A Comparison of Stochastic Frontier Approaches to Estimating Inefficiency and Total Factor Productivity: An Application to Irish Dairy Farming

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A Comparison of Stochastic Frontier Approaches to Estimating Inefficiency and Total Factor Productivity: An Application to Irish Dairy Farming

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Abstract: This paper compares standard stochastic frontier models for panel data with a number of recently developed models designed to remove unobserved heterogeneity from the inefficiency component. Results are used to construct a generalised Malmquist total factor productivity (TFP) index. We conclude that the choice of approach makes little difference where the purpose of the study is to analyse aggregate trends in TFP and its components. However, where inefficiency estimates and their dispersion are of interest, attention should be paid to how the analyst's interpretation of inefficiency relates to the underlying assumptions of the model that is used.

Keywords: Efficiency, panel data, total factor productivity, stochastic production frontier, 'true' effects models, dairy sector

JEL Codes: D24, Q12

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1. Introduction

Estimating inefficiency using the stochastic frontier approach is particularly common in the applied literature. This approach, originally proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), and later extended to panel data by Pit and Lee (1981), defines the production technology for a particular industry using a stochastic production frontier in which output is expressed as a function of inputs, a random error component and a one-sided technical inefficiency component which captures deviations below the optimal or frontier output level. Further empirically popular extensions by Kumbhakar (1990) and Battese and Coelli (1992) (amongst others) allow technical inefficiency to vary through time. A criticism of such models is that their estimated technical inefficiency levels potentially capture unobserved firm specific factors that are unrelated to inefficiency. For example, differences in the quality of the inputs used will impact on the output of the firm. If such input quality differences are not captured by the input measure included in the production function, firms with low quality inputs will show up as being more inefficient than similar firms that have access to higher quality inputs. If the quality of the input is exogenously determined, the stochastic frontier approach will provide a biased measure for the inefficiency level of this firm. Recently, Greene (2004; 2005) proposed a new class of models termed 'true' effects models designed to remove unobserved heterogeneity from the inefficiency term.[1] These models control for unobserved heterogeneity, thus yielding an inefficiency measure that captures pure technical inefficiency.[2]

In this paper, we compare results from both sets of models in an attempt to ascertain whether the choice of model impacts on the results of interest. In particular, we focus on how each model differs in terms of the estimated production parameters and associated elasticities, the inefficiency estimates and their dispersion, and the trend in total factor productivity (TFP) computed using the parameter estimates. Using farm level panel data taken from the Irish National Farm Survey, we explore efficiency and TFP for the Irish dairy sector for the period 1996 to 2005.[3] This is a particularly appropriate application for the purpose of making such a comparison given recent policy changes altering the nature of government supports that may permanently affect the size and nature of production in the sector.

Historically, support for farmers in the EU came in the form of price maintenance through supply controls, export subsidies and import tariffs and later by subsidising production by way of direct payments. The reliance on direct payments to maintain farm incomes became particularly prevalent in the 1990s. In Irish agriculture, the proportion of direct payment to total operating surplus increased from 18 per cent in 1992 to 66 per cent in 2004 (Matthews et al. (2007)).[4] As farm incomes relied more on direct payments and less on market returns, production plans shifted accordingly and farm decisions became solely based on ways to increase the level of subsidies.

In June 2003, the EU's Council of Ministers decided to replace production linked subsidies with a Single Farm Payment (SFP) to be paid regardless of the level or existence of farming

[1] See Farsi and Filippini (2004) and Farsi et al. (2006) for applications of this model.
[2] It could be argued (as is the case in many applications) that the heterogeneity that explains efficiency differences is interesting in itself. For models that allow for analysis of the determinants of inefficiency differences see for example Kumbhakar et al. (1991) or Battese and Coelli (1995).
[3] See Newman and Matthews (2006) for results on the productivity performance of the Irish dairy sector for the period 1984-1998.
[4] For cattle and cereal farms, over 100 per cent of the family farm income came from direct payments, implying that the market revenue received for output was insufficient to cover costs (Hennessy and Thorne, 2005).

activities.[5] In order to receive the SFP, farmers are required to keep their land in good agricultural and environmental condition and to comply with a number of environmental, food safety and animal welfare standards (known as 'cross compliance'). The breath of decoupling in each member state was decided by each respective government. Ireland, like many other member states, opted for full decoupling from the first of January 2005. With decoupling, the direct link between production and subsidy is broken with the intention that farmers in the future focus solely on supplying what the market demands.[6] Such a situation in Ireland would inevitably mean the closure of many farms that fail to make an adequate return on their market operations.

The policy changes implemented in 2005 will undoubtedly change the size and composition of European agriculture for years to come. Thus, understanding the production technology, dispersion of efficiency and aggregate trend in TFP are all of interest. This application is therefore ideal for the purpose of comparing the findings from the standard and more recent stochastic frontier models which provide very different treatments of the underlying efficiency effects which in many cases are important determinants of productivity growth. The paper is laid out as follows. In section 2, we describe the stochastic frontier approach to efficiency measurement and compare the standard random effects techniques commonly applied in the literature to Greene's (2002; 2004; 2005) approach designed to separate the effects of unobserved firm heterogeneity and inefficiency. The construction of the TFP index is also presented. Section 3 describes the data. Section 4 presents the empirical results focussing on comparing findings across the various models considered. Section 5 concludes the paper with recommendations for choosing an appropriate approach based on the findings of this application.

2. Methodology[7]

A farm's level of technical efficiency refers to its ability to transform inputs into outputs relative to a sample of similar farms. A farm is deemed inefficient if it could potentially increase its output level without increasing its input level, or alternatively, reduce its input level without reducing its output level. Figure 1 presents a production frontier (PF1) given a composite input (X) and output (Y) for a sample of producers. Producers operating on the production frontier are deemed fully efficient while producers operating below the frontier display some degree of inefficiency. Formally, the Farrell (1957) measures of output-orientated and input-orientated technical efficiency for farm A are given by the ratios OYa/OY* and OX*/OXa respectively. Both of these measures are bounded between zero and one with a ratio of one representing full efficiency. Technical change is represented by a shift in the frontier from one period to the next. This is displayed in figure 1 as the shift from PF1 to PF2 (technical progress). An outward shift in the frontier implies that the best/frontier farms have become more productive. To explore whether non-frontier (inefficient) farms are also producing more requires the examination of inefficiency scores through time.

[INSERT FIGURE 1 ABOUT HERE]

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[5] The level of subsidy that each farm receives is based on production levels in previous years (2000, 2001 and 2002).

[6] In the context of World Trade Organisation (WTO) rules, the SFP qualifies as a 'green box' measure of support. In order to qualify, green box subsidies must not distort trade, or at most cause minimal distortion. Such subsidies must be government-funded and unrelated to the type, volume and price of production. In theory, the resulting overall effect on the market and trade should be equivalent to a situation in which the subsidy did not exist at all.

[7] This introductory pages of this section rely heavily on Kumbhakar and Lovell (2000) and Coelli et al. (2005).

Depending on the shape of the production frontier, a fully efficient (technically) producer may not necessarily be fully scale efficient. For example, given a production frontier displaying variable returns to scale (decreasing, increasing or constant) a producer lying on the frontier may be able to increase its productivity further by changing its scale of operations.

[INSERT FIGURE 2 ABOUT HERE]

If a producer's level of productivity (defined as outputs divided by inputs and represented by lines from the origin through the point of production) can be increased by either increasing or decreasing its scale, it is not fully scale efficient. Although a farm at point A in figure 2 is lying on the production frontier (is technically efficient), there is potential to increase its productivity by moving to point C (line S3 is steeper than S1). Point C is both technically and scale efficient. Similarly, a farm at point B is also lying on the frontier (technically efficient) but could increase its productivity by producing at point C (S3 is steeper than S2). When the production frontier displays constant returns to scale, no scale efficiencies can be exploited and all producers are automatically scale efficient.

Technical change, technical efficiency and scale efficiency parameters can be estimated empirically using stochastic frontier methodologies. The stochastic frontier model proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) was extended to panel data by Pit and Lee (1981). The model assuming a Cobb-Douglas production technology can be written as follows:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{kit} + v_{it} - u_i \tag{1}$$

where y_{it} is farm i's output level at time t, x_{kit} is a vector of K production inputs (capital, labour etc), v_{it} is a statistical noise component, u_i is a non-negative technical inefficiency component and β are coefficients to be estimated. Technical change can be accommodated by adding a time trend or annual time dummy variables to the right hand side of equation (1).

In the Pit and Lee specification, it is assumed that technical inefficiency is time-invariant. This assumption may hold in short panels but becomes less and less plausible when the number of years/periods increases. It is possible, however, that inefficient farms become more efficient over time. Similarly, in unbalanced panels, it is likely that some farms become less and less efficient through time before leaving the sample entirely (shutting down). The temporal assumption that is imposed will depend upon the length of the panel, the nature of the sample (balanced or unbalanced) and also on the competitive structure of the sector in question. Highly uncompetitive sectors may be characterised by highly fluctuating efficiency trends. In this paper we are analysing ten years of unbalanced data from a highly protected and subsidised sector which has undergone considerable structural change. In such circumstances the assumption of time-invariance is extremely unlikely. The following time-varying inefficiency specifications have been employed frequently in empirical work:

$$u_{it} = u_i / \left[1 + \exp(\alpha t + \gamma t^2)\right] \qquad \text{Kumbhakar (1990)} \tag{2}$$

$$u_{it} = u_i \times \exp\left[-\eta(t - T)\right] \qquad \text{Battese and Coelli (1992)} \tag{3}$$

where $t=1,2,\ldots,T$ is time and α, γ and η are parameters to be estimated. Both specifications allow inefficiency to follow a temporal pattern. The drawback of such specifications is that they impose the same temporal pattern of inefficiency on all farms and as such a farm's efficiency ranking would not change through time. Again, this is somewhat restrictive.

The 'true' fixed and random effects models outlined in Greene (2004; 2005) and employed by Farsi and Filippini (2004) and Farsi et al. (2006) suggest that the inefficiency term in standard stochastic frontier models is absorbing time-invariant cross-farm heterogeneity which standard models inappropriately label as inefficiency. In the true fixed effects model, unobserved heterogeneity is captured by farm-specific dummy variables. This model can be estimated using a one-step maximum likelihood approach:

$$\ln y_{it} = a_i + \sum_{k=1}^{K} \beta_k \ln x_{kit} + v_{it} - u_{it} \qquad (4)$$

where a_i are farm-specific, time-invariant dummy variables and the inefficiency term is a time-varying and completely unrestricted random variable. Whether or not a_i only captures time-invariant heterogeneity or heterogeneity combined with some time-invariant inefficiency is unsettled. For example, some of the effects of being an inferior manager may be removed from the inefficiency component by the fixed effect (if inferior management is a time-invariant characteristic of the farm). For such a farm the estimated inefficiency level is likely to be biased downwards (appears more efficient). A similar argument can be applied to farms with consistently good management.

Greene's true random effects model is similar in motivation. The model is a stochastic frontier with a random constant term. This model may be estimated using Maximum Simulated Likelihood Estimation:[8]

$$\ln y_{it} = \left(\beta_0 + w_i\right) + \sum_{k=1}^{K} \beta_k \ln x_{kit} + v_{it} - u_{it} \qquad (5)$$

where w_i is a time-invariant, farm specific random term again intended to capture cross- farm time-invariant heterogeneity. The model differs from its fixed effects counterpart in that the heterogeneity term is assumed to be uncorrelated with the production inputs. If, in fact, they are correlated, the model coefficients will be biased (this issue is unimportant if the focus of the research is only on the inefficiency estimates). Both models assume the error term is independent and identically distributed normal and the inefficiency term is independent and identically distributed half normal.

Our aim is to estimate efficiency levels in an attempt to measure the ability of individual farms to convert inputs into outputs, in effect, the management ability of farmers. Theoretically, this would require analysing farms that operate under identical resources and environments. It is reasonable to assume that the data employed in this paper is quite heterogeneous. The sample covers a wide range of dairy farms from very different geographic locations which vary significantly in terms of their time-invariant resources and environments

[8] See Greene (2004; 2005) for technical details on model estimation. Both true effects models are easily implemented in LIMDEP version 8.0 (Greene, 2003).

(soil quality, climate, drainage, altitude, technology etc.). Such factors may have a significant impact on the productivity of the farm (holding management ability fixed). Using the standard models, our search for the most productive farms would fail to consider such differences. In effect, we could potentially classify many farms as inefficient just because their time-invariant resources (unobserved) are inferior. It is possible that many very good farmers slip through the net of standard models because their fixed resources are inadequate and not properly accounted for. We explore this possibility by comparing estimates from the true effects models (true fixed effects (TFE) and true random effects (TRE)) with estimates from the standard models (Pit and Lee (PL) and Battese and Coelli (BC)). In all models we assume a translog production technology and include annual time dummy variables to capture technical change.[9] The full specification is given by equation (6).

$$\ln y_{it} = \alpha + \sum_{k=1}^{K} \beta_k \ln x_{kit} + 0.5 \sum_{k=1}^{K} \sum_{j=1}^{K} \beta_{kj} \ln x_{kit} \ln x_{nit} + \sum_{t=1}^{T} \delta_t D_t + v_{it} - \mu \tag{6}$$

PL:	$\alpha = \beta_o$	and	$\mu = u_i$
BC:	$\alpha = \beta_o$	and	$\mu = u_i \times \exp[-\eta(t - T)]$
TFE:	$\alpha = a_i$	and	$\mu = u_{it}$
TRE:	$\alpha = \beta_o + w_i$	and	$\mu = u_{it}$

where D_t are annual dummy variables.

For each model, the estimated parameters and inefficiency estimates are used to construct a generalised Malmquist index. The index follows the approach outlined by Coelli et al. (2005) where TFP change from year *s* to *t* is the product of technical change (TC) (equation 7)[10], technical efficiency change (TEC) (equation 8) and scale efficiency change (SEC) (equation 9).[11]

$$TC_{s,t} = \delta_t - \delta_s \tag{7}$$

$$TEC_{s,t} = \frac{E(\exp(-u_{it}) | e_{it}}{E(\exp(-u_{is}) | e_{is}} \tag{8}$$

$$SEC = \exp\left\{ 0.5 \sum_{n=1}^{N} [\varepsilon_{nis} SF_{is} + \varepsilon_{nit} SF_{it}] \ln(x_{nit} / x_{nis}) \right\} \tag{9}$$

where $SF_{is} = (\varepsilon_{is} - 1) / \varepsilon_{is}$, $\varepsilon_{is} = \sum_{n=1}^{N} \varepsilon_{nis}$ and $\varepsilon_{nis} = \dfrac{\partial \ln q_{is}}{\partial \ln x_{nis}}$.

[9] Annual dummies are preferred to a general time trend as we wish to capture annual movements in technical change and technical efficiency change precisely, particularly the difference between 2004 and 2005 (year of decoupling).

[10] The interpretation of technical change follows that of Cuesta (2000) (based on Caves et al. (1981)), and is calculated as the difference in the parameters of the time dummy variables in years *s* and *t*.

[11] The calculation of scale efficiency change is according to Orea (2002). See Coelli et al. (2005) p. 302.

3. Data

We employ data from the Irish National Farm Survey (NFS) which is conducted annually by Teagasc, the Irish Agricultural and Food Authority. In the survey, each farm animal and hectare of crop is assigned a standard gross margin and farms are then grouped into systems according to the dominant enterprise. Farms are selected so as to attain a representative sample of each system in Ireland. The six systems are: specialist dairy, dairy and other, cattle rearing, cattle fattening, sheep and tillage. In this paper we focus on an unbalanced panel of 772 specialist dairy farms who on average contributed to the survey for 5.6 years between 1996 and 2005.

Milk output is expressed in litres and the standard production inputs are given by capital, labour, direct costs and herd size.[12] Capital includes the stock of machinery and buildings which are based on the market value as estimated by the farmer. Labour is measured in standard man days representing the number of eight hour days supplied by persons over 18 years of age. Direct costs comprise of concentrates, feed costs, machinery operating costs and lime costs. Herd size is the average number of dairy cows.

Although farms in our data are mainly involved in dairy production, the majority of farms are also involved in either or a number of the other systems. Where inputs are not explicitly assigned to the dairy enterprise (capital, labour, machinery operating costs and lime), we allocate them according to the proportion of dairy gross output to total gross output. On average, dairy gross output accounts for 75 per cent of total gross output in our dataset. In addition, all monetary figures are deflated according to annual Irish agricultural price indexes which are available from the Irish Central Statistics Office. Descriptive statistics for all variables employed are presented in table1.

[INSERT TABLE 1 ABOUT HERE]

4. Results

The four models described in section 2 are estimated using *LIMDEP* version 8.0 (Greene, 2003). The results are presented in table 2. The magnitudes of the production parameters for each model are very similar. The true effects models (TRE and TFE) perform considerably better on the number of significant variables (particularly the TRE model). Output elasticities with respect to each input (calculated at sample means) are displayed in table 3.[13] They appear reasonably robust to model choice in that they are all of a similar magnitude and significance level (the PL and BC results are statistically identical). Increasing returns to scale is prevalent in all models with the TFE model showing higher overall returns to scale (difference is significant at 5 per cent). In terms of the standard specifications, the time-variant BC model performs no better than the time-invariant PL model (based on a log-likelihood test). This is

[12] Land area was also considered however it was found to have no effect on output (based on the estimated elasticity). This implies that increasing the level of land (while holding all other inputs fixed) would not increase the level of output. As such, land was excluded from the production function specification. Its exclusion does not affect the results obtained. An additional advantage of excluding this input in all models is that since it is fixed over time it is automatically excluded from the fixed effects model, thus easing the comparison across models.
[13] All first and second order conditions with respect to each input are positive and negative respectively at the sample mean in the PL, BC and TRE models. The second order condition for herdsize is positive in the TFE model.

not unexpected as the parameter for time-varying inefficiency is not significant which implies that there is no common temporal trend in inefficiency.[14]

[INSERT TABLES 2 AND 3 ABOUT HERE]

Results from the total factor productivity (TFP) analysis for each model are displayed in figure 3. The cumulative technical change (TC), scale efficiency change (SEC) and technical efficiency change (TEC) are displayed in figures 4, 5 and 6 respectively. The overall trend in TFP is quite similar in each model. The BC model shows the highest overall increase of just over 13 per cent while the TRE and TFE models both show an increase of around 10 per cent. The main driver of TFP is technical change and trends are again very similar for each of the applied models. The TFE model shows the largest overall increase of almost 8 per cent for the ten years (compared to just over 7 per cent for the other specifications). From figure 5 it is apparent that farms have become more scale efficient over the period (are producing at a more optimal size). Again, all models show largely similar scale efficiency change trends with the TFE model again portraying a more favourable increase (the PL model's trend is not observable in figure 5 as it is identical to that of the BC model). From figure 6 it appears that the PL, TRE and TFE models all follow the same general efficiency trend (with the exception of 1999) and display no major increase in mean efficiency over the entire period. The BC model, on the other hand, shows an overall increase in mean efficiency of around two per cent between 1998 and 2001. This explains why this model yields a higher TFP index compared with the other models. The efficiency trend in the BC model is driven by the functional form assumed for the time parameterisation of the inefficiency effect. This is worrying given that the other models yield no such trend in efficiency.

[INSERT FIGURES 3 TO 6 ABOUT HERE]

Mean inefficiency estimates and correlations are presented in tables 4 and 5 respectively. In contrast to the similarities observed in the trend in inefficiency over time across models, the mean inefficiency estimates differ considerably with the PL model showing the highest level (i.e. least efficient) followed by the BC, TFE and TRE models (these differences are again significant at 5 per cent). This result is similar to that found by Farsi et al. (2006) and is due to the presence of unobserved heterogeneity in the efficiency term of the standard models (PL and BC) and its exclusion in the TFE and TRE models.

[INSERT TABLE 4 AND 5 ABOUT HERE]

Although the mean inefficiencies for the TFE and TRE models are quite different, it is evident from the correlation matrix in table 5 that these two models are capturing very similar effects (high correlation coefficient). The PL and BC specifications also produce efficiency estimates that are highly correlated. However, the correlation coefficient between the former and the latter models differ considerably. This difference is further highlighted by examining scatter plots of the efficiency rankings from each model (see figures 7, 8 and 9).

For each farm, the difference in efficiency ranking (for all competing models) is calculated and table 6 presents the means of these differences. It is apparent that the true effects models are the most comparable in terms of efficiency rank (mean difference of 19.5), followed by the standard models (mean difference of 32.08). Again, the true effects models and the

[14] There is no statistical test available for comparing the standard models and the true effects models.

standard models differ considerably (see last four rows of table 6). Figures 10 to 13 present histograms and kernel density graphs for each of the model's inefficiency estimates. It is evident that the inefficiencies from the true effects models (figures 12 and 13) are considerably less dispersed and less erratic than the standard models (figures 10 and 11).

[INSERT FIGURES 7 TO 13 AND TABLE 6 ABOUT HERE]

The difference between the true effects and standard models capture is apparent. This is not surprising given the very different inefficiency assumptions underlying each model. The PL model assumes that inefficiency is time-invariant while the BC model assumes that all farms follow an identical efficiency trend. Both of the true effects models allow inefficiency to vary freely but also attempt to separate and remove any time-invariant unobserved heterogeneity. To illustrate this latter assumption we regress (OLS) each the efficiency estimates $(\exp(-u_{it}))$ from each model on a number of potential time-invariant factors that may influence efficiency levels. In the NFS, farms are divided into three soil qualities (1-3, with 1 indicating the highest quality, 3 the lowest). We consider whether farms with higher soil quality have higher efficiency levels. We also consider whether the use of artificial insemination (AI) and the State's extension service are characteristics that positively affect efficiency levels.[15] Results from these regressions are displayed in table 7.

[INSERT TABLE 7 ABOUT HERE]

The coefficients from the standard models (PL and BC) are of the expected sign and are highly statistically significant. Efficiency levels on these farms are positively affected by soil quality, the use of AI and contact with the extension service. The results from the true effects models differ considerably. Although the majority of the independent variables are still significant in the TRE model, the magnitude of the coefficients has declined. Furthermore, the r-squared value, although relatively small in the standard models, has also declined. In the TFE model, only the use of AI is significant (again the value is much smaller than in the standard models) and the r-squared has dropped further still. Although these variables explain efficiency in the standard models, their predictive properties have declined considerably in the true effects models. Such heterogeneity, as suggested by Greene (2004; 2005), has been removed from the inefficiency term in the true effect models (particularly the TFE).

In summary, it appears that the estimated production elasticities and the general trend in TFP are not majorly affected by the choice of model. However, where inefficiency estimates and their dispersion are of interest, greater attention should be paid to the assumptions made about the inefficiency effects. The choice of model should be based on whether we think that unobserved heterogeneity is a source of inefficiency (PL and BC models) or something that should be controlled for and thus factored out of the inefficiency component when specifying the underlying technology (TRE and TFE models).

5. Conclusion

In this paper we have applied a number of alternative panel data models to an unbalanced panel of specialised dairy farmers. These models generally yielded very similar results but it

[15] The use of AI and the extension service is in general a time-invariant characteristic of Irish dairy farms. Only six per cent of farms switched (discontinued or started) the use of extension services over the period. For AI, only 4 per cent switched.

was found that the true effects models had a higher proportion of significant variables. Output elasticities with respect to each input and overall returns to scale were also largely unaffected by model choice. All models showed increasing returns to scale at sample means (particularly the true fixed effects model) suggesting that productivity improvements are possible by increasing scale.

Unfortunately there are no statistical tests available for choosing between the true effects and standard models. It is evident that the time-varying Battese and Coelli (1992) model performs no better than the time-invariant Pit and Lee (1981) specification but we cannot statistically state whether or not the true effects models fit the data better than the standard models. The true effects models appear to perform better in terms of the number of significant variables. It is also the case that the inefficiency estimates from the true effects models have a smoother distribution and are significantly less dispersed. Choosing between the two true effects models depends on what assumptions we are willing to make about correlations between the unobserved heterogeneity and the inputs. Any correlation will lead to biased coefficients in the true random effects model (inefficiency estimates will be unaffected). Since it is possible that farmer's input choices are correlated with farm characteristics that are not observed in the data but are known to the farmer (for example, soil quality), such correlations cannot be ruled out in this application, thus favouring the fixed effects specification.

Results from these models were used to construct a generalised Malmquist productivity index which decomposes TFP changes into technical change, technical efficiency change and scale efficiency change. All models yield similar trends in terms of technical change and scale efficiency change. Technical change is the largest contributor to overall TFP. Furthermore, it is apparent that farms are becoming more scale efficient each year. This is expected given the presence of increasing returns to scale and the annual expansion of farm operations (the mean number of cows increased from 37 in 1996 to 49 in 2006) and is particularly prevalent in the true fixed effects model where returns to scale is highest. Both true effects models and the time-invariant Pit and Lee (1981) model all show the same general technical efficiency trend and display no major increase in mean efficiency over the period. Alternatively, the Battese and Coelli (1992) specification displays a general increase in mean efficiency levels, particularly between 1998 and 2001. The overall trend in TFP is quite similar in each model. The true effects models both show an increase of around 10 per cent while the Battese and Coelli (1992) model shows the highest overall increase of just over 13 per cent. The exceptional performance displayed in the latter model is most likely driven by its restrictive parameterisation.

Analysis of mean inefficiency estimates, correlations and rankings illustrate the extent of the differences in the interpretation of inefficiency in each model. Greene (2004; 2005) suggests that the inefficiency term in standard stochastic frontier models is absorbing time-invariant cross farm heterogeneity which is inappropriately being labelled as inefficiency. The 'true' fixed and random effects models attempt to remove this unobserved heterogeneity from the inefficiency term. This is an appealing quality for benchmarking research and we have suggested that this could lead to a fairer description of efficiency levels, particularly in very heterogeneous panel datasets. A drawback of these models is that they could also remove any time-invariant inefficiency. The choice of model should be based on whether we think that the unobserved heterogeneity is primarily capturing time-invariant inefficiency or other time-invariant factors not related to inefficiency. If the temporal trend in efficiency is the sole concern of the research (and not the overall mean) the choice of model may be less critical.

References

Aigner, D., Lovell, C. and Schmidt, P. (1977). "Formulation and Estimation of Stochastic Frontier Production Function Models", *Journal of Econometrics*, 6(1), 21-37.

Battese, G. and Coelli, T. (1992). "Frontier Production Functions, Technical Efficiency and Panel Data: With an Application to Paddy Farmers in India", *Journal of Productivity Analysis*, 3, 153-169.

Battese, G. and Coelli, T. (1995). "A Model for Technical Inefficiency Effects in a Stochastic Frontier Function for Panel Data", *Empirical Economics*, 20, 325-332.

Caves, D., Christensen, L. and Swanson, J. (1981). "Productivity growth, scale economies, and capacity utilisation in U.S. railroads 1955-74", *American Economic Review*, 71, 994-1002.

Coelli, T., Rao, D., O' Donnell, C. and Battese, G. (2005). *An Introduction to Efficiency and Productivity Analysis* (second edition). Springer: New York.

Cuesta, R. (2000). "A Production Model With Firm-Specific Temporal Variation in Technical Inefficiency: With Application to Spanish Dairy Farms", *Journal of Productivity Analysis*, 13, 139-158.

Farsi, M. and Filippini, M. (2004). "Regulation and measuring cost efficiency with panel data models: application to electricity distribution utilities", *Review of Industrial Organisation*, 25, 1-19.

Farsi, M., Filippini, M. and Greene, W. (2006). "Application of panel data models in benchmarking analysis of the electricity distribution sector", *Annals of Public and Cooperative Economics*, 77(3), 271-290.

Farrell, M. (1957). "The measurement of productive efficiency", *Journal of the Royal Statistical* Society, 120, 253-281.

Greene, W. (2003). *LIMDEP version 8.0*. Econometric Software Inc: New York

Greene, W. (2004). "Distinguishing between heterogeneity and inefficiency: stochastic frontier analysis of the World Health Organization's panel data on national health care systems", *Health Economics*, 13(10), 959-980.

Greene, W. (2005). "Fixed and random effects in stochastic frontier models", *Journal of Productivity Analysis*, 23, 7-32.

Hennessy, T. and Thorne, F. (2005). "How decoupled are decoupled payments? The evidence from Ireland", *EuroChoices*, 4(3), 30-34.

Kumbhakar, S. (1990). "Production Frontiers, Panel Data, and Time-Varying Technical Inefficiency", *Journal of Econometrics*, 46, 201-212.

Kumbhakar, S. and Lovell, C. (2000). *Stochastic Frontier Analysis*. Cambridge University Press: Cambridge.

Kumbhakar, S., Ghosh, S. and McGuckin, J. (1991). "A Generalised Production Frontier Approach for Estimating Determinants of Inefficiency in US Dairy Farms", *Journal of Business and Economic Statistics*, 9(3), 279-286.

Matthews, A., Newman, C. and Thorne, F. (2007). "Productivity in Irish Agriculture", In *Perspectives on Irish Productivity*. Forfás: Dublin.

Meeusen, W. and van den Broeck, J. (1977). "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error", *International Economic Review*, 18(2), 435-444.

Newman, C. and Matthews, A. (2006). "The Productivity Performance of Irish Dairy Farms 1984-2000: A Multiple Output Distance Function Approach", *Journal of Productivity Analysis*, 26, 191–205.

Orea, L. (2002). "Parametric decomposition of a generalised Malmquist productivity index", *Journal of Productivity Analysis*, 18, 5-22.

Pitt, M. and Lee, L. (1981). "Measurement and Sources of Technical Efficiency in the Indonesian Weaving Industry", *Journal of Development Economics*, 9, 43-64.

Tables

Table 1: Descriptive Statistics

	Mean	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
MILK (litres)	199,845	150,978	2.25	11.67	10,092	1,536,860
HERD (number of cows)	41.38	27.05	2.02	10.23	3.50	248.57
DIRECT (euro)	16,511	13,876	3.09	20.97	204.33	178,082
CAPITAL (euro)	43,113	42,876	3.77	30.44	257.82	605,801
LABOUR (mandays)	278.80	153.71	1.94	9.26	42.41	1,388.58

Table 2: Model Results

	PL[a]		BC		TRE		TFE	
Production parameters and standard errors (in parenthesis)								
CONSTANT	*** 0.154	(0.008)	*** 0.153	(0.008)	-	-	-	-
HERD	*** 0.658	(0.015)	*** 0.658	(0.015)	*** 0.645	(0.006)	*** 0.657	(0.013)
CAPITAL	*** 0.072	(0.005)	*** 0.072	(0.005)	*** 0.074	(0.002)	*** 0.070	(0.004)
LABOUR	*** 0.087	(0.013)	*** 0.087	(0.013)	*** 0.088	(0.006)	*** 0.061	(0.009)
DIRECT	*** 0.227	(0.007)	*** 0.228	(0.007)	*** 0.215	(0.003)	*** 0.283	(0.007)
HERD*HERD	* 0.064	(0.038)	* 0.065	(0.038)	*** 0.078	(0.015)	*** 0.143	(0.025)
HERD*CAPITAL	***-0.052	(0.017)	***-0.052	(0.017)	***-0.071	(0.007)	***-0.059	(0.013)
HERD*LABOUR	-0.076	(0.052)	-0.076	(0.052)	***-0.064	(0.019)	***-0.180	(0.035)
HERD*DIRECT	-0.048	(0.031)	-0.049	(0.031)	***-0.069	(0.014)	***-0.133	(0.028)
CAPITAL*CAPITAL	0.002	(0.004)	0.002	(0.004)	*** 0.005	(0.002)	*** 0.008	(0.003)
CAPITAL*LABOUR	0.022	(0.014)	0.021	(0.014)	*** 0.031	(0.006)	*** 0.061	(0.012)
CAPITAL*DIRECT	* 0.018	(0.010)	* 0.018	(0.010)	*** 0.016	(0.005)	0.003	(0.010)
LABOUR*LABOUR	**-0.080	(0.025)	***-0.080	(0.025)	***-0.076	(0.009)	-0.015	(0.016)
LABOUR*DIRECT	*** 0.088	(0.026)	*** 0.088	(0.026)	*** 0.085	(0.012)	*** 0.078	(0.024)
DIRECT*DIRECT	0.001	(0.010)	0.001	(0.010)	0.000	(0.005)	*** 0.039	(0.012)
Annual dummy parameters and standard errors (in parenthesis)								
1997	0.011	(0.009)	0.011	(0.009)	** 0.009	(0.004)	0.008	(0.006)
1998	***-0.029	(0.009)	***-0.028	(0.009)	***-0.031	(0.004)	***-0.030	(0.007)
1999	*-0.014	(0.008)	-0.013	(0.008)	***-0.016	(0.004)	-0.011	(0.007)
2000	** 0.020	(0.008)	** 0.019	(0.008)	*** 0.016	(0.004)	*** 0.027	(0.006)
2001	*** 0.050	(0.008)	*** 0.050	(0.008)	*** 0.049	(0.004)	*** 0.054	(0.006)
2002	*** 0.030	(0.008)	*** 0.030	(0.008)	*** 0.028	(0.004)	*** 0.034	(0.006)
2003	*** 0.060	(0.008)	*** 0.060	(0.008)	*** 0.059	(0.004)	*** 0.061	(0.006)
2004	*** 0.079	(0.008)	*** 0.079	(0.008)	*** 0.078	(0.004)	*** 0.086	(0.006)
2005	*** 0.063	(0.008)	*** 0.063	(0.008)	*** 0.062	(0.004)	*** 0.071	(0.006)
Variance parameters for compound error								
SIGMA(V)	0.083	-	0.083	-	0.063	-	0.128	-
SIGMA(U)	0.235	-	0.236	-	0.091	-	0.242	-
LAMBDA	*** 2.809	(0.184)	*** 2.821	(0.012)	*** 1.441	(0.034)	*** 1.891	(0.067)
Parameter for time varying inefficiency								
ETA	-	-	-0.003	(0.003)	-	-	-	-
Means for random parameters								
CONSTANT	-	-	-	-	*** 0.031	(0.003)	-	-
Scale parameters for dists. of random parameters								
CONSTANT	-	-	-	-	*** 0.135	(0.001)	-	-
Log likelihood values								
	2567.475	-	2567.812	-	1674.262	-	2579.417	-

[a] PL, BC, TRE and TFE indicate Pit and Lee (1981), Battese and Coelli (1992), 'true' random effects and 'true' fixed effects specifications respectively. *** indicates significance of 1 per cent, ** at 5 per cent and *** at 10 per cent. All inputs have been divided by their means and converted into logs

Table 3: Elasticities and Returns to Scale

	PL		B&C		TRE		TFE	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
HERD	0.686	0.052	0.685	0.052	0.680	0.065	0.698	0.089
CAPITAL	0.075	0.012	0.074	0.012	0.079	0.018	0.065	0.019
LABOUR	0.103	0.067	0.103	0.067	0.094	0.059	0.063	0.060
DIRECT	0.210	0.034	0.210	0.034	0.209	0.024	0.272	0.035
RTS	1.074	0.064	1.074	0.064	1.063	0.071	1.098	0.059

Table 4: Mean inefficiency estimates for all models

	Mean	Standard Deviation	Skewness	Kurtosis	Minimum	Maximum
PL	0.245	0.088	0.675	3.950	0.031	0.611
BC	0.199	0.127	0.716	3.293	0.009	0.726
TRE	0.072	0.039	3.139	24.583	0.009	0.537
TFE	0.156	0.045	2.732	23.116	0.037	0.682

Table 5: Correlation matrix of inefficiency estimates

	PL	BC	TRE	TFE
PL	1.00	-	-	-
BC	0.92	1.00	-	-
TRE	0.27	0.26	1.00	-
TFE	0.08	0.07	0.94	1.00

Table 6: Mean difference in efficiency rank between models

	Mean Difference in Efficiency Rank	Standard Deviation
PL Vs BC	32.08	26.32
TRE Vs TFE	19.50	25.33
TFE VS BC	105.93	77.54
TRE Vs BC	92.95	75.21
TRE Vs PL	106.73	75.84
TFE Vs PL	95.15	72.37

Table 7: OLS regressions of efficiency estimates

	PL		BC		TRE		TFE	
	Model parameters and standard errors (in parenthesis)							
CONSTANT	*** 0.780	(0.003)	*** 0.817	(0.005)	*** 0.928	(0.002)	*** 0.854	(0.002)
SOIL2 (DV) [b]	***-0.020	(0.002)	***-0.033	(0.003)	***-0.004	(0.001)	-0.002	(0.001)
SOIL3 (DV)	***-0.038	(0.004)	***-0.062	(0.006)	*-0.004	(0.002)	-0.001	(0.002)
AI (DV)	*** 0.022	(0.003)	*** 0.032	(0.004)	*** 0.007	(0.001)	*** 0.005	(0.002)
EXTENSION (DV)	*** 0.008	(0.002)	*** 0.018	(0.003)	0.002	(0.001)	0.000	(0.001)
	R-Squared							
	0.060		0.073		0.011		0.004	

[b] DV stands for dummy variable. Descriptive statistics for all independent variables employed are available from the author

Figures

Figure 1: Production frontier, technical efficiency and technical change

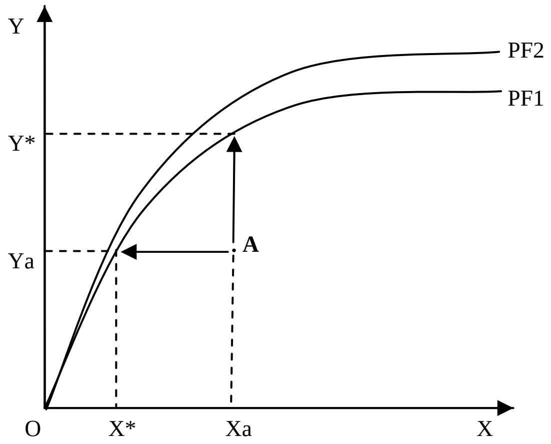

Figure 2: Scale efficiencies under variable returns to scale

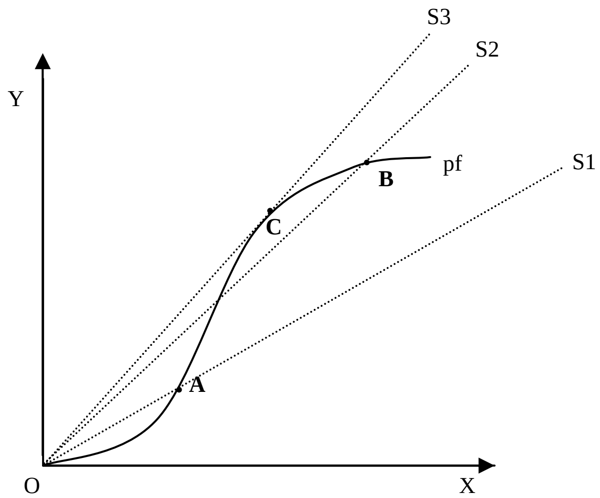

Figure 3: Cumulative total factor productivity (TFP) change, 1996-2005.

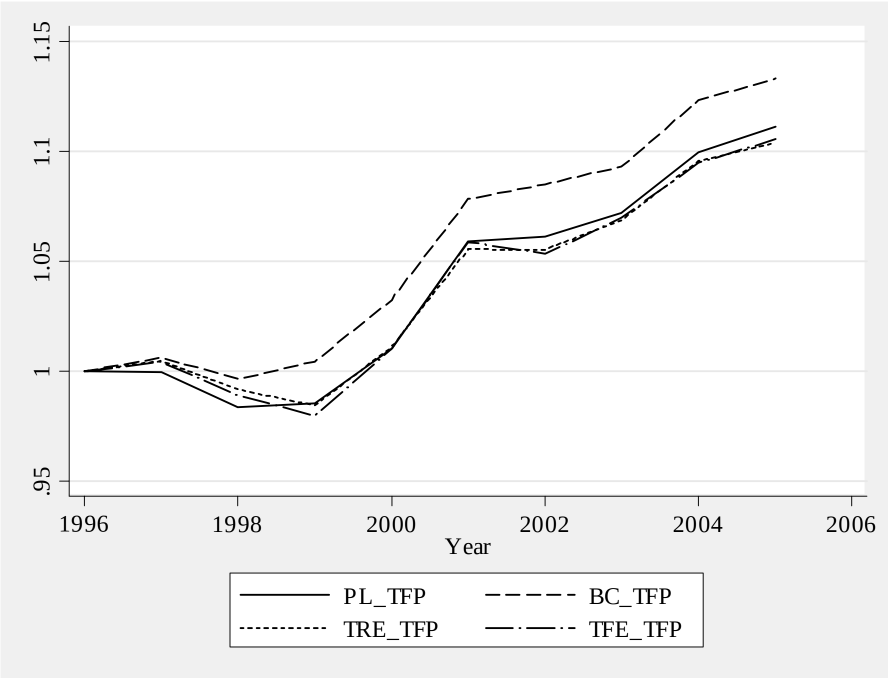

Figure 4: Cumulative technical change (TC) index for each model, 1996-2005.

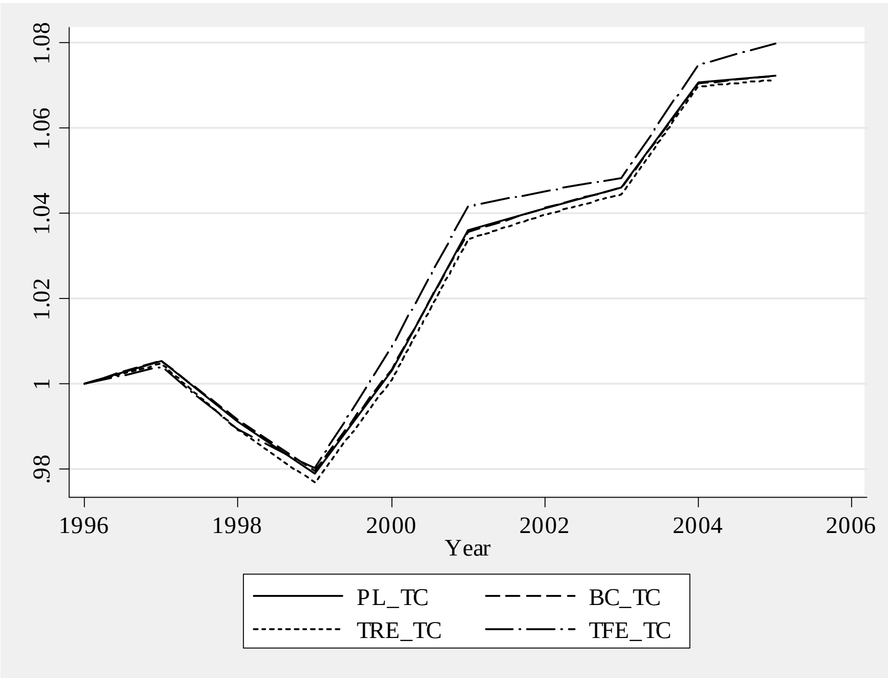

Figure 5: Cumulative scale efficiency change (SEC) index for each model, 1996-2005.

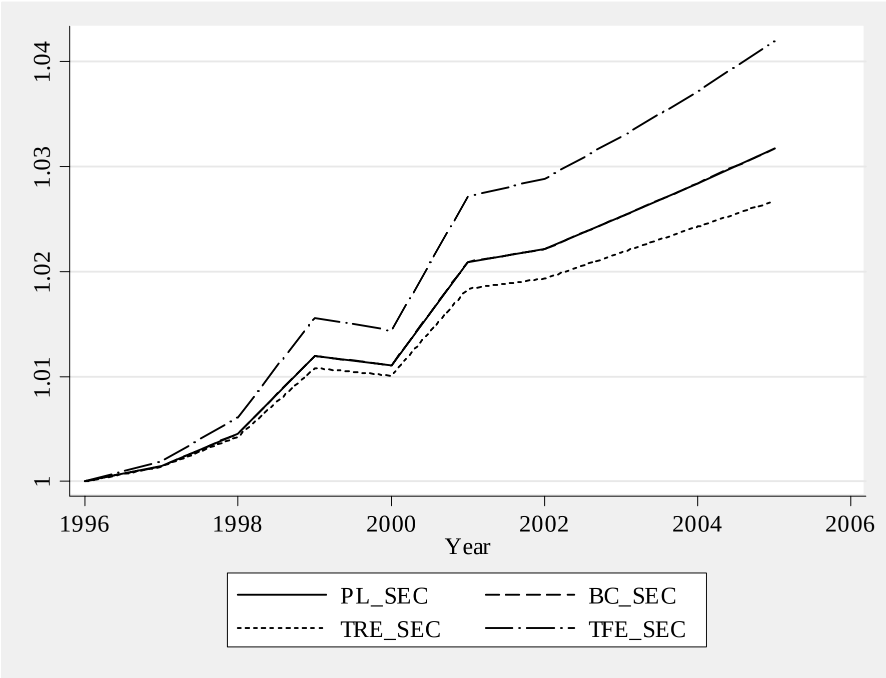

Figure 6: Cumulative technical efficiency change (TEC) for each model, 1996-2005.

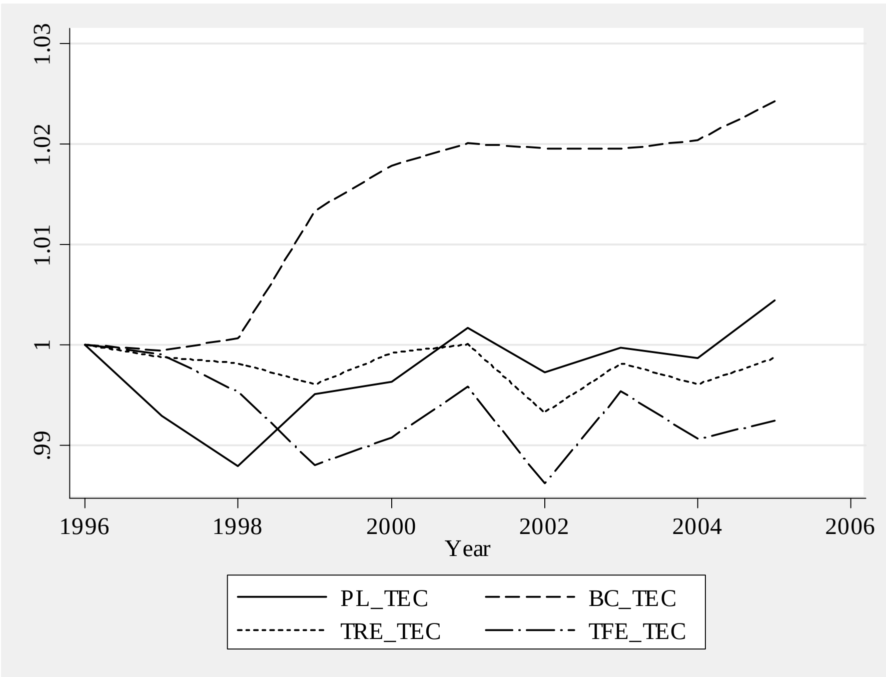

Figure 7: Scatter plot of ‘true’ random and fixed effects efficiency ranks

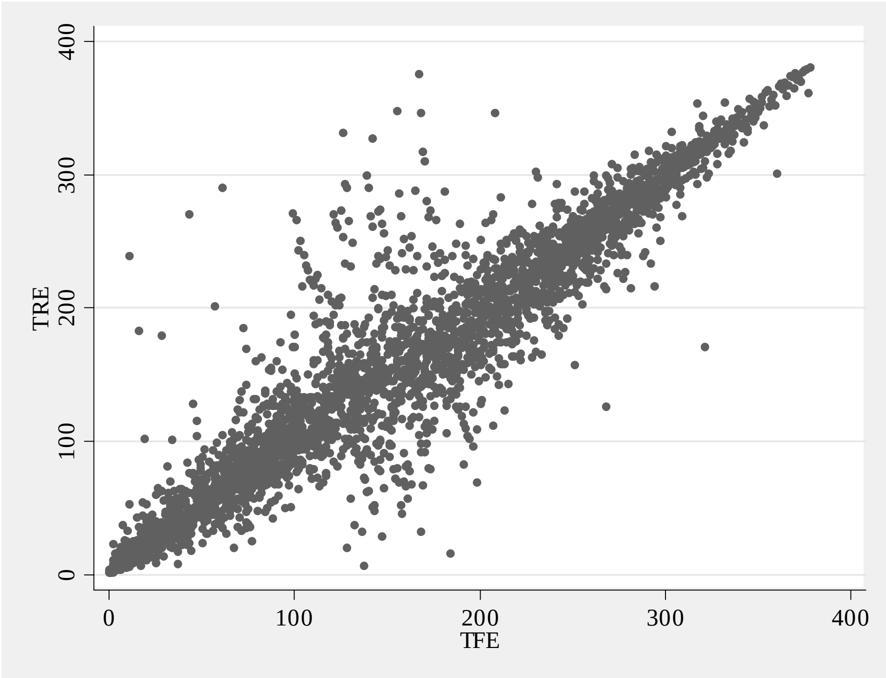

Figure 8: Scatter plot of Pit and Lee and Battese and Coelli efficiency ranks

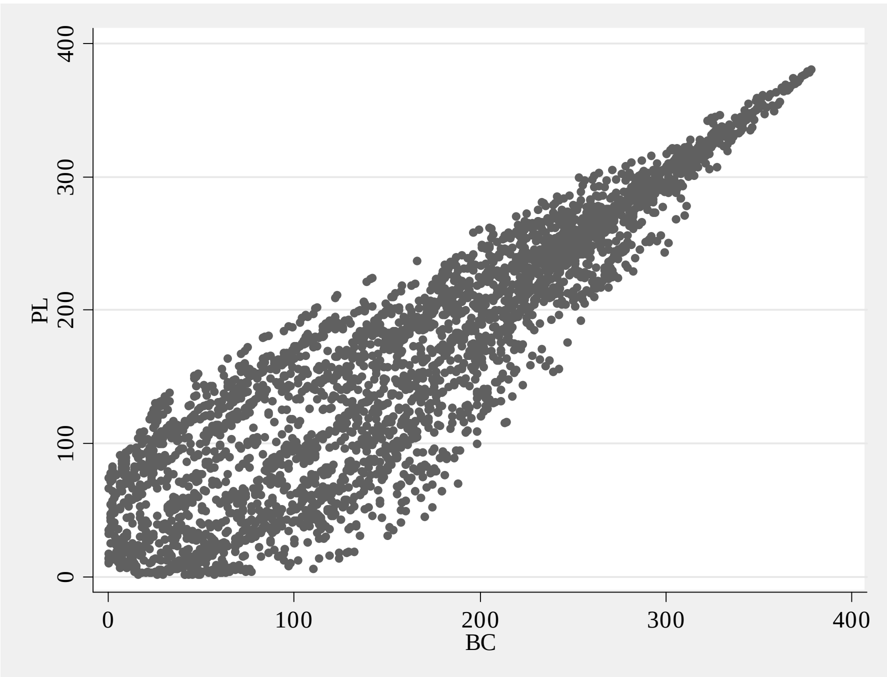

Figure 9: Scatter plot of ‘true’ random effects and Battese and Coelli efficiency ranks

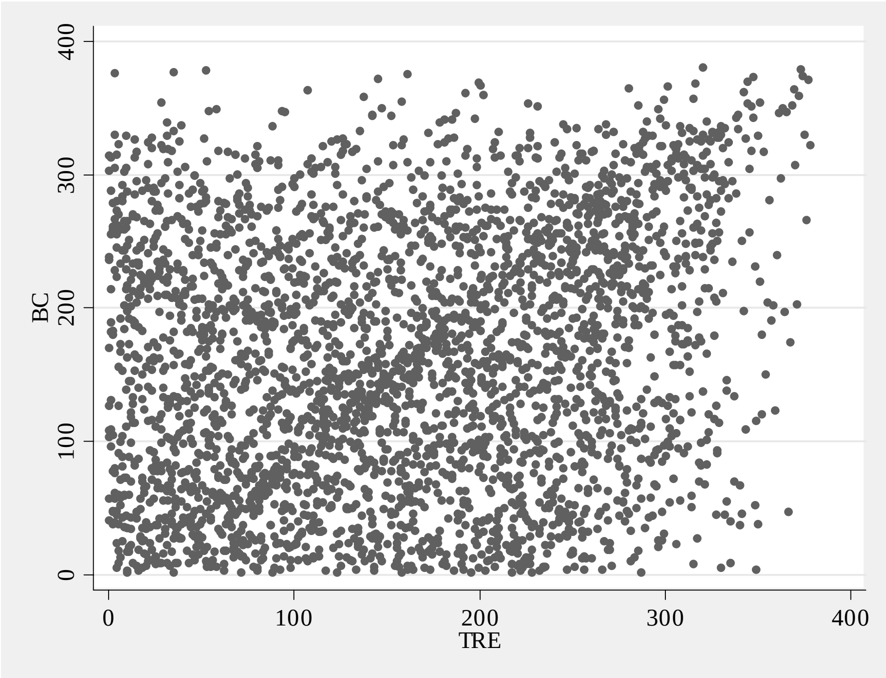

Figure 10: Histogram and kernel density of Pit and Lee (PL) inefficiency estimates

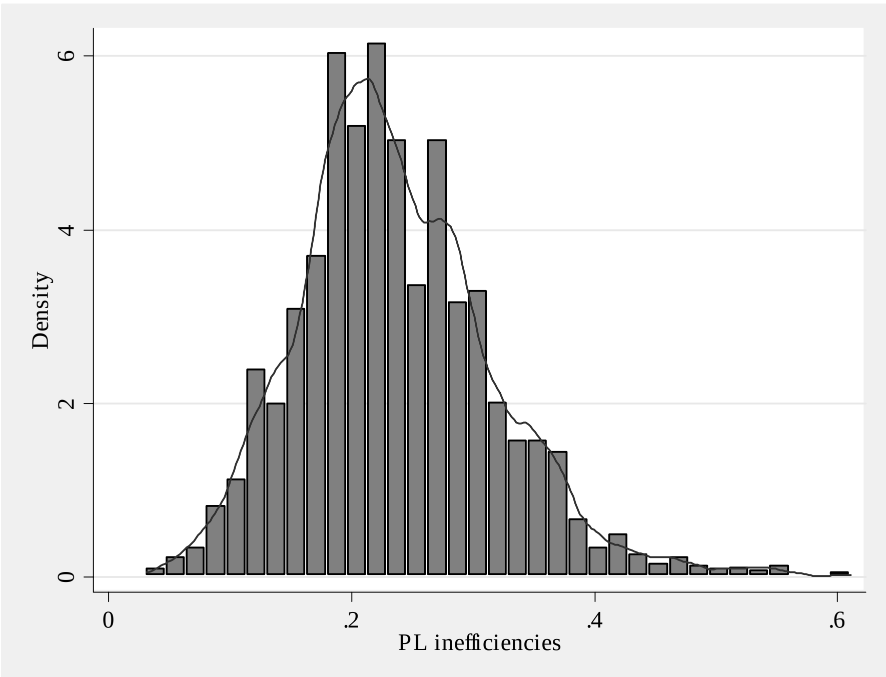

Figure 11: Histogram and kernel density of Battese and Coelli (BC) inefficiency estimates

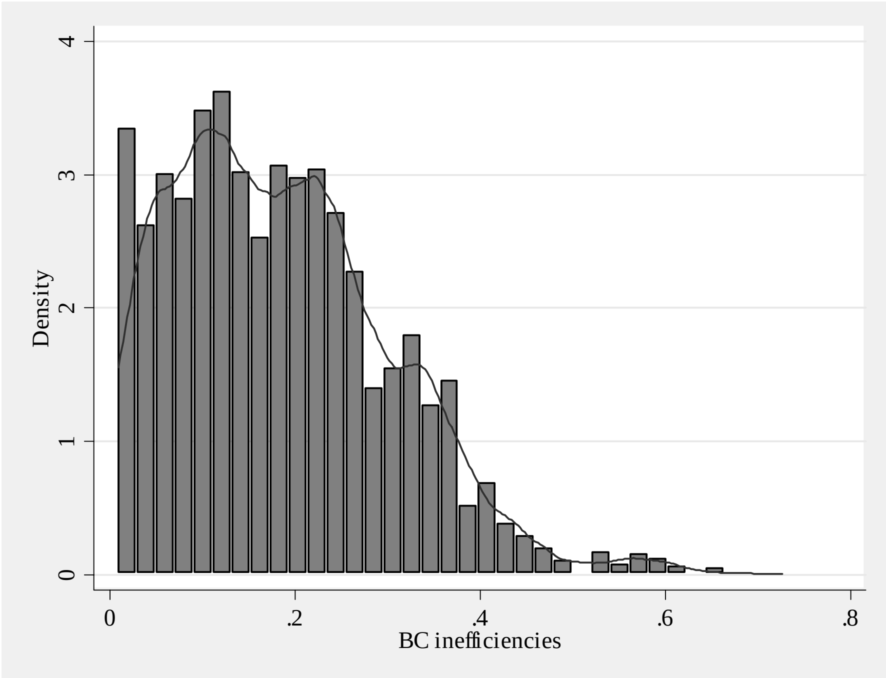

Figure 12: Histogram and kernel density of ‘true’ random effects (TRE) inefficiency estimates

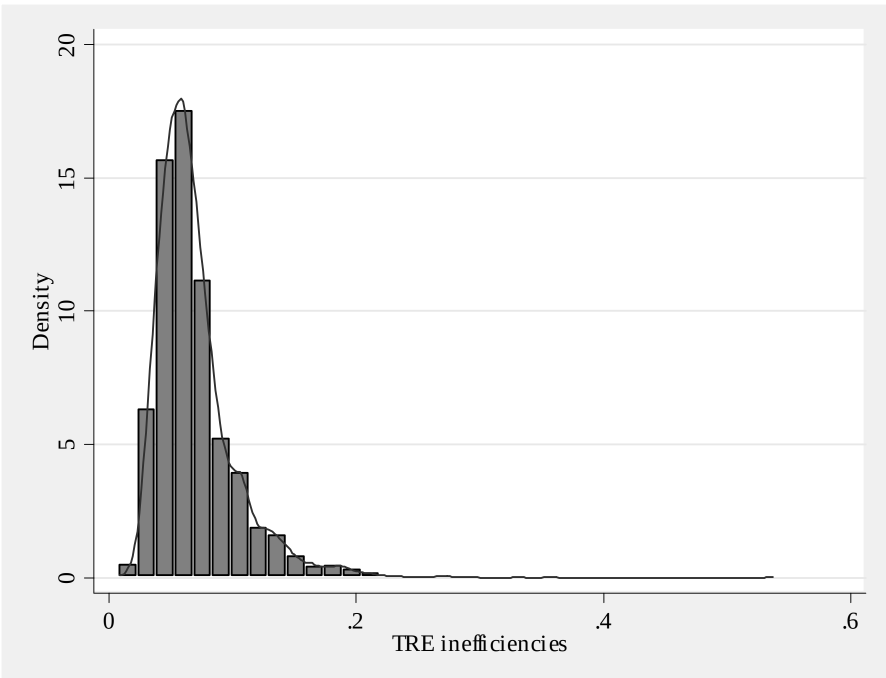

Figure 13: Histogram and kernel density of ‘true’ fixed effects (TFE) inefficiency estimates