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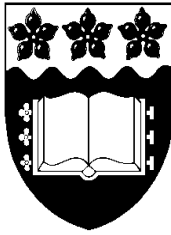
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**Identifying and Measuring Technical Inefficiency Factors:
Evidence from Unbalanced Panel Data for Thai Listed
Manufacturing Enterprises**

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Identifying and Measuring Technical Inefficiency Factors: Evidence from Unbalanced Panel Data for Thai Listed Manufacturing Enterprises

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Abstract

“This study employs stochastic frontier analysis (SFA) and two-stage DEA approaches to predict firm technical efficiency and analyse an inefficiency effects model. Aggregate translog stochastic frontier production functions are estimated under the SFA approach using an unbalanced panel data of 178 Thai manufacturing enterprises listed in the Stock Exchange of Thailand (SET), covering the period 2000 to 2008. The maximum-likelihood Tobit model is used to conduct the second-stage of the two-stage DEA model to investigate the relationship between technical inefficiency and environmental variables. Both parametric and non-parametric approaches are found to produce consistent results. The empirical evidence from both approaches highlight that Thai listed manufacturing firms had been operating under decreasing returns to scale over the period 2000 to 2008. The SFA approach reports that technical progress decreased over time, and relied on labour input. Both estimation approaches suggest that leverage (financial constraints), executive remuneration, managerial ownership, exports, some types of listed firms (i.e., family-owned firm and foreign-owned firm), and firm size have a negative (positive) and significant effect on technical inefficiency (technical efficiency). The empirical results obtained from both approaches also suggest that liquidity, external financing, and research & development (R&D) have a significantly positive (negative) effect on technical inefficiency (technical efficiency)”

Keywords: Stochastic Frontier Analysis (SFA); Data Envelopment Analysis (DEA); Technical Efficiency; Manufacturing; Thailand

***Identifying and Measuring Technical Inefficiency Factors: Evidence from Unbalanced
Panel Data for Thai Listed Manufacturing Enterprises***

I. Introduction

In recent years, Thailand has faced a real challenge of sustaining its growth and escaping from its “*middle income trap*”¹ (2008). For Thailand to transition to higher income and growth in the long term, measures to improve productivity and competitiveness over the long term in all sectors (agriculture, industry, and services) are urgently needed. In particular, measures to increase productivity in the manufacturing sector, as the main sector in Thailand accounting for 40.10 percent of Thai GDP in 2008 (Bank of Thailand, 2009), are very important. The manufacturing sector has been one of the most important sectors in the East and Southeast Asian countries. Economic growth in this region since the early 1980s has arisen primarily from the rapid expansion in manufacturing exports (Jongwanich, 2007). To analyse how best to increase Thailand’s productivity it is also necessary to conduct a firm level analysis, since firms are the engines of economic growth. It is crucial, therefore, to examine how firms can enhance their performance, as this has a direct impact on the overall growth of the economy.

The major problems causing firm-level inefficiency could be obviously observed from the 1997 Asian Financial Crisis. The Crisis highlighted problems of lack of transparency in corporate governance and a corrupt and mismanaged banking system (i.e., excessive lending to non-productive assets, lack of adequate debt monitoring) among the crisis-affected countries in South East Asia as well as Thailand. The problem of weak corporate governance was related to, for example, the dominance of controlling shareholders, the separation of voting and cash flow rights (or the disparity between control and ownership), and the limited protection of minority rights (Claessens et al., 2000). Not only the inefficient environmental

¹ Thailand moved rapidly from a low-income country to a middle-income country during the period between the 1970s to mid-1990s. This resulted from the rapid growth in per capita income during that period. Nevertheless, in recent years, real GDP growth has slowed and is now lower than that of other developing countries in East Asia. With intensifying global competition and higher commodity prices, Thailand confronts a real challenge of sustaining its growth and becoming a higher income country (World Bank Office-Thailand, 2008, p. 2).

factors discussed above caused manufacturing inefficiency in Thailand but firm-specific factors (i.e., inadequate firm size, lack of business experience, lack of research and development (R&D) investment, inefficient managerial skills, lack of internal competition, and lack of external competition or lack of learning-by-exporting experience) also affected the inefficiency performance of Thai listed manufacturing firms. After the 1997 Asian financial crisis the corporate governance system has been strengthened in Thai capital markets, such as through enhancing the institutional framework for accounting and auditing practices, improving the disclosure practice of listed companies, encouraging best practices for directors of listed companies, and relaxing foreign ownership controls (East Asia Analytical Unit, 2000, Talerngsri and Vonkhorporn, 2005, Sally, 2007). However, these environmental and firm-specific factors that affect firm inefficiency have not been empirically examined for Thai listed manufacturing enterprises. This paper aims to fill this gap, and is organized as follows: Section II provides a review of the literature. Section III describes data sources and data classification. Section IV presents empirical models which consist of the stochastic frontier analysis (SFA) and the two-stage data envelopment analysis (DEA) approaches. Hypothesis tests are analysed in Section V. The empirical results of both approaches are provided and discussed in Section VI. Implications from the results are provided in Section VII. Some conclusions are also provided in the final section.

II. Literature Review

Very few empirical studies have examined the effect of leverage (financial constraints) on a firm's technical efficiency (Dilling-Hansen et al., 2003, Sena, 2006, Mok et al., 2007, Weill, 2008). Sena (2006) and Mok et al. (2007) used the leverage ratio represented by the ratio of total debt to total assets (the D/A ratio) to investigate the effect of financial constraints on firm technical efficiency. This debt ratio captures how much a firm is constrained in its expansion. Their empirical results revealed that firms with high leverage tend to experience a decrease in their technical efficiency. This was confirmed by Goldar et al. (2003) who applied the quick ratio $[(\text{current assets} - \text{inventory}) / \text{current liabilities}]$ to examine the importance of the liquidity of Indian engineering firms on their technical efficiency, and found that liquidity has a significantly negative effect on firm technical efficiency. There are a number of theoretical studies focusing on the relative efficiency of internal versus external financing (Jensen, 1986, Gertner et al., 1994, Stein, 1997). The

conclusions from which are still controversial. Gertner et al. (1994) and Stein (1997) supported that a firm's capital is allocated more efficiently through internal financial resources than external ones, since internal financing can increase monitoring incentives, decrease entrepreneurial incentives, and have better asset redeployability. In other words, internal financing improves the efficiency of investments and resource allocation. However, Jensen (1986) argued that internal financing causes an agency problem, since managers have the opportunity to abuse internal funds, and they can easily mobilize internal funds to maximize their own interests and lack the desire or necessity to maximize shareholders' interests due to the lack of external monitoring from banks or financial institutions. Empirical studies have also revealed inconclusive results. For example, Gökçekus (1995) found no significant effects of the relative efficiency of internal versus external financial resources on a firm's technical efficiency for the Turkish rubber industry. Kim (2003) used the ratio of total interest payments on borrowed capital to total capital as a proxy for external financing. He found that this has a positive effect on a firm's technical efficiency. Focusing on research and development (R&D) a number of empirical studies have found that R&D has a positive effect on a firm's technical efficiency (Aw and Batra, 1998, Kim, 2003, Dilling-Hansen et al., 2003, Sheu and Yang, 2005). Kim (2003) found that the ratio of R&D spending to total output has a significant positive association with a firm's technical efficiency for the textile and chemical industries, but such a relationship was not found in the fabrication industry. Sheu and Yang (2005) also found that R&D, as measured by annual R&D expenditure deflated by the general Wholesale Price Index (WPI), positively influences technical efficiency in Taiwan's electronics industry.

Ownership structure is also one of the important firm-specific factors affecting a firm's performance. A number of empirical studies have examined the effect of controlling ownership on a firm's performance based on accounting or financial measures (Demsetz and Lehn, 1985, McConnell and Servaes, 1990, Leech and Leahy, 1991, Wiwattanakantang, 2001, Yammeesri and Lodh, 2003, Zeitun and Tian, 2007), but their empirical results are still inconclusive. There are both costs and benefits associated with controlling ownership. The presence of controlling ownerships (shareholders with large stakes) can deteriorate firm performance, since the interest of controlling shareholders may not align with those of non-controlling shareholders (Shleifer and Vishny, 1997, Bebchuk et al., 1999). There is a

possibility that large shareholders may conduct corrupt activities (i.e., using a firm's cash flows for their own benefits). On the other hand, according to agency theory, controlling shareholders are likely to perform better than dispersed shareholders, since a high level of ownership concentration can reduce agency costs. In practice, controlling ownership can be measured by the percentage of equity owned by the largest five shareholders (Wiwattanakantang, 2001, Yammeesri and Lodh, 2003, Zeitun and Tian, 2007). In the case of Thailand, Wiwattanakantang (2001) and Yammeesri and Lodh (2003) found that controlling ownership is positively associated with a firm's performance, as evaluated by accounting or financial measures. Similarly, managerial ownership² can help align the conflict of interests between shareholders and managers (Jensen and Meckling, 1976). If managers' interests coincide more closely with those of shareholders, the conflicts between managers and shareholders are alleviated. A number of empirical studies have found a positive linear and non-linear relationship between managerial ownership and firm performance as measured by financial profitability (Pfeffer, 1972, Morck et al., 1988, Wiwattanakantang, 2001, Yammeesri and Lodh, 2003). Very few empirical studies have examined the effect of managerial ownership on a firm's technical efficiency (see Liao et al. (2010)). Liao et al. (2010) calculated the percentage of equity owned by managers and the percentage of equity owned by the board, and examined the effects of these variables on a firm's technical efficiency as measured by a two-stage DEA. Their results found that managerial and board equities are positively related with a firm's technical efficiency, but their results are not statistically significant. In addition, very few empirical studies examined the effect of executive remuneration on a firm's technical efficiency. Baek and Pagán (2003) conducted a stochastic frontier analysis (SFA) to measure a firm's technical efficiency, and found that the level of CEO total compensation is positively associated with a firm's technical efficiency for S&P 1,500 firms.

Focusing upon different types of firm ownership a number of empirical studies have also found a positive association between foreign ownership and technical efficiency (Fukuyama et al., 1999, Goldar et al., 2003, Bottasso and Sembenelli, 2004). Empirical studies focusing upon the relationship between family ownership and firm performance have been examined in the finance literature, but very few studies linked family ownership with a

² Managerial ownership is defined as being the owner manager (Jensen and Meckling, 1976, p.56).

firm's technical efficiency. Lauterbach and Vaninsky (1999) used dummy variables for family and partnership ownership to examine the effect of family and partnership ownership on a firm's technical efficiency, conducted using the two-stage DEA approach. Their results revealed a significantly negative association between family and partnership ownership and firm technical efficiency for 280 Israeli firms. Claessens (2000) defined the controlling shareholder (ultimate owner) by adopting cut-off shareholding levels of 10 percent and 20 percent for Hong Kong, Indonesia, Japan, Korean, Malaysia, Philippines, Singapore, Taiwan, and Thailand. In the case of Thailand, Wiwattanakantung (2001) and Yammesri and Loadh (2003) investigated the effect of family ownership on a firm's performance based on accounting or financial measures. Both studies, however, used a cut-off shareholding level of at least 25 percent for Thai listed enterprises, since shareholders must have at *least 75 percent* of their voting rights to obtain the absolute power over the public limited firm due to the Public Limited Companies Act B.E. 2535 of Thailand (Section 31). Hence, this study adopts a cut-off shareholder level of at least 25 percent in classifying different types of firm ownership.

A number of empirical studies have also investigated the effect of export participation on a firm's technical efficiency (the learning-by-exporting hypothesis). Kim (2003) used the ratio of exports to total revenues as a proxy for export intensity, and found that exports positively affect technical efficiency for the food and paper industries, but such a finding is not found in the textile, chemical, and fabrication industries for Korean manufacturing industries. Dilling-Hansen et al. (2003) used a dummy variable for exports, but found no effect of exports on firm technical efficiency for 2,370 Danish firms. Granér and Isaksson (2007) used a dummy variable as a proxy for export participation, and found that exports significantly increased the technical efficiency of Kenyan manufacturing firms. Many empirical studies have also investigated the effect of firm size on a firm's performance based on a firm's technical efficiency. Their results are quite varied being based on different countries and sectors. Empirical studies have also used different proxies for firm size, which can be represented as either (i) total assets (see Kim (2003), Sheu and Yang (2005), Liao et al (2010)), (ii) the number of employees (see Bottasso and Sembenelli (2004)), and (iii) intermediate inputs (see Lundvall and Battese (2000), Hossain and Karunaratne (2004), Oczkowski and Sharma (2005)). Moreover, a number of empirical studies also investigated

the effect of firm age on a firm's technical efficiency (see Lundvall and Battese, 2000). Their findings are also quite mixed depending upon respective countries and sectors. The effect of government assistance on firm performance is also examined by a number of studies (Tzelepis and Skuras, 2004, Girma et al., 2007). Their findings are still ambiguous depending on the countries and industrial sectors studied.

III. Data Sources and Data Classification

Data Sources

The raw data used in this study was obtained from the Stock Exchange of Thailand (SET), which consists of (i) the list of board of directors and major shareholders, (ii) financial reports, (iii) annual reports of the Thai listed companies (the Form 56-1). Financial reports consist of five major components: (i) an auditor's report, (ii) statements of income, (iii) balance sheet statements, (iv) statements of cash flows, and (v) notes to financial statements. In addition, there are two types of financial reports: (i) an unconsolidated financial report and (ii) a consolidated financial report. In this study, annually consolidated financial reports are used, since all business activities of listed firms including their subsidiary companies are recorded in annually consolidated financial reports. Form 56-1 is an annual company report required by the Securities and Exchange Commission (SEC), where all Thai listed firms are obligated to disclose their annual business performance for shareholders and investors. Form 56-1 consists of three main parts: (i) executive summary, (ii) company issuing securities, and (iii) confirmation of accuracy. Part (ii) is used for this study, which consists of the listed company's information, such as (a) risk factors and risk management, (b) nature of business operation, (c) business operations of the company, (d) research and development, (e) business assets, (f) future plans, (g) legal disputes, (h) capital structure, and (i) management, (j) internal control, (k) related transactions, (l) financial position and operation performance, and (m) reference information.

Data Classification

This study classifies manufacturing listed firms from among listed firms into eight industrial sectors. The SET's eight industrial sectors consist of (1) Agro and Food Industry which can be sub grouped into (i) Agribusiness and (ii) Food and Beverage; (2) Consumer Products which can be sub grouped into (i) Fashion, (ii) Home and Office Products, and (iii) Personal Products and Pharmaceuticals; (3) Financials which can be divided into (i) Banking, (ii) Finance and Securities, and (iii) Insurance; (4) Industrials which can be classified into (i) Automotive, (ii) Industrial Materials and Machinery, (iii) Paper and Printing Materials, (iv) Petrochemicals and Chemicals, and (v) Packaging; (5) Property and Construction which can be divided into (i) Construction Materials, (ii) Property Development, and (iii) Property fund; (6) Resources (energy & utilities); (7) Services which can be divided into (i) commerce, (ii) Health Care Services, (iii) Media & Publishing, and (iv) Professional Services (Tourism & Leisure and Transportation & Logistics); (8) Technology which can be divided into (i) Electronic Components and (ii) Information and Communication technology. Besides eight industrial sectors there are also 22 listed firms under rehabilitation (NPG) in 2008. The securities of these listed firms have been suspended until they can meet the SET's rules and regulations in order to resume their trading again. With regard to International Standard Industrial Classification of all economic activities (ISIC), it is necessary to remove some listed firms that are not classified as manufacturing firms. In addition, this study also includes listed manufacturing firms that had been delisted from the SET during 2000 to 2008. As a result, 178 listed manufacturing firms over the period 2000 to 2008 will be used to conduct the empirical analysis of this study, which can be summarized in Table 1.

IV. Empirical Models

The Stochastic Frontier Analysis (SFA) and the two-stage Data Envelopment Analysis approaches are used to conduct the empirical analysis. The differences between the SFA and the DEA approaches are that the SFA requires functional forms on the production frontier, and assumes that firms may deviate from the production frontier not only due to technical inefficiency but also from measurement errors, statistical noise or other non-systematic influences (Admassie and Matambalya, 2002).

Table 1: Classification of Listed Manufacturing Firms in the SET during 2000 to 2008

No of sectors	Manufacturing Sectors	No of firms	No of firms
1	Agro & Food Industry		
	1.1 Agribusiness	20	
	1.2 Food & Beverage	20	
	Total		40
2	Consumer Products		
	2.1 Fashion	18	
	2.2 Home & Office Products	11	
	2.3 Personal Products & Pharmaceuticals	4	
	Total		33
3	Industrials		
	3.1 Automotive	12	
	3.2 Industrial Materials & Machinery	19	
	3.3 Packaging	13	
	3.4 Paper & Printing Materials	2	
	3.5 Petrochemicals & Chemicals	13	
	Total		59
4	Publishing		7
5	Construction Materials		27
6	Technology (Electronic components)		12
	Total listed manufacturing firms		178

Source: Authors

In addition, the SFA requires strong distribution assumptions of both statistical random errors (i.e., normal distribution) and non-negative technical inefficiency random variables (i.e., half-normal distribution for time-invariant inefficiency model (see Pitt and Lee (1981)), and truncated normal distribution for both the time-invariant inefficiency model (see Battese and Coelli (1988)) and the time-variant inefficiency model (see Battese and Coelli (1992,1995)). The DEA approach, however, does not impose functional forms, and uses linear programming to construct a frontier that envelops the observations of all firms. Hence, all firms are compared relative to the “best” performing firms. It also overcomes restrictions on the production and distribution of various residuals.

The Stochastic Frontier Production Function Model

The basic stochastic production function frontier was independently proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977) within a cross-sectional context. Aigner, Lovell, and Schmidt (1977) applied the method of maximum likelihood under the assumptions of a half-normal model, assuming the inefficiency components

(U_i 's) are independently and identically distributed half-normal random variables with variance σ_u^2 ($u_i \sim iid N^+(0, \sigma_u^2)$) and the statistical components (V_i 's) are independently and identically distributed normal random variables with zero means and variances σ_v^2 ($v_i \sim iid N(0, \sigma_v^2)$). In addition, Schmidt and Sickles (1984, p. 367) noted that stochastic frontier models that use cross-sectional data suffer from three serious difficulties. First, the technical efficiency of a firm can be estimated but its estimates may not be consistent, since the variance of the distribution of technical efficiency, conditional on the whole error term, for each individual producer does not vanish (becomes zero) as the size of the cross section (sample size) increases. Second, maximum likelihood estimation of the stochastic production frontier model and the separation of technical inefficiency from statistical noise, both require strong distributional assumptions of (i) technical inefficiency (e.g., half-normal distribution) and (ii) statistical noise (e.g., normal distribution). Third, maximum likelihood estimation requires an assumption that the non-negative technical inefficiency error components are not related to the independent variables in the model but, in fact, if firms perceive the level of their technical inefficiency they tend to adjust their input choices relative to the level of their technical inefficiency. In other words, the firms' technical inefficiency might be correlated with their input choices. Kumbhakar and Lovell (2000) also suggested that having access to panel data can avoid the disadvantages mentioned by Schmidt and Sickles (1984). First, panel data (repeated observations on a sample of firms) can relax the independent and strong distributional assumptions. Second, adding more observations for each firm can provide more information compared with cross sectional data, and the firm's technical efficiency can be estimated consistently since the number of observations of the firm begins to increase.

According to Schmidt and Sickles (1984) and Kumbhakar and Lovell (2000), the preferred model is the stochastic frontier production function model based on the time-variant efficiency model of Battese and Coelli (1995). The model of Battese and Coelli (1995) allows the technical efficiency levels to change over time, since firms expect to learn from their learning-by-doing experience. As the panel becomes larger the technical efficiency effects would change. The model consists of two main components. The first component is to estimate the time-varying stochastic frontier production function which contains two random errors: (i) random errors (V_{its}) and non-negative random variables (U_{its}). The first random errors, which are assumed to be independently and identically distributed normal random

variables with zero means and variances, σ_v^2 ($V_{it} \sim iid N(0, \sigma_v^2)$), can be observed, for example, when the problems of omitted variables and model misspecification arise. The second non-negative random variables which are assumed to be independently and identically distributed normal random variables as truncations at zero with $Z_{it}\delta$ means and variances σ_u^2 ($U_{it} \sim iid N(0, \sigma_u^2)$) are known as the technical inefficiency effects. In addition, these two random variables are assumed to be independently distributed for all time periods ($t=1,2,\dots,T$) and all firms ($i=1,2,\dots,N$).

The second component links firm-specific variables (i.e., types of firm ownership, firm age, and firm size) with the inefficiency effects or the non-negative random variables. In other words, this part aims to examine what firm-specific variables significantly affect the firm's inefficiency. The stochastic frontier production function and the inefficiency effects will be simultaneously estimated by the method of maximum likelihood (ML) which has desirable large sample (or asymptotic) properties. More specifically, the ML estimator is consistent and asymptotically efficient (Coelli, 2005, p. 218). FRONTIER Version 4.1 is used to conduct a single - step process in which the stochastic frontier production and the model of technical inefficiency effects are estimated simultaneously by the method of maximum likelihood estimation (Quasi-Newton methods) (see Coelli (1996)). This software utilizes the parameterisation from Battese and Corra (1977) by replacing σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$. The technical inefficiency for the i^{th} firm in the Battese and Coelli (1995) model is given by $TE_{it} = \exp(-U_{it}) = \exp(-Z_{it}\delta - W_{it})$. Applying the model of Battese and Coelli (1995), the stochastic frontier production functions in the Cobb-Douglas and translog functional forms are tested for adequate functional form. The Cobb-Douglas functional form can be written as:

$$\ln(Y_{it}) = \beta_0 + \beta_1 \ln(L_{it}) + \beta_2 \ln(K_{it}) + \beta_3 \ln(IM_{it}) + \beta_4 (t) + V_{it} - U_{it} \quad (1.1)$$

The translog functional form can be written as:

$$\begin{aligned}
Ln(y_{it}) = & \beta_0 + \beta_1 \ln(L_{it}) + \beta_2 \ln(K_{it}) + \beta_3 \ln(IM_{it}) + \beta_4 (t) + \frac{1}{2}\beta_5 \ln(L_{it}^2) + \\
& \frac{1}{2}\beta_6 \ln(K_{it}^2) + \frac{1}{2}\beta_7 \ln(IM_{it}^2) + \frac{1}{2}\beta_8 (t^2) + \beta_9 \ln(L_{it}) * \ln(K_{it}) + \\
& \beta_{10} \ln(L_{it}) * \ln(IM_{it}) + \beta_{11} \ln(L_{it}) * (t) + \beta_{12} \ln(K_{it}) * \ln(IM_{it}) + \\
& B_{13}(K_{it}) * (t) + B_{14}(IM_{it}) * (t) + V_{it} - U_{it}
\end{aligned} \tag{1.2}$$

Where:

Y_{it} = Sales revenue deflated by the manufacturing Producer Price Index (PPI) of firm i at time t

L_{it} = Employee expenses deflated by the manufacturing Producer Price Index (PPI) of firm i at time t

K_{it} = Net productive fixed assets deflated by the Producer Price Index (PPI) of capital goods of firm i at time t

IM_{it} = Intermediate inputs deflated by the Producer Price Index (PPI) of intermediate inputs of firm i at time t

V_{it} = Random error ($V_{it} \sim N(0, \sigma_v^2)$)

U_{it} = Non-negative random variable (or technical inefficiency) ($U_{it} \sim N(Z_{it}\delta, \sigma_u^2)$)

The Inefficiency Effects Model can be written as follows:

$$\begin{aligned}
U_{it} = & \sigma_0 + \sigma_1 LEV_{it} + \sigma_2 LIQ_{it} + \sigma_3 INF_{it} + \sigma_4 EXF_{it} + \sigma_5 EXC_{it} + \sigma_6 TOP5_{it} \\
& + \sigma_7 MGR_{it} + \sigma_8 EXP_{it} + \sigma_9 R\&D_{it} + \sigma_{10} GOVT_{it} + \sigma_{11} FCO_{it} \\
& + \sigma_{12} SIZE_{it} + \sigma_{13} AGE_{it} + \sigma_{14} FAM_{it} + \sigma_{15} FGR_{it} + \sigma_{16} DOM_{it} \\
& + \sigma_{17} HYD_{it} + W_{it}
\end{aligned} \tag{1.3}$$

Where:

LEV_{it} = Leverage of firm i at time t , represented by the ratio of total debt to total assets (the D/A Ratio)

LIQ_{it} = Liquidity of firm i at time t , represented by the ratio of current assets to current liabilities (the Current Ratio)

INF_{it} = Dummy for internal financing;
 $INF_{it} = 1$ if firm i at time t borrows from related parties.
 $= 0$, otherwise

EXF_{it} = External financing, represented by total interest expenses deflated by
 the general Producer Price Index (PPI)

EXC_{it} = Executive Remuneration of firm i at time t , represented by the ratio
 of top executive and board member remunerations to total employee expenses

$TOP5_{it}$ = Controlling ownership of firm i at time t , represented by the
 percentage of equity owned by the five largest shareholders

MGR_{it} = Managerial ownership of firm i at time t , represented by the percentage of equity
 owned by top executives and board members

EXP_{it} = Exports of firm i at time t , represented by the ratio of export revenue
 to total sales revenue

$R\&D_{it}$ = Dummy for Research and Development;
 $R\&D_{it} = 1$ if firm i at time t has R&D.
 $= 0$, otherwise

$GOVT_{it}$ = Dummy for Government support;
 $GOVT_{it} = 1$ if firm i at time t receives Board of Investment (BOI)'s support.
 $= 0$, otherwise

FCO_{it} = Dummy for foreign cooperation;
 $FCO_{it} = 1$ if firm i at time t engages in foreign cooperation.
 $= 0$, otherwise

$SIZE_{it}$ = Size of firm i at time t , represented by the logarithm form of total assets

AGE_{it} = Age of firm i at time t , represented by the number of operating years

FAM_{it} = Dummy for a family-owned firm;
 $FAM_{it} = 1$ if firm i at time t is a family-owned firm.
 $= 0$, otherwise

FGR_{it} = Dummy for a foreign-owned firm;
 $FGR_{it} = 1$ if firm i at time t is a foreign-owned firm.
 $= 0$, otherwise

DOM_{it} = Dummy for a domestic-owned firm;
 $DOM_{it} = 1$ if firm i at time t is a domestically-owned firm.
 $= 0$, otherwise

HYD_{it} = Dummy for a hybrid-owned firm;
 $HYD_{it} = 1$ if firm i at time t is a hybrid-owned firm.
 $= 0$, otherwise

W_{it} = Random error ($(W_{it} \sim N(0, \sigma_W^2))$)

Basic descriptive statistics for all the variables mentioned above are provided in the Appendix.

Two-stage Data Envelopment Analysis (DEA)

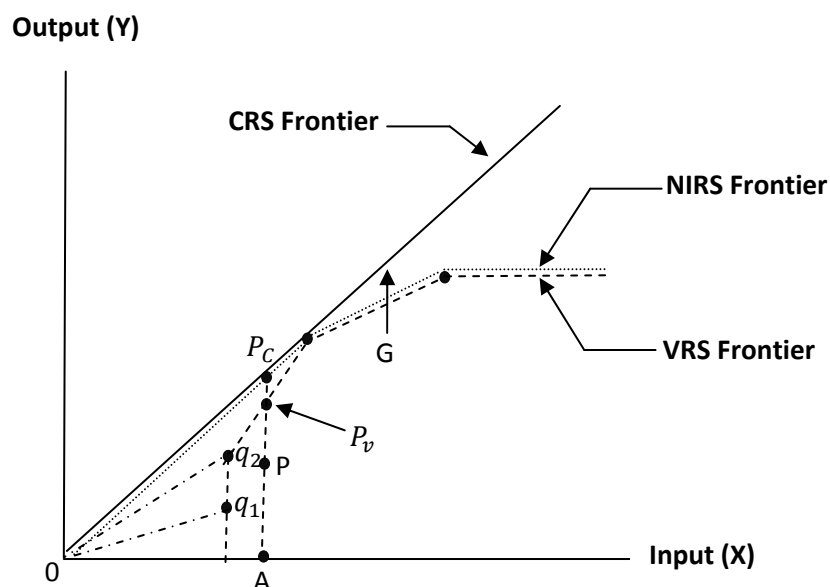
The non-parametric Data Envelopment Analysis (DEA) can also be used to predict technical efficiency, which involves the use of a linear programming method to construct a non-parametric piece-wise surface (or frontier) over the data (Coelli et al., 2005, p.162). The term “Data Envelopment Analysis (DEA)” was first introduced by Charnes, Cooper, and Rhodes (1978) (or the CCR model). The CCR model proposed an efficiency measurement obtained by maximizing the ratio of weighted outputs to weighted inputs, subject to the given constraints that all efficiency measures cannot be greater than 1. In addition, this model does not require a *priori* specification of weights or explicit functional forms in examining the relationship between inputs and outputs (Banker et al., 1984). Unlike the CCR model, Banker, Charnes, and Cooper (1984) (or the BCC model) considered variable returns to scale (by assuming the convexity assumption: $I1'\lambda = 1$), which allows separation between technical efficiency and scale efficiency. The BCC model, therefore, can determine whether a firm is operating under increasing, constant, or decreasing returns to scale for multiple outputs and inputs. This study applies the variable returns to scale (VRS) linear programming problem to predict the technical efficiency for the first-stage of the two-stage DEA approach (see Färe, Grosskopf, Logan (1983) and Banker, Charnes, and Cooper (1984)). The VRS assumes that firms are not operating at an optimal scale due to imperfect competition, government intervention, and financial constraints (Coelli et al., 2005). In addition, the output orientated model is used, assuming fixed input amounts and maximized output production. The VRS linear programming program under the output orientated model can be written as follows:

$$\begin{aligned} & \text{Max}_{\varphi, \lambda} \quad \varphi, \\ \text{st} \quad & -\varphi q_i + Q\lambda \geq 0, \quad i=1,2,\dots,n, \\ & x_i - X\lambda \geq 0, \\ & I1'\lambda \leq 1, \\ & \lambda \geq 0, \end{aligned} \tag{1.4}$$

Where: φ is a scalar. $1 \leq \varphi < \infty$, and $\varphi - 1$ is the proportional increase in outputs (q_i) which can be obtained for the i^{th} firm, while holding input amounts (x_i) constant. $\frac{1}{\varphi}$ is the efficiency score for the i^{th} firm. q_i is an output vector for the i^{th} firm. x_i is an input vector for the i^{th} firm. λ is a vector of constants. $\mathbf{1}'\lambda \leq 1$ defines non-increasing returns to scale (NIRS).

The DEA problem under equation (1.4), for example, takes the firm i , and radially expands the output vector of the firm i (q_i) as much as possible, while still remaining within the feasible output set. The inner-boundary of this output set is a piece-wise linear production possibility curve which is determined by all the firms in the sample (see Figure 1). The DEA model in linear programming (1.4) also replaces the convexity constraint which is imposed for the VRS: $\mathbf{1}'\lambda = 1$ for $\mathbf{1}'\lambda \leq 1$. The modified $\mathbf{1}'\lambda \leq 1$ indicates that the VRS can only be non-increasing. In other words, the constraint: $\mathbf{1}'\lambda \leq 1$ is set to ensure that the i^{th} firm is compared with firms that are smaller than it (see Coelli et al. (2005, p.174)). The linear programming problem (1.4) can also be illustrated in Figure 1 as follows:

Figure 1: Efficiency measurement under the output-orientated DEA model



Source: Authors

Note: Figure 1 is modified from Figures 3.7 and 6.3 of Coelli et al. (2005, p. 55, 171). The original Figures described input- and output- orientated technical efficiency measures and returns to scale (Figure 3.7), and the scale efficiency measurement under the input-orientated DEA model (Figure 6.3).

Figure 1 only explains the case of one output and one input as an example. The VRS technical inefficiency is expressed, for example, by the distance between P to P_V . The CRS technical inefficiency is expressed by the distance between P to P_C . The difference between the CRS and VRS technical inefficiencies, which is given by the distance between P_C to P_V , indicates scale inefficiency. In addition, the VRS technical efficiency can be expressed by the distance ratio AP_V to AP , while the CRS technical efficiency can be expressed by the ratio AP_C to AP . The scale efficiency is simply the ratio of the CRS technical efficiency to the VRS technical efficiency (AP_C/ AP_V). However, the disadvantage of this measure of scale efficiency is that it does not indicate whether a firm is operating under increasing, constant, or decreasing returns to scale. The term, non-increasing returns to scale ($11'\lambda \leq 1$) technical efficiency is imposed in conducting further analysis for increasing, constant, and increasing returns to scale. If the non-increasing returns to scale (NIRS) technical efficiency score is equal to the VRS technical efficiency score, for example, as is the case for point G, then decreasing returns to scale exist. If the NIRS technical efficiency score and the VRS technical efficiency score are not equal (as is the case for point P), then increasing returns to scale apply (see Färe et al. (1983)). If the CRS technical efficiency is equal to VRS technical efficiency, constant returns to scale apply.

One problem of the piece-wise linear frontier in DEA is that firms operating parallel to the axes causes the problem of “slacks”. For instance, a firm operating on the production frontier (or on the efficient point), but the amount of inputs can be reduced without changing the output, is called an “input slack” (or input excess) problem for the input-orientated model. For the output-orientated model this problem is also known as “output slack” (or output excess), since a firm’s production can be increased without using any more inputs. There are a number of ways in which to treat the problem of slack (e.g., one-stage DEA, two-stage DEA, and multi-stage DEA). One-stage DEA solves the problem through linear programming, for example the output-oriented model (1.4), where slacks are calculated residually. Two-stage DEA maximizes the sum of slacks required to move from the first-stage projected point (as for point q_1 in Figure 1) to an efficient point (as for point q_2 in Figure 1). However, two-stage DEA is applicable when there is only one efficient point to select from the vertical facet, but it is not applicable when there are two or more dimensions of slacks. As a result, multiple-stage DEA can be useful, since it is invariant to

units of measurement and its efficient projected points have input and output mixes that are similar to those of the inefficient points. These slack treatments can be applied by the Data Envelopment Analysis (Computer) Program (DEAP) version 2.1. For the DEAP software there are three choices with respect to the treatment of slacks, these are (i) one-stage DEA, (ii) two-stage DEA, and (iii) multi-stage DEA. Coelli et al. (2005, p.198) recommended multi-stage DEA. Hence, multi-stage DEA will be selected in this study to predict the VRS technical efficiency as well as the CRS technical efficiency for the first-stage of the two-stage DEA model. The second stage of the two-stage DEA model is conducted by regressing environmental variables on the firm's VRS technical inefficiency scores which are predicted from the first step of the two-stage DEA model. The firm's technical inefficiency scores are used as the dependent variable, which is obtained by subtracting the efficiency scores estimated from the DEA model from "one". The set of environmental variables are used as independent variables for the two-stage DEA model. The estimated inefficiency scores are normally bounded between zero and one. Applying the method of Ordinary Least Squares (OLS) with such a dependent variable that its values are bounded between zero and one will lead to biased and inconsistent estimators, since the OLS method is likely to predict inefficiency scores which are greater than one (Coelli et al., 2005). Therefore, the Maximum Likelihood estimation for a two-limit Tobit model³ is adopted (see Hoff (2007) and McDonald (2009)), which is given as follows:

$$(1 - \theta_{it})^* = \sigma_0 + \sum_{j=1}^{j=17} \sigma_{jt} z_{jt} + \varepsilon_{it} \quad (1.5)$$

$$(1 - \theta_{it}) = \begin{cases} (1 - \theta_{it})^* & \text{if } 0 < (1 - \theta_{it})^* < 1 \\ 0 & \text{if } (1 - \theta_{it})^* \leq 0 \\ 1 & \text{if } (1 - \theta_{it})^* \geq 1 \end{cases}$$

Where:

$(1 - \theta_{it})^*$ = Unobserved inefficiency scores of firm i and time t .

$(1 - \theta_{it})$ = Observed inefficiency scores of firm i and time t .

σ_j = Unknown parameter to be estimated for each environmental variable j at time t

ε_{it} = Random error ($(\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2))$)

³ The interval of predicted efficiency scores is [0; 1]. Efficiency scores normally concentrate at or close to 1 (or have a positive pileup at or close to 1 at the right hand side of the interval), but often none of them are at or close to 0 (see McDonald, J. (2009)). For this study inefficiency scores, however, are used instead, and therefore inefficiency scores are skewed at or close to 0, but none of them are at or close to 1.

V. Hypothesis Tests

There are a number of null hypotheses for the SFA approach that will be tested such as (i) the validation of the Cobb-Douglas production function, (ii) the absence of technical progress, (iii) the absence of neutral technical progress (iv) the absence of inefficiency effects, (v) the absence of stochastic inefficiency effects, (vi) the insignificance of joint inefficiency variables (see Table 2). A likelihood-ratio test (LR test) is used to test these hypotheses, which can be conducted as follows:

$$\lambda = -2\{\log [L(H_0)] - \log [L(H_1)]\} \quad (1.6)$$

Where, $\log [L(H_0)]$ and $\log [L(H_1)]$ are obtained from the maximized values of the log-likelihood function under the null hypothesis (H_0) and the alternative hypothesis (H_1), respectively. The LR test statistic has an asymptotic chi-square distribution with parameters equal to the number of restricted parameters imposed under the null hypothesis (H_0), except hypotheses (iv) and (v) which have a “*mixed*” chi-square distribution (see Kodde and Palm (1986)). Hypotheses (iv) and (v) involve the restriction that γ is equal to zero, which defines a point on the boundary of the parameter space (Coelli, 1996, p. 6). From Table 2 the null hypothesis (i) is to test whether the Cobb-Douglas production function is adequate for Thai listed manufacturing firms. Following equations (1.1) and (1.2) the null hypothesis ($H_0 : \beta_{LL} = \beta_{KK} = \beta_{MM} = \beta_{TT} = \beta_{LK} = \beta_{LM} = \beta_{LT} = \beta_{KM} = \beta_{KT} = \beta_{MT} = 0$) is strongly rejected at the 5 percent level of significance for the SET’s manufacturing sectors. Therefore, the Cobb-Douglas production function is not an adequate specification for the case of the SET’s manufacturing sector, compared with the specification of the Translog production function model. This also indicates that input and substitution elasticities are not constant among firms (see Lundvall and Battese, 2000).

The null hypothesis (ii) that there is no technical progress ($H_0 : \beta_T = \beta_{TT} = \beta_{LT} = \beta_{KT} = \beta_{MT} = 0$) is rejected at the 5 percent level of significance for the SET’s manufacturing sector, indicating that technical progress exists. Under the translog specification technology for (1.2), the percentage change in output in each period due to

technological change (t) is given by $\frac{\partial \ln y}{\partial t} = \theta_1 + 2\theta_2 t$ (see Coelli et al., 2005). From Table 3 technological change affects the percentage change to output by $0.089 + 2 * (-0.05) * t$. The slope of θ_2 in the translog production function (1.2) is negative, which is given by -0.05 , also indicating that technological progress tends to decrease over time. The null hypothesis (iii) that technical progress is neutral ($H_0 : \beta_{LT} = \beta_{KT} = \beta_{MT} = 0$) is also rejected at the 5 percent level of significance for the SET's manufacturing sector. This indicates that technical change not only merely affects average output, but also changes marginal rates of technical substitution. In other words the marginal rate of substitution is not dependent on time, indicating that *Hicks* neutral technology does not exist for the SET's manufacturing sector. From Table 3 the estimates of β_{LT} and β_{KT} are also significantly negative and positive, respectively, for the SET's manufacturing sector. This evidence implies that there is the existence of labour-using and capital-saving technical progress for the SET's manufacturing sector over the period 2000 to 2008. The null hypothesis (iv) which specifies that the inefficiency effects are absent from the model ($\gamma = \delta_0 = \delta_1 \dots = \delta_{17} = 0$) is strongly rejected at the 5 percent level of significance, which implies that the model of inefficiency effects exists for the case of the SET's manufacturing sector.

The null hypothesis (v) that the inefficiency effects are not "stochastic" ($\gamma = 0$) is strongly rejected, implying that the model of inefficiency effects is not reduced to a traditional mean response function. In other words, all the explanatory variables in the inefficiency effects model are not included in the production function, implying that the inefficiency effects model is applicable, and therefore the estimated parameters can be identified in the model of inefficiency effects. As a result the average response function in which all listed manufacturing firms are assumed to be fully technically efficient is not found for the case of the SET's manufacturing sector, given the assumptions of the translog stochastic frontier and the inefficiency effects model. In addition, if the estimate of the variance parameter (γ) is close to one, it indicates that overall residual variation (U_{it} s and V_{it} s) highly results from inefficiency components (V_{it} s). From Table 3 the estimated γ (0.853) is high for the SET's manufacturing sector, indicating that much of the variation in the composite error term is due to inefficiency effects (V_{it} s).

The last null hypothesis specifies that inefficiency effects are not a linear function of all explanatory variables ($H_0 : \delta_1 = \delta_2 = \dots = \delta_{16} = \delta_{17} = 0$). In other words the null hypothesis specifies that all parameters of the explanatory variables are equal to zero. All LR test statistics are greater than the critical value of an approximately chi-square distribution (see Table 2) at the 5 percent level of significance, implying that the null hypothesis that all coefficients of the explanatory variables are equal to zero is strongly rejected at the 5 percent level of significance for the SET's manufacturing sector, given the specification of the Translog stochastic frontier and the model of inefficiency effects. According to the rejection of the last null hypothesis test, the model of inefficiency effects of the SET's manufacturing sector can be assumed to be independently and identically distributed as truncations at zero of the normal distribution with mean, $Z_{it}\delta$ and variance, σ_u^2 (see Battese and Coelli (1995)). For the two-stage DEA model the null hypothesis that all parameters of the explanatory variables are equal to zero is also rejected at the 5 level of significance (see Table 4). In addition, the majority of the estimates of the Translog production frontier parameters are statistically significant at the 5 percent level of significance for the SET's manufacturing sector (see Table 3). It is also common to observe that some of the individual coefficients of the Translog stochastic frontier are not statistically insignificant due to high multicollinearity among the inputs (see Lundvall and Battese (2000), Oczkowski and Sharma (2005)).

VI. Consistency of the Results from Data Envelopment Analysis and Stochastic Frontier Analysis

Average technical efficiency scores for the SET's manufacturing sector predicted by the SFA and the DEA are quite close, given by 0.818 and 0.887 respectively (see Table 6). Average technical efficiency scores obtained from the DEA normally should be lower than those scores obtained from the SFA, since technical efficiency scores predicted by the DEA cannot be separated from the non-negative technical inefficiency components (V_{it} s) from random error terms (u_{it} s).

Table 2: Statistics for the Hypotheses Tests of the Stochastic Frontier and Inefficiency Effects Models

Null Hypothesis	Manufacturing Sector		
	LR Statistics	Critical Value	Decision
(i) Cobb-Douglas ($H_0: \beta_{LL} = \beta_{KK} = \beta_{MM} = \beta_{TT} = \beta_{LK} = \beta_{LM} = \beta_{LT} = \beta_{KM} = \beta_{KT} = \beta_{MT} = 0$)	210.43	18.31	Reject H_0
(ii) No technical progress ($H_0: \beta_T = \beta_{TT} = \beta_{LT} = \beta_{KT} = \beta_{MT} = 0$)	26.46	11.07	Reject H_0
(iii) Neutral technical change ($H_0: \beta_{LT} = \beta_{KT} = \beta_{MT} = 0$)	34.12	7.81	Reject H_0
(iv) No inefficiency effects ($H_0: \gamma = \delta_0 = \delta_1 = \dots = \delta_{17} = 0$)	628.82	29.55*	Reject H_0
(v) Non stochastic inefficiency ($H_0: \gamma = 0$)	1207.10	2.71*	Reject H_0
(vi) No joint inefficiency ($H_0: \delta_1 = \delta_2 = \dots = \delta_{16} = \delta_{17} = 0$)	292.08	27.59	Reject H_0

Source: Authors' estimates

Note: All critical values of the test statistics are subject to the 5% level of significance; * indicates a mixture of the χ^2 distribution (see Kodde and Palm, 1986).

However, if the estimated γ is close to 1 this implies that the error variation is mainly due to inefficiency effects. For this study γ is given by 0.853 which indicates that overall error variation (U_{it} s and V_{it} s) is mostly due to inefficiency components (V_{it} s), and insignificantly caused by random error terms (U_{it} s). Undoubtedly, technical efficiency scores can also be smaller than those scores obtained from DEA (see Sirasoontorn (2004)). As discussed in Figure 1 the advantage of the DEA approach is that it can examine whether each

of the listed manufacturing firms are operating under increasing returns to scale (IRS), decreasing returns to scale (DRS), or constant returns to scale (CRS). From Table 6 there is strong evidence that approximately 86 percent of the listed manufacturing firms were operating under decreasing returns to scale (DRS) on average over the period 2000 to 2008, given the specification of the output-orientated model. For a comparison analysis between the SFA and two-stage DEA approaches only the empirical results of the two-stage DEA approach under the variable returns to scale (VRS) are used to compare with the empirical results obtained from the SFA, since the VRS technical inefficiency scores obtained from the two-stage DEA are basically equivalent to “*pure*” technical inefficiency scores obtained from SFA. Moreover, the CRS technical inefficiency scores obtained from DEA can be decomposed into (i) pure technical inefficiency (or VRS technical inefficiency) and (ii) scale inefficiency (see Coelli et al., 2005, p. 172).

The empirical results of both the SFA and the two-stage DEA are found to produce quite consistent results, which are summarized in Table 5. Both approaches confirm that leverage (financial constraints) has a significantly positive effect on a firm’s technical efficiency for the SET’s manufacturing sector, implying that financially constrained firms tend to utilize their financial resources and control input costs effectively, leading to an enhancement in their technical efficiency. To confirm this conclusion, both estimation approaches also confirm that a firm’s leverage is found to be statistically significantly negatively related with its technical efficiency for the SET’s manufacturing sector. Both approaches also confirm that external financing has a statistically negative association with a firm’s technical efficiency, but the relationship is very weak since the size of the “external financing” coefficient is very small. In addition, “internal financing” is also found to have a negative effect on a firm’s technical efficiency, but the results from both approaches are statistically inconclusive. This negative result implies that the agency problem exists for the use of internal funds, since managers do not appear to maximize shareholders’ interests or have strong incentives to abuse internal funds. This is especially the case in underdeveloped countries where firms’ managerial rights are not fully developed and their information is not fully publicized, and therefore managers attempt to maximize their benefits rather than the firm’s value (Kim, 2003, p.134). The coefficient for “executive remuneration” is also found to be statistically significant for both approaches, indicating that listed manufacturing firms

with higher levels of executive remuneration tend to have more technical efficiency. According to the finance literature regarding ownership structure, the empirical results from both approaches confirm that managerial ownership has a significantly positive relationship with the firm's technical efficiency. This indicates that the agency problem is reduced, since managerial ownership can help align the conflict of interests between shareholders and managers. Controlling ownership is found to have a positive association with the firm's technical efficiency, but the significance results from both approaches are statistically different. This positive result supports the agency theory that controlling shareholders are likely to perform better than dispersed shareholders, since a high level of ownership concentration can reduce agency costs.

Learning-by-exporting evidence is also found for Thai listed manufacturing enterprises, since the empirical evidence from the two approaches confirm that the coefficient for "exports" has a significant and positive association with a firm's technical efficiency. This result implies that export market experience (i.e., new product designs and production methods), which is gained from communication between foreign partners and exporting firms, tends to improve the technical efficiency of exporting firms. However, research & development (R&D) is found to be statistically negative with the firm's technical efficiency among Thai listed manufacturing firms. This result is different from many empirical results that R&D has a positive effect on a firm's technical efficiency (see Part II). Such a negative finding also implies that most listed manufacturing firms misreported their R&D activities, since they did not intend to implement them as they reported to investors. The relationship between government assistance and a firm's technical efficiency is found to be inconclusive due to the same significance results but differences in the coefficient signs. In addition, foreign cooperation has a negative impact on a firm's technical efficiency for the SET's manufacturing sector, but such a finding is statistically weak due to the difference in the significance results between these two approaches. There is strong evidence that a firm's size tends to have a statistically positive effect on its technical efficiency. A firm's age is also found to have a positive effect on its technical efficiency, but only the empirical result from the SFA approach is statistically significant. This positive result indicates that learning-by-doing experience, as captured by the number of operating years, is found for Thai listed manufacturing enterprises. Focusing on the classification of different ownership types among listed manufacturing firms the results from both approaches indicate that family-owned firms,

foreign-owned firms, and hybrid-owned firms have a statistically positive relationship with firm technical efficiency. For domestic-owned firms the significance results from both approaches are statistically different. Joint-owned firms have a statistically negative relationship with a firm's technical efficiency, as indicated by a positive constant coefficient (the based firm). Finally, foreign-owned firms perform the best among other types of owned firms, followed by family-owned firms, hybrid-owned firms, and domestic-owned firms, given joint-owned firms as the based firm.

VII. Implications from the Results

Dealing with unbalanced panel data FRONTIER Version 4.1 can be used to analyse the time-variant efficiency model of Battese and Coelli (1995). The advantage of the stochastic frontier analysis (SFA) approach under the specification of Battese and Coelli (1995) is that it allows investigation of technical progress through an estimated production function. For the DEA approach the investigation for technological progress can be referred, for example, to the use of Malmquist TFP index which can be decomposed into “*technical efficiency change*” and “*technological change*”. A Malmquist TFP index analysed by the DEA, however, can only be applied for the case of balanced panel data. The DEA approach can examine types of returns to scale for the firm's production in both the firm-level and industry-level context, but the SFA approach can investigate types of returns to scale only for the industry-level context through an aggregate of estimated input elasticities (See Coelli et al., 2005, p. 304). This can be calculated by the sum of estimated input coefficients obtained from an estimated production function, given the specification of a Translog frontier production function (see Table 3). The result, given by 0.548 ($\beta_1 + \beta_2 + \beta_3$)⁴, indicates the existence of moderate decreasing returns to scale for Thai listed manufacturing enterprises. Similarly, the DEA approach also highlights that approximately 86% of listed manufacturing enterprises, on average, operated under decreasing returns to scale over the period 2000 to 2008 (see Table 6).

⁴ The coefficients β_1 and β_2 are statistically significant at the 5 % level of significance, but β_3 is not statistically significant at the 5 % level of significance (see Table 3).

Table 3: Maximum-Likelihood Estimates for Parameters of the Stochastic Frontier Production Function and the Inefficiency Effects Model

Stochastic Variables	Parameters	Stochastic Frontier	Inefficiency Variables	Parameters	Inefficiency Effects
Constant	β_0	3.848* (0.431)	Constant	δ_0	11.718* (0.778)
Ln(L)**	β_1	1.004* (0.132)	Leverage	δ_1	-0.032** (0.018)
Ln(K)**	β_2	-0.704* (0.107)	Liquidity	δ_2	0.208* (0.017)
Ln(IM)**	β_3	0.248 (0.142)	Internal financing	δ_3	0.498* (0.119)
t	β_4	0.089* (0.044)	External financing	δ_4	0.00007* (0.00001)
$\frac{1}{2} (\text{Ln}(L)^2)$	β_5	0.078* (0.022)	Executive remuneration	δ_5	-0.472* (0.194)
$\frac{1}{2} (\text{Ln}(K)^2)$	β_6	-0.102* (0.026)	Controlling ownership	δ_6	-0.032* (0.003)
$\frac{1}{2} (\text{Ln}(IM)^2)$	β_7	0.130* (0.028)	Managerial ownership	δ_7	-0.022* (0.003)
$\frac{1}{2} (t^2)$	β_8	-0.005 (0.005)	Exports	δ_8	-0.012* (0.002)
Ln(L)*Ln(K)	β_9	0.090* (0.023)	R&D	δ_9	0.595* (0.227)
Ln(L)*Ln(IM)	β_{10}	-0.213* (0.025)	Government assistance	δ_{10}	-0.757* (0.137)
Ln(L)* t	β_{11}	-0.020* (0.008)	Foreign cooperation	δ_{11}	0.628* (0.062)
Ln(K)*Ln(IM)	β_{12}	0.090* (0.019)	Firm size	δ_{12}	-0.674* (0.044)
Ln(K)* t	β_{13}	0.016* (0.006)	Firm age	δ_{13}	-0.039* (0.006)
Ln(IM)* t	β_{14}	-0.004 (0.007)	Family -owned firm	δ_{14}	-3.218* (0.328)
			Foreign -owned firm	δ_{15}	-3.453* (0.446)
			Domestic- owned firm	δ_{16}	-1.184* (0.187)
			Hybrid -owned firm	δ_{17}	-2.361* (0.203)
			Variance parameters		
			sigma-square	σ^2	0.938* (0.088)
			gamma	γ	0.853* (0.016)
			Log-likelihood function		-746

Source: Authors' estimates

Note: Standard errors (S.E.) are in parentheses; * indicates that the coefficients are statistically significant at the 5% level; ** L is the labour input, K is the capital input, and IM is the intermediate input (see equation (1.2)).

The significance coefficients of time interacted with capital (β_{11}) and labour (β_{13}) are negative and positive, respectively, indicating that technical change has been labour-using but capital-saving (see Table 3). This result implies that technological progress for Thai listed manufacturing firms still relies on basic production resources, such as the labour input. Similarly, the negative coefficient of time squared (β_8) also confirms that technological change has been decreasing over the period 2000 to 2008 (see Table 3). According to the empirical evidence from these two approaches, industry-specific policy guidelines are also recommended to promote technical efficiency.

Policy guidelines can be implemented as follows: (i) promote more firm ownership participation for a group of people (i.e., workers, administrative staff, managers, and owners) who control or participate in listed manufacturing firms, and encourage listed manufacturing firms to set up attractive rewards for top management and board of directors when firms achieve a certain level of profits as planned; (ii) encourage more foreign participation in listed manufacturing firms; (iii) encourage listed manufacturing firms to engage in more export participation; (iv) promote an increase in firm size. Further study can also focus on the following research issues, such as (i) investigate the SET's sub-manufacturing sectors, (ii) study non-linear effects of firm-specific variables (i.e., firm size, firm age, controlling ownership, and managerial ownership) on a firm's technical efficiency, and (iii) investigate the effect of a firm's technical efficiency on its export performance (the self-selection exporting hypothesis). In addition, there might be other inefficiency variables or other proxy variables (i.e., R&D expenditures) which can affect technical efficiency, but they are beyond the scope of this study due to data unavailability.

Table 4: Maximum-Likelihood Tobit Estimates for Parameters of the Two-Stage DEA approach

VARIABLES	PARAMETERS	DEA (VRS)	DEA (CRS)
Left censoring (value) at zero		93	19
Right censoring (value) at zero		0	0
Uncensored observations		1215	1289
Total observations		1308	1308
Dependent variable: Technical inefficiency (VRS) and Technical inefficiency (CRS)			
Constant	δ_0	0.5833* (0.04475)	0.2299* (0.03732)
Leverage	δ_1	-0.00479* (0.00219)	0.00151 (0.00191)
Liquidity	δ_2	0.00231* (0.00113)	0.00299* (0.00083)
Internal financing	δ_3	0.00522 (0.00345)	0.00905* (0.00373)
External financing	δ_4	0.0000006* (0.0000007)	0.0000003 (0.0000006)
Executive remuneration	δ_5	-0.10257* (0.02631)	-0.18573* (0.02023)
Controlling ownership	δ_6	-0.00019 (0.00016)	-0.00029* (0.00015)
Managerial ownership	δ_7	-0.00042* (0.00009)	-0.00036* (0.00009)
Exports	δ_8	-0.0001** (0.00005)	0.00001 (0.00006)
R&D	δ_9	0.01432* (0.00508)	0.01293* (0.0049)
Government assistance	δ_{10}	0.00737** (0.00407)	0.01186* (0.00411)
Foreign cooperation	δ_{11}	0.00417 (0.0035)	0.00615 (0.00383)
Firm size	δ_{12}	-0.02946* (0.00245)	-0.00189 (0.00206)
Firm age	δ_{13}	-0.00005 (0.00022)	0.00087* (0.0002)
Family- owned firm	δ_{14}	-0.02597* (0.00647)	-0.02182* (0.00675)
Foreign- owned firm	δ_{15}	-0.04207* (0.00739)	-0.03418* (0.00765)
Domestic- owned firm	δ_{16}	-0.00557 (0.00903)	-0.02287* (0.00875)
Hybrid -owned firm	δ_{17}	-0.02138* (0.00891)	-0.02237* (0.00902)
<i>Error Distribution</i>		0.05935* (0.00235)	0.06162* (0.00170)
<i>Log likelihood (unrestricted)</i>		1594	1741
<i>Log likelihood (restricted)***</i>		1405	1595
<i>LR test</i>		377*	292*
<i>Critical value</i>		27.59	27.59

Source: Authors' estimates

Note: Huber/White robust standard errors (S.E.) are in parentheses; * indicates that the coefficients are statistically significant at the 5% level; ** indicates that the coefficients are statistically significant at the 10% level; *** Inefficiency scores are regressed by a constant.

Table 5: Comparison of the Results of Maximum-Likelihood Estimates for Parameters between the SFA and the Two-Stage DEA approaches

<i>Dependent variable:</i> Technical inefficiency	<i>Manufacturing Sector</i>	
	<i>SFA (pure)</i>	<i>DEA(VRS)</i>
<i>Independent variables :</i>		
<i>Constant</i>	+*	+*
<i>Leverage</i>	-**	_*
<i>Liquidity</i>	+*	+*
<i>Internal financing</i>	+*	+
<i>External financing</i>	+*	+*
<i>Executive remuneration</i>	_*	_*
<i>Controlling ownership</i>	_*	-
<i>Managerial ownership</i>	_*	_*
<i>Exports</i>	_*	-**
<i>R&D</i>	+*	+*
<i>Government assistance</i>	_*	+**
<i>Foreign cooperation</i>	+*	+
<i>Firm size</i>	_*	_*
<i>Firm age</i>	_*	-
<i>Family- owned firm</i>	_*	_*
<i>Foreign- owned firm</i>	_*	_*
<i>Domestic- owned firm</i>	_*	-
<i>Hybrid- owned firm</i>	_*	_*

Source: Authors' estimates

Note: * indicates that the coefficients are statistically significant at the 5% level; ** indicates that the coefficients are statistically significant at the 10% level.

Table 6: Average Efficiency Scores and Types of Returns to Scale (by the Number of Listed Manufacturing Firms)

Year	Efficiency Scores			Returns to Scale (by number of firms)					
	CRSTE	VRSTE	SCALE	DRS	%	IRS	%	CRS	%
2000									
SFA	-	0.813	-	-	-	-	-	-	-
DEA	0.814	0.871	0.936	100	73%	33	24%	4	3%
2001									
SFA	-	0.809	-	-	-	-	-	-	-
DEA	0.838	0.895	0.938	109	81%	23	17%	3	2%
2002									
SFA	-	0.808	-	-	-	-	-	-	-
DEA	0.832	0.896	0.930	115	85%	18	13%	3	2%
2003									
SFA	-	0.813	-	-	-	-	-	-	-
DEA	0.890	0.927	0.960	114	83%	18	13%	5	4%
2004									
SFA	-	0.826	-	-	-	-	-	-	-
DEA	0.826	0.901	0.918	139	95%	5	3%	2	1%
2005									
SFA	-	0.823	-	-	-	-	-	-	-
DEA	0.779	0.878	0.889	138	91%	12	8%	2	1%
2006									
SFA	-	0.826	-	-	-	-	-	-	-
DEA	0.789	0.878	0.900	140	89%	15	10%	2	1%
2007									
SFA	-	0.822	-	-	-	-	-	-	-
DEA	0.784	0.876	0.897	141	91%	12	8%	2	1%
2008									
SFA	-	0.818	-	-	-	-	-	-	-
DEA	0.787	0.870	0.906	135	88%	14	9%	5	3%
2000 - 2008									
SFA	-	0.818	-	-	-	-	-	-	-
DEA	0.814	0.887	0.918	126	86%	17	12%	3	2%

Source: Authors' estimates

Note: From the left section CRSTE is the constant returns to scale technical efficiency; VRSTE is the variable returns to scale technical efficiency; SCALE is the scale efficiency. From the right section DRS is the decreasing returns to scale technical efficiency; IRS is increasing returns to scale technical efficiency; CRS is constant returns to scale technical efficiency.

VIII. Conclusions

This study has applied the stochastic frontier analysis (SFA) and the two-stage Data Envelopment Analysis (DEA) approaches. Dealing with unbalanced panel data, the SFA approach seems to be more favourable than the DEA approach in analysing firm technical efficiency and the model of inefficiency effects, since the analysis for technical progress conducted by the DEA approach is not applicable for unbalanced panel data. The DEA approach, however, can analyse types of returns to scale (i.e., decreasing returns to scale (DRS), increasing returns to scale (IRS), and constant returns to scale (CRS)) for both the firm-level and industry-level contexts, but the SFA approach only analyses returns to scale for the industry-level context. Both estimation approaches can be applied for robustness. The empirical evidence from both approaches highlighted that Thai listed manufacturing firms had been operating under decreasing returns to scale over the period 2000 to 2008.

The SFA approach also found that technical progress had been decreasing over the period 2000 to 2008, and had relied on basic production resources such as labour input. Focusing on what factors significantly influence a firm's technical inefficiency both parametric and non-parametric approaches are found to produce empirically consistent results (see Table 5). The empirical results reveal that financially constrained firms tend to improve their technical efficiency through the effective control of input costs and financial resources. On the contrary, financially healthy firms are likely to neglect increasing their technical efficiency due to financial liquidity. External financing tends to decrease the firm's technical efficiency, but its importance is very weak due to a very small estimated coefficient. There is evidence that internal financing has a negative relationship with a firm's technical efficiency, but the empirical results of both approaches are statistically different. This result highlights that managers tend to utilize internal funds ineffectively due to lack of external monitoring. Kim (2003, p.134) also emphasized that this normally exists in several underdeveloped countries where firms' managerial skills are not fully strengthened and their information is not fully disclosed, and therefore there is an opportunity for managers to maximize their benefits rather than the firm's value. Controlling and managerial ownerships have a significantly positive association with a firm's technical efficiency. This result implies that a group of people who receive direct benefits from the firm through dividends relative to the level of their cash flow or voting rights tend to monitor the firm carefully and effectively. On

the contrary, dispersed shareholders or managers who do not hold any ownership over a firm's cash flow or voting stocks are likely to monitor the firm ineffectively, since they perceive that they only receive less dividends or monthly salaries. Similarly, executive remuneration is found to have a significantly positive effect on technical efficiency. In practice, the amount of bonuses or increased salaries that executives (i.e., board of directors and managers) will receive depends upon the firm's annual net profits. In some listed firms, the amount of executive remuneration (i.e., bonuses) that executives receive is based on the percentage of the firm's annual net profits. Hence, a firm that provides high executive remuneration tends to achieve an increase in technical efficiency.

The empirical evidence for both estimation approaches also indicates that exporting firms are also likely to improve their technical efficiency due to their learning-by-exporting experience (i.e., new product designs and production methods). Firm size is also one of the factors that positively affects the firm's technical efficiency due to economies of scale. Firm age is also found to have a positive effect on its technical efficiency, but only the empirical result from the SFA approach is statistically significant. However, the effect of government assistance on technical efficiency is still inconclusive (see Table 5). Foreign cooperation is also found to have a negative effect on technical efficiency, but the results from both approaches are statistically different. Focusing on the relationship between types of firm ownership and technical efficiency it was found that foreign-owned firms perform the best, followed by family-owned firms, hybrid-owned firms, and domestic-owned firms, given joint-owned firms as the base firm. Finally, there is strong evidence from both approaches that foreign-owned firms, family-owned firms, and hybrid-owned firms have a significantly positive effect on technical efficiency, except domestic-owned firms which produce a difference in the statistically significant results of both approaches, and joint-owned firms which have a significant negative effect on technical efficiency.

Appendix: Data Summary

Variables	Unit of Variables	Mean	Median	Max	Min	Std. Dev.	Observations
Output							
Ln (Sales revenue)	Natural Logarithm	9.95	9.88	14.56	5.49	1.36	1309
Inputs:							
Ln (Labour expenses)	Natural Logarithm	7.64	7.66	11.84	3.71	1.15	1309
Ln (Fixed productive)	Natural Logarithm	8.84	8.68	13.61	3.57	1.56	1309
Ln (Intermediate inputs)	Natural Logarithm	9.51	9.40	14.26	5.28	1.45	1309
Time trend	No. of years	5	5	9	1	3	1309
Finance:							
Leverage	Ratio	0.57	0.43	29.13	0.01	1.5	1309
Liquidity	Ratio	2.4	1.57	46.2	0	2.81	1309
Internal financing	Dummy	0.35	0	1	0	0.48	1309
External financing	000 Baht	1747	203	140304	0	7721	1309
R&D	Dummy	0.8	1	1	0	0.4	1309
Ownership structure:							
Controlling ownership	Ratio	58.81	58.82	99.69	5.44	16.51	1309
Managerial ownership	Ratio	20.55	12.70	96.53	0	21.69	1309
Types of owned firms:							
Family-owned firm	Dummy	0.53	1	1	0	0.5	1309
Foreign-owned firm	Dummy	0.19	0	1	0	0.39	1309
Domestic owned firm	Dummy	0.12	0	1	0	0.32	1309
Joint owned firm	Dummy	0.07	0	1	0	0.26	1309
Hybrid owned firm	Dummy	0.09	0	1	0	0.29	1309
Executive remuneration	Ratio	0.14	0.09	7	0.0032	0.32	1309
Exports	%	32.68	19.32	100	0	33.53	1309
Other factors:							
Ln (total assets)	Natural Logarithm	14.76	14.54	19.47	11.73	1.27	1309
Firm age	No. of years	26	24	95	0	12	1309
Government assistance	Dummy	0.62	1	1	0	0.49	1309
Foreign cooperation	Dummy	0.31	0	6	0	0.54	1309

Source: Authors' estimates

References

- Admassie, A. & Matambalya, F. A. S. T. (2002), Technical Efficiency of Small- and Medium- Scale Enterprises: Evidence from a Survey of Enterprises in Tanzania, *Eastern Africa Social Science Research Review*, Vol.18, No.2, pp. 1-29.
- Aigner, D., Lovell, C. A. K. & Schmidt, P. (1977), Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics*, Vol.6, pp. 21-37.
- Aw, B. Y. & Batra, G. (1998), Technological Capability and Firm Efficiency in Taiwan (China), *The World Bank Economic Review*, Vol.12, No.1, pp. 59-79.
- Baek, H. Y. & Pagán, J. A. (2003), Executive Compensation and Corporate Production Efficiency: A Stochastic Frontier Approach, *Quarterly Journal of Business and Economics*, Vol.41, No.1/2, pp. 27-41.
- Bank of Thailand (2009), Thailand's Macro Economic Indicators. Bangkok, Bank of Thailand.
- Banker, R. D., Charnes, A. & Cooper, W. W. (1984), Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science*, Vol.30, No.9, pp. 1078-1092.
- Battese, G. E. & Coelli, T. J. (1988), Prediction of Firm-Level Technical Efficiencies with a Generalised Frontier Production Function and Panel Data, *Journal of Econometrics*, Vol.38, pp. 387-399.
- Battese, G. E. & Coelli, T. J. (1992), Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India, *Journal of Productivity Analysis*, Vol.3, pp. 153-169.
- Battese, G. E. & Coelli, T. J. (1995), A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data, *Empirical Economics*, Vol.20, pp. 325-332.
- Battese, G. E. & Corra, G. S. (1977), Estimation of a Production Frontier Model: with Application to the Pastoral Zone of Eastern Australia, *Australian Journal of Agricultural Economics*, Vol.21, No.3, pp. 169-179.
- Bebchuk, L., Kraakman, R. & Triantis, G. (1999), Stock Pyramids, Cross-Ownership, and Dual Class Equity: The Creation and Agency Costs of Separating Control from Cash Flow Rights. *Working Paper*. Cambridge, MA, National Bureau of Economic Research.
- Bottasso, A. & Sembenelli, A. (2004), Does ownership affect firm's efficiency? Panel data evidence on Italy, *Empirical Economics*, Vol.29, pp. 769-786.
- Charnes, A., Cooper, W. W. & Rhodes, E. (1978), Measuring the efficiency of decision making units, *European Journal of Operational Research*, Vol.2, pp. 429-444.
- Claessens, S., Djankov, S. & Lang, L. H. P. (2000), The Separation of Ownership and Control in East Asian Corporations, *Journal of Financial Economics*, Vol.58, pp. 81-112.
- Coelli, T. J. (1996), A Guide to Frontier Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation. *Working Papers*. Armidale, University of New England.
- Coelli, T. J., Rao, D. S. P., O'Donnell, C. J. & Battese, G. E. (2005), *An Introduction to Efficiency and Productivity Analysis 2*, Springer, New York, USA.
- Demsetz, H. & Lehn, K. (1985), The Structure of Corporate Ownership: Causes and Consequences, *The Journal of Political Economy*, Vol.93, No.6, pp. 1155-1177.
- Dilling-Hansen, M., Madsen, E. S. & Smith, V. (2003), Efficiency, R&D and ownership – some empirical evidence, *International Journal of Production Economics*, Vol.83, pp. 85-94.

- East Asia Analytical Unit (2000), *Transforming Thailand: Choices for New Millennium*, Green Advertising, Australia.
- Fare, R., Grosskopf, S. & Logan, J. (1983), The Relative Efficiency of Illinois Electric Utilities, *Resources and Energy*, Vol.5, pp. 349-367.
- Fukuyama, H., Guerra, R. & Weber, W. L. (1999), Efficiency and Ownership: Evidence from Japanese Credit Cooperatives, *Journal of Economics and Business*, No.51, pp. 473–487.
- Gertner, R. H., Scharfstein, D. S. & Stein, J. C. (1994), Internal Versus External Capital Markets The *Quarterly Journal of Economics*, Vol.109, No.4, pp. 1211-1230.
- Girma, S., Görg, H. & Strobl, E. (2007), The Effects of Government Grants on Plant Survival: A Micro-Econometric Analysis, Vol.25, pp. 701–720.
- Gökçekus, Ö. (1995), The Effects of Trade Exposure on Technical Efficiency: New Evidence from the Turkish Rubber Industry, *Journal of Productivity Analysis*, Vol.6, pp. 77-85.
- Goldar, B. N., Renganathan, V. S. & Banga, R. (2003) Ownership and Efficiency in Engineering Firms in India, 1990-91 to 1999-2000. *Working Paper*. Indian Council for Research on International Economic Relations.
- Hoff, A. (2007), Second Stage DEA: Comparison of Approaches for Modelling the DEA Score, *European Journal of Operational Research*, Vol.181, No.425-435, pp. 425-435.
- Hossain, M. A. & Karunaratne, N. D. (2004), Trade Liberalisation and Technical Efficiency: Evidence from Bangladesh Manufacturing Industries, *Journal of Development Studies*, Vol.40, No.3, pp. 87-114.
- Jensen, M. C. (1986), Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers, *American Economic Review*, Vol.76, pp. 323-318.
- Jensen, M. C. & Meckling, W. H. (1976), Theory of the Firm: Managerial Behaviour, Agency Costs and Ownership Structure, *Journal of Financial Economics*, Vol.3, pp. 305-360.
- Jongwanich, J. (2007), Determinants of Export Performance in East and Southeast Asia. *ERD Working Paper* Manila, Economic and Research Department, Asian Development Bank.
- Kim, S. (2003), Identifying and Estimating Sources of Technical Inefficiency in Korean Manufacturing Industries, *Contemporary Economic Policy*, Vol.21, No.1, pp. 132-144.
- Kodde, D. A. & Palm, F. C. (1986), Wald Criteria for Jointly Testing Equality and Inequality Restrictions, *The Econometric Society*, Vol.54, No.5, pp. 1243-1248.
- Kumbhakar, S. C. & Lovell, C. A. K. (2000), *Stochastic Frontier Analysis*, Cambridge University Press, New York.
- Lauterbach, B. & Vaninsky, A. (1999), Ownership Structure and Firm Performance: Evidence from Israel, *Journal of Management and Governance*, Vol.3, pp. 189-201.
- Leech, D. & Leahy, J. (1991), Ownership Structure, Control Type Classifications and the Performance of Large British Companies, *The Economic Journal*, Vol.101, No.409, pp. 1418-1437.
- Liao, C.-S., Yang, C.-H. & Liu, D. (2010), Efficiency, Productivity and Ownership Structure for Securities Firms in Taiwan, *Journal of Money, Investment and Banking*, No.14, pp. 46-58.
- Lundvall, K. & Battese, G. E. (2000), Firm Size, Age and Efficiency: Evidence from Kenyan Manufacturing Firms, *Journal of Development Studies*, Vol.36, No.3, pp. 146-163.
- McConnell, J. J. & Servaes, H. (1990), Additional Evidence on Equity Ownership and Corporate Value, *Journal of Financial Economics*, Vol.27, pp. 595-612.
- McDonald, J. (2009), Using Least Squares and Tobit in Second Stage DEA Efficiency Analyses, *European Journal of Operational Research*, Vol.197, No.2, pp. 792-798.

- Meeusen, W. & Broeck, J. v. D. (1977), Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error, *International Economic Review*, Vol.18, No.2, pp. 435-444.
- Mok, V., Yeung, G., Han, Z. & Li, Z. (2007), Leverage, Technical Efficiency and Profitability: an Application of DEA to Foreign-Invested Toy Manufacturing Firms in China, *Journal of Contemporary China*, Vol.16, No.51, pp. 259-274.
- Morck, R., Shleifer, A. & Vishny, R. W. (1988), Management Ownership and Market Valuation: An Empirical Analysis, *Journal of Financial Economics*, Vol.20, pp. 293-315.
- Oczkowski, E. & Sharma, K. (2005), Determinants of Efficiency in Least Developed Countries: Further Evidence from Nepalese Manufacturing Firms, *Journal of Development Studies*, Vol.41, No.4, pp. 617-630.
- Pfeffer, J. (1972), Size and Composition of Corporate Boards of Directors: The Organization and its Environment, *Administrative Science Quarterly*, Vol.17, pp. 218-228.
- Pitt, M. M. & Lee, L.-F. (1981), Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry, *Journal of Development Economics*, Vol.9, pp. 43-64.
- Sally, R. (2007), Thai Trade Policy: From Non-discriminatory Liberalisation to FTAs, *The World Economy*, Vol.30, No.10, pp. 1594-1620.
- Schmidt, P. & Sickles, R. C. (1984), Production Frontiers and Panel Data, *Journal of Business and Economic Statistics*, Vol.2, No.4, pp. 367-374.
- Sena, V. (2006), The Determinants of Firm's Performance: Can Finance Constraints Improve Technical Efficiency?, *European Journal of Operational Research*, Vol.172, pp. 311-325.
- Sheu, H.-J. & Yang, C.-Y. (2005), Insider Ownership and Firm Performance in Taiwan's Electronics Industry: A Technical Efficiency Perspective, *Managerial and Decision Economics*, Vol.26, pp. 307-318.
- Shleifer, A. & Vishny, R. W. (1997), A Survey of Corporate Governance, *Journal of Finance*, Vol.52, No.2, pp. 737-783.
- Sirasoontorn, P. (2004), Privatisation and Technical Efficiency of Thai Electricity Generation State Owned Enterprise. *The 2004 PhD Conference in Economics and Business*. Canberra, Australian National University.
- Stein, J. C. (1997), Internal Capital Markets and the Competition for Corporate Resources *Journal of Finance*, Vol.53, pp. 263-92.
- Talerngsri, P. & Vonkhorporn, P. (2005), Trade Policy in Thailand: Pursuing a Dual Track Approach, *ASEAN Economic Bulletin*, Vol.22, No.1, pp. 60-74.
- Tzelepis, D. & Skuras, D. (2004), The Effects of Regional Capital Subsidies on Firm Performance: An Empirical Study, *Journal of Small Business and Enterprise Development*, Vol.11, No.1, pp. 121-129.
- Weill, L. (2008), Leverage and Corporate Performance: Does Institutional Environment Matter?, *Small Business Economics*, Vol.30, pp. 251-265.
- Wiwattanakantang, Y. (2001), Controlling shareholders and corporate value: Evidence from Thailand, *Pacific-Basin Finance Journal*, Vol.9, pp. 323-362.
- World Bank Office -Thailand (2008), *Thailand Economic Monitor*. Bangkok, World Bank.
- Yamreesri, J. & Lodh, S. C. (2003), The Effects of Ownership Structure on Firm Performance: Evidence from Thailand. *Hawaii International Conference on Business*. Honolulu, Hawaii.
- Zeitun, R. & Tian, G. G. (2007), Does Ownership Affect a Firm's Performance and Default Risk in Jordan ?, *Corporate Governance*, Vol.7, No.1, pp. 66-82.