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## Technical Efficiency and Productivity Potential of Firms Using a Stochastic Metaproduction Frontier

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# UNIVERSIDAD DE OVIEDO

# DEPARTAMENTO DE ECONOMÍA

## PERMANENT SEMINAR ON EFFICIENCY AND PRODUCTIVITY

## TECHNICAL EFFICIENCY AND PRODUCTIVITY POTENTIAL OF FIRMS USING A STOCHASTIC METAPRODUCTION FRONTIER[♣]

**George E. Battese, D.S. Prasada Rao and Dedi Walujadi[*]**

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**Abstract**
This paper presents an empirical study of the technical efficiencies of firms in the Indonesian garment industry using panel data from the annual Census of Manufacturing Industries during 1990 to 1995. Different stochastic frontier models are used for firms in five different regions of Indonesia because of differing technologies involved. However, a stochastic metaproduction frontier is applied to obtain alternative estimates for the technical efficiencies of firms in the different regions. The mean productivity potential of firms in a given region is also estimated, using a decomposition result obtained by using both the regional and the metaproduction frontiers. The technical inefficiency effects in the stochastic frontiers are assumed to have the time-varying structure proposed by Battese and Coelli (1992).

***Key Words:*** Technical efficiency, stochastic frontier, panel data, metaproduction frontiers.

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## 1. Introduction

One of the most important and fascinating aspects of economic change in Indonesia in the last three decades has been the growth in manufacturing. Textiles and garments together have been Indonesia's largest exporters of manufactured goods, overtaking plywood in 1991. It is predicted that these industries will continue to be the most important in the foreseeable future. These industries will be the basis for Indonesia's efforts to diversify from its earlier heavy reliance on oil and gas. Among large- and medium-sized firms in 1987, the textile and garment firms accounted for 11.6 and 22.7 per cent of value added and employment, respectively; in 1995, they accounted for 21.0 and 21.1 per cent, respectively. However, since 1993, there was some concern in government circles about the stagnant earnings from garment exports (van der Eng, 1993, p. 8).

The aims of this study are to measure the technical efficiency of Indonesian garment firms in five different regions and to investigate the trends in their technical inefficiencies over the period, 1990 to 1995. The technical efficiencies of the garment firms are estimated by using different regional stochastic production frontiers for firms in several regions in Indonesia, together with a stochastic metaproduction frontier. Both types of stochastic frontier models are assumed to have time-varying technical inefficiency effects over the six-year period involved.

## 2. The Indonesian Garment Industry

In this study, the garment industry involves the manufacture of wearing apparel made from textiles (ISIC Code 32210). In 1996, the world textile and clothing trade was valued at US$1,620 billion, which made it the third largest global industry, after the information technology and tourism industries. Indonesia, with a total manufacturing value added of around US$41,186 million in 1994, was ranked eighth in size among the exporting countries. The share of textiles and clothing to value added in manufacturing in Indonesia has remained about 15 per cent during the early 1980s and 1990s. Although, in an international perspective, Indonesia’s textile and clothing industry is small, it has a significant role in the Indonesian economy. The Indonesian Central Bureau of Statistics (1997) reported that, in 1996, the export of garments was the fourth largest category of Indonesia's exports and one of the major contributors to the country's economic growth.

The emergence of Indonesian garment production as a factory-based operation is very recent. According to Hill (1992, p. 8), mechanised production of garments first arose as a factory activity in the late 1970s from its origins in tailor shops. According to the annual manufacturing survey in 1995, about 68.1 per cent of the total number of firms engaged in the garment industry employed between 20 and 99 workers, but the firms with 500 workers or more accounted for 11.3 per cent of all firms and employed 72.2 per cent of the workers in the industry.

However, the rise of the large-scale garment firms in Indonesia, in response to global forces in international markets, and frequent changes in style and fashion, has recently brought about a major restructuring in the production and management system. The capital and knowledge intensities of the large-scale garment firms have increased, and the product lines produced by many apparel firms have been widened and upgraded. In contrast with the small-scale producers, which use modified household sewing machines in their daily operations, the large-scale enterprises exclusively use industrial sewing machines and own a wide range of specialised machines. The machines used in these large firms can deal with lightweight fabrics to heavier canvases and denims. The products of these firms are controlled, to a large extent, by hand-held computers to determine types and quantities of defects by 'cut, bundle and piece'. Some of them even used computer-aided design techniques to draw patterns, automatic air pressurised work benches for the cutting of layers of material, and the latest 'full body machines' for pressing shirts and trousers (van Diermen, 1997, p. 78).

The preponderance of a few large firms, using the latest technologies in the apparel industry, also explains the remarkable increase in their share in total output, which amounted to 72.2 per cent of the total output of all garment firms in 1995, having increased from 61.3 per cent in 1990.

There is strong evidence that the garment market in Indonesia is segmented. The majority of the large-scale factories sell most of their products abroad, while the small-scale firms serve the domestic market. However, selling in foreign markets is more difficult than selling domestically. Thus, the large-scale firms, in addition to maintaining their good relationships with distributors abroad, also diversify their products and sell them in the domestic markets. Further details on the Indonesian garment industry are given by Walujadi (2000).

There is only one study on the technical efficiency of firms in the Indonesian garment industry. Hill and Kalirajan (1993) used data from the 1986 Census of Small Industry, which enumerated all firms (94,500 firms) employing 5-19 persons in that year. A stochastic frontier analysis was conducted on the data from 2,250 garment firms in the Province of West Java. Notwithstanding its limited coverage of the garment industry in Indonesia, and accounting for small-scale firms only, the study sought to explain the presence of the efficiency gap and significant inter-firm variations in performance by using a discriminant function analysis. The variables that were used in the discriminant function analysis were the years of operation, export orientation, source of finance, proportion of unpaid workers, and the proportion of female participation.

Hill and Kalirajan (1993) concluded that the frequent assertion that small firms are inferior to larger units, in terms of technical efficiency, is not supported by their results. They found that the average efficiency levels of small garment firms in West Java were comparable with those found in other studies. However, a wide range of technical efficiencies existed among the firms.

Analyses of technical efficiency of garment firms at the regional level are important and challenging for Indonesia. First, 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. Second, the annual manufacturing survey in 1995 provides evidence that Java is the dominant garment-producing region, with respect to three different criteria. Java accounts for about 95 per cent of output and employment and 84 per cent of all firms in Indonesia. It is possible that the larger-sized garment firms in Jakarta and West Java are more capital-intensive, have better access to factor inputs and new technology, have a more export-orientated production and have higher efficiency and productivity than garment firms in other regions.

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

## 3. Manufacturing Surveys and Data on Garment Firms

This study uses data on Indonesian firms in the garment industry that were collected as a part of annual surveys of firms in the manufacturing industries. Though referred to as annual surveys, they are based on a complete enumeration of all the firms in the manufacturing industries. These surveys are conducted by Indonesia's Central Bureau of Statistics (Badan Pusat Statistik or BPS) on an annual basis. The first industrial census was conducted in 1964. Since 1969, the annual manufacturing surveys have been covering all establishments with 20 or more employees. Thus, coverage of these surveys is basically restricted to medium- and large-scale establishments. In 1975, the survey included 8,883 manufacturing establishments, but the number increased to 23,374 in 1995, making it the largest complete enumeration survey conducted by the BPS. For small-scale establishments, in addition to availability of industrial censuses (conducted every ten years), data are gathered using sample surveys and are conducted for only the years, 1979, 1982, 1991 and 1993.

Being a complete enumeration of the medium- and large-scale firms, the annual Indonesian manufacturing surveys provide better and more comprehensive statistical information. Therefore, the survey results are expected to be more precise than those based on other surveys that use sampling methodology.

Based on the latest directory, the BPS sends a questionnaire to *every* industrial establishment involved in manufacturing. This is followed by personal interviews at new establishments by BPS personnel to make sure that the questions are clear enough to elicit the appropriate answers. The BPS personnel explain the objectives of the survey, clarify the contents, and ensure that the appropriate company executives complete the questionnaires. Considerable effort is expended to overcome the problems due to a lack of cooperation from respondents, often resulting in non-responses, or faulty responses due to unclear questions or deliberate errors.

The general aims of the survey for the Indonesian government are:

1. To obtain information about economic value added that is used to calculate national income accounts; and
2. To collect information on other factors needed for economic planning of the manufacturing sector.

In terms of the content of the questionnaires used, the survey covers a very wide range of questions, such as company identification, general information, various types of expenses, goods produced, other sources of income, machinery and electric motors used, inventory and stocks, amount of investment, and other information related to recently-introduced industrial development policies.

Notwithstanding the wide-ranging contents of the questionnaires, the data from the surveys have not been extensively used by academics or policy makers in empirical analyses. The present study is the first major empirical analysis involving these data.

## 4. Stochastic Frontier Models

For the purpose of this study, Indonesia is divided into five regions: four regions in Java and a fifth region comprising the remaining provinces outside Java, combined into one. Six years of panel data for the whole population of medium- and large-scale garment firms in Indonesia are used for our empirical analysis.

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 that is used to represent the production technology for garment firms *in a particular region* is defined by

$$\ell n Y_{it} = \beta_0 + \beta_0^* D_{it} + \sum_{j=1}^{5} \beta_j x_{jit} + \sum_{j \le} \sum_{k=1}^{5} \beta_{jk} x_{jit} x_{kit} + V_{it} - U_{it} \, , \qquad (1)$$

$i = 1, 2, \ldots, N; \; t = 1, 2, \ldots, 6;$

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

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

$\ell nY_{it}$ denotes the natural logarithm of the total value of manufacturing output for the *i*-th garment firm in the *t*-th year (in thousands of rupiahs, at 1990 constant prices);[1]

$D$ denotes the dummy variable for the actual annual value of investment, which has value one if the firm had a positive level of investment in the given year, and has value zero, otherwise (the subscripts, *i* and *t*, are omitted for simplicity of presentation);[2]

$x_1$ denotes the natural logarithm of the total value of operating costs of capital, hereafter referred to as *capital*;

$x_2$ denotes the natural logarithm of the total number of paid labourers, hereafter referred to as *labour*;

$x_3$ 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 maximum of the total amount of actual investments and the value of 1-D for the firm, hereafter referred to as *investment*;[3]

$x_5$ denotes the time variable, where $x_5 = 1, 2, \ldots, 6$ for 1990, 1991, …, 1995, respectively;

the $V_{it}$s are assumed to be independently and identically distributed as $N\left(0, \sigma_v^2\right)$ random variables, independent of the $U_i$s;

the $U_i$s are assumed to be independently and identically distributed non-negative random variables, obtained by truncation (at zero) of the $N\left(\mu, \sigma^2\right)$ distribution; and

the $\beta s, \eta, \mu, \sigma_v^2$ and $\sigma^2$ are unknown parameters to be estimated.

In this model, the technical inefficiency effect for the *i*-th garment firm in the given region in the *t*-th year, $U_{it}$, is defined to be the product of an exponential function of time, $exp[-\eta(t-T)]$, involving the unknown parameter, $\eta$, and the non-negative random variable, $U_i$, which is the technical inefficiency effect for the *i*-th firm in 1995, the *last year* for our data set. If $\eta$ is positive, then $-\eta(t-T) \equiv \eta(T-t)$ is positive for $t < T$ and so

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[1] All variables in our analysis that are expressed in monetary units are in thousands of rupiahs, relative to 1990 prices.

[2] This dummy variable is used because, for some firms, the investment variable, $x_4$, had zero values. This approach for handling zero observations was proposed by Battese (1997).

[3] The variable, $x_4$, is equal to the logarithm of investments if investments are positive, and zero otherwise.

$exp[-h(t\text{-}T)] > 1$, which implies that the technical inefficiencies of firms decline over time. However, if h is negative, then $-h(t\text{-}T) < 0$ and thus the technical inefficiencies increase over time.

The $V_{it}$-random variables are random errors that might be due to different uncontrollable factors related to the production process, including measurement errors in the output of garments, or the effects of other variables not accounted for in the production function.

The stochastic frontier model, defined by equations (1)-(2), is estimated using data on garment firms in the given region. The technical efficiency of the *i*-th garment firm in that region at the *t*-th time period, defined by $TE_{it} = exp(-U_{it})$, is estimated relative to the regional stochastic frontier, as indicated 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 (1)-(2). However, if the technical efficiencies of all garment firms across regions in Indonesia are to be estimated relative to a *common frontier*, then Battese and Rao (2001) suggest that a stochastic metaproduction frontier be used. The stochastic metaproduction frontier[4] is defined analogously to the regional frontier of equations (1)-(2) and is estimated using data on *all garment firms across all regions*. Battese and Rao (2001) suggest a decomposition by which the technical efficiencies of firms in a given region, and their productivity potential, may be estimated relative to the metaproduction frontier. This approach, which is outlined in the Appendix, is applied in our analysis of data on all Indonesian garment firms in the following section.

## 5. Empirical Results

### 5.1. Estimates and tests

The maximum-likelihood estimates of the parameters in the regional and metaproduction frontiers were obtained by using the FRONTIER 4.1 program (Coelli, 1996). The null hypothesis that the Cobb-Douglas frontier is an adequate

[4] The concept of a *stochastic frontier* metaproduction frontier used in this paper is similar to that of the standard metaproduction frontier approach, proposed by Hayami (1969) and Hayami and Ruttan (1970, 1971). These functions are discussed in more detail in Battese and Rao (2001).

representation of the data was strongly rejected, as was the null hypothesis that there was no technical change in the garment firms between 1990 and 1995, for all regions and for the metaproduction frontier for Indonesia. The technical inefficiency effects in all regional stochastic frontiers and the metaproduction frontier were significant, so that the traditional average response functions are not adequate representations of the data on the garment firms in the respective situations. However, for East Java and the Outer Islands, the null hypothesis that the technical inefficiency effects are time-invariant was not rejected. In addition, the null hypothesis that the inefficiency effects for East Java had half-normal distribution was not rejected. The maximum-likelihood estimates for the parameters of the preferred stochastic frontiers for the different regions and the metaproduction frontier are presented in Table 1.

**Table 1: The maximum-likelihood estimates of the translog stochastic production frontiers with the preferred inefficiency models for garment firms in different regions and for Indonesia, 1990-1995[a]**

| Variable | Coeff. | Jakarta | West Java | Central Java | East Java[b] | Outer Islands[c] | Indonesia[d] |
|---|---|---|---|---|---|---|---|
| **Stochastic Frontier** | | | | | | | |
| Constant | $\beta_0$ | 7.08<br>(0.41) | 8.99<br>(0.42) | 10.60<br>(0.47) | 10.57<br>(0.66) | 6.20<br>(0.58) | 7.79<br>(0.20) |
| Investment dummy | $\hat{a}_0^*$ | -0.10<br>(0.21) | -0.19<br>(0.19) | -0.34<br>(0.18) | -0.21<br>(0.29) | -0.09<br>(0.26) | -0.216<br>(0.098) |
| Capital | $\beta_1$ | 0.667<br>(0.089) | 0.097<br>(0.069) | 0.542<br>(0.066) | 0.303<br>(0.097) | 0.485<br>(0.081) | 0.463<br>(0.029) |
| Labour | $\beta_2$ | 0.86<br>(0.12) | 1.60<br>(0.11) | 0.97<br>(0.12) | 1.42<br>(0.15) | 0.98<br>(0.16) | 0.979<br>(0.054) |
| Materials | $\beta_3$ | -0.532<br>(0.053) | -0.737<br>(0.059) | -1.148<br>(0.082) | -1.16<br>(0.11) | -0.337<br>(0.092) | -0.572<br>(0.029) |
| Investment | $\beta_4$ | -0.024<br>(0.037) | 0.022<br>(0.033) | 0.069<br>(0.038) | 0.072<br>(0.056) | 0.047<br>(0.050) | 0.029<br>(0.018) |
| Year | $\beta_5$ | 0.069<br>(0.046) | -0.026<br>(0.050) | -0.082<br>(0.053) | -0.111<br>(0.057) | -0.200<br>(0.058) | -0.032<br>(0.026) |
| $(\text{Capital})^2$ | $\beta_{11}$ | -0.0204<br>(0.0080) | 0.0126<br>(0.0047) | 0.0217<br>(0.0067) | 0.0241<br>(0.0057) | 0.0221<br>(0.0048) | 0.0115<br>(0.0024) |
| $(\text{Labour})^2$ | $\beta_{22}$ | 0.021<br>(0.016) | 0.091<br>(0.014) | -0.008<br>(0.018) | 0.061<br>(0.023) | 0.035<br>(0.020) | 0.0443<br>(0.0077) |

**Table1: (cont.)**

| Variable | Coeff. | Jakarta | West Java | Central Java | East Java[b] | Outer Islands[c] | Indonesia[d] |
|---|---|---|---|---|---|---|---|
| (Materials)$^2$ | $\beta_{33}$ | 0.0726 | 0.0896 | 0.1161 | 0.1176 | 0.0852 | 0.0834 |
| | | (0.0022) | (0.0026) | (0.0043) | (0.0056) | (0.0047) | (0.0015) |
| (Investment)$^2$ | $\beta_{44}$ | 0.0003 | 0.0004 | -0.0020 | -0.0003 | 0.0003 | -0.00031 |
| | | (0.0012) | (0.0013) | (0.0014) | (0.0025) | (0.0019) | (0.00064) |
| (Year)$^2$ | $\beta_{55}$ | 0.0251 | 0.0275 | 0.0241 | 0.0264 | 0.0256 | 0.0250 |
| | | (0.0030) | (0.0029) | (0.0031) | (0.0039) | (0.0043) | (0.0016) |
| Capital × Labour | $\beta_{12}$ | 0.048 | -0.014 | 0.036 | 0.009 | 0.047 | 0.0160 |
| | | (0.017) | (0.013) | (0.017) | (0.018) | (0.016) | (0.0068) |
| Capital × Materials | $\beta_{13}$ | -0.0312 | -0.0143 | -0.0756 | -0.0501 | -0.0746 | -0.0492 |
| | | (0.0072) | (0.0075) | (0.0093) | (0.0099) | (0.0088) | (0.0035) |
| Capital × Investment | $\beta_{14}$ | 0.0014 | 0.0042 | 0.0003 | -0.0062 | -0.0038 | -0.00156 |
| | | (0.0018) | (0.0014) | (0.0017) | (0.0022) | (0.0018) | (0.00078) |
| Capital × Year | $\beta_{15}$ | 0.0104 | -0.0100 | -0.0081 | -0.0027 | -0.0099 | 0.0014 |
| | | (0.0059) | (0.0053) | (0.0052) | (0.0062) | (0.0067) | (0.0025) |
| Labour × Materials | $\beta_{23}$ | -0.0935 | -0.160 | -0.088 | -0.151 | -0.116 | -0.1001 |
| | | (0.0094) | (0.011) | (0.013) | (0.017) | (0.015) | (0.0052) |
| Labour × Investment | $\beta_{24}$ | -0.0051 | -0.0008 | 0.0016 | 0.0074 | 0.0073 | -0.0002 |
| | | (0.0024) | (0.0019) | (0.0026) | (0.0032) | (0.0031) | (0.0011) |
| Labour × Year | $\beta_{25}$ | 0.0167 | 0.0088 | 0.0123 | -0.000 | -0.014 | 0.0077 |
| | | (0.0071) | (0.0078) | (0.0083) | (0.010) | (0.011) | (0.0041) |
| Materials × Investment | $\beta_{34}$ | 0.0029 | -0.0039 | -0.0018 | -0.0017 | -0.0027 | 0.00059 |
| | | (0.0011) | (0.0010) | (0.0017) | (0.0020) | (0.0019) | (0.00062) |
| Materials × Year | $\beta_{35}$ | -0.0188 | -0.0017 | 0.0030 | 0.0064 | 0.0217 | -0.0053 |
| | | (0.0042) | (0.0048) | (0.0060) | (0.0061) | (0.0064) | (0.0027) |
| Investment × Year | $\beta_{45}$ | -0.0003 | 0.00085 | -0.00060 | -0.0017 | -0.0002 | -0.00016 |
| | | (0.0009) | (0.00074) | (0.00097) | (0.0012) | (0.0012) | (0.00045) |
| **Variance Parameters** | | | | | | | |
| | $s_s^2$ | 0.229 | 0.1040 | 0.0826 | 0.114 | 0.145 | 0.153 |
| | | (0.011) | (0.0083) | (0.0078) | (0.013) | (0.017) | (0.047) |
| | $\gamma$ | 0.582 | 0.384 | 0.367 | 0.555 | 0.397 | 0.478 |
| | | (0.020) | (0.037) | (0.042) | (0.057) | (0.061) | (0.014) |
| | $\eta$ | -0.114 | 0.048 | 0.012 | - | - | -0.028 |
| | | (0.018) | (0.023) | (0.030) | | | (0.013) |
| | $\mu$ | 0.730 | 0.400 | 0.348 | - | 0.480 | 0.541 |
| | | (0.086) | (0.033) | (0.059) | | (0.086) | (0.032) |
| **Loglikelihood Fn.** | | -932.47 | -369.63 | -105.79 | -29.47 | -347.9 | -2244.1 |

[a] The standard errors are given under the parameter estimates correct to two-significant digits. The estimates are given to the same number of digits behind the decimal points as the standard errors.

[b] The null hypothesis, $H_0$: $\eta=\mu=0$, was not rejected for East Java, so that the technical inefficiency effects for East Java are assumed to be time-invariant and have half-normal distribution.
[c] The null hypothesis, $H_0$: $\eta=0$, was not rejected for the Outer Islands, so that the technical inefficiency effects for the Outer Islands are assumed to be time-invariant.
[d] The parameters estimated in the last column are for the translog frontier, in which data on all garment firms in Indonesia are included in the analysis. All sub-models of the translog metaproduction frontier were rejected by the data. This defines the metaproduction frontier for all regions, except Jakarta, for which the estimated values were less than the regional frontier.

The individual parameters of the regional production frontiers and the metaproduction frontier are not directly interpretable as elasticities because the input data were not scaled to have zero means in their logarithms. Output elasticity estimates for the different input variables are presented and discussed below.

It is noteworthy that the estimates for the γ-parameter, defined by $\gamma = \sigma^2 / \sigma_s^2$, where $\sigma_s^2 = (\sigma^2 + \sigma_v^2)$, vary from 0.367 to 0.582 and are significantly different from zero for all five regional frontiers and the metaproduction frontier. For the regional frontier for Jakarta and the metaproduction frontier, the technical inefficiencies are estimated to increase over time (the η-estimates are negative for these two cases). However, for the regional frontiers for West Java and Central Java, the technical inefficiency effects are estimated to decline over time.

It is important to examine if all the regions share the same technology. If all the firm-level data are generated from a single production frontier and the same underlying technology, there are no real reasons for attempting a decomposition of efficiency levels derived using the metaproduction frontier. A formal test of the null hypothesis, that the regional stochastic frontier models are the same for all firms in Indonesia, is obtained using the likelihood-ratio (LR) statistic. This is obtained by using the values of the log-likelihood functions for the regional frontiers and the metaproduction frontier.

The value of the LR statistic is 923.56,[5] which far exceeds 133.6, the 95th percentile for the Chi-square distribution with 104 degrees of freedom. This result strongly suggests that the five regional stochastic frontiers for garment firms in Indonesia are not the same. Hence, the stochastic metaproduction frontier model is not the same as the

[5] 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 loglikelihood function for the metaproduction frontier and $ln[L(H_1)]$ is the sum of the loglikelihood functions for the different regional production frontiers.

regional models. These results show that significant differences between various regional technologies exist, and, therefore, the metaproduction frontier can be used for a detailed decomposition analysis, as outlined below.

### 5.2. Output elasticities and technical change

The output elasticities with respect to capital, labour, materials and investment, together with technical change, are estimated at the mean input values for the different regional stochastic frontiers and the metaproduction frontier. The estimates are presented in Table 2.

**Table 2: Output elasticities and technical change obtained from the regional stochastic frontiers and the metaproduction frontier for the Indonesian garment firms**

| Variable | Jakarta | West Java | Central Java | East Java | Outer Islands | Indonesia * |
|---|---|---|---|---|---|---|
| *Capital* | 0.095 | 0.110 | 0.096 | 0.070 | 0.057 | 0.073 |
| *Labour* | 0.239 | 0.158 | 0.137 | 0.243 | 0.280 | 0.220 |
| *Materials* | 0.695 | 0.761 | 0.796 | 0.619 | 0.530 | 0.738 |
| *Investment* | 0.014 | 0.021 | -0.005 | 0.011 | 0.017 | 0.010 |
| *Tech. Change* | 0.171 | 0.097 | 0.105 | 0.117 | 0.110 | 0.125 |

* The estimates in this column are from the metaproduction frontier.

A comparison of the elasticities for particular inputs in Table 2 needs to be done with caution because the mean input levels are not the same for the different regions and Indonesia as a whole. A few similarities of output elasticities are noted among the regional frontiers and the metaproduction frontier. Jakarta, East Java and the Outer Islands have output elasticities that are quite close to those of the metaproduction frontier. The elasticities of capital, labour and materials for West Java and Central Java are of quite similar magnitude. Also, the estimates for technical change from the regional stochastic frontiers and the metaproduction frontier are quite close, and indicate technical progress.

### 5.3. Technical efficiencies of firms

The main advantage of using the stochastic metaproduction frontier over the regional production frontiers is that the efficiency scores obtained from the former are comparable across regions, whereas those obtained from the latter are not. As stated above, the metaproduction frontier approach assumes that all regions have access to the same technology. However, firms in the different regions may operate on a different part of the production possibility curve, depending upon resource endowments, adoption and diffusion of technology, relative factor prices, and economic environments.

The mean technical efficiencies obtained from the regional stochastic frontiers and the metaproduction frontier are presented in Table 3 for the six years involved. The technical efficiencies from the regional frontiers are greater than those obtained from the metaproduction frontier, except for Jakarta and for 1990 in West Java. For Jakarta, the regional frontier yielded estimated outputs that were greater than those for the translog frontier that was estimated using data for all firms in Indonesia. The estimated mean technical efficiencies for garment firms in Jakarta are thus defined by the corresponding values from the regional frontier.

**Table 3: Mean technical efficiencies of the Indonesian garment firms by regions and years, obtained from the regional stochastic frontiers and the metaproduction frontier**

| Year | Jakarta | | West Java | | Central Java | | East Java | | Outer Islands | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Regional | Meta* | Regional | Meta | Regional | Meta | Regional | Meta | Regional | Meta |
| 1990 | 0.664 | 0.664 | 0.603 | 0.603 | 0.687 | 0.578 | 0.837 | 0.609 | 0.631 | 0.628 |
| 1991 | 0.636 | 0.636 | 0.617 | 0.599 | 0.700 | 0.579 | 0.837 | 0.585 | 0.631 | 0.612 |
| 1992 | 0.598 | 0.598 | 0.627 | 0.589 | 0.700 | 0.566 | 0.837 | 0.575 | 0.631 | 0.609 |
| 1993 | 0.569 | 0.569 | 0.647 | 0.587 | 0.705 | 0.559 | 0.837 | 0.572 | 0.631 | 0.605 |
| 1994 | 0.530 | 0.530 | 0.663 | 0.581 | 0.705 | 0.549 | 0.837 | 0.563 | 0.631 | 0.597 |
| 1995 | 0.485 | 0.485 | 0.677 | 0.575 | 0.707 | 0.544 | 0.837 | 0.552 | 0.631 | 0.575 |
| Mean | 0.581 | 0.581 | 0.640 | 0.589 | 0.701 | 0.561 | 0.837 | 0.574 | 0.631 | 0.603 |
| Min. | 0.152 | 0.152 | 0.165 | 0.162 | 0.334 | 0.230 | 0.487 | 0.302 | 0.352 | 0.220 |
| Max. | 0.972 | 0.972 | 0.963 | 0.959 | 0.976 | 0.939 | 0.968 | 0.875 | 0.943 | 0.947 |
| St Dv | 0.135 | 0.135 | 0.111 | 0.109 | 0.094 | 0.095 | 0.089 | 0.081 | 0.111 | 0.125 |

* The metaproduction frontier for Jakarta is defined to be the same as the Jakarta regional frontier because the translog frontier, estimated using all data for Indonesia, yielded values for Jakarta that were less than those from the Jakarta regional frontier.

### 5.4. Productivity potential of regions

Using the approach of Battese and Rao (2001), the outputs of firms can be considered relative to their appropriate regional stochastic frontiers and the metaproduction frontier. This gives the simple identity relationship

$$1 = \frac{e^{x_i \beta}}{e^{x_i \beta^*}} \cdot \frac{e^{V_i}}{e^{V_i^*}} \cdot \frac{e^{-U_i}}{e^{-U_i^*}} . \qquad (3)$$

where the numerator terms are the components of the stochastic frontier for the i-th firm's output in terms of its regional frontier and the denominator terms are the components of the metaproduction frontier for the i-th firm. Battese and Rao (2001) refer to the three ratios on the right-hand side of equation (3) as the *productivity potential ratio*, the *random error ratio* and the *technical efficiency ratio*, respectively.

A similar expression to that of equation (3) is obtained by considering the expected output, conditional on the mean input vales, under the regional and metaproduction frontiers. Given the assumptions for the models defined in equations (1)-(2), the identity of interest is

$$1 = \frac{e^{\bar{x}\beta}}{e^{\bar{x}\beta^*}} \cdot \frac{e^{\frac{1}{2}\sigma_v^2}}{e^{\frac{1}{2}\sigma_{v^*}^2}} \cdot \frac{E\left(e^{-U_i}\right)}{E\left(e^{-U_i^*}\right)} \qquad (4)$$

where $PPR \equiv \frac{e^{\bar{x}\beta}}{e^{\bar{x}\beta^*}}$ is the mean productivity potential ratio;

$RER \equiv \frac{e^{\frac{1}{2}\sigma_v^2}}{e^{\frac{1}{2}\sigma_{v^*}^2}}$ is the mean random error ratio; and

$TER \equiv \frac{E\left(e^{-U_i}\right)}{E\left(e^{-U_i^*}\right)}$ is the mean technical efficiency ratio.

Estimates for the productivity potential ratio (PPR) and the technical efficiency ratio (TER), based on estimates for the values in equation (4) are presented in Table 4. The values of the productivity potential ratio are less than one, except for Jakarta. The four regions other than Jakarta, have productivity levels between about 70 per cent and 95 per cent of the potential levels, according to the metaproduction frontier. These values can be interpreted as the technological gap faced by the garment firms in these four regions when their performances are compared with the national level. The values of the technical efficiency ratio are greater than one for the last four regions, indicating that the mean technical efficiencies relative to the regional frontiers are *larger* than those obtained from the metaproduction frontier, as indicated in Table 3. These technical efficiency ratios indicate the order of the bias of the technical efficiencies obtained by using the regional frontiers, relative to the technology available to firms in the industry.

**Table 4: Mean regional productivity potential and technical efficiency ratios, using stochastic frontier models with time-varying inefficiency effects**

| Region | PPR | TER |
|---|---|---|
| Jakarta | 1.000 | 1.000 |
| West Java | 0.927 | 1.087 |
| Central Java | 0.811 | 1.250 |
| East Java | 0.696 | 1.458 |
| Outer Islands | 0.952 | 1.046 |

East Java has the lowest productivity potential ratio, which indicates that it is the region that is the least productive relative to its national competitors. The results of the present study indicate that the productivity potential ratio for the time-varying inefficiency model varies across regions, but the garment firms in Jakarta have a productivity potential ratio equal to one. This is a consequence of our method of estimation, in which the metaproduction frontier for firms in Jakarta is defined by the regional frontier for Jakarta, because the estimated metaproduction frontier gave values less than those for the Jakarta regional frontier.

## 6. Conclusions

With the main objective of providing comparable technical efficiency scores for firms across regions, the technical efficiencies of garment firms in Indonesia are estimated using a stochastic metaproduction frontier. In addition, we have estimated regional productivity potential and efficiency levels by using a decomposition result involving both the regional stochastic frontiers and the metaproduction frontier.

The data used in this study support the view that mean productivity potential and technical efficiency ratios give additional explanation compared with the analysis based only on individual regional stochastic production frontiers. The productivity potential ratio plays an important part in explaining the ability of the garment firms in one region to compete with other garment firms from different regions at the national level. This ratio provides an estimate of the technology gap between the region and the country as a whole.

The analysis of technical efficiency using a stochastic metaproduction frontier also gives a better overview of the comparability of technical efficiency scores across regions. However, some questions still remain about how efficiency changes over time. Further investigations with other models for technical inefficiency effects are clearly desirable.

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**Appendix: A Decomposition of Technical Efficiency and Productivity Potential Using Regional and Metaproduction Frontiers**

This Appendix is based on Battese and Rao (2001).

**A.1. The Frontier Models**

It is assumed that the inputs and outputs for firms in the garments industry are such that stochastic production frontier models are defined for different regions. Suppose that for the *j*-th region, there are sample data on $N_j$ firms that produce garment outputs from the various inputs, such that the stochastic frontier model for this region is defined by

$$Y_{ij} = f(x_{ij}, \beta_j)e^{V_{ij}-U_{ij}}, \quad i = 1, 2, \ldots, N_j, \qquad \text{(A1)}$$

where the $V_{ij}s$ are assumed to be identically and independently distributed as $N(0, \sigma_v^2)$-random variables, independent of the $U_{ij}s$, which are defined by the truncation (at zero) of the $N(\mu_{ij}, \sigma^2)$-distributions, where the $\mu_{ij}s$ are defined by some appropriate inefficiency model, e.g., one of the Battese and Coelli (1992, 1995) models. For simplicity, the subscript, *j*, is omitted so the model for the *j*-th region is given by

$$Y_i = f(x_i, \beta)e^{V_i-U_i} \equiv e^{x_i\beta+V_i-U_i}. \qquad \text{(A2)}$$

The stochastic metaproduction frontier model for firms in all regions of the industry is expressed by

$$Y_i = f(x_i, \beta^*)e^{V_i^*-U_i^*} \equiv e^{x_i\beta^*+V_i^*-U_i^*}, \quad i = 1, 2, \ldots, N, \qquad \text{(A3)}$$

where $N = \sum_{j=1}^{R} N_j$ is the total number of sample firms in all (R) regions; and the assumptions for the $V_i^*s$ and the $U_i^*s$ are analogous to those for the $V_is$ and the $U_is$, respectively.

If the assumptions for the regional stochastic frontiers, associated with equations (A1) and (A2), are reasonable for given sample data, then the corresponding assumptions associated with the stochastic metaproduction frontier of equation (A3) may not be appropriate (e.g., the $V_i^*s$ may not be identically distributed over all regions). The parameters of a given regional frontier are estimated using data from firms *in that region*. The parameters of the metaproduction frontier model are estimated using data from firms *in all regions* (in the combined data set).

In the discussion below, the parameter vectors, $\beta$ (for the *j*-th regional frontier) and $\beta^*$ (for the metaproduction frontier), are assumed to be known. The productivity and technical efficiency of firms in the *j*-th region can be investigated using either the frontier for the *j*-th region or the metaproduction frontier.

The maximum-likelihood estimates of the parameters of the metaproduction frontier model do not necessarily result in the estimated function being an *envelope* of the individual regional production functions. However, it is possible to constrain the estimation of the metaproduction frontier, such that it is an envelope of observations for efficient firms in all regions. For example, if the estimated metaproduction frontier is estimated to have values less than the regional function in a given region, then the metaproduction frontier could be defined to coincide with the regional function for that region or over some other range of the inputs. Alternatively, a constrained mathematical programming algorithm, such as in data envelopment analysis (DEA) could be used in the estimation of the metaproduction frontier. However, such methods do not adequately account for the presence of traditional random errors, and assume that all deviations from the "frontier" are due to inefficiency.

### A.2. Productivity Potential and Efficiency Levels

The observed output for the *i*-th firm in the *j*-th region can be expressed by $Y_i = e^{x_i\beta + V_i - U_i}$ or $Y_i = e^{x_i\beta^* + V_i^* - U_i^*}$, as specified by equations (A2) and (A3), respectively, where it follows that the relationship, $x_i\beta + V_i - U_i = x_i\beta^* + V_i^* - U_i^*$, is satisfied.

It is expected that the deterministic values, $x_i\beta$ and $x_i\beta^*$, satisfy the inequality, $x_i\beta \le x_i\beta^*$, because $x_i\beta^*$ is from the metaproduction frontier. If the metaproduction frontier were estimated to be an envelope function for efficient firms, then the relationship would be satisfied by the estimated functions.

The ratio of the two models yields the identity relationship:

$$1 = \frac{e^{x_i b}}{e^{x_i b^*}} \cdot \frac{e^{V_i}}{e^{V_i^*}} \cdot \frac{e^{-U_i}}{e^{-U_i^*}} \quad \text{(A4)}$$

The three ratios on the right-hand side of this equation are called the *productivity potential ratio* (PPR), the *random error ratio* (RER) and the *technical efficiency ratio* (TER), i.e.,

$$PPR_i \equiv \frac{e^{x_i b}}{e^{x_i b^*}} \equiv e^{-x_i(b^* - b)}, \quad RER_i \equiv \frac{e^{V_i}}{e^{V_i^*}} \equiv e^{V_i - V_i^*}, \text{ and } \quad TER_i \equiv \frac{e^{-U_i}}{e^{-U_i^*}} \equiv \frac{TE_i}{TE_i^*}.$$

The productivity potential ratio indicates the potential for productivity increases for the given region, according to currently available technology for firms in a given region relative to the technology available in the whole industry. This ratio and the technical efficiencies (and, hence, the technical efficiency ratio) can be estimated for each individual firm. The technical efficiency of firm *i*, relative to its regional frontier, $TE_i \equiv e^{-U_i}$, can be estimated by $\hat{TE}_i \equiv E\left(e^{-U_i} \middle| E_i \equiv V_i - U_i\right)$. The technical efficiency of firm *i*, relative to the metaproduction frontier, can be similarly estimated, i.e., $\hat{TE}_i^* \equiv E\left(e^{-U_i^*} \middle| E_i^* \equiv V_i^* - U_i^*\right)$. Clearly, $E_i^* \equiv E_i - x_i\left(b^* - b\right)$.

Consider the technical efficiency ratio $TER_i \equiv \frac{TE_i}{TE_i^*} \equiv \frac{e^{-U_i}}{e^{-U_i^*}}$: Generally this ratio is expected to be greater than or equal to 1. Because $U_i$ and $U_i^*$ are random variables, there is a non-zero probability that the ratio, $TER_i$, less than unity.

A similar expression to that of equation (A4) can be obtained in terms of the expected output, as presented in equation (4) of the text of the paper. Clearly, only two of the ratios in equation (4) need to be estimated in any empirical application.