of the partial output elasticities with respect to inputs, defined as:

$$\text{RTS} = \sum_{j=1}^{6} E_j \quad (12)$$

3.4. Data and Variables

The data were collected from a random sample of rice farmers in three provinces of the Mekong River Delta in southern Vietnam. This is the main rice cultivation area of Vietnam, contributing more than 50% of the total rice cultivation area and production and more than 90% of the total rice export volume. Rice is cultivated in the MRD across 13 provinces, with production conditions such as soil quality, cultivated-land resources, and freshwater resources varying significantly. To obtain a representative sample of the cultivated areas, we used a three-stage stratified random sampling method to select the sample sites. Three provinces were selected to conduct the survey, namely the An Giang, Can Tho, and Bac Lieu provinces. The final sample includes 344 farmers covering three cropping seasons in the 2016/17 production year, generating an unbalanced panel set of 945 farmer–season observations. The number of surveyed farmers from the An Giang, Can Tho, and Bac Lieu provinces is 137 (398 observations), 108 (318 observations), and 93 (229 observations), respectively. The descriptive statistics of the data and definitions of variables are presented in Table 2.

On average, rice farmers in the MRD cultivate 2.37 hectares of land per household and earn $3440.56 per household per cropping season (Table 2). Each rice farming household spends approximately $197.44 on seed, $442.33 on fertilizers, $247.37 on hired and family labor, $568.91 on chemicals, and $511.86 on capital per cropping season. The effect of cropping seasons is also considered in this study; each one varies in terms of temperature, rainfall, sunshine hours, humidity, and the occurrence of rice diseases and natural disasters. The sample comprised 36%, 36%, and 27% of observations from seasons 1, 2, and 3, respectively. Season 1 was treated as the baseline in the estimated model because it is the main cropping season in the MRD, and dummy variables D_S2 and D_S3 represent seasons 2 and 3, respectively.

Rice farmers usually adopt different rice varieties according to the production conditions and cropping season. We grouped the adopted rice varieties into two groups: (1) the conventional rice variety group, treated as the baseline, and (2) the high-quality rice variety (HQRV) group, dominated by OM5451, Jasmine, RVT, DS1, and OM4900. The adoption rate of HQRV in the MRD was 43% for the study period.

Table 2. Descriptive statistics of input and output variables.

Definitions	Variables	Mean	S.D.	Min	Max
Outputs and inputs					
Revenue from paddy (USD)	y	3440.56	3426.92	114.54	31,982.38
Land (the planted rice area, Ha)	x_1	2.37	2.11	0.13	16.90
Seed (expenditure on seed, USD)	x_2	197.44	200.98	5.29	2233.48
Fertilizer (expenditure on all used fertilizers, USD)	x_3	442.33	433.51	12.33	3303.97
Labor (expenditure on hired and family labor, USD)	x_4	247.37	174.07	21.15	1651.98
Chemical (expenditure on pesticides and herbicides, USD)	x_5	568.91	550.07	19.12	4507.71
Capital (expenditure on land preparation, seeding, irrigation, and harvesting, USD)	x_6	511.86	489.85	21.81	4460.13
Winter–Spring (S1)	Baseline	0.36	0.48	0	1
Summer–Autumn (S2)	D_S2	0.36	0.48	0	1
Autumn–Winter (S3)	D_S3	0.27	0.45	0	1
Conventional rice varieties	Baseline	0.57	0.49	0	1
High-quality rice varieties	D_HQRV	0.43	0.49	0	1

Notes: S.D. denotes the standard deviation. 1 USD = ~22,700 VND in 2016–2017.

4. Results and Discussion

4.1. Estimates of Stochastic Production Frontier Function

The parameter estimates of the Pooled, RE, TRE, and GTRE models are presented in Table 3. The GTRE model was estimated using simulated maximum likelihood (MGTRE) and Bayesian (BGTRE) methods. The Pooled, RE, and TRE models were implemented in Stata software. The MGTRE was implemented in NLOGIT6 software, while the BGTRE was implemented using JAGS in R through the 'apear' package (Hailu 2013). We used parameter estimates of the TL functional form because the CD functional form was rejected in all models. The LR values ($\text{LR} = -2 * (\log L_{CD} - \log L_{TL})$) for the Pooled, RE, TRE, and GTRE models are 78.07, 66.65, 46.22, and 51.27, respectively, all greater than the 1% critical value of $\chi^2_{0.99}$ (21) = 38.30. The results show that the estimate for the variance parameter, $\lambda = \sigma_u/\sigma_v$, is relatively large and statistically significant, indicating that inefficiency effects exist in this model and dominate over statistical noise or measurement errors. The presence of technical inefficiency is also confirmed by the statistically significant parameter estimates of σ_u and σ_h. As the differences between the Pooled, RE, TRE, and GTRE models all relate to estimates of variance parameters, conventional log likelihood ratio tests are not appropriate as the restricted parameter is at the boundary of the parameter space (Andrews 2001). Gutierrez et al. (2001) suggest that the correct p values of the test will be one half of those conventionally estimated due to the use of a 50:50 chi squared mixing function. We compare the restricted models to the GTRE model using Wald tests and find that we reject all restrictions (RE model: p values < 0.0001, Pooled model: p value < 0.0001; TRE model: p value = 0.0401). This confirms the presence of heterogeneity and persistent or transient inefficiency in the data set and suggests that the Pooled, RE, and TRE models are not adequate representations of the data. The estimates of variance parameters for farm heterogeneity (σ_w) and persistent inefficiency (σ_h) are statistically significant in both MSLE and Bayesian models, confirming the presence of farm heterogeneity and persistent inefficiency (Table 3). This result is in line with those reported by Filippini and Greene (2016), Alberini and Filippini (2018), and Filippini et al. (2018b). We also follow the approach of Badunenko and Kumbhakar (2016) by computing three variance ratios: (1) the ratio of variance parameters of persistent technical inefficiency to random heterogeneity ($\lambda_0 = \sigma_h/\sigma_w$); (2) the ratio of variance parameters of transient technical inefficiency to classical noise ($\lambda = \sigma_u/\sigma_v$); and (3) the ratio of variance parameters of persistent technical inefficiency to transient technical inefficiency ($\Lambda = \sigma_h/\sigma_u$). A large value for the first and/or second ratios (λ_0 and λ should be >1) indicates that the estimates of transient and persistent inefficiencies are accurate and reliable. The results of the MGTRE model show that the values for the first and second ratios are relatively high, with λ_0 = 0.476/0.041 = 11.70 and λ = 0.326/0.094 = 3.47. The third ratio has a value of Λ = 0.476/0.326 = 1.46. This result is relatively close to the values of scenario S4 ($\lambda_0 = 5$, $\lambda = 5$, and $\Lambda = 1$) reported in Table 6 of Badunenko and Kumbhakar (2016), revealing 'Good' reliability of transient and persistent efficiency estimates. This confirms that our estimations of transient and persistent technical inefficiency are reliable and appropriate. Therefore, the GTRE model is preferred for estimating transient and persistent TEs. We estimate both MGTRE and BGTRE to ensure the robustness of the estimates.

Table 3. Parameter estimates of the translog stochastic production function for all models.

Variable	Pooled			RE			TRE			MGTRE			BGTRE				
	Coef. †		S.E.	Coef. †		S.E.	Coef. †		S.E.	Coef. †		S.E.	Coef. ‡		S.D.	[95% C.I.]	
Intercept	0.427	***	0.019	0.332	***	0.024	0.413	***	0.019	0.523	***	0.019	0.519	s	0.027	0.468	0.573
$\ln x_1$	0.975	***	0.075	0.991	***	0.096	0.905	***	0.088	0.919	***	0.068	0.479	s	0.060	0.353	0.596
$\ln x_2$	−0.068	*	0.038	−0.112	**	0.045	−0.064		0.041	−0.071	**	0.033	0.057	s	0.018	0.027	0.093
$\ln x_3$	0.073	**	0.033	0.096	**	0.044	0.086	**	0.038	0.098	***	0.031	0.145	s	0.038	0.077	0.228
$\ln x_4$	−0.075	***	0.024	−0.068	**	0.031	−0.082	***	0.028	−0.070	***	0.023	0.060	s	0.021	0.022	0.100
$\ln x_5$	0.007		0.042	0.045		0.053	0.015		0.047	0.020		0.038	0.076	s	0.023	0.029	0.120
$\ln x_6$	0.095	**	0.047	0.053		0.060	0.154	***	0.053	0.115	***	0.044	0.240	s	0.044	0.151	0.327
$0.5\ln {x_1}^2$	−1.019	*	0.575	−0.628		0.662	−0.738		0.619	−0.920	*	0.538	0.060		0.175	−0.313	0.306
$\ln x_1 \ln x_2$	0.642	***	0.208	0.524	**	0.246	0.459	**	0.227	0.571	***	0.186	0.005		0.032	−0.062	0.062
$\ln x_1 \ln x_3$	0.224		0.211	0.176		0.243	0.165		0.232	0.207		0.199	0.030		0.073	−0.127	0.150
$\ln x_1 \ln x_4$	0.385	**	0.165	0.247		0.208	0.385	**	0.184	0.349	**	0.154	−0.005		0.047	−0.097	0.089
$\ln x_1 \ln x_5$	−0.139		0.159	−0.142		0.192	−0.184		0.164	−0.135		0.162	0.010		0.047	−0.060	0.097
$\ln x_1 \ln x_6$	0.224		0.273	0.146		0.337	0.204		0.287	0.201		0.285	−0.039		0.108	−0.261	0.148
$0.5\ln {x_2}^2$	−0.156		0.102	−0.177		0.129	−0.094		0.110	−0.134		0.093	0.001		0.023	−0.042	0.046
$\ln x_2 \ln x_3$	−0.096		0.075	−0.139		0.090	−0.108		0.080	−0.093		0.069	−0.002		0.020	−0.042	0.037
$\ln x_2 \ln x_4$	−0.022		0.074	0.014		0.086	0.018		0.078	−0.012		0.065	0.002		0.017	−0.031	0.035
$\ln x_2 \ln x_5$	0.081		0.080	0.080		0.091	0.061		0.082	0.067		0.077	−0.015		0.019	−0.051	0.018
$\ln x_2 \ln x_6$	−0.492	***	0.115	−0.361	**	0.142	−0.362	***	0.125	−0.436	***	0.115	0.010		0.022	−0.037	0.051
$0.5\ln {x_3}^2$	−0.092		0.107	0.027		0.121	−0.051		0.114	−0.069		0.103	0.014		0.050	−0.099	0.109
$\ln x_3 \ln x_4$	0.114		0.093	0.214	*	0.116	0.106		0.102	0.107		0.089	0.004		0.023	−0.038	0.051
$\ln x_3 \ln x_5$	0.103		0.064	0.095		0.074	0.105		0.066	0.093		0.065	−0.008		0.025	−0.050	0.037
$\ln x_3 \ln x_6$	−0.160		0.135	−0.234		0.155	−0.122		0.151	−0.142		0.130	−0.022		0.067	−0.110	0.108
$0.5\ln {x_4}^2$	−0.162	*	0.089	−0.101		0.112	−0.164		0.103	−0.141		0.090	0.001		0.024	−0.049	0.048
$\ln x_4 \ln x_5$	−0.141	**	0.063	−0.152	*	0.079	−0.145	**	0.068	−0.131	*	0.071	−0.010		0.018	−0.047	0.021
$\ln x_4 \ln x_6$	−0.229	**	0.109	−0.267	*	0.139	−0.251	**	0.122	−0.214	**	0.107	0.007		0.031	−0.062	0.063
$0.5\ln {x_5}^2$	0.012		0.053	0.056		0.065	0.017		0.058	0.027		0.054	0.017		0.016	−0.014	0.048
$\ln x_5 \ln x_6$	−0.052		0.115	−0.098		0.140	0.016		0.120	−0.046		0.117	−0.005		0.035	−0.069	0.058
$0.5\ln {x_6}^2$	0.527	**	0.222	0.626	**	0.260	0.341		0.230	0.473	*	0.243	0.010		0.128	−0.191	0.231
D_HQRV	−0.035	*	0.018	−0.082	***	0.020	−0.024		0.019	−0.038	**	0.015	−0.027		0.022	−0.072	0.016
D_S2	−0.284	***	0.017	−0.318	***	0.017	−0.277	***	0.015	−0.287	***	0.018	−0.292	s	0.015	−0.322	−0.264
D_S3	−0.297	***	0.020	−0.364	***	0.020	−0.294	***	0.018	−0.305	***	0.020	−0.309	s	0.017	−0.341	−0.276
Model properties																	
λ	3.396	***	0.021	0.895	***	0.017	6.614	***	0.024	3.561	***	0.424	12.184	s	3.914	4.986	18.799
σ_u	0.362	***	0.014	–			0.353	***	0.013	0.328	–	–	0.342	s	0.011	0.320	0.364
σ_v	0.107	***	0.009	0.216	***	0.006	0.053	***	0.015	0.092	–	–	0.033	s	0.011	0.017	0.058
σ_w	–			–			−0.106	***	0.011	0.044	***	0.006	0.237	s	0.011	0.216	0.257
σ_h	–			0.193	***	0.019	–			0.455	**	0.222	0.125	s	0.014	0.099	0.152
N	945			945			945			945			945				

Notes: Coef. and S.E. denote coefficient and standard error, respectively. †, ***, **, * represent the significant levels at 1%, 5%, and 10%, respectively. ‡ s represents statistical significance.

The input and output data were normalized by their sample mean and then log-transformed; thus, the first-order coefficients of SF models can be interpreted as partial output elasticities with respect to inputs at the sample mean. For model estimates with MLE/SMLE, estimates of first-order input parameter values are as expected, positive and statistically significant, except for seed and labor inputs, which are negative and significant, and chemical input, which is not statistically significant. However, when we imposed monotonicity and curvature constraints on the estimates in the BGTRE estimation, all first-order coefficients were positive and statistically significant. The estimated coefficients of the models are reported in Table 3.

We computed partial output elasticities with respect to individual inputs using Equation (11); the results are summarized in Table 4. The RTS value is around unity, implying that rice production in the MRD almost achieved a constant RTS, which is consistent with other studies on rice farming in the MRD (Huy 2009; Tung 2013), the Philippines (Villano and Fleming 2006), and Bangladesh (Bäckman et al. 2011). In terms of individual inputs, rice output is most responsive to land, capital, and fertilizer input use. Chemical, seed, and labor inputs have much lower output elasticity estimates; the values for seed and labor are positive only for the monotonicity, constrained (Bayesian) estimation.

Table 4. Partial output elasticities with respect to inputs and returns to scale.

Inputs	Pooled		RE		TRE		MGTRE		BGTRE	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Land	0.85	0.30	0.87	0.29	0.82	0.24	0.82	0.27	0.46	0.06
Seed	–0.03	0.12	–0.06	0.12	–0.03	0.09	–0.04	0.10	0.06	0.01
Fertilizer	0.07	0.08	0.09	0.11	0.08	0.08	0.09	0.08	0.14	0.01
Labor	–0.06	0.09	–0.06	0.09	–0.07	0.09	–0.06	0.08	0.06	0.00
Chemicals	0.02	0.09	0.06	0.10	0.02	0.08	0.03	0.08	0.08	0.01
Capital	0.17	0.27	0.12	0.25	0.21	0.20	0.18	0.24	0.25	0.03
RTS	1.02	0.07	1.02	0.08	1.02	0.07	1.02	0.06	1.05	0.02

The estimates for dummy variables representing cropping seasons 2 (D_S2) and 3 (D_S3) were negative and statistically significant, implying that farmers produce lower paddy outputs outside the main cropping season (season 1). The estimate of the parameter for the dummy variable of HQRVs (D_HQRV) was negative and statistically significant in the MGTRE model and its nested models but insignificant in the BGTRE model, suggesting a lack of robust statistical evidence on output differences between HQRV adopters and non-adopters.

4.2. Transient and Persistent Efficiency Analysis

Table 5 presents the summary statistics of TE scores for rice farming estimated from all models. In general, the mean and dispersion of TE vary across models (also see Figure 1) but show some consistency. For example, the lower bound to the dispersion (min TE) is between 0.25 and 0.28 for all models that allow for transient inefficiency. The upper bounds for transient and persistent efficiencies are in the mid- to high-90s for most models.

Table 5. Descriptive summary of technical efficiency estimates for all models.

Model	Mean	S.D.	Min	Max
Pooled	0.77	0.14	0.25	0.97
RE	0.86	0.07	0.59	0.96
TRE	0.77	0.14	0.25	0.98
MGTRE_T	0.84	0.11	0.28	0.97
MGTRE_P	0.91	0.04	0.68	0.97
MGTRE_O	0.76	0.11	0.27	0.94
BGTRE_T	0.78	0.13	0.28	0.95
BGTRE_P	0.91	0.01	0.86	0.94
BGTRE_O	0.71	0.12	0.25	0.89

Note: GTRE_O = GTRE_T * GTRE_P.

The mean persistent efficiency is 0.86 if estimated using a model that ignores transient efficiency (RE) but higher (0.91) when estimated using other models, namely, the MGTRE and BGTRE models. This implies that persistent inefficiency was overestimated by 5% when farm heterogeneity and transient inefficiency are not adequately considered. In contrast, the mean transient TE estimated in all models remains relatively stable around 0.77–0.78, except for the MGTRE model, where it is higher (MGTRE_T = 0.84). This difference results in different overall TE estimates for the MSLE (0.76) and Bayesian (0.71) methods. Our results are similar to the findings in other studies on the TE of rice farming in Vietnam; for example, mean TE of 0.76–0.79 (Huy 2009) and 0.82 (Khai and Yabe 2011). This result indicates that Vietnamese rice farmers in the MRD perform inefficiently, especially in the short term, with transient inefficiency being the dominant component of overall inefficiency. This is due to the factors affecting short-term performance, including alkaline soils, flooding, rice diseases, and natural disasters. In the long term, rice farmers are facing limitations on their cultivation land.

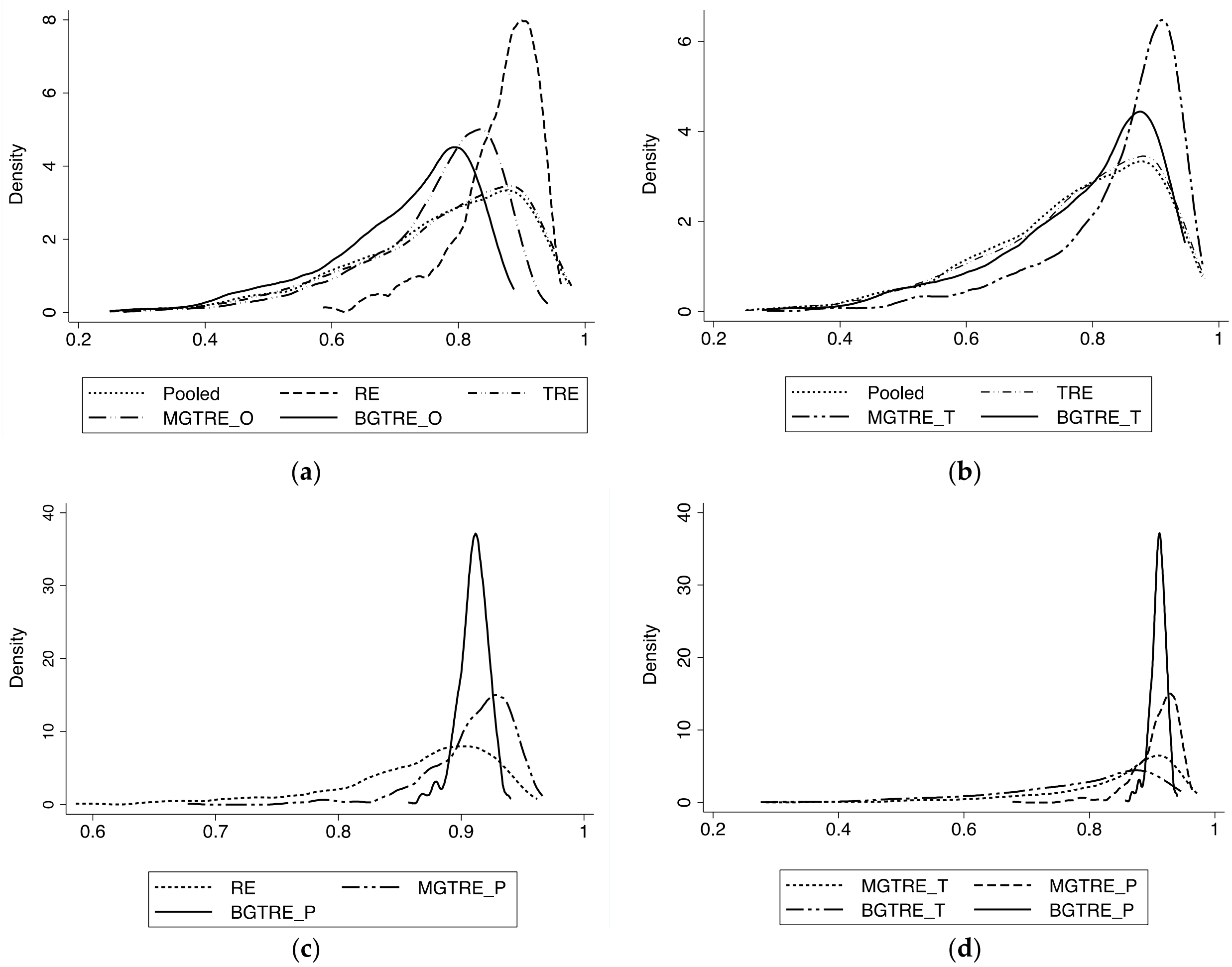

Figure 1. (**a**) Distributions of overall technical efficiency (TE) of all models; (**b**) Transient TE of all models; (**c**) Persistent TE of all models; and (**d**) Transient and persistent TEs of MSLE and Bayesian GTRE models.

This finding is consistent with the findings of Nguyen et al. (2023), who studied the effect of credit access and weather shocks on the production efficiency of rice farmers in Vietnam. They found that weather shocks, farm mechanization, education, and land fragmentation are major sources of rice farming inefficiency. Their findings revealed that access to credit plays an important role in mitigating the negative effects of weather shocks on rice farming inefficiency. They suggested that policies should be focused on promoting rural credit markets, farm mechanization, land defragmentation, and rural education to help rice farmers improve their rice farming inefficiency. Cao et al. (2023) examined the impacts of natural disasters (such as droughts, typhoons, and floods) and pest infestations on the technical efficiency of rice farming in Vietnam. They found that exposure to natural disasters and pest infestations leads rice farmers to reduce their investments in rice farming, resulting in technical inefficiency. They suggested that support policies should be prioritized to facilitate farmers' access to agricultural insurance. The study by Ho and Shimada (2019) on the impacts of climate-smart agriculture and climate change adaptation on the technical efficiency of rice farming in Vietnam's Mekong Delta shows that climate change adaptation responses, including climate-smart agriculture adoption, could help rice farmers improve rice farming technical efficiency by 13%–14% compared to non-adaptation responses. If rice farmers only adopted climate-smart agriculture practices, they could improve their technical efficiency by 5%–8% compared to the non-adopters. In addition, studies in Bangladesh, such as Rahman (2003) on profit efficiency among Bangladeshi rice farmers and Biswas et al. (2021) on the impact of agriculture extension services on the technical efficiency of rural paddy farmers in southwest Bangladesh, found that the variations in rice farming efficiency among farmers are explained by experience, infrastructure, soil fertility, tenancy, extension services, and a share of non-agricultural income. These are also constraints that Vietnamese rice farmers are facing. Thus, policymakers could use this evidence to design the appropriate policies to improve rice farming efficiency.

We examine the correlations of the TE scores from the different models, and the result is presented in Figure 2. In general, the GTRE model is highly correlated with the models that allow for transient inefficiency (Pooled and TRE), but not with the RE model, which only estimates persistent inefficiency. This is reasonable, as the overall technical inefficiency is dominated by transient inefficiency. The transient TEs estimated in the Pooled, TRE, and MGTRE models are highly correlated, with correlation coefficients of 0.84 to 0.97. The persistent TEs obtained from RE, MGTRE, and BGTRE are also highly correlated, with coefficients of 0.83 to 0.86. This suggests that while the presence of random farm heterogeneity cannot be rejected, its effect on TE estimates is trivial in our case. The correlation between transient and persistent efficiencies is as low as 0.21 and 0.16 in the MGTRE and BGTRE models, respectively, implying that transient and persistent efficiencies differ and should be identified separately (Adom et al. 2018). The overall TE obtained from the MSLE and Bayesian estimation methods is highly correlated (0.86–0.97), confirming the robustness of our estimates using the estimation method.

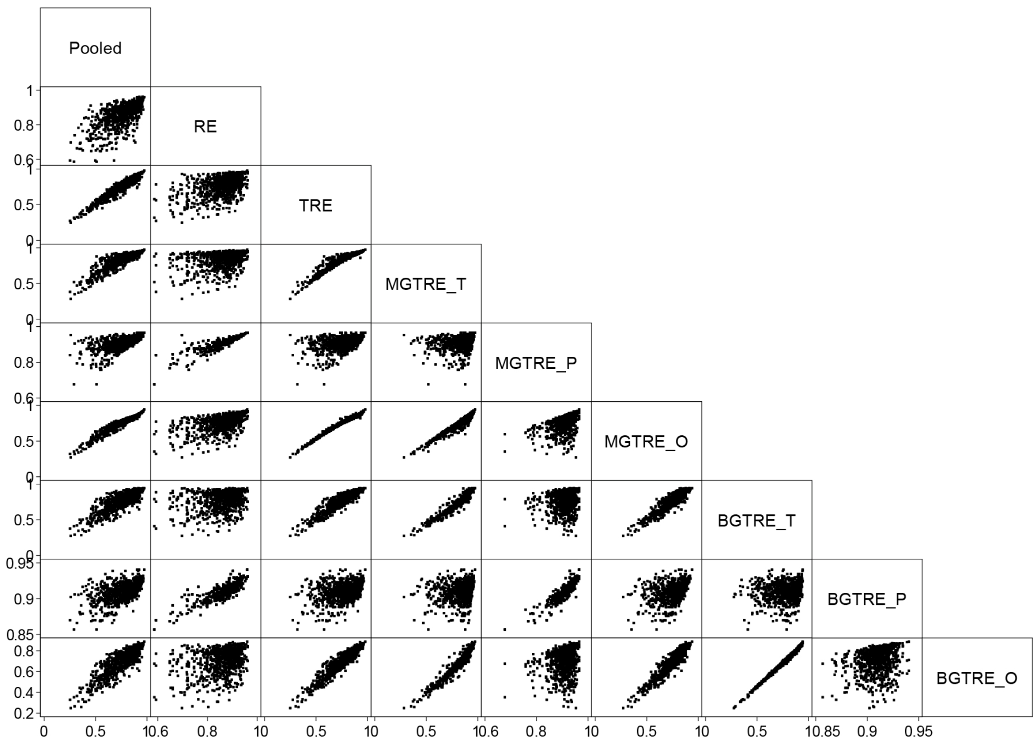

Figure 2. Scatterplot matrices of pairwise technical efficiency estimates for all models.

5. Conclusions and Policy Implications

This study estimated the transient and persistent TEs of rice farming in Vietnam's MRD using the GTRE model approach proposed by Filippini and Greene (2016). The model was estimated using both MSLE and Bayesian methods to check the robustness of parameter estimates. Models that are nested in the GTRE model (Pooled, RE, and TRE) were also estimated and compared. The unbalanced panel data set comprises 945 observations collected from 344 rice households about their production activities during three cropping seasons in 2016/17. Samples were identified using a three-stage stratified random sampling technique.

The parameter estimates of the stochastic frontier models show that the GTRE model is more appropriate than its restricted versions for modeling heterogeneity in production and the inefficiency of rice farmers, and the estimates of transient and persistent efficiencies are reliable. In particular, we compare the restricted models (Pooled, RE, and TRE) to the GTRE model using Wald tests and find that all restricted models were rejected at 5% (all p values < 0.05), confirming the presence of heterogeneity and persistent or transient inefficiency in the data set and suggesting that the restricted models are not adequate representations for the data. The estimates of variance parameters for farm heterogeneity (σ_w) and persistent inefficiency (σ_h) are statistically significant in both MSLE and Bayesian models, confirming the presence of farm heterogeneity and persistent inefficiency. The results of the MGTRE model show that the values for the first and second ratios are relatively high, with $\lambda_0 = 0.476/0.041 = 11.70$ and $\lambda = 0.326/0.094 = 3.47$. The third ratio has a value of $\Lambda = 0.476/0.326 = 1.46$. This result is relatively close to the values of scenario S4 ($\lambda_0 = 5$, $\lambda = 5$, and $\Lambda = 1$) reported in Table 6 of Badunenko and Kumbhakar (2016), revealing 'Good' reliability of transient and persistent efficiency estimates. This confirms that our estimations of transient and persistent technical inefficiencies are reliable and appropriate. Therefore, the GTRE model is preferred for estimating transient and persistent TEs. The estimated results of the MSLE and Bayesian methods are consistent, confirming the robustness of the estimates.

An analysis of partial output elasticities with respect to inputs shows that the output is inelastic with respect to all inputs and has a constant RTS (1.05), and that the output is most elastic with respect to cultivated land area (0.46). We did not find reliable evidence on the impact of rice variety on rice output, but we found strong statistical evidence on the negative effects of seasonal factors on rice outputs, with lower predicted outputs for seasons 2 (–0.292) and 3 (–0.309).

The mean overall TE of rice farming in Vietnam's MRD is approximately 0.71, with transient (short-term) efficiency being the dominant component (0.78). This suggests that rice farmers could increase their outputs if their technical inefficiencies, especially transient inefficiency, were eliminated. This research suggests that supportive policies should be targeted to address short-term and long-term inefficiencies, with short-term inefficiency as a priority. In the short term, training programs and extension services should focus on supporting rice farmers to improve soil quality and skills for dealing with rice diseases and natural disasters. In the long term, policies should focus on increasing farm size, land ownership, land defragmentation, infrastructure upgrades, and climate-smart agriculture practice adoption. In addition, the rural credit and agricultural insurance markets should be promoted to better support financial aid for rice farmers dealing with natural disasters and pest infestations and investing in farm mechanization.

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Appendix A

Table A1. Prior specification for Bayesian estimation of the GTRE model.

Parameter/Variable	Prior
Translog coefficients and intercept shifters	$\alpha, \beta_j, \beta_{jk}, \beta_l$ ~ N(0.0, 10), i.e., normally distributed with a precision (variance) of 0.1 (10)
Noise term	v_{it} ~ N(0.0, 1/*hv*), i.e., normally distributed with a precision (variance) parameter of *hv* (*1/hv*) *hv* ~ G(0.001, 0.001), i.e., the precision parameter is gamma distributed with shape and rate values of 0.001 (i.e., a mean of 1 and a variance of 1000)
Persistent and transient inefficiency terms	u_i, u_{it} ~ N(0, *h.u*)T(0,1000), i.e., normally distributed with a precision of *h.u* truncated to 0 to 1000 *h.u* ~ G(5, 10*log(*rstar*)*log(*rstar*)), where *rstar* is the expected mode of the efficiency distribution, which is usually set to 0.875 (See Griffin and Steel (2007)), giving the precision parameter a diffuse prior with a mean of 28 and a variance of about 157
Heterogeneity term	w_i ~ N(0.0, 1/*h.wi*), i.e., normally distributed with a precision (variance) parameter of *h.wi* (*1/h.wi*) *h.wi* ~ G(0.5, 1/*h.wi.prec*), where *h.wi.prec* is set to a relatively high value (4), as in Tsionas and Kumbhakar (2014), with a mean of 2 and a variance of 8

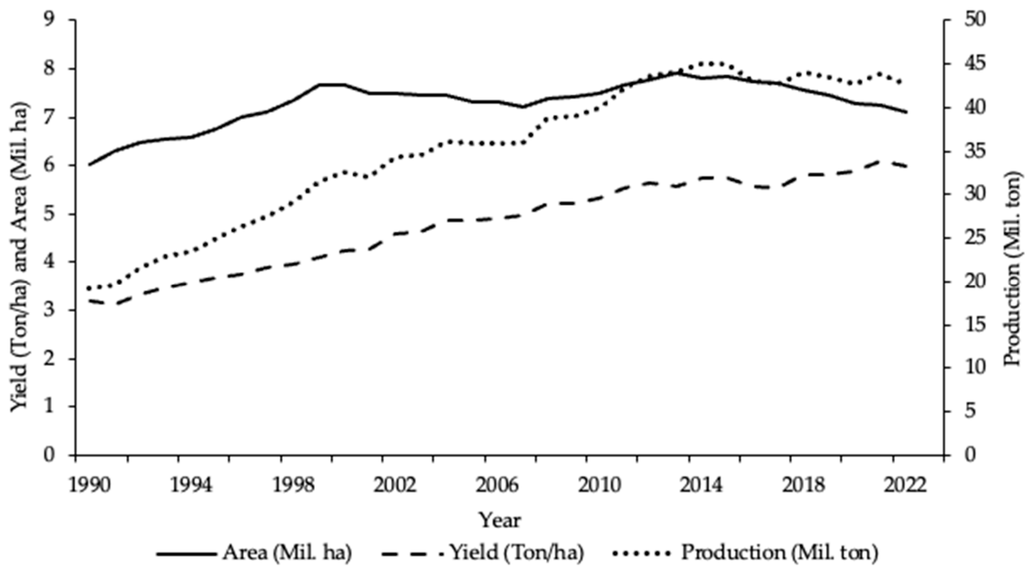

Figure A1. Planted area, yield, and production of paddy in Vietnam, 1990–2022. Source: GSO (2023b).

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