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A Metafrontier Production Function for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating Under Different Technologies

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Abstract

This paper presents a metafrontier production function model for firms in different groups having different technologies. The metafrontier model enables the calculation of comparable technical efficiencies for firms operating under different technologies. The model also enables the technology gaps to be estimated for firms under different technologies relative to the potential technology available to the industry as a whole. The metafrontier model is applied in the analysis of panel data on garment firms in five different regions of Indonesia, assuming that the regional stochastic frontier production function models have technical inefficiency effects with the time-varying structure proposed by Battese and Coelli (1992).

JEL Classification: C23, C51, C63, D24, L6

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The technical efficiencies of firms that operate under a given production technology, which is assumed to be defined by a stochastic frontier production function model, are not comparable with those of firms operating under different technologies. Battese and Rao (2002) presented a stochastic metafrontier model by which comparable technical efficiencies can be estimated. However, the model of Battese and Rao (2002) assumes that there are two different data-generation mechanisms for the data, one with respect to the stochastic frontier that is relevant for the technology of the firms involved, and the other with respect to the metafrontier model. This paper presents a modified model that assumes that there exists only one

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data-generation process for the firms that operate under a given technology. The metafrontier function, defined in this paper, is an overarching function of a given mathematical form that encompasses the deterministic components of the stochastic frontier production functions for the firms that operate under the different technologies involved.

The model proposed in this paper is applied to the estimation of the technical efficiencies of Indonesian garment firms in five different regions, using panel data on medium- and large-scale garment firms over the period, 1990 to 1995. The technical efficiencies of the garment firms are estimated by using different stochastic production frontiers for firms in the five regions in Indonesia, together with the metafrontier production function that is defined below. Details of the garment industry in Indonesia and other aspects of the data are presented in Battese et al. (2001).

1. A Metafrontier Model

Suppose that the inputs and outputs for firms in a given industry are such that stochastic frontier production function models are appropriate for R different groups within the industry. Suppose that, for the jth group, there are sample data on N_j firms that produce one output from the various inputs and the stochastic frontier model for this group is defined by

$$Y_{it(j)} = f(\mathbf{x}_{it(j)}, \boldsymbol{\beta}_{(j)}) e^{V_{it(j)} - U_{it(j)}}, \quad i = 1, 2, \ldots, N_j, \; t = 1, 2, \ldots, T, \; j = 1, 2, \ldots, R, \tag{1}$$

where $Y_{it(j)}$ denotes the output for the ith firm in the tth time period for the jth group; $\mathbf{x}_{it(j)}$ denotes a vector of values of functions of the inputs used by the ith firm in the tth time period for the jth group;[1] $\boldsymbol{\beta}_{(j)}$ denotes the parameter vector associated with the x-variables for the stochastic frontier for the jth group involved; the $V_{it(j)}$s are assumed to be identically and independently distributed as $N(0, \sigma^2_{v(j)})$-random variables, independent of the $U_{it(j)}$s, which are defined by the truncation (at zero) of the $N(\mu_{it(j)}, \sigma^2_{(j)})$-distributions, where the $\mu_{it(j)}$s are defined by some appropriate inefficiency model, for example, one of the Battese and Coelli (1992, 1995) models. For simplicity of presentation, the model for the jth group is assumed to be given by

$$Y_{it} = f(\mathbf{x}_{it}, \boldsymbol{\beta}_{(j)}) e^{V_{it(j)} - U_{it(j)}} \equiv e^{\mathbf{x}_{it}\beta_{(j)} + V_{it(j)} - U_{it(j)}}. \tag{2}$$

This expression assumes that the exponent of the frontier production function is linear in the parameter vector, $\boldsymbol{\beta}_{(j)}$, so that $\mathbf{x}_{it}$ is a vector of functions (e.g., logarithms) of the inputs for the ith firm in the tth time period involved.

The metafrontier production function model for firms in the industry is expressed by

$$Y_{it}^{*} \equiv f(\mathbf{x}_{it}, \boldsymbol{\beta}^{*}) = e^{\mathbf{x}_{it}\boldsymbol{\beta}^{*}}, \quad i = 1, 2, \ldots, N = \sum_{j=1}^{R} N_j; t = 1, 2, \ldots, T, \tag{3}$$

where β^{*} denotes the vector of parameters for the metafrontier function such that

$$\mathbf{x}_{it}\boldsymbol{\beta}^{*} \geq \mathbf{x}_{it}\boldsymbol{\beta}_{(j)}. \tag{4}$$

The metafrontier production function is thus defined as a deterministic parametric function (of specified functional form) such that its values are no smaller than the deterministic components of the stochastic frontier production functions of the different groups involved, for all groups and time periods. The metafrontier is assumed to be a smooth function and not a segmented envelope of the stochastic frontier functions for the different groups. A graph of the metafrontier function is presented in Figure 1.

Three stochastic frontier models are indicated in Figure 1. The observed values are indicated by numbers that correspond to the particular regional frontiers, whereas their corresponding (unobservable) stochastic frontier outputs are indicated by the numbers in circles above them. The values of the curves corresponding to the circled

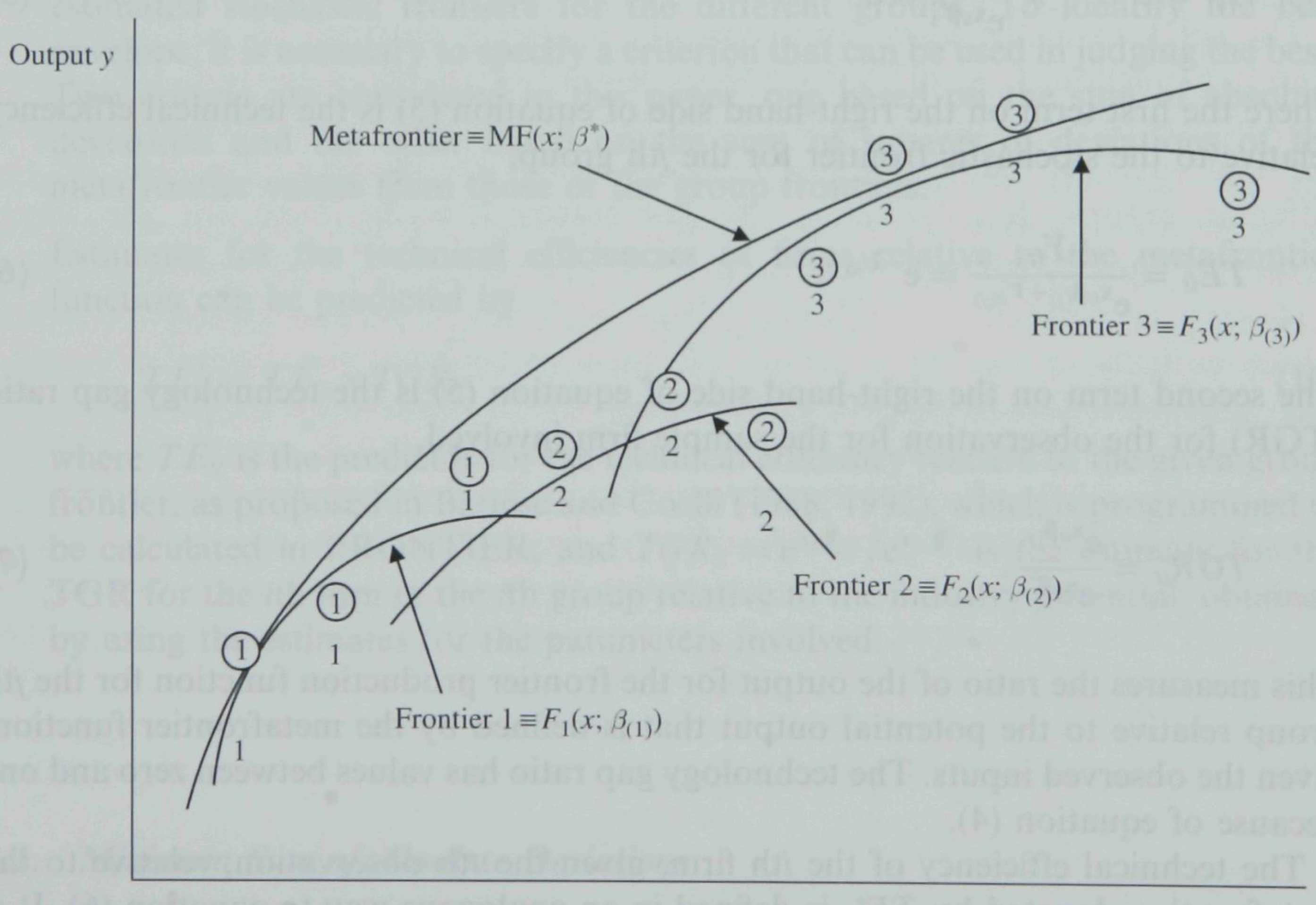

Figure 1. Metafrontier function model.

numbers can be considered as means of the potential stochastic frontier outputs for the given levels of the inputs. The metafrontier function has values that are no less than the deterministic functions associated with the stochastic frontier models for the different groups involved. Some stochastic frontier outputs, and even their corresponding stochastic frontier outputs, may exceed values of the metafrontier, as indicated in Figure 1.

The metafrontier model of equations (3) and (4) is related to the concept of the metaproduction function that was defined by Hayami and Ruttan (1971, p. 82) as, "The metaproduction function can be regarded as the envelope of commonly conceived neoclassical production functions." However, in our model, the metafrontier function is a production function of specified functional form that does not fall below the deterministic functions for the stochastic frontier models of the groups involved. Battese and Rao (2002) give a more extensive literature review and proposed a stochastic metafrontier model that assumes a different data-generation mechanism for the metafrontier than for the different group frontiers. The model in this paper assumes that data-generation models are only defined for the frontier models for the firms in the different groups.

The observed output for the ith firm at the tth time period, defined by the stochastic frontier for the jth group in equation (2), is alternatively expressed in terms of the metafrontier function of equation (3) by

$$Y_{it} = \mathrm{e}^{-U_{it(j)}} \times \frac{\mathrm{e}^{\mathbf{x}_{it}\boldsymbol{\beta}_{(j)}}}{\mathrm{e}^{\mathbf{x}_{it}\boldsymbol{\beta}^*}} \times \mathrm{e}^{\mathbf{x}_{it}\boldsymbol{\beta}^* + V_{it(j)}} \tag{5}$$

where the first term on the right-hand side of equation (5) is the technical efficiency relative to the stochastic frontier for the jth group,

$$TE_{it} = \frac{Y_{it}}{\mathrm{e}^{\mathbf{x}_{it}\boldsymbol{\beta}_{(j)} + V_{it(j)}}} = \mathrm{e}^{-U_{it(j)}}. \tag{6}$$

The second term on the right-hand side of equation (5) is the technology gap ratio (TGR) for the observation for the sample firm involved,

$$TGR_{it} = \frac{\mathrm{e}^{\mathbf{x}_{it}\boldsymbol{\beta}_{(j)}}}{\mathrm{e}^{\mathbf{x}_{it}\boldsymbol{\beta}^*}}. \tag{7}$$

This measures the ratio of the output for the frontier production function for the jth group relative to the potential output that is defined by the metafrontier function, given the observed inputs. The technology gap ratio has values between zero and one because of equation (4).

The technical efficiency of the ith firm, given the tth observation, relative to the metafrontier, denoted by TE_{it}^*, is defined in an analogous way to equation (6). It is the ratio of the observed output relative to the last term on the right-hand side of equation (5), which is the metafrontier output, adjusted for the corresponding random error, i.e.,

$$TE^*_{it} = \frac{Y_{it}}{e^{\mathbf{x}_{it}\boldsymbol{\beta}^* + V_{it(j)}}}. \tag{8}$$

Equations (5)–(8) imply that an alternative expression for the technical efficiency relative to the metafrontier is given by

$$TE^*_{it} = TE_{it} \times TGR_{it}. \tag{9}$$

Thus the technical efficiency relative to the metafrontier function is the product of the technical efficiency relative to the stochastic frontier for the given group and the TGR. Because both the latter measures are between zero and one, the technical efficiency relative to the metafrontier is also between zero and one, but is less than the technical efficiency relative to the stochastic frontier for the group of the firm.

The parameters and measures associated with the metafrontier model of equations (2)–(4) can be estimated as follows:

1. Obtain the maximum-likelihood estimates, $\hat{\boldsymbol{\beta}}_{(j)}$, for the $\boldsymbol{\beta}_{(j)}$-parameters of the stochastic frontier for the jth group using, for example, the FRONTIER program (Coelli, 1996);
2. Obtain estimates, $\hat{\boldsymbol{\beta}}^*$, for the $\boldsymbol{\beta}^*$-parameters of the metafrontier function such that the estimated function best envelopes the deterministic components of the estimated stochastic frontiers for the different groups. To identify the best envelope, it is necessary to specify a criterion that can be used in judging the best. Two criteria are considered in this paper, one based on the sum of absolute deviations and the other based on the sum of squares of deviations of the metafrontier values from those of the group frontiers.
3. Estimates for the technical efficiencies of firms relative to the metafrontier function can be predicted by

$$T\hat{E}^*_{it} = T\hat{E}_{it} \times TG\hat{R}_{it}, \tag{10}$$

where $T\hat{E}_{it}$ is the predictor for the technical efficiency relative to the given group frontier, as proposed in Battese and Coelli (1988, 1992), which is programmed to be calculated in FRONTIER; and $TG\hat{R}_{it} = e^{\mathbf{x}_{it}\hat{\boldsymbol{\beta}}_{(j)}}/e^{\mathbf{x}_{it}\hat{\boldsymbol{\beta}}^*}$ is the estimate for the TGR for the ith firm in the jth group relative to the industry potential, obtained by using the estimates for the parameters involved.

1.1. Minimum Sum of Absolute Deviations

Given the estimates for the parameters of the group stochastic frontiers, $\hat{\boldsymbol{\beta}}_{(j)}$, $j = 1, 2, \ldots, R$, obtained by Step (1) above, the $\boldsymbol{\beta}^*$-parameters can be estimated by solving the optimization problem below:

$$\min L \equiv \sum_{t=1}^{T}\sum_{i=1}^{N}\left|(\ln f(\mathbf{x}_{it}, \boldsymbol{\beta}^*) - \ln f(\mathbf{x}_{it}, \hat{\boldsymbol{\beta}}_{(j)})\right| \tag{11}$$

$$\text{s.t. } \ln f(\mathbf{x}_{it}, \boldsymbol{\beta}^*) \geq \ln f(\mathbf{x}_{it}, \hat{\boldsymbol{\beta}}_{(j)}). \tag{12}$$

There are several interesting features to the application of this criterion. First, the deviations used here are essentially logarithms of $f(\mathbf{x}_{it}, \boldsymbol{\beta}^*)/f(\mathbf{x}_{it}, \hat{\boldsymbol{\beta}}_{(j)})$, which represent the radial distance between the metafrontier and the jth group frontier, evaluated at the observed input vector for a firm in the jth region. Thus, the use of (11) and (12) implies that the resulting metafrontier minimizes the sum of logarithmic radial distances between the metafrontier and the group frontiers.[2] Second, since the optimization is subject to the inequality restrictions in (12), all the deviations involved are positive and, therefore, the absolute deviations are simply equal to the deviations. Third, if $f(\mathbf{x}_{it}, \boldsymbol{\beta}^*)$ in equation (3) is assumed to be log-linear in the parameters (as it is in this paper), the optimization problem in (11) and (12) simplifies to the following linear programming (LP) problem:

$$\min L \equiv \sum_{i=1}^{N}\sum_{t=1}^{T}(\mathbf{x}_{it}\boldsymbol{\beta}^* - \mathbf{x}_{it}\hat{\boldsymbol{\beta}}_{(j)}) \tag{13}$$

$$\text{s.t. } \mathbf{x}_{it}\boldsymbol{\beta}^* \geq \mathbf{x}_{it}\hat{\boldsymbol{\beta}}_{(j)}. \tag{14}$$

The solution to the above problem is equivalently obtained by minimizing the objective function, $L^* \equiv \bar{\mathbf{x}}\boldsymbol{\beta}^*$, subject to the linear restrictions of equation (12), where $\bar{\mathbf{x}}$ is the row vector of means of the elements of the $\mathbf{x}_{it}$-vectors for all observations in the data set. This follows because the estimates of the stochastic frontiers for the different groups, $\hat{\boldsymbol{\beta}}_{(j)}, j = 1, 2, \ldots, R$, are assumed to be fixed for the linear programming problem.

1.2. *Minimum Sum of Squares of Deviations*

Minimization of the objective function in (11) and (12) assigns the same weight for all the radial distances for all the firms in the sample. An alternative approach is to estimate the parameters of the metafrontier function by minimizing the sum of squares of the deviations of the values on the metafrontier function from the group-specific stochastic frontiers at the observed input levels. This method assigns higher weights to the deviations associated with firms that have larger technology gap ratios. This leads to the following optimization problem:

$$\min L^{**} \equiv \sum_{t=1}^{T}\sum_{i=1}^{N}(\mathbf{x}_{it}\boldsymbol{\beta}^* - \mathbf{x}_{it}\hat{\boldsymbol{\beta}}_{(j)})^2 \tag{15}$$

subject to the restrictions of equation (14).

This approach is similar to the use of the least-squares criterion. The optimization problem in (15), identical to a constrained least-squares estimation, is a quadratic programming (QP) problem that minimizes the Euclidean distances of the values on the metafrontier from those on the estimated stochastic frontier functions.

Standard errors for the estimators for the metafrontier parameters can be obtained using simulation or bootstrapping methods.

2. Empirical Application

This study uses data on firms in the Indonesian garment industry that were collected in the annual surveys of firms in the manufacturing industries by Indonesia's Central Bureau of Statistics for 1990 to 1995. Coverage of these surveys is basically restricted to medium- and large-scale establishments, which have at least 20 employees.

Analyses of technical efficiency of garment firms at the regional level are important and challenging for Indonesia. From a policy point of view, it is of interest to distinguish the regional differences in mean efficiency levels and to determine whether the regions share some common characteristics.

For the purpose of the present study, Indonesian garment firms are grouped into five regions: Jakarta; West Java; Central Java; East Java; and the Outer Islands (the other provinces are pooled together because of the smaller numbers of firms in these regions). By performing the stochastic frontier analysis separately at the regional levels, the study permits the parameters of the empirical model to be different for these five regions. The regional-level analyzes are believed to be desirable because it is likely that the garment firms in the different regions are operating under different technologies. The estimation of a metafrontier production function for the Indonesian garment industry enables a comparison of the technical efficiencies of firms in different regions, together with an analysis of the technology gaps of firms in particular regions, relative to the technology available to the industry as a whole.

Empirical results are obtained by using the stochastic frontier production model with time-varying inefficiency effects, proposed by Battese and Coelli (1992). The translog stochastic frontier production function model, which is assumed to represent the production technology for garment firms in a particular region, is defined by

$$\ln Y_{it} = \beta_0 + \sum_{m=1}^{5} \beta_m x_{mit} + \sum_{m=1}^{5} \sum_{k \geq m}^{5} \beta_{mk} x_{mit} x_{kit} + \beta_{00} D_{it} + V_{it} - U_{it}, \tag{16}$$

where the U_{it}s are assumed to be defined by

$$U_{it} = \{\exp[-\eta(t - T)]\} U_i, \quad i = 1, 2, \ldots, N; \ t = 1, 2, \ldots, 6; \tag{17}$$

$\ln Y_{it}$ denotes the natural logarithm of the total value of manufacturing output for the ith garment firm in the tth year (in thousands of rupiahs, at 1990 constant prices);[3] x_1 denotes the natural logarithm of the total value of operating costs (including expenditures on electricity, fuel and lubricants, maintenance and repairs of capital goods, and rents of buildings and machinery), hereafter referred to as capital;[4] x_2 denotes the natural logarithm of the total number of paid laborers, hereafter referred to as labor; x_3 denotes the natural logarithm of the total value of costs of raw materials purchased by the firm, hereafter called materials; x_4 denotes the natural logarithm of the total amount of investments[5] (if positive) and zero otherwise (i.e., the logarithm of the maximum of the investments and $1 - D$, where D denotes the dummy variable for the actual annual value of investments, which has value one if the firm had a positive level of investments[6] in the given year, and has value zero, otherwise); x_5 denotes the time variable, where $x_5 = 1, \ldots, 6$ for $1990, \ldots, 1995$, respectively; (the subscripts, i and t, are omitted above for simplicity of presentation); the V_{it}s are assumed to be independently and identically distributed as $N(0, \sigma_v^2)$ random variables, independent of the U_is; the U_is are assumed to be independently and identically distributed non-negative random variables, obtained by truncation (at zero) of the $N(\mu, \sigma^2)$-distribution; and the $\beta s, \eta, \mu, \sigma_v^2$ and σ^2 are unknown parameters to be estimated.[7]

The stochastic frontier model, defined by equations (16) and (17), is estimated using data on garment firms in a given region. The technical efficiency of the ith garment firm, given the observation for the tth period, relative to its regional frontier, $TE_{it} = \exp(-U_{it})$, is predicted as proposed in Battese and Coelli (1992). Thus, the technical efficiencies of individual garment firms are generally estimated relative to the technology of that region, as defined by the stochastic frontier model (16) and (17). However, the technical efficiencies of all garment firms across regions in Indonesia can also be estimated relative to a metafrontier function, as defined in Section 2.

A basic summary of the observations on the variables for the different regions is presented in Table 1. These statistics indicate that there are considerable differences among the five regions so far as the means and standard deviations of the outputs and inputs are concerned. The total number of firms involved in the five regions is 1,958 and the total number of observations for all firms is 6,864.

The maximum-likelihood estimates of the parameters in the regional frontiers were obtained using the FRONTIER 4.1 program (Coelli, 1996). The null hypothesis that the technical inefficiency effects were not present in a given region, given the specifications of the stochastic frontier model, was rejected for all regions. Thus the technical inefficiencies were significant in all regions. The null hypothesis that the Cobb-Douglas frontier is an adequate representation of the data was strongly rejected, as was the null hypothesis that there was no technical change[8] in the garment firms between 1990 and 1995, for all regions.

It is important to examine if all the regions share the same technology. If all the firm-level data were generated from a single production frontier and the same underlying technology, there would be no good reason for estimating the efficiency levels of firms relative to a metafrontier production function. A likelihood-ratio (LR) test of the null hypothesis, that the regional stochastic frontier models are the same for all firms in Indonesia, was calculated after estimating the stochastic frontier by pooling the data from all the five regions. The value of the LR statistic was 923.56,[9]

Table 1. Summary statistics for data on firms in the Indonesian garment industry.

Variable	Jakarta	West Java	Central Java	East Java	Outer Islands
Output					
Mean	3,411,182	6,783,808	1,187,306	695,653	1,104,721
St. Deviation	7,686,469	14,565,361	4,437,915	1,713,850	2,125,442
Capital					
Mean	47,866	88,153	17,163	12,820	15,237
St. Deviation	160,998	160,301	70,101	44,827	35,749
Labor					
Mean	210.46	435.15	106.25	99.48	103.63
St. Deviation	371.33	721.85	276.58	204.22	175.33
Materials					
Mean	1,699,913	3,442,291	647,345	337,305	516,507
St. Deviation	3,790,158	7,319,204	2,339,360	792,515	1,006,120
Investments					
Mean	6,029,905	2,838,416	2,198,630	626,039	1,363,024
St. Deviation	48,720,572	32,886,553	28,872,722	15,098,716	21,380,873
Number of firms	727	434	304	179	314
Number of obs.	2,334	1,724	1,133	669	1,004

Source: Empirical results, based on Indonesia's Annual Manufacturing Survey 1990–1995. The values of output and inputs are expressed in thousands of 1990 rupiahs.

which is highly significant. This result strongly suggests that the five regional stochastic frontiers for garment firms in Indonesia are not the same.

The preferred models for the technical inefficiency effects were not the same for the five regions. The maximum-likelihood estimates for the parameters of the preferred stochastic frontiers for the five regions are presented in Table 1 of Battese et al. (2001). The maximum-likelihood estimates for the parameters of the stochastic frontier production function for Indonesia (obtained by using the data on all firms in Indonesia), together with the estimates of the metafrontier obtained by linear and quadratic programming, are presented in Table 2 below. Simulations were used to get estimates of the sampling variability of the metafrontier estimators, which derives from the sampling variability of the regional frontiers estimates. Specifically, we used the estimated asymptotic distributions of the regional frontier estimators[10] to draw $M = 5{,}000$ observations on the regional frontier parameters. Each draw was then used to calculate the right-hand side of the constraints in a new LP/QP problem. The estimated standard errors of the metafrontier estimators were calculated as the standard deviations of the M solutions to these LP/QP problems. All metafrontier results were obtained using the GAUSS programming language.

There are insignificant differences between the LP and QP estimates for the parameters of the metafrontier function, but there are significant differences between the metafrontier coefficients and their corresponding coefficients of the stochastic frontier for Indonesia. The latter estimates were used in Battese et al. (2001) to approximate estimates for the parameters of the metafrontier function. These

Table 2. Maximum-likelihood estimates of the translog stochastic frontier for Indonesia, together with estimates of parameters of the metafrontier production function.[a]

Variable	Coeff.	Indonesia (SF)	Meta (LP)	Meta (QP)
Constant	β_0	7.79 (0.20)	8.29 (0.47)	7.95 (0.38)
Investments dummy	β_{00}	−0.216 (0.098)	0.10 (0.24)	0.04 (0.22)
Capital	β_1	0.463 (0.029)	0.525 (0.083)	0.521 (0.072)
Labor	β_2	0.979 (0.054)	1.26 (0.12)	1.19 (0.11)
Materials	β_3	−0.572 (0.029)	−0.788 (0.092)	−0.705 (0.071)
Investments	β_4	0.029 (0.018)	−0.048 (0.044)	−0.040 (0.040)
Year	β_5	−0.032 (0.026)	0.098 (0.050)	0.076 (0.046)
(Capital)^2	β_{11}	0.0115 (0.0024)	0.0290 (0.0056)	0.0264 (0.0049)
(Labor)^2	β_{22}	0.0443 (0.0077)	0.059 (0.014)	0.058 (0.013)
(Materials)^2	β_{33}	0.0834 (0.0015)	0.1082 (0.0059)	0.1014 (0.0037)
(Investments)^2	β_{44}	−0.00031 (0.00064)	0.0021 (0.0017)	0.0017 (0.0016)
(Year)^2	β_{55}	0.0250 (0.0016)	0.0284 (0.0036)	0.0284 (0.0035)
Capital × Labor	β_{12}	0.0160 (0.0068)	0.009 (0.016)	0.003 (0.014)
Capital × Materials	β_{13}	−0.0492 (0.0035)	−0.079 (0.010)	−0.0736 (0.0080)
Capital × Investments	β_{14}	−0.00156 (0.00078)	−0.0003 (0.0017)	−0.0004 (0.0017)
Capital × Year	β_{15}	0.0014 (0.0025)	0.0095 (0.0062)	0.0115 (0.0061)
Labor × Materials	β_{23}	−0.1001 (0.0052)	−0.126 (0.014)	−0.116 (0.012)
Labor × Investments	β_{24}	−0.0002 (0.0011)	−0.0018 (0.0025)	−0.0028 (0.0023)
Labor × Year	β_{25}	0.0077 (0.0041)	0.0163 (0.0076)	0.0151 (0.0073)
Materials × Investments	β_{34}	0.00059 (0.00062)	0.0020 (0.0015)	0.0028 (0.0013)
Materials × Year	β_{35}	−0.0053 (0.0027)	−0.0225 (0.0061)	−0.0220 (0.0056)
Investments × Year	β_{45}	−0.00016 (0.00045)	−0.00031 (0.00099)	−0.0012 (0.0010)

Note: [a]The estimated standard errors are given in parentheses correct to two-significant digits. The coefficient estimates are given to the same number of digits behind the decimal points as the standard errors.

estimates gave unsatisfactory results for the technical efficiencies and the technology gap ratios.

2.1. *Technical Efficiencies and Technology Gap Ratios*

Values of the TGR, together with the technical efficiencies obtained from the regional stochastic frontiers (TE) and the metafrontier (TE*) were computed for all firms in the different regions. Basic summary statistics for these measures are presented in Table 3, where the metafrontier technical efficiencies are from the LP estimates only (because those from the QP estimates were almost identical to those from the LP estimates). The mean values of the technology gap ratio vary from about 0.52 (for East Java) to 0.90 (for Jakarta). These results imply that, for East Java, the garment firms produce, on average, only about 52% of the potential output given the technology available to the industry as a whole. However, firms in Jakarta

Table 3. Summary statistics for the TGRs and the technical efficiencies obtained from the regional stochastic frontiers and the metafrontier production function for Indonesian garment firms.

Region/Statistic	Mean	Minimum	Maximum	St. Dev.
Jakarta				
Regional TE	0.590	0.156	0.972	0.134
Tech. Gap Ratio	0.903	0.017	1.000	0.094
Metafrontier TE*	0.530	0.009	0.942	0.125
West Java				
Regional TE	0.640	0.165	0.963	0.111
Tech. Gap Ratio	0.715	0.058	1.000	0.126
Metafrontier TE*	0.457	0.042	0.878	0.108
Central Java				
Regional TE	0.701	0.334	0.976	0.094
Tech. Gap Ratio	0.607	0.225	1.000	0.095
Metafrontier TE*	0.426	0.101	0.835	0.087
East Java				
Regional TE	0.837	0.487	0.968	0.089
Tech. Gap Ratio	0.516	0.272	0.870	0.082
Metafrontier TE*	0.432	0.181	0.727	0.083
Outer Islands				
Regional TE	0.631	0.352	0.944	0.111
Tech. Gap Ratio	0.731	0.171	1.000	0.144
Metafrontier TE*	0.463	0.075	0.821	0.124

Note: [a]The linear programming estimates for the metafrontier coefficients are used in this table.

produce, on average, about 90% of the potential output. It is interesting to note that in all regions, except East Java, the regional frontiers were tangent to the metafrontier (the maximum value for the technology gap ratio, namely one, was obtained in each of these four regions). Frequency distributions for the technology gap ratios for the observed firms are presented in Figure 2. There was substantial variability in the technology gap ratios for firms in all regions, but much less variability for firms in Jakarta.

Garment firms in Jakarta achieved the highest mean technical efficiencies relative to the metafrontier. For the other regions, the technical efficiencies calculated relative to the metafrontier function were substantially smaller than those calculated from the regional frontiers. Garment firms in East Java had the highest mean technical efficiency relative to their regional stochastic frontier, but they tended to be furthest from the potential outputs defined by the metafrontier function.

The study of the reasons for the wide variations in the TGRs and the technical efficiencies in the different regions for both the regional stochastic frontiers and the metafrontier is worthy of further investigation.

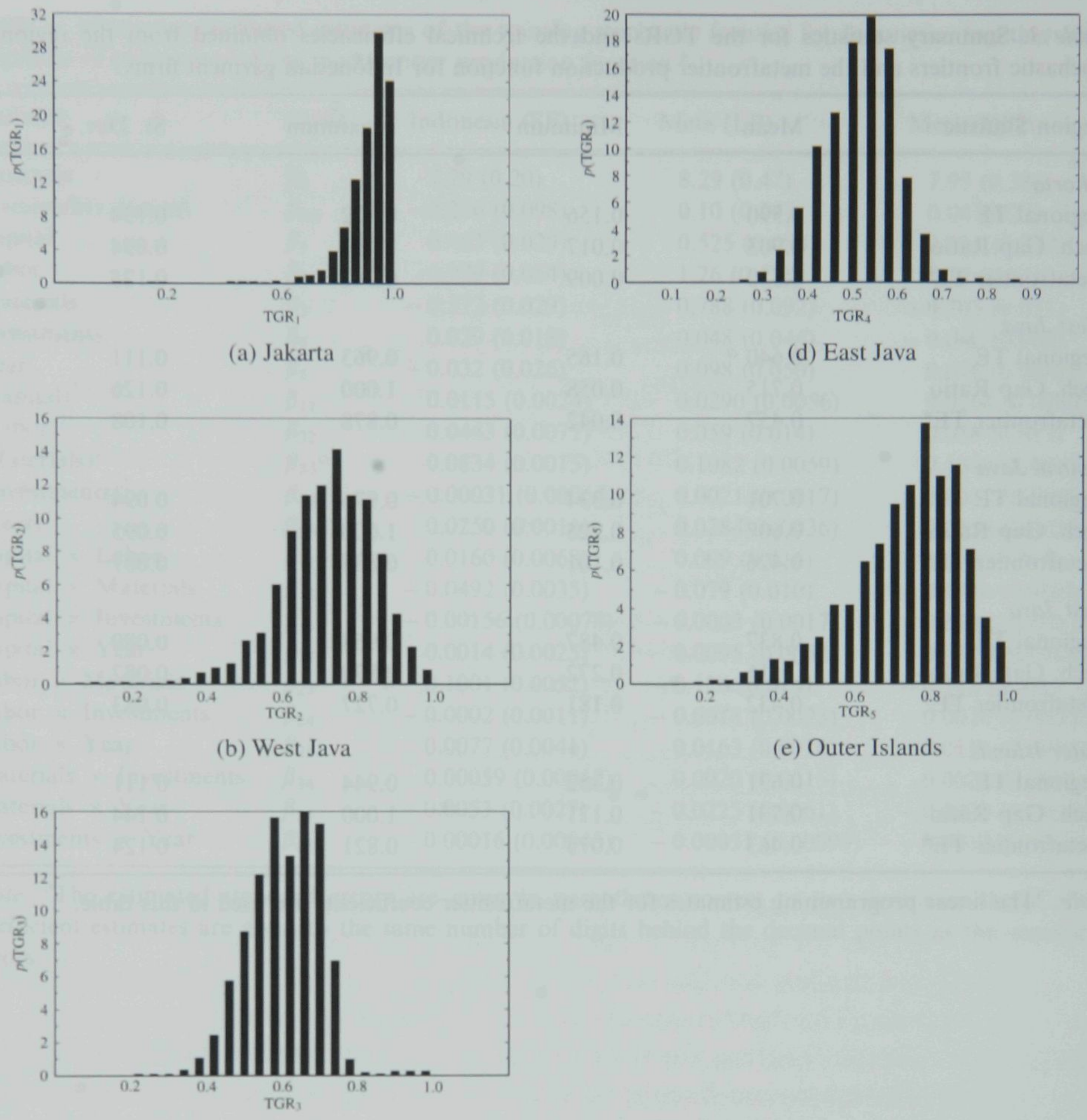

Figure 2. Frequency distributions of TGRs for garment firms in different regions of Indonesia.

3. Conclusions

With the main objective of providing comparable technical efficiency scores for firms across different technologies, a metafrontier production function model is proposed and applied in the analysis of the technical efficiencies of garment firms in five regions of Indonesia. The methodology proposed enables the estimation of regional TGRs by using a decomposition result involving both the regional stochastic frontiers and the metafrontier. Further theoretical and applied studies with other models for technical inefficiency effects are clearly desirable.

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Notes

1. For a translog production function, $\mathbf{x}_{it(j)}$ would contain the logarithms of the different inputs, their squares and cross-products.
2. The radial distance is used in defining the input and output distance functions that form the basis for all productivity comparisons (see Coelli et al., 1998, Chapter 3).
3. All variables that are in monetary units are in thousands of rupiahs, expressed in 1990 prices.
4. The total operating costs is used as a proxy for the value of capital services.
5. Investments are specified in the production function because they are usually targeted at the upgrading of technology and so they could be associated with technological changes.
6. Because investments were not always positive, the dummy variable, D, is used for handling zero observations, as proposed by Battese (1997).
7. The subscript, j, used in equations (1)–(15) to distinguish a particular region, is not included in the empirical model of equation (16) for simplicity of presentation.
8. This refers to no time effects (or exogenous technological changes) in the production frontier. However, as stated in the specification of the frontier model in equation (16), the level of investments may be associated with technological change. Hence, another test of no technical change involves testing that all coefficients associated with time and investments were zero.
9. The LR statistic is defined by $\lambda = -2\{\ln[L(H_0)/L(H_1)]\} = -2\{\ln[L(H_0)] - \ln[L(H_1)]\}$, where $\ln[L(H_0)]$ is the value of the loglikelihood function for the stochastic frontier estimated by pooling the data for all regions and $\ln[L(H_1)]$ is the sum of the values of the loglikelihood functions for the five regional production frontiers. The degrees of freedom for the Chi-square distribution involved are 104, the difference between the number of parameters estimated under H_1 and H_0.
10. The parameters of the regional frontiers were estimated by maximum likelihood so the estimators are asymptotically normally distributed.

References

Battese, G. E. (1997). "A Note on the Estimation of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values." *Journal of Agricultural Economics* 48, 250–252.

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

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

Battese, G. E. and D. S. P. Rao. (2002). "Technology Gap, Efficiency and a Stochastic Metafrontier Function." *International Journal of Business and Economics* 1(2), 1–7.

Battese, G. E., D. S. P. Rao and D. Walujadi. (2001). "Technical Efficiency and Productivity Potential of Garment Firms in Different Regions in Indonesia: A Stochastic Frontier Analysis Using a Time-varying Inefficiency Model and a Metaproduction Frontier." CEPA Working Papers, No. 7/2001, School of Economics, University of New England, Armidale, p. 27.

Coelli, T. J. (1996). "A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation." CEPA Working Papers, No. 7/96, School of Economics, University of New England, Armidale, p. 33.

Coelli, T. J., D. S. P. Rao and G. E. Battese. (1998). *Introduction to Efficiency and Productivity Analysis*. Boston: Kluwer Academic Publishers, p. 271.

Hayami, Y. and V. W. Ruttan. (1971). *Agricultural Development: An International Perspective*. Baltimore: Johns Hopkins University Press.