The Estimation of Technical Efficiency Effects Models
with an Example Applied to the Thai Manufacturing
Sector

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Abstract

This paper does two things. First, it presents alternative approaches to the standard methods of estimating productive efficiency using a production function. It favours a parametric approach (viz. the stochastic production frontier approach) over a non-parametric approach (e.g. data envelopment analysis); and, further, one that provides a statistical explanation of efficiency, as well as an estimate of its magnitude.

Second, it illustrates the favoured approach (i.e. the ‘single stage procedure’) with estimates of two models of explained inefficiency, using data from the Thai manufacturing sector, after the crisis of 1997. Technical efficiency is modelled as being dependent on capital investment in three major areas (viz. land, machinery and office appliances) where land is intended to proxy the effects of unproductive, speculative capital investment; and both machinery and office appliances are intended to proxy the effects of productive, non-speculative capital investment.

The estimates from these models cast new light on the five-year long, post-1997 crisis period in Thailand, suggesting a structural shift from relatively labour intensive to relatively capital intensive production in manufactures from 1998 to 2002.

Key words: productive efficiency; stochastic production frontier; Thai manufacturing sector

JEL Codes: C210, L640, N650, L690, L850

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1 Introduction

The purpose of this paper is to examine the effect that capital investment has on manufacturing efficiency levels. It does so using stochastic production frontier analysis, in which not only is inefficiency measured, but its extent is explained. The paper has two parts. In the first, alternative methodologies to the standard average production function are considered. Thus, deterministic and stochastic production frontiers are considered, culminating with the recommendation that the so-called ‘single-stage procedure’ for technical efficiency effects models is best fitted to our purpose. In the second part, we reviews recent applications of the single-stage procedure, and then apply it to manufacturing in Thailand for the five years beyond the 1997 economic crisis. We find evidence of a shift from relatively labour intensive to relatively capital intensive manufactures over this period.

The analysis of productive efficiency would not be complete without an examination not only of its relative magnitude (the focus of earlier work in the literature), but also of those variables that explain variations in producer performance (the focus of this work). Such variables may influence technical
efficiency in many ways. For example, they could influence the structure of the technology by which conventional inputs are converted to outputs; or they could influence the efficiency with which inputs are converted into outputs. Examples of such variables include: the degree of competition, size of the firm, managerial experience, and ownership characteristics. Attempts to incorporate these explanatory variables into efficiency measurement models, in a variety of ways, some more satisfactory than others, include Pitt and Lee (1981), Sickles, Good, and Johnson (1986), Deprins and Simar (1989a, 1989b), Kumbhakar, Ghosh and McGuckin (1991) and Reifschneider and Stevenson (1991), Bauer and Hancock (1993), Berger, Hancock, and Humphrey (1993), Huang and Liu (1994), Battese and Coelli (1995), and Berger and Mester (1997).

The precursors to our models are several. The field was started with the work of Farrell (1957) who used a linear programming method to measure productive efficiency. This led to development of the widely adopted technique of data envelopment analysis (DEA) e.g. as expounded by Charnes, Cooper and Rhodes (1978). The next major step was taken by Aigner and Chu (1986) and others, specifying a deterministic production function, for which $Y_i$ was the maximum output from a set of inputs $x_i$ with $\beta$ a parameter vector (e.g. of the slope and intercept parameters of a Cobb Douglas specifications of the production function) for the $i$ th producer in a cross section of firms. These deterministic models were estimated by linear or quadratic programming, and whilst they did provide parameter estimates, they lacked a statistical foundation from which inferences could be made.

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1 Kumbhakar and Lovell, (2002)
about these parameters. Thereafter, statistical models for cross-sectional data were
developed by Schmidt (1976), and those who followed him, in which \( Y_i = f(x_i; \beta) \exp(\varepsilon_i) \) for \( \varepsilon_i \leq 0 \). This one-sided error approach of Schmidt (1976) was improved
by Aigner, Amemiya and Poirieer (1976) who introduced a parameter \( \theta \) to measure
the relative variability of two sources of error: the one due to (one sided)
inefficiency error, and the other to symmetric input or output error. Then \( \theta \) is
estimated alongside \( \beta \). Building on this, the stochastic production frontier approach
was developed simultaneously by Meeusen and van der Broeck (1977) and Aigner,
Lovell and Schmidt (1977). In their approach, \( \varepsilon_i = V_i - U_i \), where \( V_i \) is a symmetric
error, and \( U_i \) is an independent one sided error. Estimation is by maximum
likelihood, given its desirable properties (e.g. briefly: efficiency, BAN, consistency,
sufficiency, invariance). Jondrow et al (1982) went on to show how individual
producers’ technical inefficiency could be computed using the mean or the mode of
the conditional distribution of \( U_i \) given \( \varepsilon_i \). Pitt and Lee (1981) were to extend this
cross-sectional maximum likelihood estimation method to panel data. This form of
analysis subsequently was extended to time varying efficiency, for panels of data, by
Kumbhakar (1990), Cornwell, Schmidt and Sickles (1990) and Battese and Coelli
(1992). Hitherto, the statistical model of Battese and Coelli (1992) had been the
most popular technique to be adopted in applied stochastic production frontier work.

Crucial to the analysis here, is the development, beyond the above, of methods that
explain efficiency itself, to methods that jointly estimate its influence along with
other parameters. Several models which link efficiency with explanatory variables
will be discussed, taking note of their novelty as well as their limitations. The development of these models is undertaken in Section 2. It starts with the first literature to consider those variables which may affect the performance of firms directly, through their influence on the structure of the production frontier. It proceeds to consider the two-stage approach, in which explanatory variables are incorporated into the efficiency model, but are assumed to have no direct influence on the structure of the production frontier. Finally, it concludes with the development of the single-stage approach models, which is regarded as the most useful approach in the present context. Such models have independent inefficiency component, and the parameters of the stochastic frontier and the inefficiency model are estimated simultaneously. In Section 3 we survey some recent empirical studies and consider the specification of our model, which will be used later in our illustration of this form of analysis, applied to evidence on manufacturing industry in Thailand. The empirical results from the estimated model of Section 3 are then presented in Section 4. These results are discussed in detail in Section 5. Finally, our conclusions are stated in Section 6.

2 Technical Efficiency Effects

In the early studies in which the issue of the explanatory variables were investigated, such variables were assumed to affect the performance of firms directly, through their influence on the structure of the production frontier. Pitt and Lee (1981),
Sickles, Good, and Johnson (1986), and more recent studies, including Bauer and Hancock (1993), Berger, Hancock, and Humphrey (1993), and Berger and Mester (1997), are among those who follow this approach. The production frontier then takes the form of

$$\ln Y_i = \ln f(x_i, z_i; \beta) + V_i - U_i$$

(1)

where $z = (z_1, \ldots, z_q)$ is a vector of explanatory variables that influence the structure of the production process by which inputs $x$ are converted to output $Y$, and $\ln f(x_i, z_i; \beta)$ is the deterministic part of the stochastic production frontier $\ln f(x_i, z_i; \beta) + V$. In such a model, the estimable parameter vector $\beta$ includes within it both technological and environmental parameters.

This model has the same structure as a conventional stochastic production frontier, and all the estimation techniques subsequently developed expand upon those in the conventional model. However, with the assumption of independently and identically distributed error terms, $U_i$ and $V_i$, the elements of $z_i$, as well as $x_i$, are typically assumed to be uncorrelated with each of these disturbance terms. Thus, these explanatory variables affect the performance of firms, not by influencing their efficiencies (with which they are assumed to be uncorrelated), but by influencing the structure of the production frontier, which bounds the relationship between inputs and outputs. Therefore, what is accomplished by this formulation may be described as a more accurate characterization of production possibilities, and consequently, it entails more precise estimation of producer efficiencies.\(^2\) Even so, a main concern of

\(^2\) Kumbhakar and Lovell (2000), pp.263
this formulation, namely the source of variations in efficiency, remains to be explained.

2.1 Two-Stage Approach

In attempting to incorporate explanatory variables into the efficiency model, one approach has been to utilize a two-stage estimation procedure. In the first stage, a stochastic frontier \( \ln Y_i = \ln f(x_i; \beta) + V_i - U_i \) is estimated, typically by the method of maximum likelihood, under the usual distributional assumptions of identically and independently distributed random variables \( V_i \) and \( U_i \). The estimated efficiencies are then regressed against the explanatory variables in a second-stage regression of the general form

\[
E(U_i | V_i - U_i) = g(z_i; \delta) + w_i
\]  

In (2) the \( w_i \) are distributed independently and identically as \( N(0, \sigma_w^2) \), and \( \delta \) is a parameter vector to be estimated.

In this two-stage approach, it is hypothesized that the explanatory variables, \( z_i \), influence the output, and thus the performance, of the firms indirectly through its effects on firms’ efficiency. Technically speaking, these explanatory variables do not influence the structure of the production frontier, but instead, influence the efficiency with which producers approach the production frontier. Therefore, the elements of \( z_i \) are correlated with the \( U_i \) if the \( z_i \) have, indeed, effects on firms’ efficiency. Unfortunately, this is in conflict with the assumption of identically distributed \( U_i \) that is made in the first-stage, in which \( E(U_i) \) is a constant, and is
equal to \(\left(\frac{2}{\pi}\right)^{1/2} \sigma_U\); while, in the second-stage, it becomes \(E(U_i|V_i - U_i)\) which varies with \(z_i\), as shown by equation (2).

Alas, this approach suffers from another econometric problem. That is, since it must be assumed that the elements of \(z_i\) are uncorrelated with the elements of \(x_i\), the maximum likelihood estimates of \(\beta, \sigma_V^2\), and \(\sigma_U^2\) are biased, due to the omission of the relevant variables \(z_i\) in the first-stage estimation of the frontier. Consequently, the estimated efficiency obtained from the second-stage regression will itself be biased, as it is estimated with a biased representation of the production frontier.

### 2.2 Single-Stage Approach

In order to overcome the drawbacks (as noted above) of the two-stage approach, Deprins and Simar (1989a, 1989b) suggest a production frontier with

\[
\ln Y_i = \ln f(x_i; \beta) - U_i \tag{3}
\]

\[
E(U_i|z_i) = \exp\{\delta z_i\} \tag{4}
\]

where \(\beta\) and \(\delta\) are the technological and environmental parameter vectors to be estimated, and \(\exp\{\delta z_i\}\) expresses the systematic part of the relationship between technical inefficiency and the explanatory variables. Thus, the single-stage production frontier becomes

\[
\ln Y_i = \ln f(x_i; \beta) - \exp\{\delta z_i\} + w_i \tag{5}
\]

where the \(w_i\) are assumed to have zero mean and a constant variance. Also, \(w_i\) is not identically distributed since its support depends on \(z_i\). This frontier model is nonlinear in the parameters and can be estimated by either nonlinear least squares, or
by maximum likelihood estimation, if a suitable one-sided distribution for \( U_i \) is specified.

This approach is an important improvement on the first two approaches mentioned above. First, it provides an explanation of efficiency, which is not a characteristic of the first approach. Second, it provides an adjustment to raw efficiency scores, which reflect the nature of the operating environments in which they were achieved. Third, it solves difficulties unresolved by the second approach, in that the omitted variables and independence problems are avoided by incorporating the explanatory variables into a single frontier estimation stage. However, the major drawback of this approach is that it is based on a deterministic frontier model, which contains no symmetric error component to capture the effects of random noise in the production process.

Kumbhakar, Ghosh and McGuckin (1991) propose that a production frontier with random noise in the production process be introduced, through the error component \( V_i \), so that

\[
\ln Y_i = \ln f(x_i; \beta) + V_i - U_i \quad \text{(6)}
\]

\[
U_i = \delta z_i + w_i \quad \text{(7)}
\]

where the technical inefficiency term, \( U_i \), is associated with the systematic component \( \delta z_i \) and a random component \( w_i \). This therefore yields a single-stage production frontier model

\[
\ln Y_i = \ln f(x_i; \beta) + V_i - (\delta z_i + w_i) \quad \text{(8)}
\]

However, because of the restriction that \( U_i \geq 0 \), \( w_i \) is required to be \( \geq -\delta z_i \), which, in turn, should avoid imposing the condition that \( \delta z_i \geq 0 \). Nevertheless, in order to
be able to derive the likelihood function, the restriction of \( w_i \geq -\delta'z_i \), as well as distributional assumption on \( w_i \) and \( V_i \), have to be imposed. To resolve this matter, these authors impose distributional assumptions on \( U_i \) and \( V_i \) instead. They assume that \( V_i \) is distributed with \( N(0, \sigma^2_V) \) and that \( U_i \) has a truncated normal structure, with variable mode depending on \( z_i \), as in \( N^+(\delta'_z, \sigma^2_U) \), and these conditions do not require that \( \delta'_z \geq 0 \).

Reifschneider and Stevenson (1991), have formulated a model that can eliminate the statistical problems that occur with this additive formulation in the Kumbhakar, Ghosh and McGuckin (1991) model. They proposed a hybrid model that combines features of the Deprins and Simar (1989a, b) models with features of the Kumbhakar, Ghosh and McGuckin (1991) model. The technical inefficiency term is now defined as

\[
U_i = g(z_i; \delta) + w_i
\]

(9)

and the production frontier is, as with equation (6), of the form:

\[
\ln Y_i = \ln f(x_i; \beta) + V_i - U_i
\]

The effects of random noise are captured by the error component \( V_i \). The requirement that \( U_i = g(z_i; \delta) + w_i \geq 0 \) is ensured by specifying a functional form for the systematic component of inefficiency satisfying \( g(z_i; \delta) \geq 0 \), and also by assuming the distribution of the random component of inefficiency \( w_i \) is \( N^+(0, \sigma^2_w) \). Hence, the single-stage production frontier becomes

\[
\ln Y_i = \ln f(x_i; \beta) - g(z_i; \delta) + V_i - w_i
\]

(10)
The assignment of a one-sided distribution to \( w_i \) simplifies estimation of the model by eliminating the statistical problems arising from the additive formulation of Kumbhakar, Ghosh and McGuckin. However, this simplification does not come without cost, since the two conditions of \( g(z_i; \delta) \geq 0 \), and that \( w_i \) is iid \( N^+(0, \sigma_w^2) \) are sufficient, but not necessary for \( U_i \geq 0 \). Also, the restriction of \( w_i \geq 0 \) has an interesting economic implication. For, if \( w_i \geq 0 \), then \( U_i \geq g(z_i; \delta) \), and thus inefficiency, \( U_i \), is at least as great as the minimum possible inefficiency achievable in an environment characterized by the explanatory variables \( z_i \). Hence, the function \( g(z_i; \delta) \) in equation (9) can be interpreted as a deterministic minimum inefficiency frontier.

Huang and Liu (1994) proposed a model very similar to the Kumbhakar, Ghosh and McGuckin (1991) and Reifschneider and Stevenson (1991) models. With the same identification of the production frontier and the technical inefficiency relationship as those in Reifschneider and Stevenson (1991), they rearrange equation (10), so that

\[
\ln Y_i = \ln f(x_i; \beta) + V_i - [g(z_i; \delta) + w_i]
\]

making it very similar to the model proposed by Kumbhakar, Ghosh and McGuckin (1991), (cf. equation (8)), except that \( \delta' z_i \) is replaced by \( g(z_i; \delta) \). Therefore, the requirement that \( U_i = [g(z_i; \delta) + w_i] \geq 0 \) is met by truncating \( w_i \) from below, such that \( w_i \geq -g(z_i; \delta) \), and by assigning a distribution to \( w_i \) such as \( N(0, \sigma_w^2) \). Thus, instead of truncating a normal distribution with variable mode from below, at zero, as in Kumbhakar, Ghosh and McGuckin (1991), Huang and Liu (1994) truncate a normal
distribution with a zero mode, from below, at a variable truncation point \([- g(z_i; \delta)]\).

This therefore allows \(w_i \leq 0\), but enforces \(U_i \geq 0\).

The essential novelty of this model lies in the fact that, using the function \(g(z_i; \delta)\), it is possible to introduce interactions between elements of \(z_i\) and elements of \(x_i\). To illustrate, Huang and Liu (1994) express the function \(g(.)\) as:

\[
g(z_i, x_i; \delta) = \sum_q \delta_q z_{iq} + \sum_q \sum_n \delta_{qni} z_{iq} \ln x_{ni}
\]  

(12)

The condition that sets the Huang and Liu (1994) model apart from all the other stochastic frontier models mentioned above is as follows. They show that when the exogenous variables interact with the inputs, they can have non-neutral effects on technical efficiency, whereas for all other variables it is assumed that technical inefficiency is neutral, with respect to its impact on input usage.

Later in 1995, Battese and Coelli proposed a model resembling that of Huang and Liu (1994), save for two features. First, their model was formulated for panel data, rather than cross-sectional data. And second, they did not include inputs in their specification of \(g(z_i; \delta)\). Their model, which is similar to those of Kumbhakar, Ghosh and McGuckin (1991), consists of the following specification:

\[
\ln Y_{it} = \ln f(x_{it}; \beta) + V_{it} + U_{it}
\]

\[
U_{it} = \delta' z_{it} + w_{it}
\]  

(13)

With the non-negativity requirement \(U_{it} = \delta' z_{it} + w_{it} \geq 0\), the random variable \(w_{it}\) is defined by the truncation of the normal distribution with zero mean and variance \(\sigma_w^2\), \(N(0, \sigma_w^2)\), such that the point of truncation is \(\delta' z_{it}\), i.e. \(w_{it} \geq -\delta' z_{it}\). Thus, these assumptions are consistent with the distributional assumption that \(U_{it}\) is distributed
as \( N^+(\delta z_{it}, \sigma_U^2) \). This formulation differs from that of Reifschneider and Stevenson (1991) in that the \( w_{it} \) are not identically distributed, nor are they required to be non-negative. Further, the mean \( \delta z_{it} \) of the normal distribution is truncated by zero, to obtain the distribution of \( U_{it} \), where this random variable is not required to be non-negative for every producer, so that \( w_{it} \leq 0 \) is possible in a relatively unfavourable environment.

The technical efficiency of the \( i \)th producer at the \( t \)th observation is, thus, given by

\[
TE_{it} = \exp\{-U_{it}\} = \exp\{-\delta z_{it} - w_{it}\}
\]

A predictor for this is provided by

\[
E[\exp\{-U_{it}\} | (V_{it} - U_{it})] = \exp\{ -\mu_{*it} + \frac{1}{2} \sigma^2_t \} \left[ \frac{\Phi[\frac{\mu_{*it}/\sigma_t - \sigma_t^2}{\Phi(\mu_{*it}/\sigma_t)}]}{\Phi(\mu_{*it}/\sigma_t)} \right]
\]

where \( \mu_{*it} = \frac{\sigma_v^2(\delta z_{it}) - \sigma_U^2(w_{it})}{\sigma_v^2 + \sigma_U^2} \)

\[
\sigma^2_t = \frac{\sigma_v^2\sigma_U^2}{\sigma_v^2 + \sigma_U^2}
\]

This model by Battese and Coelli (1995) is generally the favoured one for evaluating the stochastic production frontier, when explanatory variables for determining technical efficiency are incorporated. It is the model that is used for estimation in the illustrative examples of the next sub-section (2.3) and in the substantive new estimates reported in Sections 3, 4 and 5 below.

2.3 Empirical Studies
Not surprisingly, given its merits, several empirical studies already have been conducted using the single-stage approach proposed by Battese and Coelli (1995). This section reviews a number of these applied contributions, in order to provide preliminary illustrations of the approach to be taken further by us in our econometric work on the manufacturing sector of Thailand in Sections 3 and 4 below. Works that have been conducted elsewhere on the manufacturing sector include the paper of Driffield and Munday (2001). They used three-digit data from the UK Censes of Production for the period of 1984 to 1992. They examine the determinants of technical efficiency in UK manufacturing, focusing particularly on the role of foreign investment and on the spatial agglomeration of similar industrial activities. Their results show that foreign ownership is indeed a determinant of technical efficiency in UK manufacturing, although its effects were found to vary according to industry characteristics. Thus, for sectors that were relatively more productive and regionally concentrated, the effects of foreign investment were found to be higher.

As another example, consider the work of Battese et al. (2001) which used a stochastic frontier model in their study of technical efficiencies of firms in the Indonesian garment industry, in five different regions, for the period from 1990 to 1995. Their results showed that there were substantial efficiency differences among the firms across the five regions.

Uğur (2003) examined the technical efficiency levels in the electrical and optical equipment industry in the Irish manufacturing sector, and explored the factors that would affect these levels. They utilized firm level panel data over the period from 1991 to 1999, and found that investment intensity and labour quality
played an important role in explaining technical inefficiency levels. However, they found no significant relationship between export intensity and the technical inefficiency levels of individual firms in all but one sector.

Kneller and Stevens (2006) examined two potential sources of inefficiency (namely, differences in human capital and R&D) for nine industries in twelve OECD countries over the period of 1973 to 1991. They found that inefficiency in production does indeed exist and depends upon the level of human capital of the country’s workforce. However, evidence that the level of R&D spending would affect efficiency was shown to be less robust.

Apart from works focussing on the manufacturing sector, many empirical studies have also been conducted on the agricultural and fisheries sectors. Examples include the work on the technical inefficiency of the Swedish lobster fishery by Eggert (2000), in which the level of, and determinants of, technical efficiency of Swedish fishing vessels was analysed using a translog stochastic production frontier that included a model for vessel-specific technical efficiencies. This technical inefficiency effect was found to be highly significant in explaining the level of, and variation in, vessel revenues. This indicates that fishermen become more efficient, the longer they have been fishing, but that their vessels became less efficient over time. Finally, it was found that the size of the vessel did not affect efficiency.

Coelli et al. (2003) applied a stochastic production frontier model to measure total factor productivity growth, technical efficiency change and technological change in Bangladeshi crop agriculture. Estimation was based on 31 observations from 1960/61 to 1991/92, using data for 16 regions. Their results revealed that
technical change followed a U-shaped pattern, rising from the early 1970s. However, technical efficiency declined throughout. The combined effect of slow technical progress, dominated by the fall in technical efficiency, resulted in total factor productivity declining, with an increasing rate of decline. TFP change was shown to depend on ‘green revolution’ technology, and agricultural research expenditures.

Belloumi and Matoussi (2005) compared estimates of technical efficiency, obtained from the stochastic frontier approach for two samples of private and GIC (i.e. collective association) farmers in Tunisia, which were characterized by a severe scarcity of water and a high degree of salinity. The technical inefficiency effects were modelled as a function of farm-specific socioeconomic factors, and environmental factors. The results showed that both systems were technically inefficient, but that the GIC farmers were technically less efficient, compared to the private ones, as they were more severely affected by water salinity.

These empirical examples have provided useful illustrations of the use of the single stage approach developed by Battese and Coelli (1995). This background has the benefit that it led us to the more technically satisfactory model specification that is set out in the next section.

3 Model Specification

As stated earlier, the objective of this paper is to examine the relationship between the level of productive capital investments and the efficiency level. Ideally, in order to explore this, the data on each category of capital investment should be used as an
explanatory variable in the technical efficiency effects model. Unfortunately, such disaggregated data on capital categories were not available in the pre-crisis period. Therefore, an alternative method needs to be adopted. One way in which this difficulty can be resolved is by relating the increase in capital investments to the change in the inefficiency level in the post-crisis period. A negative relationship between the increase in a particular type of capital investment and the inefficiency level would imply that any improvement in the post-crisis efficiency level was, at some level, affected by the increase in that particular capital investment. Then, if it is possible to show that the increase in productive capital investments (e.g. in machinery and office appliance) has indeed reduced the inefficiency term, it would possible that the improvement in the efficiency level was partly a result of the increase in investment in more productive capital.

Following Battese and Coelli (1995), the production frontier is assumed to take the form of the Cobb-Douglas production function, which can be expressed as

$$\ln Y_{it} = \beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) + \left(V_{it} - U_{it}\right)$$  \hspace{1cm} (18)

where the technical inefficiency component is defined as

$$U_{it} = \delta_1 z_{1it} + \delta_2 z_{2it} + \delta_3 z_{3it} + w_{it}$$  \hspace{1cm} (19)

Here, technical inefficiency, captured by $U_{it}$, is assumed to be influenced by the increase in capital investments in three major areas, viz. land, machinery, and office appliances. Land is assumed to proxy unproductive, speculative capital investment$^3$, while machinery and office appliances are assumed to proxy productive capital

$^3$ Land is used to proxy the unproductive and/or speculative investment in this case, since, in the pre-crisis period, the Thai economy was characterized as being a ‘bubble’ economy, where many manufacturers over-invested in the real estate sector, in order to benefit from the fast rate of price increase within it.
investment. This approach follows the method employed by Young (1995), in which capital input was divided into five categories consisting of: residential buildings; non-residential buildings; other durable structures; transport equipment; and machinery. In our paper here, the addition to capital investment in land, \( z_{1it} \), is measured by the ratio of the change in value of gross additions of land to the number of employee. The addition to capital investment in machinery \( z_{2it} \) is measured by the ratio of the change in value of gross additions of machinery and equipment to the number of employee. And the addition to capital investment in office appliances \( z_{3it} \) is measured by the ratio of the change in value of gross additions of office appliances to the number of employees.

Therefore, the single-stage production frontier is estimated using the specification

\[
\ln Y_{it} = \beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) - \delta_1 z_{1it} - \delta_2 z_{2it} - \delta_3 z_{3it} + V_{it} - w_{it} \tag{20}
\]

and the technical efficiency of production for the \( i \)th industry at the \( t \)th observation is defined by

\[
TE_{it} = \exp\{-U_{it}\} = \exp\{-\delta_1 z_{1it} - \delta_2 z_{2it} - \delta_3 z_{3it} - w_{it}\} \tag{21}
\]

Predictions of the technical efficiencies are based on the conditional expectation given by the model assumptions of equations (15), (16) and (17) above. The technical efficiency will take the value of one if an industry has an inefficiency effect equal to zero, and will be less than one otherwise.

Several parameters need to be tested, including the \( \gamma, \delta_L, \delta_M \), and \( \delta_{OF} \). The variance-ratio parameter \( \gamma = \sigma_Y^2/(\sigma_Y^2 + \sigma_U^2) \), is important in testing the stochastic production frontier \( (H_1) \) against the alternative of the traditional average production
function \((H_0)\). If, under the latter, the null hypothesis \(\gamma = 0\) cannot be rejected, the average production function would be a better representation of the post-crisis manufacturing sector, suggesting that no technical inefficiency is present. The \(\delta\) parameters \(\delta_L, \delta_M,\) and \(\delta_{OF}\) represent the effects of capital investment on technical inefficiency. If the null hypothesis of \(\delta_i = 0\) cannot be rejected, then it suggests that this particular type of capital does not have a significant effect on efficiency. Otherwise, the value of \(\delta\) is expected to be negative if the associated capital improves the efficiency level of the production process. On the other hand, a positive \(\delta\) indicates a reduction in efficiency. Tests of hypotheses on parameters can be performed using the generalized likelihood ratio test statistic defined by

\[
\Lambda = -2[\ln(H_0) - \ln(H_1)]
\]

This test statistic has approximately a \(\chi^2\) distribution, or a mixed \(\chi^2\) in the case that involves testing \(\gamma = 0\), with degrees of freedom equal to the difference between the numbers of parameters involved under the null and alternative hypotheses, see Kodde and Palm (1986).

4 Empirical Results for Thai Manufacturing

The context of the empirical work of this section is the economic crisis of 1997 in Thailand. Following rapid and sound economic development in the 1950s, Thailand had become a ‘bubble’ economy by the 1990s. On 2\(^{nd}\) July 1997 Thailand was forced to abandon its fixed exchange rate, and great structural change in the economy followed. Earlier work, Arunsawadiwong (2006, Ch. 8), using the half-
normal, time-invariant efficiency model of Pitt and Lee (1981) finds mean efficiency in Thai manufacturing to be 56% pre-crisis (1993-1996) as compared to 74% post-crisis (1998-2002). A paired samples test confirmed that pre- and post-crisis means were significantly different. Twenty industries out of the twenty four in manufactures had experienced improved efficiency. That work focussed on measuring efficiency, whilst this work focuses on explaining efficiency.

Here, we are estimating post-crisis production frontiers for Thai manufacturing, in order to investigate the impact of post-crisis restructuring on manufacturing efficiency. In doing so, we use the software program FRONTIER 4.1, developed by Tim Coelli (1996) for all estimation. This is a customised single purpose programme for the maximum likelihood estimation of a range of stochastic production frontier models, including that specified in equation (20) above, which is based on the Battese and Coelli (1995) model. In the cases considered, estimation is non-linear, and uses a Quasi-Newton approach, and specifically the Davidon-Fletcher-Powell algorithm. The data used were obtained from the National Statistical Office (NSO) of Thailand. They were compiled by direct interview for the nationwide Manufacturing Industrial Survey. The establishments that made returns for this survey were those engaged primarily in manufacturing (category D International Industrial Classification of All Economic Activities; ISIS: Rev.3) which employed ten or more persons. Data were selected for 24 major manufacturing industries of Thailand, with the list of these industries being presented in Table 3 of this paper. The data extracted were variables for value added ($Y$), headcounts ($L$), book value of
capital \((K)\) and a decomposition of capital into three further variables, namely land \((l)\), machinery \((m)\), and office appliance \((of)\). Value added \((Y)\) was measured as value of gross output minus intermediate consumption. Headcount \((L)\) was measured by the number of persons who worked in or for the establishment, including working proprietors, active business partners, unpaid workers and workers permanently worked outside the establishment. Book value of capital \((K)\) was measured as the net value of capital after deducting the accumulated depreciation at the end of the year. Capital includes land, building, machinery and equipments, vehicles, and office appliances. Land \((l)\) was defined as land and buildings that are used for the production of outputs. Machinery \((m)\) was defined as machinery and equipments that are used for the production of outputs. And Office Appliances \((of)\) were defined as appliances that are used in the office to facilitate the production of outputs. There were 88 observations for four years (four, and not five, as 2001 data were not collected by the NSO Thailand). Three explanatory variables, the additions to capital investment in Land, Machinery, and Office Appliances, are assumed to influence the efficiency of Thai manufacturing industry. Two models are used, Model 1, based on equation (20) and Model 2 based on equation (22). The results from estimation are presented in the third column of Table 1.

First, let us consider Model 1. We start with the estimates of the output elasticity of capital \((Assets)\), \(\beta_1\), and the output elasticity of labour \((Employ)\), \(\beta_2\). The coefficient estimate for capital, \(\beta_1\), is 0.5514, while that for labour, \(\beta_2\) is lower, at 0.3003. This suggests that the structure of the post-crisis manufacturing sector is relatively capital intensive. The inefficiency coefficient estimate of the addition to
land investment \((\text{Land})\), \(\delta_L\), is 0.0017, indicating that the additional investment in land will result in a decline of efficiency, and hence will lead to a deterioration in this sector’s productivity. On the other hand, the inefficiency coefficient estimate of the addition to machinery, \(\delta_M\), and of the addition to office appliances, \(\delta_{OF}\), are equal to -0.0000712, and -0.0012, respectively. These indicate that the additional investment in machinery, as well as in office appliances, will improve technical efficiency, and hence, the overall productivity of these sectors.

Table 1: Maximum likelihood estimates of the technical efficiency models for the post-crisis period

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter</th>
<th>MLE Estimates</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\beta_0)</td>
<td></td>
<td>4.1578</td>
<td>4.0997</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1.0877)</td>
<td>(0.9060)</td>
</tr>
<tr>
<td>Ln Assets</td>
<td>(\beta_1)</td>
<td></td>
<td>0.5514</td>
<td>0.5447</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.1466)</td>
<td>(0.0911)</td>
</tr>
<tr>
<td>Ln Employ</td>
<td>(\beta_2)</td>
<td></td>
<td>0.3003</td>
<td>0.3152</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.1618)</td>
<td>(0.1179)</td>
</tr>
<tr>
<td>Land</td>
<td>(\delta_L)</td>
<td></td>
<td>0.0017</td>
<td>0.0013</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0007)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>Machinery</td>
<td>(\delta_M)</td>
<td></td>
<td>-0.7120E-04</td>
<td>-0.6379E-04</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.2992E-04)</td>
<td>(0.2804E-04)</td>
</tr>
<tr>
<td>Office Appliances</td>
<td>(\delta_{OF})</td>
<td></td>
<td>-0.0012</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0017)</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(\sigma^2)</td>
<td></td>
<td>0.3324</td>
<td>0.3380</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0552)</td>
<td>(0.0549)</td>
</tr>
<tr>
<td></td>
<td>(\gamma)</td>
<td></td>
<td>0.1186E-06</td>
<td>0.1000E-07</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.1166E-04)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td></td>
<td>(n)</td>
<td></td>
<td>88</td>
<td>88</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td></td>
<td></td>
<td>-76.4666</td>
<td>-76.8563</td>
</tr>
</tbody>
</table>

Note: MLE estimates of Model 1 [equation (20)] were obtained using the method of Battese and Coelli (1995) for a Cobb-Douglas production function and a technical inefficiency term \(U_{it}\) influenced by 3 capital components: \(\text{Land}\), \(\text{Machinery}\), and \(\text{Office Appliances}\).

MLE estimates of Model 2 [equation (22) below] were obtained using the method of Battese and Coelli (1995) for a Cobb-Douglas production function.
and a technical inefficiency term $U_{it}$ influenced by 2 capital components: Land and Machinery.
Standard errors are in brackets.

These estimates are then tested for their significance, using likelihood ratio tests. Table 2 presents the relevant test statistics obtained from these hypothesis tests. Firstly, the variance-ratio parameter, $\gamma$, is used to test the average production function against the production frontier. If the null hypothesis $H_0: \gamma = 0$ cannot be rejected, this would suggest that the post-crisis manufacturing sector had no inefficiency in the production process, and hence that the traditional average production function (which assumes all the producers are producing efficiently) is a more appropriate choice of model. Whilst the estimated variance parameter ($\gamma$) presented in Table 1 is nominally small, suggesting that the inefficiency effects could be of marginal significance, the results of the hypothesis test shown in Table 2 indicate that $H_0: \gamma = 0$ should be rejected, as the calculated $\chi^2$ statistic is equal to 8.7769. Therefore, it can be concluded that in the post-crisis period, although the efficiency level was rather high, some inefficiency in the production process still persisted. Therefore, the average production function is rejected as an adequate representation of this period. Hence, the production frontier, based on the Battese and Coelli (1995) model, is preferred as the more appropriate representation.
Table 2: Tests of hypotheses for parameters of the technical inefficiency component

<table>
<thead>
<tr>
<th>Assumptions</th>
<th>Null Hypothesis</th>
<th>$\chi^2$-statistic</th>
<th>$\chi^2_{0.95}$-value</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>$\gamma = 0$</td>
<td>8.7769</td>
<td>8.761$^*$</td>
<td>Reject $H_0$</td>
</tr>
<tr>
<td>Model 1</td>
<td>$\delta_L = 0$</td>
<td>6.2336</td>
<td>3.84</td>
<td>Reject $H_0$</td>
</tr>
<tr>
<td>Model 1</td>
<td>$\delta_M = 0$</td>
<td>7.8351</td>
<td>3.84</td>
<td>Reject $H_0$</td>
</tr>
<tr>
<td>Model 1</td>
<td>$\delta_{OF} = 0$</td>
<td>0.7795</td>
<td>3.84</td>
<td>Cannot Reject $H_0$</td>
</tr>
<tr>
<td>Model 2</td>
<td>$\gamma = 0$</td>
<td>7.9974</td>
<td>7.045$^*$</td>
<td>Reject $H_0$</td>
</tr>
<tr>
<td>Model 2</td>
<td>$\delta_L = 0$</td>
<td>7.8487</td>
<td>3.84</td>
<td>Reject $H_0$</td>
</tr>
<tr>
<td>Model 2</td>
<td>$\delta_M = 0$</td>
<td>7.5070</td>
<td>3.84</td>
<td>Reject $H_0$</td>
</tr>
</tbody>
</table>

Note: Hypotheses are tested using the general likelihood ratio test $\Lambda = -2[\ln(H_0) - \ln(H_1)]$

Following this, the next set of hypothesis tests investigate whether coefficients of the technical inefficiency explanatory variables $\delta_L$, $\delta_M$, and $\delta_{OF}$ are significant. If any of the following null hypotheses $H_0$: $\delta_L = 0$, or $H_0$: $\delta_M = 0$, or $H_0$: $\delta_{OF} = 0$ cannot be rejected, then the associated explanatory variable will be dropped out of the model and a more parsimonious specification will be used. The results from these tests are also shown in Table 2. The null hypotheses $H_0$: $\delta_L = 0$, as well as $H_0$: $\delta_M = 0$ are both rejected at the 95% significance level, indicating that the additions to the land investment and machinery investment, do indeed, have significant effects on the inefficiency level, and thus on the efficiency of the industry’s ability to convert inputs into outputs. However, the hypothesis $H_0$: $\delta_{OF} = 0$ cannot be rejected, hence this implies that the effect of the addition to office

$^*$ Any likelihood ratio test statistic involving a null hypothesis which includes the restriction that $\gamma$ is zero does not have a chi-square distribution because the restriction defines a point on the boundary of the parameter space. In this case the likelihood ratio statistic has been shown to have a mixed $\chi^2$ distribution. In this case, critical values for the generalized likelihood ratio test are obtained from Table 1 in Kodde and Palm (1986).
appliance investment is not significant. Therefore, this variable will be dropped out of our model.

Taking the implied action, the revised specification (Model 2) for the Battese and Coelli (1995) single-stage production frontier becomes

$$\ln Y_i = \beta_0 + \beta_1 \ln(K_i) + \beta_2 \ln(L_i) - \delta_L z_{Lit} - \delta_M z_{Mit} + V_{it} - w_{it}$$  \hspace{1cm} (22)

and the technical efficiency of production for the $i$th industry at the $t$th observation is

$$TE_i = \exp(-U_{it}) = \exp(-\delta_L z_{Lit} - \delta_M z_{Mit} - w_{it})$$  \hspace{1cm} (23)

which from here, will be referred to as Model 2.

The coefficient estimates for Model 2 are also presented in Table 1. Estimates of the output elasticity of capital $\beta_1$, and the output elasticity of labour, $\beta_2$, are similar to those of Model 1, being equal to 0.5447 and 0.3152, respectively. Again, this suggests that the structure of the manufacturing sector is relatively capital intensive. Further, the inefficiency coefficient estimate of the addition to Land investment is again positive, at 0.0013, indicating an increasing relationship between technical inefficiency and the additional investment in Land. Therefore, the positive sign of the coefficient estimate is robust under changed model specification, again suggesting that the greater is the investment in land undertaken by the manufacturing sector, the lesser is the efficiency of its utilization. This strengthens the evidence for a decline in the sector’s productivity through the adverse effect on the individual firms’ efficiency. With Model 2 we again find the inefficiency coefficient estimate of the addition to Machinery is negative (being equal to -0.00006379). This strengthens the finding that additional investment in Machinery
will improve technical efficiency (viz. reduce technical inefficiency), and hence will help to raise the overall productivity of the sector.

Once again, significance tests are needed for the model specification (frontier against average), which involves employing likelihood ratio tests. Referring to the fourth row of Table 2, the hypothesis test for the variance-ratio parameter, \( \gamma \), rejects the null hypothesis \( H_0: \gamma = 0 \) at 95% significance level for Model 2, thus again indicating that the inefficiency still exists; and reinforcing the superiority of the Battese and Coelli (1995) type of production frontier, against the traditional OLS average production function. Hypothesis tests on the significance of the technical inefficiency explanatory variables \( \delta_L \) and \( \delta_M \) (in rows 6 and 7 of Table 2) indicate that both \( H_0: \delta_L = 0 \) and \( H_0: \delta_M = 0 \) are rejected. These results imply that the additional investment in both \( Land \) and \( Machinery \) do indeed have significant effects on the inefficiency level (raising/lowering it, respectively), and thus, on the efficiency of the industry’s ability to convert inputs into outputs (lowering/raising it, respectively). We conclude that the post-crisis manufacturing sector has been modelled effectively by the production frontier method of equation (22), in which the technical inefficiency exists in the production process, and is significantly affected by the two explanatory variables, lowering efficiency with additions to investment in \( Land \), and increasing efficiency with additions to investment in \( Machinery \).

Finally, the technical efficiency (TE) estimates of the industries (see general form in equation 14), together with the mean technical efficiency, are calculated according to the specification of equation (23) above (this being Model 2). The
values obtained are presented in Table 3. Again, it should be noted here that data for 2001 are unavailable, as the National Statistical Office (NSO) was unable to conduct the survey in that year. The grand mean efficiency for the post-crisis period is considered relatively high at 0.8496, suggesting that in the post crisis period, most of the industries were operating rather close to the production frontier, with only industry 10 – (Petroleum in Table 3) the coke, petroleum and nuclear industry, and industry 13 (Non-Metallic in Table 3) – the non-metallic mineral products, that showed rather low efficiency, comparatively. The explanation for such a dramatic decline in the efficiency level for industry 10, Petroleum, in 2002 (with the efficiency level calculated at only 0.1000) is at heart a statistical artefact. Prior to 2001, this industry was dominated by one single stage-owned company, the Petroleum Authority of Thailand PCL (PTT), which had been very inefficient and had been facing a severe problem of debt. Therefore, in 2001, the company was restructured, and was ordered to increase its registered capital by 8,500 million Baht (around 220.79 million US dollar). This led to a ‘pseudo-increase’ in its measured input, and hence reduced its measured efficiency level, as estimated by the Battese and Coelli (1995) model. In the case of industry 13, Non-Metallic, the decline in its efficiency level in 1999 was the result of decreasing demand for products in this category, such as cement, lignite, gypsum, and ballclay, following the pattern of decline in the construction and mining sectors. However, the situation improved in 2000 owing to the assistance from a major joint-venture partner⁴. This led to higher exports of these products, which changed this industry from being very domestically

oriented to being rather export oriented, with over 30 percent of its total production
going overseas by the year 2000.

Table 3: Technical Efficiency Estimates of the TE Effects model

<table>
<thead>
<tr>
<th>Industry</th>
<th>1998</th>
<th>1999</th>
<th>2000</th>
<th>2002</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>0.8445</td>
<td>0.8532</td>
<td>0.8674</td>
<td>0.8724</td>
</tr>
<tr>
<td>Tobacco</td>
<td>0.9037</td>
<td>0.9201</td>
<td>0.9563</td>
<td>0.9939</td>
</tr>
<tr>
<td>Textiles</td>
<td>0.8820</td>
<td>0.9351</td>
<td>0.9693</td>
<td>0.9242</td>
</tr>
<tr>
<td>Wearing Apparel</td>
<td>0.9524</td>
<td>0.9689</td>
<td>0.9779</td>
<td>0.9408</td>
</tr>
<tr>
<td>Leather Products</td>
<td>0.8374</td>
<td>0.8887</td>
<td>0.9339</td>
<td>n/a#</td>
</tr>
<tr>
<td>Footwear</td>
<td>0.9558</td>
<td>0.9809</td>
<td>0.9404</td>
<td>n/a#</td>
</tr>
<tr>
<td>Wood</td>
<td>0.8497</td>
<td>0.9045</td>
<td>0.9200</td>
<td>0.8761</td>
</tr>
<tr>
<td>Paper</td>
<td>0.7891</td>
<td>0.8388</td>
<td>0.8545</td>
<td>0.8634</td>
</tr>
<tr>
<td>Publishing</td>
<td>0.7886</td>
<td>0.7902</td>
<td>0.8125</td>
<td>0.8353</td>
</tr>
<tr>
<td>Petroleum</td>
<td>0.7261</td>
<td>0.4893</td>
<td>0.7749</td>
<td>0.1000</td>
</tr>
<tr>
<td>Chemical</td>
<td>0.8119</td>
<td>0.8442</td>
<td>0.7980</td>
<td>0.8593</td>
</tr>
<tr>
<td>Rubber &amp; Plastic</td>
<td>0.8370</td>
<td>0.9327</td>
<td>0.8880</td>
<td>0.9182</td>
</tr>
<tr>
<td>Non-Metallic</td>
<td>0.5498</td>
<td>0.3258</td>
<td>0.6923</td>
<td>0.7270</td>
</tr>
<tr>
<td>Mineral</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basic Metals</td>
<td>0.7659</td>
<td>0.7780</td>
<td>0.7465</td>
<td>n/a#</td>
</tr>
<tr>
<td>Fabricated Metal</td>
<td>0.8133</td>
<td>0.8475</td>
<td>0.8976</td>
<td>0.8963</td>
</tr>
<tr>
<td>Machinery</td>
<td>0.8827</td>
<td>0.8422</td>
<td>0.9063</td>
<td>0.8878</td>
</tr>
<tr>
<td>Computing</td>
<td>0.9897</td>
<td>0.9467</td>
<td>0.9472</td>
<td>0.9933</td>
</tr>
<tr>
<td>Electrical</td>
<td>0.9404</td>
<td>n/a#</td>
<td>n/a#</td>
<td>0.9234</td>
</tr>
<tr>
<td>Communication</td>
<td>0.8553</td>
<td>0.9409</td>
<td>0.9819</td>
<td>n/a#</td>
</tr>
<tr>
<td>Medical</td>
<td>0.8859</td>
<td>0.9586</td>
<td>0.9706</td>
<td>n/a#</td>
</tr>
<tr>
<td>Vehicles</td>
<td>0.6866</td>
<td>0.6658</td>
<td>0.7463</td>
<td>0.7535</td>
</tr>
<tr>
<td>Transport</td>
<td>0.8163</td>
<td>0.8341</td>
<td>0.9284</td>
<td>0.8940</td>
</tr>
<tr>
<td>Equipment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Furniture</td>
<td>0.7556</td>
<td>0.7831</td>
<td>0.9300</td>
<td>0.9450</td>
</tr>
<tr>
<td>Jewellery</td>
<td>0.8826</td>
<td>0.9442</td>
<td>0.8559</td>
<td>n/a#</td>
</tr>
</tbody>
</table>

Mean | 0.8334 | 0.8354 | 0.8824 | 0.8447 |
Mean | 0.8496 (n = 88)

Note: Technical Efficiency estimates were obtained using the method of Battese and Coelli (1995) for a Cobb-Douglas production function and a technical inefficiency term $U_i$ influenced by 3 capital components: Land, Machinery, and Office Appliances. Because Office Appliances were insignificant, computation used equation (22) which in this paper is referred to as Model 2.

# Data are not available for that period, thus no values for technical efficiencies were calculated.
From Table 3, penultimate row, we see that the annual mean efficiency was 0.8334, 0.8354, 0.8824, and 0.8447, for 1998, 1999, 2000, and 2002, respectively. One interesting point here is that at first sight Table 3 seems to show that the annual mean efficiency is showing a slightly increasing trend. This is unambiguous for food, tobacco, leather products, paper, publishing, communications, medical and furniture. Further, it is arguable for textiles, wearing apparel, wood, chemicals, fabricated metals, vehicles and transport. However, the annual mean efficiency does not show this, largely because of periodic acute inefficiencies in industry 10 (Petroleum) and 13 (Non-Metallic) in 1999 and 2002. To illustrate, if industry 10 is dropped as an outlier, the mean efficiencies are then 0.8381, 0.8511, 0.8873, and 0.8885 for 1998, 1999, 2000, and 2002, respectively. This seems to show a mildly increasing trend. However, a test of the null hypothesis $H_0: \mu_{98} = \mu_{99} = \mu_{00} = \mu_{02}$ is not be rejected at the 5 percent level of significance. So, whilst the seeds of efficiency improvement seem to have been planted, a sustained effect is not confirmed solidly from the evidence.

5 Implication of the Results

The results from Model 2, the stochastic production frontier with the technical inefficiency explanatory variables (i.e. the addition to land and machinery investment) suggested by Battese and Coelli (1995), indicate that in the 5 post-crisis years, from 1998 to 2002, the manufacturing sector of Thailand experienced a
structural shift from being labour intensive to being capital intensive. The coefficient estimates of the post-crisis output elasticity of capital and the output elasticity of labour are equal to 0.5447 and 0.3152, respectively. This finding is consistent with the conclusions reached using the traditional average Cobb-Douglas production function, and the Battese and Coelli (1992) error components model in Arunsawadiwong (2006; Ch. 6, Ch. 8).

The factors behind such structural changes can be seen as involving five main causes. First, the shakeout of firms of lesser efficiency and lesser technological advance, with consequential improvement in the overall efficiency level of individual manufacturing industries, and of the manufacturing sector as a whole. Second, the reduction of the amount of labour used in the production processes as a result of the labour quantity adjustment to the crisis, leading to shifts in the output elasticity of inputs used. Third, the adjustment in relative price, due to the reduction in interest rates as well as rigidity of wage, resulting in the substitution of capital for labour within firms in the manufacturing sector, hence shifting its structure from being labour intensive to being capital intensive. Furthermore, the government policies in facilitating capital investment including the soft loans provision for businesses that need capital upgrading or start-ups, and the tariffs reduction for import of capital goods, also helped to bring about this structural shift. And finally, the post-crisis financial market reformation has resulted in a healthier investment environment in which the ability to access loans by firms with good investment projects was greatly enhanced. Therefore, capital investment in the manufacturing
sector increased, especially in the more productive investment areas, such as machinery.

As we have seen, this last point, about the determinants investment behaviour in the manufacturing sector, is the main focal point of our paper. As regards data, our economic statistics reveal that there was an improvement in the gross output (GO) to capital expenditure (CE) ratio, $GO/CE$, in the post-crisis period (1998-2002). This result suggests that there might have been an increase in the usage of more productive capital over this time period, with this contributing to the observed increase in gross output. It can be argued that although the level of total private investment declined significantly in the post-crisis period, the manufacturing sector has benefited from the healthier investment climate which itself was a result of post-crisis financial market reform and restructuring, leading to our observed increases in efficiency levels. Dollar and Hallward-Driemeier (2000) have argued that, because the pre-crisis interest rates were so high, the majority of the investments in that period were speculative investments, such as those in the stock market and the real estate sector, which were perceived as the only types of investment that could possibly generate adequate returns. It was the manufacturing sector that suffered from precisely such circumstances. They have also argued that, even in the pre-crisis period, investment projects within the manufacturing sector itself were excessively concentrated in the unproductive areas, such as investment in buildings and land, since they appeared to generate higher returns than those arising from manufacturing output per se. Also, domestic manufacturers often preferred these strategies (viz. investing in real estate, building larger plants,
acquiring more land) as these perceived to increase company values. Thus, by the
time of the 1997 crisis, the majority of manufacturers were reported to have
excessive land holdings and excessive plant size. Fortunately, the post-crisis
investment climate has turned favourably towards productive investment. This can
be seen to have resulted from factors like the reduction in domestic interest rates,
and the reformation of financial institutes’ lending behaviour.

The analysis in this paper provides further support for such arguments. The
non-zero variance-ratio parameter ($\gamma$) indicates that although the efficiency level is
now rather high, there is still some persistence of inefficiency in post-crisis
manufacturing production processes. The positive value of $\delta_L$, although small, is
highly significant. This suggests that the greater was the investment in land, the
lower was the efficiency in manufacturing production. This result is in accordance
with the widely-held view (hitherto often not substantiated by solid analysis) that
many Thai manufacturers were already invested excessively in land and real estate
prior to the crisis. Thus, further investment in these areas was unlikely to generate
greater efficiency, and in some cases might have even resulted in a decline in
efficiency. Therefore, it seems reasonable to argue that the Thai manufacturing
sector suffered from over-investment in unproductive capital, prior to the 1997
economic crisis, with concomitant low levels of efficiency and productivity.
Consequently, the competitiveness of the country declined. This brought about the
decline of export growth, which had been the main driving force of the country’s
economic growth. Declining exports, the weakening of economic growth, the bubble
in real estate and stock markets, as well as bulky external debt, provided a

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5 Dollar and Hallward-Driemeier, (2000)
compelling opportunity for currency speculators to attack the Thai Baht, creating the basis for the 1997 economic crisis.

Nevertheless, this crisis could still be seen, ultimately, as being beneficial to the Thai manufacturing sector. In many industries within manufactures, post-crisis efficiency and productivity have improved significantly. One of the reasons for this has probably been the post-crisis financial restructuring. Arguably, this benefited the manufacturing sector by allowing new productive investment (especially the capital investment) to take place. The negative value of $\delta_M$, which we have used to proxy these productive types of investment, suggests that increased investment in machinery and equipment has improved the post-crisis efficiency of manufacturing, and as a result, has enhanced its productivity. Thus the Thai manufacturing sector paradoxically became the beneficiary of the crisis, in terms of productivity and competitiveness. As a cautionary note, the negative sign of the technical inefficiency variable $\delta_M$ also implies that there is still room for the Thai manufacturing sector to improve its efficiency further, for example by increasing investment in machinery and equipment. As argued by Krugman (1994), growth based only on higher resource mobilization can not be sustained in the long-run. Rather, growth should be built up from technological progress and increased efficiency, that is to say, by fostering so-called ‘efficiency-led sustainable growth’.

6 Conclusion
In this paper, the relationship between varieties of capital investment and technical efficiency has been examined, based on the Battese and Coelli (1995) model. Estimates were obtained of the output elasticity of capital and the output elasticity of labour. Two explanatory variables, the addition to capital investment in land and the addition to capital investment in machinery and equipment, were found to have significant but different impacts on efficiency. On the one hand, the positive value of the coefficient for additional investment in land suggests that the higher were such investments, the greater were inefficiencies (i.e. the lower were efficiency levels). On the other hand, the negative value of the coefficient of additional investment in machinery and equipment suggests that such investments improve the efficiency of the manufacturers. These results support that the view that post-crisis efficiency improved partly because of the increase in productive capital mobilised by the post-crisis financial market restructuring, as well as because of the reduction in domestic interest rates. This suggests that, pre-crisis, the Thai manufacturing sector had suffered from insufficient *productive* capital investment, but that this condition abated in the aftermath of the crisis, leading to signs of improvements in efficiency in the immediate post-crisis period.

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