A Stochastic Frontier Analysis on Firm-level Total Factor Productivity and Technical Efficiency in Korea

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Abstract

The conventional index number approach to the analysis of total factor productivity cannot distinguish between a shift of production function (technical progress) and a movement along a production function (technical efficiency). This paper attempts to separate technical efficiency from the productivity measurement using the econometric approach based on the stochastic frontier production models. This study will be limited to the models that take firms' heterogeneity into account because most of the available panel data consist of a large cross-section and relatively short time series. To the extent that firms' production is characterized by heterogeneous production conditions, estimation techniques that do not account for unobserved heterogeneity lead to biased efficiency estimates. The sources of total factor productivity growth are decomposed into technical progress, the changes in technical efficiency, the changes in allocative efficiency, and the scale effects by using the estimated parameters in the stochastic-frontier production models.

Keywords: Productivity decomposition, Technical efficiency, Stochastic frontier production model

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I. Introduction

Productivity is an important indicator that represents the growth of each economic agent. By utilizing data on productivity by country or industry as the OECD database or EU KLEMS, the productivities of several countries are compared and large-scale researches are actively conducted in order to consistently discuss productivity measures and computing methodologies. Japan's RIETI has developed the Japan Industrial Productivity Database (JIP Database) and is carrying out researches on productivity and other activities that could improve statistical data by initiating projects that promote the productivity of several industries or firms. Korea also, with the Korea Productivity Center as the central figure, has been building up a Korea Industrial Productivity Database (KIP Database). Until today, productivity analysis by industry has been predominant. However, many researchers analyzing productivity point out that the existing approaches are quite limited because they do not reflect the characteristics of a firm, which is the standard unit that makes actual decisions and implements economic activities. Existing approaches are limited to either establishment-level analysis or comparative analysis on the industry unit. It is necessary, therefore, to analyze productivity using the firm-level micro data.

In researches on firms, what has been actively researched recently, together with researches on productivity, is the analysis on technical efficiency of a firm. Inefficiency occurs from a firm's external and internal factors. A firm should begin by striving to identify such internal factors of inefficiency in order to eliminate these factors and thereby enhance its competitiveness and achieve long-run growth. This is why it is necessary to analyze the efficiency of Korean firms and researches on the determinants that promote efficiency.

The objectives of this paper are to discuss empirical and theoretical issues related to identifying and estimating the sources of firms' productivity growth and technical efficiency in terms of econometric approaches. By its construction, the index number analysis approach, which is the mainstay methodology of productivity analysis, cannot distinguish between a production function shift, which means technical progress, and a movement along a production function, which means changes in technical efficiency. The econometric approach is a flexible technique not only for identifying the sources of productivity growth but also for considering the technical efficiency of firms by explicitly specifying the underlying production (or cost or profit) structure. Therefore, this paper attempts to separate technical efficiency from the productivity measurement using the econometric approach, especially the stochastic frontier production models. By using stochastic frontier models, technical efficiency can be directly estimated, and the estimated parameters of the underlying structure are used to derive an index of total factor productivity growth.

In the following Section II, we describe the Kumbhakar (2000) method and adopted stochastic frontier models for the decomposition of TFP. Then Section III presents the results of an empirical analysis including econometric results with the summary description of database. Finally, we summarize conclusions in Section IV.

II. The Stochastic Frontier Production Models and Decomposition of TFP

Kumbhakar (2000) addresses the estimation and decomposition of TFP change using micro panel data in a parametric framework. The Solow (1957) measure of productivity change, and thus the index number analysis approach, is widely used for measuring TFP, but this approach is nothing but the index of technical change when the constant returns to scale (CRS) production technology and perfect efficiency are assumed. If efficiency change is omitted from the analysis, its omission will lead to an overstatement of the unexplained residual. Kumbhakar (2000) focuses on the parametric econometric modeling of production systems and the estimation of TFP changes from the empirical production, cost, and profit functions. Furthermore, TFP change is decomposed into the technical-change, scale economies, and technical- and allocative-inefficiency components. The contributions of the technical- and allocative-inefficiency effects are separately identified and estimated.

Starting with the deterministic production frontier,

$$y_{it} = f(x_{it}, t; \beta)\exp(-u_{it}),\ i = 1, 2, ..., N,\ t = 1, 2, ..., T \tag{1}$$

where y_{it} is the output for firm i at time t, $f(x_{it}, t; \beta)$ the deterministic stochastic production frontier with the technology parameter vector to be estimated, x_{it} an input vector, t a time trend serving as a proxy for technical change, and $u_{it} \geq 0$ the technical inefficiency. Totally differentiating the logarithm y in equation (1) with respect to time[1],

$$\begin{aligned} \dot{y} &= \frac{d \ln f(x,t)}{dt} - \frac{du}{dt} \\ &= TP + \sum_j \varepsilon_j \dot{x}_j - \frac{du}{dt} \end{aligned} \tag{2}$$

where $\varepsilon_j = \dfrac{\partial \ln f(x,t)}{\partial \ln x_j}$. A conventional Divisia index of productivity (TFP) change is defined as the difference between the rate of change in the output and the rate of change in the input quantity index, and so

$$T\dot{F}P = \dot{y} - \sum_j S_j \dot{x}_j \tag{3}$$

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[1] For simplicity, the "it" subscripts will be omitted from this point onward.

where S_j denotes the observed expenditure share of input j. By inserting equation (3) in equation (2), the growth of TFP can be represented as

$$\begin{aligned} \dot{y} &= \frac{d\ln f(x,t)}{dt} - \frac{du}{dt} = TP + \sum_j \varepsilon_j \dot{x}_j - \frac{du}{dt} = T\dot{F}P + \sum_j S_j \dot{x}_j \\ \therefore T\dot{F}P &= TP - \frac{du}{dt} + \sum_j (\varepsilon_j - S_j)\dot{x}_j \\ &= TP - \frac{du}{dt} + (RTS-1)\sum_j \lambda_j \dot{x}_j + \sum_j (\lambda_j - S_j)\dot{x}_j \end{aligned} \tag{4}$$

where $RTS = \sum_j \varepsilon_j$ denotes the returns to scale and $\lambda_j = \varepsilon_j / \sum_k \varepsilon_k = \varepsilon_j / RTS$. Thus, in equation (4), TFP growth can be decomposed into technical change (TC), technical-efficiency change (TE), scale effects (SE), and allocative-efficiency change (AE).

Many literatures show that recent domestic researches attempt to analyze productivity by applying Kumbhakar (2000). However, despite the fact that care should be taken in measuring technical efficiency, since the characteristics of Kumbhakar (2000)'s methodology are such that the results of productivity analyses are affected depending on how the method of measuring the estimated value of changes in technical efficiency is designed, this fact has not been sufficiently taken into account. The limitations of such literatures are summarized as follows. First, as mentioned previously, the stochastic frontier models that are used in the existing literatures are very limited. Table 1 shows that all, except Lee and Pyo(2007), estimated efficiency by employing Battese and Coelli(1992). This is only a part of stochastic frontier models that are already known. The model itself has existing limitations. Existing models have continued to be improved and more rational models have continued to be developed, but these have seldom been reflected in domestic researches. Second, it is necessary to establish and accurately use stochastic frontier models that are suitable to the given research objectives and to the characteristics of data being used. The frequently used Battese and Coelli (1992) model, for instance, has the advantages of estimating the changes of time-varying efficiency being taken into account. However, it is limited in that efficiency of all sample firms demonstrates the same time-varying pattern. By using the cross-section data models in the analysis using panel data, it sometimes commits error because it cannot utilize the advantages that panel data have.

Table 1 Empirical Studies on Korea's TFP Decomposition Using Kumbhakar (2000)

Study	Industry	Period	Cross-section	Observations	Production Technology	Stochastic Frontier Model	Dependent Variable	Time-varying Component	Results
Kim and Han (2001)	Manufacturing	1980-1994	508 Listed Companies	6,203	Translog Function	Battese and Coelli (1992)	Value-added	○	● Productivity growth was driven mainly by technical progress ● Changes in technical efficiency had a significant positive effect ● Allocative efficiency had a negative effect.
Kang and Park(2004)	Total Industry	1995-2002	2223 Firms	17,784	Translog Function	Battese and Coelli (1992)	Sales	○	● Since financial crisis, restructuring mainly depended on an increase in the total factor productivity by reducing employment and selling assets without significant increase in TFP.
Han(2005)	Manufacturing	1986-2000	358 Listed Companies	5,370	Translog Function	Battese and Coelli (1992)	Sales	○	● The Contribution of technical progress was higher than that of technical efficiency improvement in the TFP growth. ● The industries with higher(lower) rate of technical change experienced the lower(higher) rate of technical efficiency change.

Lee and Pyo(2007)	Total Industry	1984-1997	32 Industries	448	Translog Function	Lee (2006)	Gross Output	○	● Productivity growth was driven mainly by changes in technical efficiency in 1980s. ● Productivity growth was driven mainly by technical progress in 1990s.
Pai(2007)	IT Manufacturing	1992-2004	Establishments	21,681	Translog Function	Battese and Coelli (1992)	Value-added	○	● The productivity growth of IT manufacturing was driven mainly by technical progress. ● Poor technical and allocative efficiency hindered the productivity growth.
Kang and Lee(2008)	Port-Logistics Industry	1990-2003	10 Industries	140	Translog Function	Battese and Coelli (1992)	Value-added	○	● The main component of TFP growth is not efficiency change but technical progress.

As previously stated, many stochastic frontier models have been developed for the estimation of technical efficiency, and it is important to choose the most appropriate model or the one that is most suitable for the purpose of analyzing the available data. This study was limited to the consideration of the models that take into account firms' heterogeneity because the used data consist of a large cross-section and relatively short time series. Also due to the short time series, the models that consider the time-varying pattern of technical efficiency were excluded in this analysis even though such models are currently the state-of-the-art models. All the models are based on the specification given in equation (5).

$$y_{it} = \alpha_0 + \mathbf{x'_{it}}\boldsymbol{\beta} - u_{it} + v_{it}, i = 1, 2, ..., N, t = 1, 2, ..., T \tag{5}$$

This model postulates that the error term $v_{it} - u_{it}$, is made up of both the statistical-noise term v_{it}, a two-sided error term representing the usual statistical noise found in any relationship, and of the one-sided error term $u_{it} \geq 0$ representing technical inefficiency. The frontier is $\alpha_0 + \mathbf{x_{it}'}\boldsymbol{\beta} + v_{it}$, which is stochastic because it includes v_{it}.

The differences among the alternative models are related to the assumptions imposed on the stochastic components. Table 2 summarizes the five models that are used in this paper. The first model is a fixed-effects model following Schmidt and Sickles (1984). This model can be defined as below.

$$y_{it} = \alpha_i + \mathbf{x'_{it}}\boldsymbol{\beta} + v_{it}, \alpha_i = \alpha_0 - u_i \tag{6}$$

$$\begin{aligned} y_{it} &= \max(\alpha_i) + \mathbf{x'_{it}}\boldsymbol{\beta} + v_{it} + [\alpha_i - \max(\alpha_i)] \\ &= a + \mathbf{x'_{it}}\boldsymbol{\beta} + v_{it} - u_i,\ u_i = \max(\alpha_i) - \alpha_i \geq 0 \end{aligned} \tag{7}$$

The most efficient firm's u_i in the sample is 0, and the estimated efficiency in this model is not an absolute but a relative value. The fixed-effects specifications are estimated as "within" estimators without any additional distributional assumption regarding α_i since they are treated as firm constants.

Model 2 is the Pitt and Lee (1981) model specified in line with the Mundlak (1978) formulation. Pitt and Lee (1981) introduced the maximum-likelihood estimator in equation (5) by making some assumptions. They take distributional assumptions on two error terms, $v_{it} \sim i.i.d\ N(0, \sigma_v^2)$ and $u_i \sim i.i.d\ N^+(0, \sigma_u^2)$, and u_i, v_{it} and $\mathbf{x_i}$ are independent of each other. Basically, the approach of Mundlak (1978) involves modeling the correlation of unobserved heterogeneity with the regressors in an additional equation, under the assumption that the unobserved environmental-production factors are correlated with the group means of the explanatory variables. To explicitly account for this correlation, the following auxiliary regression can be introduced (Mundlak, 1978):

$$\alpha_i = \gamma \overline{X}_i + \delta_i, \quad \overline{X}_i = \frac{1}{T_i} \sum_{i=1}^{T_i} X_{it}, \quad \delta_i \sim N(0, \sigma_\delta^2) \tag{8}$$

where X_{it} is the vector of the explanatory variables and γ a vector of the parameters to be estimated. The model 2 specification can avoid the heterogeneity bias and at the same time gives reasonable estimates of inefficiency. Moreover, other time-invariant explanatory variables can also be included in the model.

Model 3 is a pooled-frontier model in which the firm-specific effect is assumed to be zero. Thus, the sample is considered a series of cross-sectional subsamples pooled together. This model is based on the original production frontier model proposed by Aigner *et al.* (1977). Unlike models 1 and 2, model 3 can estimate time-varying efficiency.

Model 4 is the “true” fixed-effects model, which contains α_i, representing the additional firm-specific effects and thus, the unobservable heterogeneity of firms. Strictly speaking, the application of fixed effects to the stochastic-frontier model, primarily that of Schmidt and Sickles (1984), is a reinterpretation of the linear-regression model with fixed effects, not of the frontier models. Following Greene (2005), the "true" fixed-effects model is specified as

$$y_{it} = \alpha_i + \mathbf{x'_{it}}\boldsymbol{\beta} + v_{it} - u_{it} \tag{9}$$

This model is estimated by maximum likelihood. Unlike the usual fixed-effects specification, in which the fixed effects are interpreted as inefficiency, the fixed effects in Greene's model represent the unobserved heterogeneity.

Finally, model 5 is the "true" random effects model following Greene (2005) and modified by the Mundlak (1978) specification. As with the fixed-effects model, the random-effects model, especially that of Pitt and Lee (1981), can be improved into

$$\begin{aligned} y_{it} &= \alpha_i + \mathbf{x'_{it}}\boldsymbol{\beta} + v_{it} - u_{it} \\ \alpha_i &\sim N(0, \sigma_\alpha^2) \end{aligned} \tag{10}$$

This model not only includes a firm-level source of heterogeneity (α_i), which is potentially correlated with the explanatory variables but also allows for a time-varying inefficiency term. The Mundlak (1978) adjustment is also applied to model 2, as given in equation (8). The improved random-effects model can estimate time-varying efficiency.

Table 2 Econometric Specification: Stochastic-Frontier Models

	Model 1 **[FE]**	**Model 2** **[RE (MLE) with Mundlak's Formulation]**	**Model 3** **[Pooled (ALS)]**	**Model 4** **["True" FE]**	**Model 5** **["True" RE with Mundlak's Formulation]**
Firm-specific Component α_i	Fixed	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T_i}\sum_{i=1}^{T_i} X_{it}$ $\delta_i \sim N(0, \sigma_\delta^2)$	None	Fixed	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T_i}\sum_{i=1}^{T_i} X_{it}$ $\delta_i \sim N(0, \sigma_\delta^2)$
Random Error ε_{it}	$i.i.d(0, \sigma_\varepsilon^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$
Inefficiency	$\max\{\hat{\alpha}_i\} - \hat{\alpha}_i$	$E[u_i \mid u_i + v_{it}]$	$E[u_{it} \mid u_{it} + v_{it}]$	$E[u_{it} \mid u_{it} + v_{it}]$	$E[u_{it} \mid \delta_i + \varepsilon_{it}]$

III. Empirical Results

3.1 Data and Descriptive Statistics

This study uses data from *Survey of Business Structure and Activities*, which consists of unified firm-level micro panel data including even information on management activities for policymaking by the government and for firms' business strategy establishment, as well as basic information. The purpose of conducting *Survey of Business Structure and Activities*[2] is to provide basic data for the firm of various economic policies for businesses by examining the actual conditions of firms' management strategies and the changes in their industrial structure, through a comprehensive survey of diverse economic activities, such as the diversification, globalization, and affiliation of the country's business firms. The first survey was conducted in 2006, and the same survey will be conducted every year. The database for three consecutive years (2005-2007) has been built.

For analysis purposes, the industrial sectors to be used are summarized in Table 3. Since each industrial sector has a different set of characteristics, estimating the same production structure in all the sectors seems unreasonable. Therefore, it is assumed that all firms can be classified into four sectors. In this case, the firms within the same sector have common production parameters to be estimated, and the production structure between the sectors is different.

Table 3 Sectoral Classification

Code	Sector	
1	Manufacturing	ICT(Computer, Manufacture of Communication Equipment)
2		Other Manufacturing/Mining/ Electricity, Gas and Water Supply
3	Service	Producer Service
4		Non-producer Service

Table 4 shows the descriptive statistics of the variables that were used for the estimation of the stochastic-frontier production functions.

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[2] Report on Business Structure and Activities (2007).

Table 4 Variable Definition and Descriptive Statistics

	Variables	Observations	Mean	Standard Deviation	Minimum	Maximum	Fraction of Variance due to the "Between" Variation [3]
Gross Output	Y	29,808	143,477.8	1,395,764.0	0.6	117,000,000.0	0.987
Capital	K	29,808	44,908.4	430,460.8	0.8	29,000,000.0	0.993
Labor	L	29,808	284.5	1,392.3	3.0	85,813.0	0.992
Materials	M	29,808	108,490.8	964,666.6	0.9	72,000,000.0	0.985

(Note: Unit: Gross Output, Capital, Materials: Million won, Labor: Person)

The standard deviation indicates a high degree of heterogeneity among the firms in the sample. The last column of the table presents the fraction of the variance of each variable due to the variation between the different firms. The figures indicate that all the variables under consideration show a significant variation between the firms rather than within the firms. Therefore, it can be concluded that this dataset is more similar to cross-sectional data rather than time series. This finding justifies the use of models involving heterogeneity.

3.2 Testing for the Separability of the Production Function

Prior to analysis for the estimation of technical efficiency, it is necessary to define the functional form for the production function. In the real production process, output is produced using the inputs of capital, labor, and intermediate materials. The value-added function, however, consists of the aggregate indices of heterogeneous inputs: capital and labor. This means that the value-added function should not be affected by the change in the intermediate inputs. To use the value-added function for analysis purposes, it has to be assumed that the value-added function, which is the function of only

[3] "Within" variation and "between" variation are defined as $\sum_i \sum_j (x_{ij} - \bar{x}_i)^2$ and $\sum_i \sum_j (\bar{x}_i - \bar{x}_j)^2 = \sum_i n_i (\bar{x}_i - \bar{x})^2$, respectively. Here, x represents each variable.

capital and labor, is independent of the input of intermediate materials. This assumption is referred to as the separability of the real value-added function from the gross output. If the result of the separability test does not accept this assumption, then the studies on the value-added function are incorrect, and gross output as a measure of output is the proper concept.

The translog gross output production function with three inputs can be specified as follows:

$$\ln y_{it} = \alpha_0 + \sum_j \alpha_j \ln x_{ijt} + \frac{1}{2}\sum_j \sum_l \beta_{jl} \ln x_{lit} \ln x_{jit} + v_{it} \qquad (11)$$
$$j, l = L, K, M$$

where the subscripts i and t are the individual firms ($i = 1, 2, ..., N$) and the time ($t = 1, 2, ..., T$), respectively; y_{it} the output; and x_{ijt} the input factors; and where the subscripts j and l are the labor (L), capital (K), and intermediate materials (M). v_{it} is the typical statistical error term with $N(0, \sigma_v^2)$.

Following Pyo and Ha (2007), if $\beta_{km} = \beta_{lm} = 0$ in equation (11), then the translog gross output production function can be expressed as equation (12). Thus, the separability assumption can be accepted by the data.

$$\log Q = Y(\log K, \log L) + G(\log M) \qquad (12)$$

The test statistics for the fixed- and random-effects models are summarized in Table 5. Since all the test statistics are sufficiently beyond the critical values at the 1% significant level, the hypothesis of separability is rejected. Therefore, based on these results, it may be inferred that the value-added function-based productivity analysis may be incorrect and that it is more appropriate to use gross output as an output measure.

Table 5 Test Statistics of the Separability Test

	LR Test	Wald Test
Fixed-Effects Model	3170.94	1068.82
Random-Effects Model	-	3907.29

3.3 Estimation of the Technical Efficiency and Comparison of the Alternative Models[4]

The translog stochastic-frontier function that was used in the estimation can be specified as equation (13). The function consists of one output, three inputs, and two error terms. Since the period that the data pertain to is very short (three years), the time variable is not considered in the analysis.

$$\ln y_{it} = \alpha_0 + \sum_j \alpha_j \ln x_{ijt} + \frac{1}{2}\sum_j \sum_l \beta_{jl} \ln x_{lit} \ln x_{jit} + v_{it} - u_{it} \qquad (13)$$
$$j, l = L, K, M$$

where the subscripts i and t are the individual firms ($i = 1, 2, ..., N$) and the time ($t = 1, 2, ..., T$), respectively; y_{it} the output; and x_{ijt} the input factors; and where the subscripts j and l are the labor (L), capital (K), and intermediate materials (M). The statistical-noise term v_i is a two-sided error term that follows $N(0, \sigma_v^2)$ and that represents the usual statistical noise found in any relationship, and $u_i \geq 0$ is a one-sided error term representing technical inefficiency. In this paper, it is assumed that v_{it} is independent of u_{it}, and if necessary, it is also assumed that u_{it} follows $N(0, \sigma_u^2)^+$. In the first two models (1 and 2), the firm's inefficiency is assumed to be constant over time, thus captured by the firm-specific effects. In models 3, 4, and 5, on the other hand, the firm's inefficiency can vary over time. In these models, the skewed stochastic-error term is interpreted as inefficiency. In all the models, except for the fixed-effects model, it is assumed that the

[4] The estimation results of the production function's parameters can be obtained by email on request from the author.

firm's technical efficiency is not correlated with the explanatory variables.

At first, a Hausman test of the null hypothesis that the firm-specific effects are uncorrelated with the explanatory variables was conducted in the fixed-effects model. The test statistic yielded $\chi^2(9) = 553.50$ and the null hypothesis was rejected. Therefore, the specifications that do not allow for these correlations may produce biased and inconsistent results. Thus, the random-effects models, which assume no correlation between the firm-specific effects and the explanatory variables, can be said to be too restrictive and to provide inferior estimates. On the other hand, the fixed-effects model can be expected to produce unbiased and consistent estimates of the stochastic-production-function parameters.

If the inefficiency is believed to be persistent, the models with time-invariant inefficiency, such as models 1 and 2, may be more relevant. In the case, however, of the panel data with large cross-sections and short time series, the incidental-parameter problem may occur, and therefore, model 2 can be said to be more suitable than model 1. The heterogeneity bias is expected to be relatively low in models 2 and 5, which directly control the correlation between the individual effects and the explanatory variables although they are random-effects models. A test of the null hypothesis that the Mundlak terms are jointly equal to zero is rejected for both models with the Mundlak (1978) adjustment. The values of the likelihood ratio statistic for each industrial sector are 129.0, 919.0, 550.4, and 64.1 for the random effects with the Mundlak (1978) adjustment. Thus, for models 2 and 5, the Mundlak (1978) adjustment is useful in obtaining consistent results. In fact, the estimators of model 2 are almost identical to the fixed-effects estimators of model 1 (the "within" estimators), and are thus unbiased. If the time-varying pattern of inefficiency is assumed, models 3, 4, and 5 are more reasonable. Since model 3 does not consider the characteristics of the panel data, it is inferior to the other models. As shown above, the results of the Hausman test are rejected, and the fixed-effects model is more relevant than the random-effects model. It can be concluded intuitionally, however, that model 5 is the best model for the examination of efficiency using the panel data employed in this analysis because the possibility of the incidental-parameter problem is intrinsic to model 4, and model

5 combined with the Mundlak (1978) adjustment takes care of the fact that technical inefficiency is correlated with the explanatory variables. In sum, model 5 can be said to be the best model for the examination of efficiency using the panel data employed in this analysis, for the following three reasons: (1) this model can consider the time-varying pattern of efficiency; (2) heterogeneity can be taken into account; and (3) the estimated parameters are unbiased and consistent.

Table 6 provides a summary of the weighted averages of the estimated efficiency measures using different models for each industrial sector. The efficiency scores are taken to be equal to the inefficiency scores ($1-\exp(-u_{it})$) obtained from the regression model. The share of each firm's sales to a sector is used as the weight. An examination of the result will reveal that each model has a different estimated-efficiency score. The estimated-efficiency score using the Schmidt and Sickles (1984) method shows very unrealistic values compared with the other models' results. This seems to be due to the features of the Schmidt and Sickles (1984) model. Since in this model, relative technical efficiency is estimated rather than absolute technical efficiency, the wider the gap is, the smaller the efficiency that is estimated. Especially, a problem arises when the maximum efficiency is an outlier. Based on the results obtained from all the models, except for model 1, the Schmidt and Sickles (1984) method, the estimated technical efficiency ranges from 77% to 86%. Moreover, the results indicate that the introduction of the Mundlak (1978) adjustment, in which the correlation between the explanatory variables and firm-specific heterogeneity is accounted for in the models, can decrease the heterogeneity bias. In fact, compared to the other models, model 5, which considers the heterogeneity bias and firm-specific heterogeneity, shows the highest estimates of technical efficiency, and among the sectors, the estimate of the producer service sector is the highest.

Table 6 Average Efficiency Scores by Technique: 2005-2007

	Observation	Model 1 [FE]	Model 2 [RE (MLE) with Mundlak's Formulation]	Model 3 [Pooled (ALS)]	Model 4 [“True” FE]	Model 5 [“True” RE with Mundlak's Formulation]
ICT	3744	0.365	0.847	0.865	0.847	0.887
nonICT	16074	0.388	0.819	0.855	0.818	0.855
ProdServ	4080	0.072	0.608	0.665	0.653	0.919
Serv	5847	0.289	0.734	0.732	0.717	0.743
Total	29745	0.301	0.767	0.798	0.774	0.859
2005						
ICT	1248	0.363	0.841	0.861	0.847	0.896
nonICT	5358	0.388	0.818	0.847	0.810	0.844
ProdServ	1360	0.071	0.605	0.650	0.642	0.915
Serv	1949	0.288	0.733	0.735	0.722	0.742
Total	9915	0.302	0.766	0.792	0.770	0.854
2006						
ICT	1248	0.368	0.847	0.865	0.846	0.882
nonICT	5358	0.388	0.820	0.856	0.819	0.855
ProdServ	1360	0.073	0.613	0.672	0.660	0.919
Serv	1949	0.289	0.735	0.731	0.716	0.740
Total	9915	0.303	0.770	0.801	0.772	0.858
2007						
ICT	1248	0.369	0.851	0.869	0.848	0.883
nonICT	5358	0.389	0.820	0.861	0.823	0.864
ProdServ	1360	0.072	0.606	0.671	0.656	0.921
Serv	1949	0.289	0.734	0.730	0.713	0.746
Total	9915	0.299	0.766	0.801	0.775	0.863

Table 7 contains the Spearman rank correlation coefficients, computed at the firm level, from the five different estimation techniques. These coefficients show how close the rankings of the firms are to one another, using the full sample of firms. For the models with time-varying efficiency, the efficiency score is computed as the firm's average efficiency score over the sample period. The result shows that the use of different models leads to different rankings of estimated efficiency. Therefore, it can be concluded that it is important to choose the most appropriate model or that which is most suitable for analysis purposes and considering the available data.

Table 7 Spearman Rank Coefficients

	Model 1 [FE]	Model 2 [RE (MLE) with Mundlak's Formulation]	Model 3 [Pooled (ALS)]	Model 4 ["True" FE]	Model 5 ["True" RE with Mundlak's Formulation]
Model 1	1				
Model 2	0.482	1			
Model 3	0.470	0.856	1		
Model 4	0.326	0.332	0.675	1	
Model 5	-0.069	0.290	0.440	0.178	1

3.4 Decomposition of the Productivity Change Using the Stochastic-Frontier Production Model

In the previous section, several stochastic-production-frontier models were compared considering the firms' heterogeneity. Among these models, model 5, the "true" random-effects model with the Mundlak (1978) adjustment, will be used in the analysis in this section, which will attempt to decompose productivity as model 5 is considered the most suitable model as far as the available data and the purpose of analysis are concerned. The functional form of production to be used is the same as that in the previous section. The translog stochastic-frontier function used in the estimation can be specified as equation (13). Since the period that the data pertain to is very short (three years), the time variable was not considered in the analysis. Therefore, among the effects, technical change (TC) is assumed to be zero.

$$\ln y_{it} = \alpha_0 + \sum_j \alpha_j \ln x_{ijt} + \frac{1}{2}\sum_j \sum_l \beta_{jl} \ln x_{lit} \ln x_{jit} + v_{it} - u_{it}$$
$$j, l = L, K, M$$

Table 8 shows the average output elasticity of each industrial sector for the period 2005-2007. The estimate of returns to scale (RTS), which combines the output elasticity of the capital (ε_K), of labor (ε_L), and of the intermediate outputs (ε_M), shows an increasing return to scale (IRS) when it is greater than 1, a constant return to scale (CRS) when it is equal to 1, and a decreasing return to scale

(DRS) when it is less than 1. The estimate of RTS for the ICT sector exhibits IRS, with a magnitude of 1.253. This result is similar to that obtained by Pai (2007). On the other hand, the other sectors exhibit DRS, with 0.92, 0.866, and 0.982 magnitudes, respectively.

The main findings of the present study are summarized in Table 9. Table 9 presents the changes in technical efficiency (TE), scale effects (SC), allocative efficiency (AE), and total factor productivity growth($T\dot{F}P$) of each sector for 2005-2007. It is shown that the contributions of each factor to productivity growth differ according to the industrial sector. First, the estimate of TFP growth in the producer service sector is negative, and the other sectors' TFP growth is positive. Second, in the case of the changes in technical efficiency, all the sectors, except for the ICT sector, show positive growth. A poor contribution of technical efficiency to productivity growth in the ICT sector was also shown in the study conducted by Pai (2007). Third, the changes in allocative efficiency contribute positively to the productivity growth in all the sectors. Lastly, in the ICT sector, the scale effect helps improve the firm's productivity, but in the other sectors, it does not.

Table 8 Output Elasticities of the Input Factors

	Observation	**Capital**	**Labor**	**Materials**	RTS
ICT	3,744	0.143	0.093	1.017	1.253
nonICT	16,074	0.042	0.061	0.823	0.926
ProdServ	4,080	0.105	0.066	0.695	0.866
Serv	5,847	0.034	0.060	0.888	0.982
total	29,745	0.077	0.069	0.848	0.994

Table 9 The Rate of Changes in Technical Efficiency (TE), Scale Component (SC), Allocative Efficiency (AE), and Total Factor Productivity Growth ($T\dot{F}P$)

	$T\dot{F}P$	TE	AE	SC
ICT	0.025	-0.006	0.022	0.009
nonICT	0.006	0.010	0.013	-0.017
ProdServ	-0.026	0.003	0.022	-0.052
Serv	0.001	0.004	0.013	-0.015
total	0.002	0.004	0.017	-0.019

IV. Concluding Remarks

In this paper, we attempt to discuss empirical and theoretical issues related to identifying and estimating the sources of firms' productivity growth and technical efficiency using micro level panel datasets in Korea for the period of 2005-2007. In econometric approach, prior to analysis for the estimation of technical efficiency, it is necessary to define the functional form for the production function. Based on the test statistics for the fixed- and random-effects models, the hypothesis of separability is rejected. Therefore, it may be inferred that the value-added function-based productivity analysis may be incorrect and that it is more appropriate to use gross output as an output measure. Many stochastic frontier models have been compared for the estimation of technical efficiency, and it is important to choose the most appropriate model or the one that is most suitable for the purpose of analyzing the available data. In this analysis, the true random effects model with Mundlak's adjustment can be said to be the best model for the examination of efficiency using the panel data employed in this study, for the following three reasons: (1) this model can consider the time-varying pattern of efficiency; (2) heterogeneity can be taken into account; and (3) the estimated parameters are unbiased and consistent. The estimated technical efficiency ranges from 77% to 86%. Moreover, the results indicate that the introduction of the Mundlak (1978) adjustment, in which the correlation between the explanatory variables and firm-specific heterogeneity is accounted for in the models, can decrease the heterogeneity bias. In fact, compared to the other models, the true random effects model with Mundlak's adjustment, which considers the heterogeneity bias and firm-specific heterogeneity, shows the highest estimates of technical efficiency, and among the sectors, the estimate of the producer service sector is the highest.

Next, it is shown that the contributions of each factor to productivity growth differ according to the industrial sector. First, the estimate of TFP growth in the producer service sector is negative, and the other sectors' TFP growth is positive. Second, in the case of the changes in technical efficiency, all the sectors, except for the ICT sector, show positive growth. A poor contribution of technical efficiency to productivity growth in the ICT sector was also shown in the study conducted by Pai (2007). Third, the changes in allocative efficiency contribute positively to the productivity growth in all the sectors. Lastly, in the ICT sector, the scale effect helps improve the firm's productivity, but in the other sectors, it does not.

There are many methodologies and approaches that analyze the productivity and efficiency of firms, but to derive significant results, it is very important to choose a methodology that fits the purpose of the analysis and the data to be used in it. Since the results can be greatly affected by the choice of classification criteria and models when analyzing the factors that determine productivity and efficiency, needless to say, care should be taken in choosing such classification criteria and models.

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