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PRODUCTIVITY GROWTH, EFFICIENCY, AND EXPORT ORIENTATION – EVIDENCE FROM VIETNAMESE SMALL AND MEDIUM ENTERPRISES

By

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A thesis submitted in partial fulfilment of the requirements

for the degree of Master of Research

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October 2016

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LIST OF ABBREVIATIONS

CRS	Constant Returns to Scale
DMU	Decision Making Unit
DEA	Data Envelopment Analysis
GDP	Gross Domestic Product
RTS	Returns to Scale
SFA	Stochastic Frontier Analysis
SMEs	Small and Medium Enterprises
TFP	Total Factor Productivity
TOPS	Technically Optimal Productive Scale
VRS	Variable Returns to Scale

ABSTRACT

This study uses the DEA-based Malmquist index to measure and examine the firm-level total factor productivity and its components (i.e., technical efficiency, scale efficiency, and technological change) of small and medium enterprises in two Vietnamese manufacturing industries (wood and manufacturing, and rubber and plastic) for the period from 2005 to 2013. It then applies an endogenous switching regression model to analyses the effects of export participation on the productivity and efficiency of a firm, explicitly controlling for the effect of self-selection into foreign markets. The findings confirm the superiority in technical efficiency of exporters over non-exporters, especially in the rubber and plastic industry. In addition, exporters use more labor-intensive technology to align with Vietnam's competitive advantage. Moreover, productivity is found to be driven by pure efficiency change rather than other sources. Lastly, previous export status is the key factor that affects the decision to export.

STATEMENT

I hereby certify that this thesis has not been submitted for a higher degree to any other university or institution. The sources of information used and the extent to which the work of others has been utilized are acknowledged in the thesis.

Ngoc Thi Anh Hoang

ACKNOWLEDGMENTS

I would like to express my profound gratitude to my supervisor, Dr. Daehoon Nahm, for his patience, motivation, and continuous support for my study and research. I not only received his devoted guidance but also obtained valuable knowledge in his econometrics classes. I could not have completed my thesis without his advice.

I would also like to thank to my co-supervisor, Dr. Michael Dobbie, who gave me constructive comments to improve my thesis.

Finally, special thanks to my family for providing me with unconditional support throughout my life. My sincere thanks go to my friends for listening and encouraging me throughout my higher degree studies.

CHAPTER 1 - INTRODUCTION

1.1 Background

It is a well-known fact that for many countries (especially developing countries) export promotion polices can increase productivity, one of the key drivers of economic growth. Evidence supporting the link between productivity growth rate and rapid growth in the number of manufacturing exporters is to be found in some Asia countries (Dollar and Sokoloff (1990); Pack and Page (1994); Pack (2000)). In particular, export orientation has promoted impressive growth in some East Asian economies by absorbing knowledge and foreign technology (Pack & Westphal, 1986; Pack, 1992). In Vietnam, an export-oriented industrialization strategy was launched in the early 1990s. This strategy successfully fostered Vietnam's economic growth and confirmed the crucial role of exporting in increasing the country's capacity and raising productivity. Thereafter, the export-GDP ratio improved from 36 percent in 1990 to 86.4 percent in 2014 (World Bank, 2016a). In addition, Nomura and Kimura (2015) reported that Vietnam's Total Factor Productivity (TFP hereafter), which is measured by Gross Domestic Product (GDP) per combined units, accelerated from 1.1% on average per year in the period before 1990 to 2.3% on average annually in the period 1990-2013. They also revealed that TFP accounted for over 30% of economic growth in Vietnam during that period.

From a microeconomic perspective, much empirical work on the explanations for the superior productivity of exporters is based on two hypotheses: learning-by-exporting and self-selection. The learning-by-exporting hypothesis argues that exporting producers improve their productivity via knowledge and expertise gained from engaging in export markets (Westphal et al., 1984; Keesing & Lall, 1992; Grossman & Helpman, 1993; Van Biesebroeck, 2005; De Loecker, 2007). In other words, exporting has an effect on firm productivity. The other hypothesis, self-selection, suggests that to participate and succeed in international trade, firms have to be more productive to overcome the barrier of the entry costs. This hypothesis explains the impact of firm productivity on the decision to enter in the export market. A considerable amount of empirical evidence supporting the self-selection mechanism has been found (Bernard & Jensen, 1999; Melitz, 2003; López, 2005; Wagner, 2007).

In the literature on productivity, “productivity” and “efficiency” are used interchangeably but they have some differences. Productivity is considered as the ratio of a firm’s output(s) to its input(s) while efficiency measures the distance to the production frontier. In fact, (technical) efficiency change is one source of productivity growth. To decompose changes in productivity into its component parts, the Malmquist index proposed by Färe and others (1992; 1994) has been used extensively. There are many ways to derive the Malmquist index, but the index based on Data Development Analysis (DEA) is the most popular in the empirical literature. DEA is a non-parametric technique that does not provide inefficiency noise but prevents the misspecification errors of the functional form. Using linear programming, DEA measures the relative technical efficiency of each individual firm to the production frontier constructed by all firms in a sample at one point of time. As a result, a firm is technically efficient when it runs on the frontier and its technical efficiency score being unity.

Quite a few studies examine the impact of export orientation on firm efficiency performance. Recently, Hassan et al. (2010) divided Bangladesh’s manufacturing sector into export-oriented firms and import-oriented firms and used the DEA-based Malmquist productivity index to compare the improvement in technical efficiency, technology and scale efficiency of these two groups. They found that all exporters experienced productivity growth and technological progress but only 63% of exporting firms improved their technical efficiency. However, export-oriented firms gained a higher level of improvement in technical efficiency than their counterparts. Likewise, Oh (2011) employed the Malmquist index and concluded that export participation has an impact on productivity growth. Other studies have attempted to measure technical efficiency scores using DEA and analyse the influence of exporting on technical efficiency. While Kapelko and Oude Lansink (2015) confirmed the linkage between export orientation and technical efficiency, Mok et al. (2010) and Moral-Pajares et al. (2015) did not draw a clear conclusion. The findings by Mok et al. (2010) support market concentration as a means to improve efficiency. In other words, firms selling mainly in either the domestic market or the world market experience a high level of technical efficiency rather than trying to conquer both markets. Moral-Pajares et al. (2015) affirmed that producers having an active attitude to export, which is measured by whether there exists a person or department in charge of export activities, gain superior efficiency levels. However, their findings show that export share does not affect firm efficiency performance.

For empirical evidence of efficiency in Vietnam, H. T. Pham et al. (2010) implemented the Stochastic Frontier Analysis (SFA) approach to evaluate technical efficiencies of manufacturing firms in 2003 and confirmed the association between export orientation and firm technical efficiency. Similarly, Minh et al. (2012) applied SFA to analyse productivity growth, technological progress, and efficiency change in the manufacturing sector over the period 2003-2007. However, they did not investigate the relationship between exporting and efficiency. Exploiting another approach, DEA, Vixathep and Matsunga (2012) verified that export markets contribute a higher level of efficiency and that export activities affect firm-level technical efficiency.

Despite of the numerous studies regarding the learning-by-exporting hypothesis, mixed and unclear results are found in the literature. In addition, there has still been little evidence of the association between export orientation and the enhancement of firm efficiency performance, particularly in Vietnam. Taking a different approach, the endogenous switching regression model, my study analyses the factors that impact efficiency (and productivity) under the presence of the self-selection bias of exporting decision. To the best of my knowledge, this study is the first attempt to apply the endogenous-switching model to the analysis of the effect of self-selection of exporting on a firm's productivity. An important difference between the endogenous-switching analysis and the typical approach of employing an export dummy is that the former allows the slope coefficients as well as the intercepts of the regression models to differ between exporters and non-exporters, while treating the decision to be an exporter as endogenous. In this way, detailed information about any factors that contribute toward the differences in productivity and efficiency between the two groups can be examined. It also investigates the drivers of export participation. Moreover, my study focuses on the private sector which has been the driving force of Vietnam economic growth. It tries to add more evidence to the mixed literature supporting the association between efficiency/productivity and export orientation, and provides new evidence in the thin literature on efficiency in emerging and transition economies, especially in Vietnam.

1.2 Objectives of the study

The study uses the updated panel data of Vietnamese Small and Medium Enterprises (SMEs) over the period 2005-2013 to provide further understanding of the relationship between export participation and firm-level efficiency/productivity. The main objectives of study are followed by:

1) to decompose TFP growth into technical efficiency change, technological change, and scale efficiency change to understand the sources of productivity growth in Vietnam manufacturing sector;
2) to derives the export premium by analysing the differences between exporters and non-exporters;
3) to investigate the factors that affect the firm efficiency/productivity while controlling the selectivity issue of export decision using the endogenous switching regression model;
4) to analyse the drivers of export decision.

1.3 Research questions

1) What are the sources of firm productivity growth?
2) How do exporters differ from non-exporters in terms of some characteristics and performance indicators?
3) What are the drivers of export participation?

1.4 Contributions

The study aims to make several contributions as follows:

1) It sheds light on the thorough analysis of the sources of productivity growth of Vietnamese manufacturing SMEs by decomposing TFP Malmquist index into components such as technical efficiency change, technological change, and scale efficiency change.
2) It provides new evidence to the mixed and unclear picture of the relationship between export orientation and productivity.
3) It adds evidence to the thin literature on the impact of export activities on firm efficiency.

4) It attempts to stimulate the policy options for promoting exporting as one of the main drivers of economic growth.

1.5 Structure of the thesis

The remainder of the study is organised as follows. The next section, chapter 2, gives a brief literature review of productivity and its sources, provides empirical evidence on the relationship between efficiency/productivity and export activities, and also sets out some relevant methodologies. Chapter 3 presents detailed methodologies such as super-efficiency DEA, Malmquist productivity index, and endogenous switching regression model. Chapter 4, results and discussion, supplies sample data and the descriptive analysis of firm characteristics and export participation, and then discusses the sources of productivity growth and determinants of firm efficiency/productivity. Finally, chapter 5 provides some conclusions drawn from the analysis.

CHAPTER 2 - THEORETICAL BACKGROUND AND LITERATURE REVIEW

This chapter reviews the literature on the measures of efficiency and productivity growth and on the association between efficiency (and productivity) and environmental variables while controlling for the self-selection of exporting decision. Firstly, the chapter provides some essential notations and theory behind the measurement of efficiency and productivity. Next, it presents the historical development of the Data Development Analysis (DEA) approach and the Malmquist productivity index. It also reviews the empirical evidence on the relationship between efficiency/productivity and environmental variables. Finally, it focuses on the endogenous switching regression framework to account for the endogeneity and selectivity issues of the decision to export.

2.1 Theory behind measurement of efficiency and productivity

2.1.1 Production process

Production is defined as a procedure that converts certain goods and services (inputs) into other goods and services (outputs) (Frisch, 1965). During the process, the original forms of input are lost and transformed.

Figure 2.1 **- The production process**

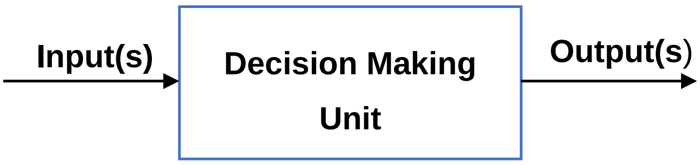


Figure 2.1 illustrates the production process of a producer or a decision-making unit (DMU hereafter). The production referred in the study is not only the manufacturing process which uses raw materials, labour, and fixed capital to produce goods and services but any method involved in converting input(s) into output(s). For instance, a bank uses operating costs and financial expenses to maximise the number of loan accounts and deposits; a university utilises inputs of students, staff, and operating expenses to obtain a range of academic outputs. In other words, production refers to any conversion process to generate possibly maximum outputs from a set of given inputs.

2.1.2 Production frontier

Frisch (1965) considered a production function as a mathematical representation of the transformation of inputs to obtain the maximal outputs attainable from each level of inputs. To estimate a production frontier, two techniques are used most: parametric (stochastic) and non-parametric (deterministic). The stochastic frontier assumes a specific form for the production function while the deterministic frontier has no requirement of functional form. In addition, the deterministic frontier is formed from the observed input-output correspondences. The production frontier is regarded as a benchmark to compute the efficiency scores. If DMUs operate on the frontier, they are technically efficient. Otherwise, they are considered as inefficient because they are beneath the frontier.

2.1.3 Productivity vs. Efficiency

The two concepts "productivity" and "efficiency", as mentioned above, are commonly used interchangeably but they have some differences. Fried et al. (2008) defined "productivity" as the ratio of a producer's output to its input. This ratio is quite simple to measure in a scenario of one input and one output. However, when the producer uses multiple inputs to obtain multiple outputs, these inputs and outputs must be properly aggregated. Productivity growth is then computed by taking the difference between output growth and input growth. In addition, in this study, the productivity referred to is total factor productivity, which involves a combination of inputs of production.

Fried et al. (2008) also elucidated the term "efficiency" as the distance between an observed output (or input) to an optimal output (or input) that is located on a best-practice frontier. It means that the observed output is compared to the maximum attainable output using the given input and technology; or the observed input is compared to the minimum possible input to generate the given output with the given technology.

2.1.4 Distance function

The concepts of a distance function and production frontier are closely related and useful in describing the technology and measuring firm efficiency. Shephard (1953) and Malmquist (1953) independently introduced the notion of distance function $d(x, y)$ which involves radial contraction and expansion of an input x or output vector y. Distance function is classified into input distance function and output distance function. An input distance function considers a minimal proportional reduction of the inputs used with the given outputs while an output distance function looks for a maximal proportional augmentation of the outputs obtained with the given inputs. If $d^k(y^k, x^k) \equiv 1$, the k-th firm is assumed technically efficient and hence its distance function does not impose any inefficiency.

2.1.5 Returns to scale

The returns to scale (RTS) of a point/DMU on a production frontier is defined as a proportionate increase of outputs resulting from an increase in inputs. If the outputs and inputs expand by the same percentage, the frontier at that point exhibits constant returns to scale (CRS). Otherwise, if an increase in the inputs leads to an unequal proportional rise in the outputs, the frontier is variable returns to scale (VRS).

2.1.6 Technical efficiency

A formal definition of technical efficiency was introduced by Koopmans (1951). A DMU is regarded as technically efficient if it cannot obtain any more output without decreasing another output or increasing one or more inputs. Correspondingly, a technically efficient DMU cannot reduce any input without diminishing at least one output or increasing at least one other input. Therefore, a technically inefficient DMU still has room to improve. It could produce the same outputs with less input(s) or raise one or more outputs with the same inputs.

Debreu (1951) and Farrell (1957) proposed an estimate of technical efficiency as the maximum radial contraction in all inputs for feasibly given technology and outputs or the maximum radial expansion in all outputs with feasibly given technology and inputs. Therefore, the concepts of technical efficiency and distance function are related. Accordingly, technical efficiency is also classified into input or output orientation. An output-oriented technical efficiency is equal to the output distance function. However, an input-oriented technical efficiency is the reciprocal of the input distance function. Further explanation of the relationship between technical efficiency and distance function is provided in the chapter Methodology.

2.1.7 Scale efficiency

Recall that a DMU is deemed technically efficient if it lies on the frontier. However, it still could increase its productivity by moving to the point called technically optimal productive scale (TOPS) (Coelli et al., 2005). This increase in productivity is referred to as scale efficiency. In addition, the TOPS point is defined as the point on the production frontier at which a ray from the origin is the tangent to the frontier. Hence, all other points on the production frontier are less productive than the TOPS point. If the frontier has CRS, all the points on the frontier are equally productive.

Figure 2.2 **- Productivity, technical efficiency, and scale efficiency**

(*source: Coelli et al. (2005)*)

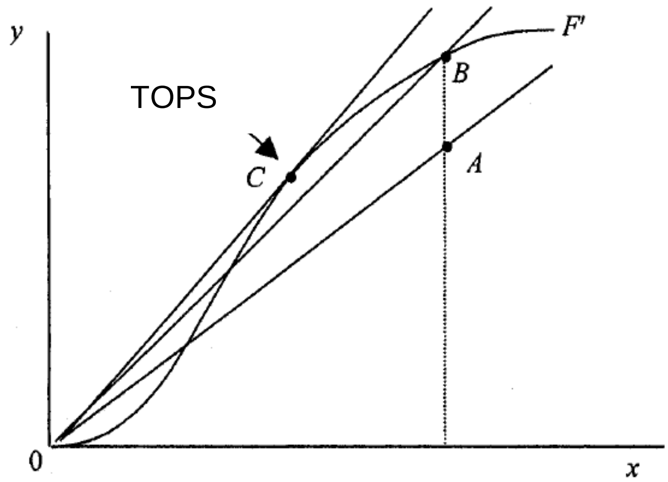


Figure 2.2, which depicts a production frontier with one input (x) and one output (y), illustrates the differences between productivity, technical efficiency and scale efficiency. The technically efficient VRS frontier is depicted by curve F. Any DMU whose input-output combination lies on this frontier (eg. C and B) is technically efficient, while a DMU with an input-output combination below the VRS frontier (eg. A) is technically inefficient. In this illustration, where DMUs produce one output using a single input, the productivity of a DMU is the slope of the ray from the origin through the DMU's input-output combination. Hence, the figure shows that C achieves the highest productivity and A the lowest productivity among the three DMUs. The ray from the origin that is tangential to the VRS frontier (OC) represents the CRS frontier, and the tangent point (C) represents the TOPS. Hence, DMU C is both technically efficient and efficient in scale resulting in the highest productivity. However, B, which is on the VRS frontier but not on the CRS frontier, is technically efficient but not

efficient in scale, resulting in a level of productivity lower than C. A is neither technically efficient nor efficient in scale, resulting in the lowest productivity.

2.2 Application of the Data Envelopment Analysis to the Measurement of Efficiency

Technical efficiency is a proxy for a firm's ability to achieve the maximum outputs from given inputs (Farrell, 1957). Efficiencies of firms are measured relatively to the production frontier. And the unknown production frontier is usually estimated through the Stochastic Frontier Analysis (SFA) or the Data Envelopment Analysis (DEA) method. The SFA is a parametric approach proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). It assumes a function for the production technology and incorporates statistical noise into the function. On the other hand, the DEA, a non-parametric technique, does not restrict the production technology to a predetermined functional form. Furthermore, the DEA requires no assumption about the underlying distribution of the inefficiency term. These are advantages of the DEA method over the SFA method as the former enables us to avoid several assumptions that may be too restrictive. However, those advantages come at some cost. The standard DEA assumes that all inefficiencies are under the control of the firm and fails to take into account the effects of a measurement error and statistical noises on efficiency. Consequently, the standard DEA does not allow typical statistical tests of the econometric approach. Due to the simplicity and the above-mentioned advantages of the DEA over the SFA, DEA has gained extensive analytical development and empirical applications.

The idea behind DEA is to construct the frontier by enveloping a group of DMUs and then to use that frontier as a benchmark to estimate the relative efficiency of each DMU. Since the advent of DEA by Charnes et al. in 1978, Liu et al. (2013) revealed that one-third of DEA papers are purely methodological while the rest are application embedded. In addition, most of articles in the first twenty years of its development were purely methodological. Since then application articles have grown rapidly. There were more than 4,000 published articles and around 3,000 unpublished dissertations and papers at conferences by 2008 (Emrouznejad et al., 2008). Moreover, Emrouznejad et al. (2008) indicate that there were 2,500 authors with the average of two authors per publication.

2.2.1 Development of the DEA methodologies

Since Charnes et al. (1978) introduced DEA, there has been an impressive growth in methodological development. This study reviews the major DEA models including CRS and VRS models, the slack-based measure, additive model, and super-efficiency model.

2.2.1.1 The CRS and VRS models

DEA is based on linear programming to form a non-parametric piecewise best-practice frontier using the sample data. Charnes et al. (1978) proposed an input-oriented model and assumed CRS. The input-oriented DEA seeks the potential proportional contractions in inputs while holding the current levels of outputs constant. The output-oriented DEA looks for the potential proportional expansions in output while retaining the current levels of inputs. Assume that there are m inputs and q outputs for each DMU from the sample of n DMUs. The basic DEA is presented by the following mathematical programming problem with the purpose of finding the optimal weights for r-th DMU:

$$max\ \frac{\sum_{j=1}^{q} u_j y_{jr}}{\sum_{i=1}^{m} v_i x_{ir}}$$

$$subject\ to \quad \frac{\sum_{j=1}^{q} u_j y_{jr}}{\sum_{i=1}^{m} v_i x_{ir}} \leq 1, \qquad j = 1, 2, \ldots, q;$$

$$u_j, v_i \geq 0. \qquad i = 1,2, \ldots, m; \tag{2.1}$$

where u_j and v_i are j-th output weight and i-th input weight, respectively.

The above problem (2.1) is referred to as the CCR (Charnes, Cooper and Rhodes) model. It involves obtaining optimal values for $\mathrm{u_j}$ and $\mathrm{v_i}$, such that the efficiency measure of r-th DMU is maximised, subject to the constraints that all efficiency measures must not be higher than 1. However, this problem can have an infinite number of solutions, for example, $(\mathrm{u_j}, \mathrm{v_i})$ and $(\alpha \mathrm{u_j}, \alpha \mathrm{v_i})$ are both solutions. Therefore, applying the theory of fractional programming by Charnes and Cooper (1962), problem (2.1) can be converted to the following model:

$$max\ \sum_{j=1}^{q} \mu_j y_{jr}$$

$$subject\ to \quad \sum_{i=1}^{m} v_i x_{ir} = 1$$

$$\sum_{j=1}^{q} \mu_j y_{jr} - \sum_{i=1}^{m} v_i x_{ir} \ \leq \ 0\,, \qquad r = 1,2, \dots, n;$$

$$\mu_j, v_i \ \geq \ 0 \qquad (2.2)$$

However, the assumption of CRS requires the observed DMUs to operate at an optimal scale. Hence, some authors including Fare et al. (1983) and Banker et al. (1984) suggest relaxing the CRS assumption and account for VRS by adding the constraint $\sum_{k=1}^{n} \lambda_k = 1$. The well-known VRS-DEA model is referred to as the BCC (Banker, Charnes and Cooper) model.

2.2.1.2 The slacks-based measures and additive model

In 1985, Charnes et al. proposed an additive DEA model which incorporates both input reduction and output augmentation simultaneously. The additive model is based on input and output slacks (s_i^- and s_j^{+}', , respectively) as follows:

$$max \sum_{i=1}^{m} s_i^- + \sum_{j=1}^{q} s_j^+$$

$$subject\ to \quad \sum_{k=1}^{n} \lambda_k x_{ik} + \ s_i^- \ \leq \ x_{ir} \qquad i = 1, 2, \dots, m;$$

$$\sum_{k=1}^{n} \lambda_k y_{jk} - \ s_j^+ \ \geq \ y_{jr} \qquad j = 1, 2, \dots, q;$$

$$\lambda_k, s_i^-, s_j^+ \ \geq 0 \qquad (2.6)$$

The model (2.6) assumes CRS and, hence, to impose VRS technology, the convexity constraint ($\sum_{k=1}^{n} \lambda_k = 1$) could be added to the model. Both s_i^- and s_j^+ identify an excess utilisation of the i-th input and a shortfall in the j-th output. A DMU is additive-efficient if all slacks are zero at the optimum. However, simple summation of slacks as the objective in (2.6) may be inappropriate when inputs and outputs are measured in non-commensurable units. Additionally, the model (2.6) does not provide a valid measure of inefficiency as the CCR and BCC models do.

To overcome the weaknesses in the additive model, Tone (2001) developed the slack-based measure (SBM) which is constant to measurement units and unchanged with respect to slacks.

$$min\ p = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ir}}{1 + \frac{1}{q}\sum_{j=1}^{q} s_j^+ / y_{jr}}$$

$$subject\ to \quad \sum_{k=1}^{n} \lambda_k x_{ik} + s_i^- \leq x_{ir} \qquad i = 1, 2, \dots, m;$$

$$\sum_{k=1}^{n} \lambda_k y_{jk} - s_j^+ \geq y_{jr} \qquad j = 1, 2, \dots, q;$$

$$\lambda_k, s_i^-, s_j^+ \geq 0 \tag{2.7}$$

The objective function, p, varies between zero and one and hence is an efficiency score as described in the CCR and BCC models.

2.2.1.3 Super-efficiency models

Although all the DMUs that operate on the frontier are deemed efficient, they are not equally productive. Therefore, ranking those DMUs is an important problem. One solution to the ranking issue is the super-efficiency model introduced by Andersen and Petersen (1993). The super-efficiency model suggests implementing the standard DEA models with the exclusion of the DMU being measured from the reference set. Thus the DEA frontier is constructed by the remaining DMUs.

However, the super-efficiency model may have infeasible solutions in the case of VRS technology (Zhu (1999) and Seiford and Zhu (1999a)). To address this problem, Lovell and Rouse (2003) modified the standard super-efficiency model by scaling up (down) the inputs (outputs). As a result, the same efficiency scores as the standard super-efficiency model are generated for DMUs having feasible solutions, and super-efficiency scores are found for those facing infeasibility. Another approach to resolving the infeasible issue was proposed by Chen (2004). Chen argued that an efficient DMU could make input savings under output orientation or output surplus under input orientation when infeasibility occurs in the VRS super-efficiency model. Thus, his method attempts to fully characterize super-efficiency by using both input- and output-oriented VRS super-efficiency models. However, Chen's method would not work when both input-oriented and output-oriented models find solutions.

In 2009, Cook et al. proposed a modified VRS super-efficiency model that addresses infeasible problems of efficient DMUs. In cases of infeasibility, they recommended the decrease in both inputs and outputs under the input orientation or the increase in both inputs and outputs under the output orientation to reach the frontier. Lee et al. (2011) extended the models developed by Chen (2005) and Cook et al. (2009), and proposed a two-stage procedure to calculate super-efficiency scores. This approach may also consider infeasibility as inefficient performance and highest super-efficiency due to the presence of input saving or output surplus. In stage one, the model by Lee et al. (2011) tries to detect input saving under output orientation or output surplus under input orientation. If there exists any input saving or output surplus, the infeasibility occurs for the measured DMU. Then, in stage two, a modified VRS super-efficiency model is suggested to find the super-efficiency scores for all DMUs. As a result, feasible solutions would have zero input saving or zero output surplus and the super-efficiency scores are identical to the scores achieved by the conventional super-efficiency model. For those efficient DMUs that have an infeasibility issue, the super-efficiency scores that incorporate both input and output movements would be generated from the modified super-efficiency model. Subsequently, Chen and Liang (2011) combined the two-stage procedure by Lee et al. (2011) and the adjusted DEA model by Cook et al. (2009) into a single DEA model. This approach actually integrates the advantages of both techniques.

2.2.2 DEA applications

Liu et al. (2013) reported that the industries that have attracted the largest number of DEA application papers are banking, hospital, agriculture and farm, transportation, and education. This study attempts to review DEA applications in banking, agriculture and farm, and manufacturing. The reasons for choosing those three areas are that (1) Banking is the most DEA-applied industry in the literature; (2) many papers on DEA using Vietnamese data were found in agriculture and farm; and (3) the manufacturing is the sector on which this study undertakes its analysis.

2.2.2.1 Banking

In banking, DEA articles account for 10.31% of the total of papers presented for the period 2005-2009 (Liu et al., 2013). In 1985, Sherman and Gold initially applied DEA to study bank efficiency. Their results show that, distinguishing it from other profitability-oriented techniques, DEA provides meaningful insights about bank branch performance. A subsequent work, Rangan et al. (1988), measured the technical efficiency of a group of U.S. banks under CRS and indicated that the biggest cause of inefficiency was wasting inputs or pure technical inefficiency. They were the pioneers in applying the two-step contextual technique to banking. The two-step contextual method includes the first step of measuring efficiency and the second step of analysing the impact of environmental variables on technical efficiency.[1] Following Rangan et al. (1988) by employing the two-step model, Favero and Papi (1995) investigated 174 Italian banks and reported that productive specialization, size, and location contribute to explain efficiency.

In addition, Elyasiani and Mehdian (1990), Berg et al. (1992), and Berg et al. (1993) examined changes in efficiency over time periods using the DEA-based Malmquist index. Elyasiani and Mehdian (1990) measured the efficiency of large U.S. commercial banks between 1980 and 1985 while Berg et al. (1992) attempted to analyse productivity growth of Norwegian banks during the 1980s. Berg et al. (1993) then applied DEA to the banking industries of Finland, Norway, and Sweden. Subsequently, Seiford and Zhu (1999b), Luo (2003), and Lo and Lu (2006) studied efficiency of U.S. banks and Taiwanese financial holding companies using two-stage production process that is a simple application of Network DEA. They separated profitability and marketability stages to assess efficiencies in each stage.

Furthermore, DEA-based banking efficiency is also studied in Asian countries such as Korea (Shin & Kim, 2011; Sufian, 2011), and Japan (Drake et al., 2009) using the slack-based measure with a profit/revenue-based approach. DEA is applied not only in developed countries but also in emerging and developing countries. Oliveira and Tabak (2005) compared the efficiency in banking systems between developed and developing countries. The findings indicated no significant difference in banking efficiency among developed and emerging countries although developing Asian banking systems had shown an upward trend

[1] Note that some studies used the term “two-stage” instead of “two-step” approach.

before the Asian crisis. In respect of China, Drake et al. (2006) analysed the efficiency of Hong Kong's banking industry while Avkiran (2011) used super-efficiency and K. Wang et al. (2014) exploited additive two-stage DEA to investigate Chinese banking efficiency. Other DEA applications in the banking industry in emerging markets include India (Kumar & Gulati, 2009), Indonesia (Sufian, 2010), and Thailand (Sufian & Shah Habibullah, 2010). In Vietnam, DEA papers have also applied various methodologies. Some have used traditional DEA (Dang-Thanh, 2012b) or made a comparison between DEA and SFA (Nguyen, 2014), DEA with the Malmquist index (Hùng, 2007) or the two-step approach including DEA with Tobit regression (Dang-Thanh, 2012a; Minh et al., 2013).

2.2.2.2 Agriculture and farm

Färe et al. (1985) first applied DEA to estimate technical efficiency in agriculture using a sample from the Philippines. Sharma et al. (1997) and Sharma et al. (1999) then compared efficiencies based on DEA and SFA methods and pointed out that DEA generates more robust results than SFA. The works of L. W. Tauer (1995), L. Tauer and Stefanides (1998), and Fraser and Cordina (1999) measured the efficiency of dairy farms. While L. W. Tauer (1995) used the Malmquist productivity index with the behaviour of maximising profits and minimising costs, L. Tauer and Stefanides (1998) exploited the two-step contextual method with Tobit regression in the second step to identify the environmental factors that affect the efficiencies. The two-step contextual method with Tobit approach was explored by Dhungana et al. (2004), Hansson (2007), and Speelman et al. (2008), for farm samples in Nepal, Greece, Sweden, and South Africa respectively. In addition, bootstrapping techniques have gained attention in agriculture with studies by Balcombe, Davidova, et al. (2008) and Balcombe, Fraser, et al. (2008). Recently, Atici and Podinovski (2015) proposed DEA for output profiles exhibiting specialisation using a sample of Turkish farms.

In Vietnam, several DEA studies measure efficiency in farming. Some of them used two-step analysis with DEA and Tobit regression such as Rios and Shively (2005), Hanh (2009), Khai and Yabe (2011), and Nhut (2011). Others used DEA with bootstrap techniques including Minh and Long (2008), Tung (2013) and Linh et al. (2015), or made a comparison between DEA and SFA such as Huynh-Truong (2009).

2.2.2.3 Manufacturing

As reported by Liu et al. (2013), only 4.66% of all application-embedded papers are studies of the manufacturing sector over the period 2005-2009 although manufacturing was on the top-seven industries that make up more than 50% of DEA application works. Chavas and Cox (1990) is considered to be one of the earliest studies on DEA of the manufacturing sector. They measured technical change and productivity in the context of cost minimising behaviour.

A following study, Co and Chew (1997), classified Japanese and U.S manufacturing firms into two groups, labelled DEA efficient firms and DEA inefficient firms. They provided evidence for the question whether the different treatments of research and development (R&D) expenditures result from the country of origin (America or Japan) or from the ability to utilise firm resources efficiently. In addition, DEA is used for benchmarking (Leachman et al., 2005) and ranking (Saeidi et al., 2013) in manufacturing. Leachman et al. (2005) examined the world mobile producers' relative manufacturing performance to assess the competitiveness of a firm with its major rivals while Saeidi et al. (2013) applied DEA to rank woven fabric defects. Some other studies explored other DEA-based methodologies such as super slack-based model (Düzakın & Düzakın, 2007), and fuzzy DEA (Y.-M. Wang et al., 2009).

In Vietnam, DEA applications in manufacturing have not been widely exploited. To my knowledge, Vixathep and Matsunaga (2012) is the first study to investigate the manufacturing sector's DEA efficiency. They used the two-step approach with DEA and regressions (OLS and Tobit) to measure technical efficiency and address determinants of technical efficiency using a sample of Vietnam's garment industry. They found that the efficiency of the garment industry could be substantially improved.

2.3 Application of the DEA-based Malmquist Index method

Malmquist (1953) developed the Malmquist input index by comparing the input consumption of a DMU over two points in time. Caves et al. (1982) extended the work of Malmquist to define the Malmquist productivity index. Because Malmquist productivity index is based on a distance function $d(.)$, this index can be either input oriented or output oriented. Later, Fare et al. (1992, 1994) introduced a DEA-based Malmquist productivity measure which evaluates the change in productivity over time. The basic idea behind the construction of the index involves measuring the radial distance of inputs and outputs relative to the reference technology in two periods, t and t+1. The measure is constructed as the geometric mean of two Malmquist productivity indexes. The index can be decomposed into two components, namely, technical efficiency change (relative to CRS) and technical change. And the technical efficiency change could be then decomposed into pure efficiency change (relative to the VRS) and scale efficiency change. Technical efficiency change assesses the variation in technical efficiency over two periods. Technical change describes the progress, stagnation, or regression of the best-practice technologies while scale efficiency change captures the improvement in scale of operations.

Since the introduction of DEA-based Malmquist productivity index by Färe et al. (1994), the approach has been used extensively. Färe et al. (1995) decomposed the change in productivity into changes in technical efficiency and technology for Taiwanese manufacturing industries. Their findings support the idea that R&D activities benefit technical progress and affirmed that technical change and efficiency change may exhibit different patterns. Subsequently, also measuring productivity changes in Taiwanese manufacturing sectors in a comparison with those of Korea, Hsiao and Park (2005) classified manufacturing sectors into three categories consisting of traditional, basic, and high-tech industries and constructed category-wide meta frontiers to provide more information on which industries drive productivity and the growth rate of technology.

The Malmquist index has also been customised to make it appropriate for particular measurement purposes. For example, Yörük and Zaim (2005) constructed the Malmquist-Luenberger productivity measure to incorporate the existence of negative externalities. Moreover, network DEA with the Malmquist index is employed such as in the work of C.-Y. Lee and Johnson (2011). Network DEA reveals the multi-stage process in which outputs of one stage become inputs to another stage. For instance, C.-Y. Lee and Johnson (2011) divided the production system into three stage: production design, demand support, and operations. They then extended the decomposition of the DEA-based Malmquist productivity index in a more detailed way. Other studies on the Malmquist index cover the manufacturing sector in OECD countries (Arcelus & Arozena, 1999), Australia and New Zealand (Färe et al., 2001), Singapore (Tan, 2006), Italy (Sena, 2001), China (Ma et al., 2002), and India (Joshi & Singh, 2010).

Besides the manufacturing sector, the Malmquist productivity index is applied in other industries such as health care (Burgess Jr & Wilson, 1995; Pilyavsky & Staat, 2008; Chowdhury et al., 2014), banking (Elyasiani & Mehdian, 1990; Dias & Helmers, 2001; Elyasiani & Wang, 2012), and education (Rahimian & Soltanifar, 2013).

2.4 Analysis of the effects of environmental variables (two-step approach)

2.4.1 The two-step approach

Two-step models are quite common in efficiency analysis. They include the first step of using non-parametric DEA to estimate efficiency and the second step of employing the regression to determine environmental factors that influence efficiency. The two-limit Tobit (i.e. value of dependent variable limits at zero and one) has been adopted as the popular choice for the second step evaluation. Several studies, such as Bjurek et al. (1992), Oum and Yu (1994), Chilingerian (1995), Ruggiero and Vitaliano (1999), Vestergaard et al. (2002), Latruffe et al. (2004), Bravo-Ureta et al. (2007), and Çelen (2013), have used this approach. Hoff (2007) compared the predicted performance in the second-step DEA using Tobit, ordinary least square (OLS), unit-inflated beta model by Cook et al. (2000), and quasi-maximum likelihood estimation (QMLE) model of Papke and Wooldridge (1993). It is probable that DEA scores only obtain a value of one, but not zero. Thus, the author argued that the two-limit Tobit technique is actually a misspecification. However, when applying this in a sample of the Danish fishing industry over six months in 2002, Hoff found that it is sufficient to use OLS and Tobit to model the relationship between DEA scores and exogenous variables. He also concluded that neither the Tobit nor Papke-Wooldridge's model perform better than OLS. Put together, OLS is good enough for modelling the second step of the analysis between DEA efficiency and environmental variables. McDonald (2009) went on to indicate that DEA efficiency scores are fractional data instead of censored data. Hence, the Tobit model is inapplicable to the second-step approach, and OLS provides an unbiased and consistent estimator. Moreover, if White's heteroskedasticity-consistent standard errors are computed, hypothesis tests can be validly undertaken.

In addition, the drawback that DEA provides no information of the uncertainty of an estimate was addressed by Efron (1992), using the bootstrap method. The main idea of bootstrapping is that the estimator is resampled and then the bootstrap confidence intervals are calculated using the empirical distribution of resampled estimates to derive the statistical inferences. Accordingly, the appropriate confidence intervals for the DEA scores can be determined. Bootstrapping has been widely applied in investigating the sensitivity of efficiency measures to the variation in samples, especially when DEA results are well reported to be sensitive to sample composition. Several papers advocated the bootstrap techniques in DEA such as Atkinson and Wilson (1995), Ferrier and Hirschberg (1997), and Simar and Wilson (1998, 1999). Since then, applications of the bootstrap technique have been made in several areas such as hotels (A. Assaf et al., 2010), airports (Curi et al., 2011), hospital (Staat, 2006), and mining (Tsolas, 2011). Moreover, Simar and Wilson (2007) extended the bootstrap DEA to double bootstrap for two-step models in which bootstrapping is applied for both DEA efficiency score in step one and for estimates of the regression between DEA efficiency score and environmental variables in step two. Recently, a few applications of the double bootstrap technique have occurred including Barth and Staat (2005), Latruffe et al. (2008), Balcombe, Fraser, et al. (2008), Odeck (2009), Alexander et al. (2010), A. G. Assaf and Agbola (2011), and Kounetas and Papathanassopoulos (2013).

For the manufacturing sector, most of papers have used Tobit or OLS for the second-step analysis of the DEA approach. For example, J. D. Lee et al. (1998) employed OLS to explain the impact of environmental variables such as static efficiency, effective protection rate, output growth, market concentration, output price variation, and capital productivity on productivity growth, technical change and efficiency change. Leachman et al. (2005) identified research and development (R&D) commitment, outsourcing rate, and inventory turnover as influencing factors on manufacturing performance obtained from DEA using OLS and Tobit techniques. Moreover, Kim and Park (2006) examined the relationship between R&D and the Malmquist TFP index and its two components employing a two-way (i.e. time and cross-section) fixed-effects model. In Vietnam, Vixathep and Matsunaga (2012) analysed determinants of technical efficiency with OLS and Tobit regressions.

2.4.2 Analysis of the effects of exporting on productivity and efficiency

A growing body of literature has examined the association between export activities and productivity. Two common explanations for the superior productivity of exporting firms are self-selection and learning-by-exporting. The self-selection mechanism shows the causal link running from productivity to export while the learning-by-exporting hypothesis suggests the learning effects of exporting on firm productivity. The self-selection hypothesis argues that firms that are more productive choose to participate in export markets due to the existence of the sunk entry costs. These costs consist of transportation, marketing, personnel for managing foreign networks, and costs for modifying the current domestic products to serve foreign markets. Hence, less productive firms rarely overcome this entry barrier. A numerous number of studies find empirical evidence supporting the self-selection mechanism (Bernard & Jensen, 1999; López, 2005; Melitz, 2003; Wagner, 2007a). Exporting to more developed countries also helps exporters to achieve superiority of firm performance over non-exporters (Damijan et al., 2004; Pisu, 2008; Serti & Tomasi, 2009).

On the other hand, the learning-by-exporting hypothesis suggests that exporting producers improve their productivity via knowledge flows from foreign customers and competitors (Westphal et al., 1984; Keesing & Lall, 1992; Grossman & Helpman, 1993; Van Biesebroeck, 2005; De Loecker, 2007). Moreover, firms that enter into world markets face more intensely competitive pressure than those that serve only the domestic market (Aw & Hwang, 1995; Delgado et al., 2002). However, evidence regarding learning-by-exporting provides a mixed picture (Wagner, 2007a). Some studies confirm the learning-by-exporting effect with various exporter premia while others find no evidence in favour of this effect (International Study Group on Exports and Productivity (ISGEP), 2008; Singh, 2010). Besides, as reported by Martins and Yang (2009), the learning-by-exporting impact is greater in emerging economies than in developed ones. Martins and Yang also found the stronger impact of export activities on firm-level productivity in the year the producers start to export than in later years. Furthermore, firms achieve higher productivity when they increase the number of export markets into which they extend (Ruane & Sutherland, 2005; Wagner, 2007b; Andersson et al., 2008; Castellani et al., 2010).

From the two-step DEA analysis above, OLS and Tobit are appropriate techniques. However, if the potential for self-selection bias and endogeneity exists, OLS and Tobit yield biased and inconsistent estimators. To overcome these issues, the endogenous switching regression model introduced by Maddals and Nelson (1975) has been developed. In their paper, maximum likelihood estimation was applied but unbounded log likelihood was found in some cases. Endogenous switching relates to the issue of an explanatory variable being a binary regime switching in which only one regime is observed if a selection condition is met.

Moreover, the correlation between unobserved factors and the selection process is also considered in the endogenous switching regression model. In other words, the explanatory variable that affects the switching process is the only potentially endogenous variable. The model could be fitted to one equation at a time via either maximum likelihood estimation or two-step estimation. The two-step procedure includes the first step of using a Probit model to predict the probability of the two regimes and the second step of adding the obtained inverse Mills' ratio to the main model as an explanatory variable. However, two-step least square and maximum likelihood estimation methods are inefficient and derive inconsistent standard errors (Lokshin & Sajaia, 2004). Therefore, full-information maximum likelihood is considered to be the technique to simultaneously fit binary part (selection equation) and continuous part (main equation) to yield consistent standard errors. The endogenous switching regression model has been applied in various areas including labour economics (Van der Gaag & Vijverberg, 1988; Pederson et al., 1990; Hartog & Oosterbeek, 1993; Sakellariou, 2012), housing demand (Manrique & Ojah, 2003; Choi & Min, 2009), and agriculture (Alene & Manyong, 2007; Abdulai & Huffman, 2014).

In this study, export status is considered as a potential endogenous variable. This is due to the fact that some unobserved factors may correlate with export status. Moreover, becoming an exporter is a non-random process because a firm self-selects into international markets. Hence, the endogenous switching regression framework is appropriate for my second-step analysis. With a different approach to model the association of efficiency (or productivity) and export activities, my study tries to identify the determinants of efficiency/productivity with accounting for the self-selection bias of exporters. To the best of this author's knowledge, the endogenous switching regression model has not been applied to the second-step procedure to investigate the relationship between efficiency/productivity and environmental variables in accounting for the selectivity of the choice to engage in exporting.

To sum up, this chapter reviews the literature on efficiency and productivity using DEA and the Malmquist index. In addition, it provides the background for using the two-step approach and endogenous switching regression model. In the next chapter, the study will describe the methodologies used in detail.

CHAPTER 3 - METHODOLOGY

The study employs a two-step procedure consisting of: (1) using super-efficiency Data Envelopment Analysis (DEA) to compute technical super-efficiency scores and then decompose productivity growth into technical efficiency change, technological progress, and scale efficiency change; and (2) applying the endogenous switching regression model to examine the determinants of efficiency/productivity accounting for the selection bias of export decision. This chapter describes the standard DEA model, the conventional and modified super-efficiency DEA models, the Malmquist productivity index, export premium, and the endogenous switching regression model for panel data.

3.1 Technical efficiency and decomposing productivity change into technical efficiency, technological change, and scale efficiency change

3.1.1 Data Envelopment Analysis (DEA) approach

Under the DEA approach, the technical efficiency score of a firm is measured relatively to the production frontier, which is formed by the best performers out of all firms in the sample. Technical efficiency is developed on the concept of distance function, and its measurement can be either input-oriented or output-oriented[2] In 1953, both Malmquist and Shephard introduced the notion of a distance function to describe a production technology using multiple inputs and outputs without specifying a behavioural objective, eg. minimizing costs or maximizing profits. In a mathematical manner, an input distance function is defined as:

$$d_i(x, y) = \max\{\rho : \left(\frac{x}{\rho}\right) \in L(y)\}$$

Here, $L(y)$ is the input set which illustrates all input vectors, x, used to produce the given output vector y. The input distance function $d_i(x, y)$ seeks a maximum ρ or minimum radial contraction of input vector x given the output vector y. Input-oriented technical efficiency represents the ability to improve the efficiency by proportionally reducing all

[2] In some cases, it can be a combination of input and output orientations (eg., the directional distance and the hyperbolic distance functions).

inputs without changing the quantity of output(s). Mathematically, the input-oriented technical efficiency is the reciprocal of the input distance function.

On the other hand, an output distance function $d_o(x, y)$ is described as:

$$d_o(x, y) = \min\{\delta: \left(\frac{y}{\delta}\right) \in P(x)\}$$

where $P(x)$ is the output set that represents production possibility sets of output vectors y produced using the given input vector x. The output distance function looks for a minimum δ or maximum radial expansion of vector output y, given the input vector x. The output-oriented technical efficiency estimates the amount of output proportionally expanded without requiring more inputs, hence equalling the output distance.

To illustrate the concepts of input and output distance functions, Farrell (1957) used a simple example with two inputs x_1, and x_2 and one output q for input orientation and two outputs q_1, and q_2 and a single input x for output orientation as the figures below show:

***Figure 3.1* - Input-oriented technical efficiency**

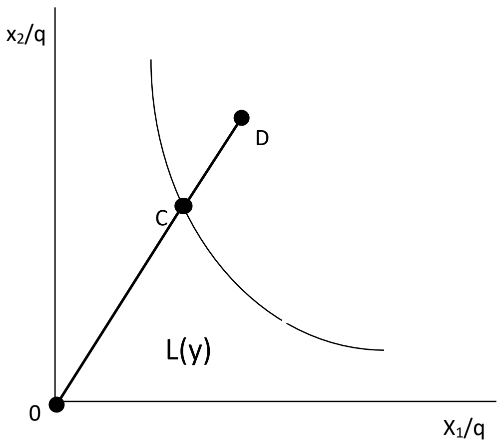
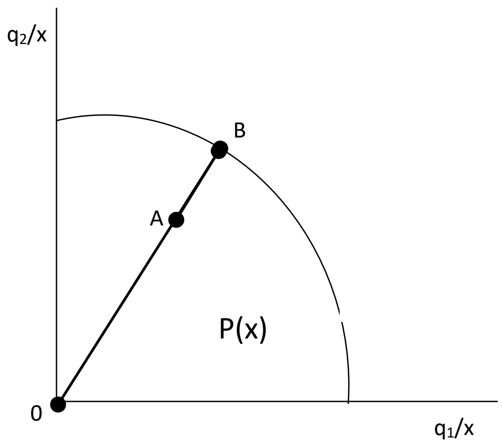


***Figure 3.2* - Output-oriented technical efficiency**



From the input orientation in figure 3.1, technical inefficiency is represented by the amount CD or the percentage term CD/OD. CD is the quantity by which all inputs could be reduced without changing the quantity of output(s). Therefore, technical efficiency is measured by one minus CD/OD, which is equivalent to OC/OD. The input set L(y) is the area below the curve. Similarly, from the output orientation in figure 3.2, AB illustrates the technical inefficiency, which is the proportional increase in output(s) without altering the quantities of inputs. Correspondingly, AB/OB is a decision-making unit's (DMU's) inefficiency as a proportion. Hence, technical efficiency is equal to one minus AB/OB, which is equivalent to OA/OB. The output set P(x) is the area bounded by the curve and the two axes.

Either under input orientation or output orientation, a technical efficiency score takes a value between zero and one. In other words, the closer a DMU is to the frontier, the higher the efficiency score the DMU achieves. If a DMU operates on the frontier (e.g point C or B), the DMU's technical efficiency takes a value of one and that DMU is considered fully technically efficient.

Charnes et al. (1978) introduced the DEA approach to estimate the productive efficiency of a sample of individual DMUs in a non-parametric manner. This DEA specification is often referred to as the CCR (Charnes, Cooper, and Rhodes) model. The DEA method forms a frontier by linearly connecting the best performers in the sample and it compares the levels of inputs or outputs for one DMU against the frontier. The input-oriented DEA method finds the distance of the input quantities used by each DMU r by solving the following linear programming (LP) problem:

$$
\begin{aligned}
& min_{\theta,\lambda}\theta \\
& subject\ to \sum_{k=1}^{n} \lambda_k x_{ik} \le \theta x_{ir} && i = 1, 2, \ldots, m; \\
& \qquad \textstyle\sum_{k=1}^{n} \lambda_k y_{jk} \ge y_{jr} && j = 1, 2, \ldots, q; \\
& \qquad \lambda_k \ge 0 && k = 1, 2, \ldots, n.
\end{aligned}
\tag{3.1}
$$

where:

- x_{ik} : input i of k-th DMU, assuming that m inputs are used
- y_{jk}: output j of k-th DMU, assuming that q outputs are produced
- λ_k: weights for inputs and outputs in forming the frontier (the intensity variables)
- n: the number of DMUs.

The value of θ is the technical efficiency score of the DMU, which ranges between zero and one. If a DMU's score θ is one, the DMU is technically efficient. The linear programming problem (1) must be solved for each DMU in the sample. The LP problem defined by (3.1) is the input-oriented DEA model and it is the envelopment form of the problem (2.2). It seeks a radial contraction of inputs without changing the quantity of outputs. Similarly, the output-oriented DEA model can be stated as follows:

$$
\begin{aligned}
& max_{\delta,\lambda}\delta \\
& subject\ to \sum_{k=1}^{n} \lambda_k x_{ik} \leq x_{ir} && i = 1, 2, \dots, m; \\
& \sum_{k=1}^{n} \lambda_k y_{jk} \geq \delta y_{jr} && j = 1, 2, \dots, q; \\
& \lambda_k \geq 0 && k = 1, 2, \dots, n. \qquad (3.2)
\end{aligned}
$$

where:

- x_{ik} : input i of k-th DMU, assuming that there are m inputs used
- y_{jk}: output j of k-th DMU, assuming that there are q outputs produced
- λ_k: intensity variables

Note that the value of δ is higher than one and $\delta - 1$ is the proportional expansion of outputs of r-th DMU with no change in input quantities. Hence, $1/\delta$ is the technical efficiency score of a DMU and it satisfies $0 \leq \frac{1}{\delta} \leq 1$. $1/\delta$ is also the output distance.

The above DEA models proposed by Charnes et al. (1978) assume constant returns to scale (CRS), which implies that an increase in all inputs by a proportion leads to an increase in outputs by the same proportion. However, the assumption CRS would be unrealistic if not all firms operate at an optimal scale. Fare et al. (1983) and Banker et al. (1984) relax the CRS assumption to allow a production technology exhibiting variable returns to scale (VRS). VRS indicates a more (increasing returns to scale) or less (decreasing returns to scale) proportional rise in outputs resulting from the rise in all inputs. To account for the VRS assumption, one more constraint $\sum_{k=1}^{n} \lambda_k = 1$ should be added to the CCR models presented above. This constraint ensures that inefficient DMUs are only benchmarked against similar-sized DMUs. The scale efficiency of a DMU is measured by comparing the technical efficiency against the VRS frontier with the technical efficiency against the CRS frontier.

The present study employs the output-oriented DEA model because firm managers are believed to have more control over quantities of outputs than over inputs. Some materials used in the production need to be imported from other countries. For example, the timber supply is limited, being exploited from plantation forests, and most of timbers are imported from international markets. Similarly, some chemicals and other materials used in the production of rubber and plastics products also come from importing. In addition, input or output orientation may have little effect on the efficiency scores obtained (Coelli et al., 2005). The best practice is the study's main interest, despite the fact that the efficient reference set may differ upon the choice of orientation. Therefore, the output-oriented specification is used for the rest of this chapter.

3.1.2 Super-efficiency model

Andersen and Petersen (1993) developed the super-efficiency DEA model to solve the ranking problem of efficient DMUs. The difference between the super-efficiency model and the standard DEA model is the exclusion of a measured DMU from the reference set. This means that the best-practice production frontier is formed by the remaining DMUs in the sample. Therefore, the super-efficiency scores can be greater than one. This result for efficiency scores that are not censored at one is regarded as an econometrical advantage when applying the endogenous switching regression model in the second step analysis of the study. Another advantage is that even the performances of efficient DMUs can be differentiated, making the regression estimates more efficient than those obtained via a Tobit-type model.

The output-oriented variable returns to scale (VRS) super-efficiency model for r-th DMU is specified as:

$$
\begin{aligned}
& max_{\,\delta,\lambda} \delta^{super} \\
& subject\ to \sum_{k=1,k\neq r}^{n} \lambda_k x_{ik} \leq x_{ir} && i = 1, 2, \dots, m; \\
& \qquad\qquad \sum_{k=1,k\neq r}^{n} \lambda_k y_{jk} \geq \delta^{super} y_{jr} && j = 1, 2, \dots, q; \\
& \qquad\qquad \sum_{k=1 k\neq r,}^{n} \lambda_k = 1 \\
& \qquad\qquad \lambda_k \geq 0 && k = 1, 2, \dots, n;\ k \neq r \qquad (3.3)
\end{aligned}
$$

Note that for inefficient DMUs, the super-efficiency model yields identical efficiency scores as the standard DEA does. However, the super-efficiency model may have infeasible solutions in the case of VRS technology for efficient DMUs (Zhu (1999) and Seiford and Zhu (1999)). To overcome the problem of infeasibility, this study applies the modified model by Chen and Liang (2011). This approach combines the models of Cook et al. (2009) and H.-S. Lee et al. (2011) into a single DEA model. It also considers super-efficiency as input saving or output surplus obtained by efficient DMUs. For example, if the model (3.3) is feasible, the obtained score δ^{super} represents the input saving of DMU_r. If infeasibility occurs, DMU_r only exhibits output super-efficiency or output surplus. In other words, if feasible solutions exist, the super-efficiency scores are equivalent to the scores obtained from the standard super-efficiency DEA model. If infeasibility arises, super-efficiency scores are generated from the modified model with the integration of both input and output movements. Put another way, to reach the DEA frontier constructed by the reference set without the DMU under valuation, both input and output may decrease (increase) when infeasible solutions are found in the input-oriented (output-oriented) VRS super-efficiency model. The Chen and Liang output-oriented super-efficiency model is expressed as follows:

$$\min \gamma + M * \sum_{i=1}^{m} \alpha_i$$

$$\textit{subject to} \quad \sum_{k=1;k\neq r}^{n} \lambda_k\, x_{ik} \ \leq (1+\alpha_i)x_{ir}, \qquad i = 1,2, \ldots m,$$

$$\sum_{k=1;k\neq r}^{n} \lambda_k\, y_{kj} \ \geq (1-\gamma)y_{jr}, \qquad j = 1,2, \ldots, q,$$

$$\sum_{k=1;k\neq r}^{n} \lambda_k = 1$$

$$\lambda_k \ \geq 0,\ \alpha_i \geq 0, \qquad k = 1, 2, \ldots, n,\ \ k \neq r \qquad (3.4)$$

where M is the user-defined large positive number and in the study. It is set to 100,000 as suggested in Cook et al. (2009). Note that $\frac{1}{1-\gamma^*} = \frac{1}{\delta^{super}}$ when model (3.3) has feasible solutions. When some $\alpha_i^* > 0$, infeasibility occurs and the super-efficiency score is defined as $\frac{1}{1-\gamma^*} + \frac{1}{I}\sum_{i\in I}(1+\alpha_i)$ with I is the set of $\alpha_i > 0$.

3.1.3 Malmquist Productivity Index

Extending the work of Caves et al. (1982), Fare et al. (1994) decomposed Malmquist productivity index using distance function. An output distance function seeks a maximal proportional increase in outputs while inputs are held constant. More specifically, the output-oriented Malmquist productivity index for period t+1 in comparison with period t is defined as the geometric mean of the output indices evaluated against the frontiers in the two periods:

$$m_o(x^{t+1}, y^{t+1}, x^t, y^t) = \sqrt{\frac{d_o^t(x^{t+1}, y^{t+1}) d_o^{t+1}(x^{t+1}, y^{t+1})}{d_o^t(x^t, y^t) d_o^{t+1}(x^t, y^t)}} \tag{3.5}$$

where

- x^{t+1}, x^t: input vectors at period t+1 and t, respectively
- y^{t+1}, y^t: output vectors at period t+1 and t, respectively
- $d_o^t(x^{t+1}, y^{t+1})$: output distance of the observation in period t+1 to the technology frontier in period t
- $d_o^t(x^t, y^t)$: output distance of the observation in period t to the technology frontier in period t
- $d_o^{t+1}(x^{t+1}, y^{t+1})$: output distance of the observation in period t+1 to the technology frontier in period t+1
- $d_o^{t+1}(x^t, y^t)$: distance of the observation in period t to the technology frontier in period t+1

Note that value of m_o indicates the productivity growth or decline. If $m_o > 1$, there is a productivity growth from period t to period t+1. On the contrary, if $m_o < 1$, there is a productivity decline from period t to period t+1.

Alternatively, the same index can be presented as follows:

$$m_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{d_o^{t+1}(x^{t+1}, y^{t+1})}{d_o^t(x^t, y^t)} \sqrt{\frac{d_o^t(x^{t+1}, y^{t+1}) d_o^t(x^t, y^t)}{d_o^{t+1}(x^{t+1}, y^{t+1}) d_o^{t+1}(x^t, y^t)}} \tag{3.6}$$

This definition shows how the Malmquist index can be decomposed into the parts that represent the changes in the technical efficiency and the technology. That is,

$$Technical\ efficiency\ change\ = \frac{d_o^{t+1}(x^{t+1}, y^{t+1})}{d_o^t(x^t, y^t)} \tag{3.7}$$

$$Technical\ change = \sqrt{\frac{d_o^t(x^{t+1},y^{t+1})d_o^t(x^t,y^t)}{d_o^{t+1}(x^{t+1},y^{t+1})d_o^{t+1}(x^t,y^t)}} \tag{3.8}$$

Hence, productivity growth is decomposed as:

$$TFP\ growth\ = Technical\ efficiency\ change\ x\ Technical\ change \tag{3.9}$$

A value of technical change index greater than one represents technological progress, while a value lower than one implies a technological regress.

To measure scale efficiency, technical efficiency defined by (3.7) is measured against both the VRS and CRS frontiers. Then, technical efficiency evaluated against the CRS frontier is regarded as the combination of scale efficiency and pure technical efficiency, and pure technical efficiency is evaluated against the VRS frontier. That is, the technical efficiency change index defined by (3.7) is decomposed into the following two indices:

$$Pure\ efficiency\ change = \frac{d_{ov}^{t+1}(x^{t+1},y^{t+1})}{d_{ov}^t(x^t,y^t)} \tag{3.10}$$

$$Scale\ efficiency\ change = \frac{d_{oc}^{t+1}(x^{t+1},y^{t+1})/d_{ov}^{t+1}(x^{t+1},y^{t+1})}{d_{oc}^t(x^t,y^t)/d_{ov}^t(x^t,y^t)} \tag{3.11}$$

Here, the subscript o describes output orientation while the subscripts c and v denote CRS and VRS, respectively. The technical efficiency change and decomposition of the productivity growth becomes as follows:

$$Pure\ Efficiency\ Change\ (VRS)\ = \frac{Technical\ Efficiency\ Change\ (CRS)}{Scale\ Efficiency\ Change} \tag{3.12}$$

$$TFP\ growth\ = \\ Pure\ efficiency\ change\ x\ Scale\ efficiency\ change\ x\ Technical\ change \tag{3.13}$$

To obtain those distance functions in the index, the following six linear programming problems must be solved for each firm in the sample:

$$\begin{aligned} & d_{ov}^t(x_r^t, y_r^t)^{-1} = max_{\ \vartheta,\lambda}\vartheta^{super} \\ & subject\ to\ \ \textstyle\sum_{k=1,k\neq r}^{n}\lambda_k x_{ik}^t \leq x_{ir}^t && i = 1,2,\dots,m; \\ & \qquad \textstyle\sum_{k=1,k\neq r}^{n}\lambda_k y_{jk}^t \geq \vartheta^{super} y_{jr}^t && j = 1,2,\dots,q; \\ & \qquad \textstyle\sum_{k=1k\neq r,}^{n}\lambda_k\ =\ 1 \\ & \qquad \lambda_k \geq 0 && k = 1,2,\dots,n;\ k \neq r \end{aligned} \tag{3.14}$$

$$
\begin{aligned}
&d_{ov}^{t+1}(x_r^{t+1}, y_r^{t+1})^{-1} = max_{\ \vartheta,\lambda}\vartheta^{super} \\
&subject\ to\ \ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k x_{ik}^{t+1} \leq x_{ir}^{t+1} && i = 1, 2, \dots, m; \\
&\qquad\qquad\ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k y_{jk}^{t+1} \geq \vartheta^{super} y_{jr}^{t+1} && j = 1, 2, \dots, q; \\
&\qquad\qquad\ \textstyle\sum_{k=1k\neq r,}^{n} \lambda_k \ = \ 1 \\
&\qquad\qquad\ \lambda_k \geq 0 && k = 1, 2, \dots, n;\ k \neq r
\end{aligned} \tag{3.15}
$$

$$
\begin{aligned}
&d_{oc}^{t}(x_r^{t}, y_r^{t})^{-1} = max_{\ \vartheta,\lambda}\vartheta^{super} \\
&subject\ to\ \ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k x_{ik}^{t} \leq x_{ir}^{t} && i = 1, 2, \dots, m; \\
&\qquad\qquad\ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k y_{jk}^{t} \geq \vartheta^{super} y_{jr}^{t} && j = 1, 2, \dots, q; \\
&\qquad\qquad\ \lambda_k \geq 0 && k = 1, 2, \dots, n;\ k \neq r
\end{aligned} \tag{3.16}
$$

$$
\begin{aligned}
&d_{oc}^{t+1}(x_r^{t+1}, y_r^{t+1})^{-1} = max_{\ \vartheta,\lambda}\vartheta^{super} \\
&subject\ to\ \ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k x_{ik}^{t+1} \leq x_{ir}^{t+1} && i = 1, 2, \dots, m; \\
&\qquad\qquad\ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k y_{jk}^{t+1} \geq \vartheta^{super} y_{jr}^{t+1} && j = 1, 2, \dots, q; \\
&\qquad\qquad\ \lambda_k \geq 0 && k = 1, 2, \dots, n;\ k \neq r
\end{aligned} \tag{3.17}
$$

$$
\begin{aligned}
&d_{oc}^{t}(x_r^{t+1}, y_r^{t+1})^{-1} = max_{\ \vartheta,\lambda}\vartheta^{super} \\
&subject\ to\ \ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k x_{ik}^{t} \leq x_{ir}^{t+1} && i = 1, 2, \dots, m; \\
&\qquad\qquad\ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k y_{jk}^{t} \geq \vartheta^{super} y_{jr}^{t+1} && j = 1, 2, \dots, q; \\
&\qquad\qquad\ \lambda_k \geq 0 && k = 1, 2, \dots, n;\ k \neq r
\end{aligned} \tag{3.18}
$$

$$
\begin{aligned}
&d_{oc}^{t+1}(x_r^{t}, y_r^{t})^{-1} = max_{\ \vartheta,\lambda}\vartheta^{super} \\
&subject\ to\ \ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k x_{ik}^{t+1} \leq x_{ir}^{t} && i = 1, 2, \dots, m; \\
&\qquad\qquad\ \textstyle\sum_{k=1,k\neq r}^{n} \lambda_k y_{jk}^{t+1} \geq \vartheta^{super} y_{jr}^{t} && j = 1, 2, \dots, q; \\
&\qquad\qquad\ \lambda_k \geq 0 && k = 1, 2, \dots, n;\ k \neq r
\end{aligned} \tag{3.19}
$$

Problems (3.14) and (3.15) estimate the technical efficiency (or reciprocal of the distance functions) relative to VRS technology while the four remaining equations (3.16) - (3.19) consider CRS technology. These six linear programming problems enable us to compute the indices for technical efficiency change (CRS), pure efficiency change (VRS) and technical change. Then the scale efficiency change is derived from the equation (3.12) by dividing technical efficiency change by pure efficiency change. Similarly, scale efficiency is computed by dividing technical efficiency relative to the CRS frontier by technical efficiency relative to the VRS frontier. The productivity index is measured by the product of two terms in equation (3.9) (i.e. technical efficiency change and technology change) or three terms in equation (3.13) (i.e. pure efficiency change, scale efficiency change, and technology change). Recall that for infeasible cases relating to the VRS frontier, the Chen and Liang (2011) model is applied to generate super-efficiency scores. In addition, the linear programming problems (3.14) - (3.19) are implemented using the econometrics software program *Shazam*.

3.1.4 Export premium: comparing exporters vs. non-exporters

Export premium analysis has been conducted widely in the literature (Hiep & Ohta, 2009; Mukim, 2011; T. T. T. Pham, 2015). An export premium is regarded as the mean differences in percentage of firm characteristics, controlling for location, firm ownership, and year. The export premium is derived by regressing each of the relevant firm characteristics, efficiency, and productivity measures on export status (EXP_i), controlling for time, ownership, and location.

$$lnC_i = \alpha_0 + \alpha_1 EXP_i + F_{year} + F_{location} + F_{ownership} \tag{3.20}$$

Where C_i is the i-th firm's characteristics or efficiency or productivity indicators. These indicators are presented in the table 3.1. EXP_i is a dummy variable denoting whether the firm is an exporter (or the firm has an export share in its total sales). F_{year}, $F_{location}$, and $F_{ownership}$ indicate time, location, and ownership fixed effects, respectively. The coefficient α_1 captures the export premium for each firm in the sample. Therefore, percentage of export premium is considered as $(e^{\alpha_1} - 1) * 100$ for each firm characteristic.

Table 3.1 – **Variable definition for firm characteristics and productivity indicators**
Note: all variables in monetary terms are adjusted for the constant price of year 2005

Variables	**Definition and measures**
Output value	Output value obtained from the survey
Value added	Output - indirect costs – raw material used
Total labour	Number of employees
Average wage	Ratio of total wages over total labour
Total assets	Value of total assets
Capital	Value of fixed assets
Capital intensity	Ratio of fixed assets over total labour
Labour productivity	Ratio of value added over total labour
Capital productivity	Ratio of value added over fixed assets
Technical efficiency	Obtained from the super-efficiency DEA model
Scale efficiency	Obtained from the super-efficiency DEA model
TFP	The product of three terms including technical efficiency, scale efficiency, and technical index.

3.1.5 Endogenous switching regression for panel data

The endogenous switching regression model is implemented because the study's model has export status as an explanatory variable that splits the sample into exporters and non-exporters and the decision to export is a non-random selection choice. More specifically, firms self-select to become exporters or not. A salient feature of self-selection is that a firm's output or productivity is observed in only one regime situation and which regime the firm falls into is not randomly determined. The endogenous switching model incorporates a model for selection into a two-equation regression model that includes one equation for each regime. The definitions of all variables in the model are described in Table 3.2 below. (Note that all variables in monetary terms were adjusted for the constant price of year 2005.)

Table 3.2 **– Variable definition for endogenous switching regression model**

	Variable	Definition
Main equation		
Dependent variables	TE (VRS)	Pure technical efficiency, obtained from the first step of analysis using super-efficiency DEA
	SE	Scale efficiency, obtained from the first step of analysis using super-efficiency DEA
	TFP	Total Factor Productivity, obtained from the first step of analysis using super-efficiency DEA (TFP=TE*SE Change*Technology index)
Independent variables	Capinten	Capital intensity, measured by ratio of fixed assets over total labour in logarithm form.
	Avewage	Average wage, measured by ratio of total wages over total labour in logarithm form
	Mcity	Main cities, a dummy (1/0) receiving 1 if a firm is located in Ho Chi Minh city or Ha Noi capital.
	Micro	A dummy (1/0) receiving 1 if a firm size is micro (total employees are less than 10), World Bank classification. This is the base category.
	Small	A dummy (1/0) receiving 1 if a firm size is small (total employees are between 10 and 49), World Bank classification.
	Med	A dummy (1/0) receiving 1 if a firm size is medium (total employees are between 50 and 299), World Bank classification.
Selection equation		
Dependent variable	Exp	A dummy (1/0) receiving 1 if a firm is an exporter.
Additional Independent variable	Lexp	Lagged value of export status, assuming that export status before 2005 would be the same as the status in 2005.

The endogenous switching regression model could be estimated by the two-stage method where the selection model is estimated first and then the models of interest are estimated while controlling for selection bias. However, as Lokshin and Sajaia (2004) point out, this estimation technique yields inefficient coefficient estimates and the standard errors computed in the usual way are inconsistent. They instead recommend a full-information maximum likelihood approach where the selection model and the equations of interest are simultaneously estimated in one step, yielding consistent estimates for the regression coefficients and their standard errors.

The endogenous-switching model is specified as follows:

The selection model

$$I_i^* = Z_i'\gamma + u_i \quad (3.21)$$

$$I_i = 1 \; if \; I_i^* > 0$$

$$I_i = 0 \; if \; I_i^* \leq 0$$

$$Regime\ 1: y_{1i} = X_i'\beta_1 + \varepsilon_{1i}\ if\ I_i = 1 \tag{3.22}$$

$$Regime\ 2: y_{0i} = X_i'\beta_0 + \varepsilon_{0i}\ if\ I_i = 0 \tag{3.23}$$

where I_i^* is the latent variable representing the likelihood of becoming an exporter, I_i is 1 for exporters and 0 for non-exporters, y_{1i} and y_{0i} are the dependent variables in the equations of interest; X_{1i} and X_{0i} are vectors of weakly exogenous variables that influence firm efficiency or productivity; β_1, β_0, and γ are the regression coefficient vectors; Z_i is the vector of characteristics that affect the decision to export; and u_i, ε_{1i}, ε_{0i} are the random error terms. Subscripts 1 and 0 denote exporters and non-exporters, respectively. Variables in Z_i include previous export status which represents the sunk entry costs supported by the self-selection hypothesis, capital intensity, average wage, firms located in main cities or not, and firm size (micro, small, and medium). I_i^* is a latent variable and unobservable. What can be observed isI_i that describes the observed decision to become exporter of the firm.

One important assumption made in the model is that export status is endogenously determined. In other words, some unobserved factors that affect the probability of becoming an exporter could also influence the efficiency or productivity that the firm achieves. This selectivity effect is corrected in the maximum likelihood estimation by incorporating the conditional mean of the random error term. Note that the selection equation includes one more variable, lagged export status, to improve the identification.

Equations (3.21)-(3.23) of the endogenous switching regression model are only suitable for cross-section data while the study uses sample panel data. Therefore, the model is modified to account for the feature of longitudinal data. The selection equation is adjusted as follows:

$$I_{it}^* = Z_{it}'\gamma + v_i + u_{it} \tag{3.24}$$

$$I_{it} = 1\ (exporter)\ if\ I_{it}^* > 0$$

$$I_{it} = 0\ (non - exporter)\ if\ I_{it}^* \leq 0$$

where v_i is heterogeneity and u_{it} is the random component of the latent variable. The two efficiency/productivity equations are similarly modified as:

$$y_{it}^1 = X_{it}'\beta_1 + w_i^1 + \varepsilon_{it}^1\ \ if\ I_{it} = 1 \tag{3.25}$$

$$y_{it}^0 = X_{it}'\beta_0 + w_i^0 + \varepsilon_{it}^0\ \ if\ I_{it} = 0 \tag{3.26}$$

where w_i^1 and w_i^0 are individual heterogeneity, and ε_{it}^1 and ε_{it}^0 represent idiosyncratic errors. The error terms u_{it}, ε_{it}^1, and ε_{it}^0 are assumed to have a trivariate normal distribution with zero mean and covariance matrix specified as follows:

$$Cov(u_{it}, \varepsilon_{it}^1, \varepsilon_{it}^0) = \begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{0u} \\ \sigma_{1u} & \sigma_1^2 & . \\ \sigma_{0u} & . & \sigma_0^2 \end{bmatrix}$$

where σ_u^2 is the variance of the error term in the selection model, and σ_1^2 and σ_0^2 are the variances of the error terms in the main equations. σ_{1u} is the covariance of ε_{it}^1 and u_{it} while σ_{0u} is the covariance of ε_{it}^0 and u_{it}.

Since some explanatory variables, such as capital intensity and wage rate, are likely to be correlated with a firm's heterogeneity, the random effects model cannot be used. Furthermore, due to the non-linearity of the models, the fixed effects model is also inappropriate. To address this issue, the study is based on the ideas of Mundlak (1978) and Chamberlain (1984) to present unobserved heterogeneity as a deterministic function of observed variables. Specifically, the heterogeneity terms v_i, w_i^1, and w_i^0 are expressed as a function of the within-group means of the explanatory variables:

$$v_i = \bar{Z}_i{}'\varphi, \qquad w_i^1 = \bar{X}_i{}'\alpha_1, \qquad and\ w_i^0 = \bar{X}_i{}'\alpha_0$$

Here, $\bar{Z}_i = \frac{\sum_t^T Z_{it}}{T_i}$ and $\bar{X}_i = \frac{\sum_t^T X_{it}}{T_i}$, T_i is number of time periods for individual firm i, and φ, α_1, and α_0 denoting the coefficient vectors. Once the heterogeneity terms are replaced with these within-group means, the model is then estimated as the pooled model. The study uses the command *movestay* in STATA to obtain the full-information maximum likelihood estimates of the parameters of the endogenous switching regression model. This routine was developed by (Lokshin and Sajaia (2004)). Given the selectivity, there are four conditional expectations of firm efficiency/productivity:

$$E(lny_{it}^1 | I = 1, X_{it}, \bar{X}_i, \bar{Z}_i) = X_{it}'\beta_1 + \alpha_1\bar{X}_i + \sigma_{1u}\frac{\phi(Z_{it})}{\Phi(Z_{it})} \qquad (3.27)$$

$$E(lny_{it}^1 | I = 0, X_{it}, \bar{X}_i, \bar{Z}_i) = X_{it}'\beta_1 + \alpha_1\bar{X}_i - \sigma_{1u}\frac{\phi(Z_{it})}{1-\Phi(Z_{it})} \qquad (3.28)$$

$$E(lny_{it}^0 | I = 1, X_{it}, \bar{X}_i, \bar{Z}_i) = X_{it}'\beta_0 + \alpha_0\bar{X}_i + \sigma_{0u}\frac{\phi(Z_{it})}{\Phi(Z_{it})} \qquad (3.29)$$

$$E(lny_{it}^0 | I = 0, X_{it}, \bar{X}_i, \bar{Z}_i) = X_{it}'\beta_0 + \alpha_0\bar{X}_i - \sigma_{0u}\frac{\phi(Z_{it})}{1-\Phi(Z_{it})} \qquad (3.30)$$

where $\phi(.)$ and $\Phi(.)$ are the probability density function and cumulative distribution function for the standardised normal distribution, respectively. The expectation (3.27) measures the expected efficiency/productivity of an exporter when it chooses to become an exporter. The expectation (3.30) represents the expected efficiency/productivity of a non-exporter when it chooses to serve only the domestic market. However, expectations (3.28) and (3.29) are counterfactual. They estimate the expected efficiency/productivity of a non-exporter if it decided to export and the expected efficiency/productivity of an exporter if it chose to not export, respectively. As noted earlier, the productivity or efficiency in these counterfactual situations is unobservable.

In short, the standard endogenous switching regression model is modified by adding within-group averages to account for heterogeneity in the panel data. The STATA commands *movestay* and *mspredict* are used to implement the model and measure the expected efficiency/productivity of firms in the sample.

CHAPTER 4 - RESULTS AND DISCUSSION

This chapter reports the data sample and empirical results for the estimation of productivity growth and its components, and an analysis of their determinants, especially the effect of being an exporter.

4.1 Technical efficiency, productivity and its components (DEA-based Malmquist Index)

4.1.1 Data sample

This thesis uses firm-level data from small and medium enterprise (SME) surveys carried out as collaborative research efforts of four organisations: (1) the Central Institute for Economic Management of Vietnam Ministry of Planning and Investment, (2) the Institute of Labour Science and Social Affairs of Vietnam Ministry of Labour, Invalids and Social Affairs, (3) the Department of Economics of University of Copenhagen, and (4) the Royal Embassy of Denmark in Vietnam. These surveys focus on Vietnam's private sector, mainly in manufacturing area, thus only collects data of only formal and informal SMEs. These enterprises fall into six categories: household businesses, private or sole proprietorship firms, partnerships, collectives/cooperatives, limited liability companies, and joint stock firms. Household enterprises are regarded as firms that do not meet the conditions of the Vietnam Enterprise Law. Unsurprisingly, state-owned enterprises, joint ventures, and foreign-owned firms that are mostly large-sized, are excluded from the surveyed data. The SME surveys cover information for 5 years (2005, 2007, 2009, 2011, and 2013) and for 12,405 firms, in which around 6% are exporters. Firms are classified according to 4-digit ISIC (International Standard Industrial Classification) level. However, the study exploits data from three industries that are considered the most export-concentrated. They cover wood, furniture, and rubber and plastic. However, some firms switched from the wood industry to the furniture industry and vice versa during the sample period. Hence, the study combines these two industries into one industry called wood and furniture products for the purpose of analysis. A panel of 177 firms operating in those industries was constructed. Due to some inconsistent and odd observations over the period, four firms were excluded from the sample. In short, the final 5-year panel consists of 173 manufacturing SMEs in wood and furniture, and rubber and plastic industries.

4.1.2 Private sector in Vietnam

Since the implementation of "*Doi Moi*" in 1989, a renewal program that gave the economy its market orientation, the role of the private sector has been recognised and strengthened. Accordingly, economic growth has thriven with the impressive annual rate of 8.75% over 1992-1997, 6.91% over 2000-2007, and 5.98% over 2010-2015 (World Bank, 2016b). In particular, in years impacted by financial crises (1998, 2008, 2009), the growth rate lowered but still outperformed other Asian countries. For example, the rate of 5.4% in 2009 was higher than Indonesia (4.5%), Philippines (0.9%), Malaysia (-1.7%), Singapore (-2%), and Thailand (-2.3%) (Leung, 2010). After the promulgation of the Enterprise Law (2001), and its amendment by the Enterprise Law (2006) and the Investment Law (2006), the number of registered and operating non-state enterprises surged to 388,232 firms in 2014 compared to 35,004 firms in 2000 (GSO, 2005, 2015). The statistics also show that these non-state firms accounted for more than 95% of total firms (consisting of state-owned, non-state, and foreign investment enterprises). In addition, 95% of new companies are SMEs, and almost 90% of manufacturing firms are SMEs (Hakkala & Kokko, 2007). These figures demonstrate the rapid development of the manufacturing SMEs in the private sector. In addition, there was a dramatic change in structure between state and non-state enterprises. According to GSO (2016), before 2005, domestic firms were mainly large-sized state enterprises and accounted for more than 88% of employment and 50% of the state's budget. However, by 2014, non-state firms made up around 60% of employment and 33% of state budget. Therefore, the role of the private sector in Vietnam economy has been more and more influential over the years.

4.1.3 Descriptive analysis

The study uses one output and four inputs in the super-efficiency DEA model. The output is the value of the output and the inputs are fixed capital, number of employees, cost of raw materials, and energy costs. All output and inputs in monetary terms are deflated using appropriate deflators to derive the real values in the year 2005. The definitions of these output and inputs with their deflators are showed in table 4.1. The output, raw material cost, and energy cost are deflated using the GDP deflator for the manufacturing sector. Fixed capital (measured by market value of fixed assets at the end of each year) is converted to a real value using the GDP deflator for gross fixed capital formation. All the deflators used to convert nominal values to real values were obtained from the information published by the General Statistics Office of Vietnam.

Table 4.1 **– Definition of output and inputs**

Input/Output	Measure	Deflator
Output	Value of output in $million VND	GDP deflator for the manufacturing sector (base year = 2005)
Input 1	Fixed Capital (measured by market value of fixed assets at the end of each year ($million VND)	GDP deflator for gross fixed capital formation (base year 2005)
Input 2	Number of employees	
Input 3	Cost of raw material used in $million VND	GDP deflator for the manufacturing sector (base year 2005)
Input 4	Value of energy costs (electricity and fuel) in $million VND	GDP deflator for the manufacturing sector (base year = 2005)

Table 4.2 shows the average of real value of all output and inputs in each year and for each industry over the sample period 2005-2013. All inputs and output share the same pattern of steady increase from 2005 to 2009. However, the pattern changes from 2009, which is the year of the global financial crisis. After reaching a peak in 2009, the output and material cost moderately decreased in 2011, followed by a modest rise in 2013. Similarly, energy costs declined between 2009 and 2011 but bounced back in 2013. The input of total labour fell over the period 2009-2013, with the sharpest fall in 2013. On the contrary, the pattern of the changes in fixed capital differs slightly. There is a dramatic rise from 2009 to 2011, followed by a significant drop between 2011 and 2013. In addition, all values of inputs and output of the rubber and plastic products are substantially bigger than the values of wood and furniture products.

Table 4.2 **– Summary statistics on periods and manufacturing industries (mean value)**

Time period/Industry	Output (VND$'000)	Capital (VND$'000)	Number of employees	Cost of raw material (VND$'000)	Energy cost (VND$'000)
2005	1,969,666	1,795,070	19	1,406,757	82,557
2007	2,609,896	2,401,717	21	1,703,340	103,418
2009	4,240,906	3,618,536	40	2,838,822	115,730
2011	3,609,024	6,659,109	17	2,359,268	91,973
2013	3,873,402	4,717,310	15	2,552,821	126,065
2005-2013	3,257,058	3,837,275	22	2,169,678	103,691
Wood and Furniture	2,117,420	2,602,200	21	1,328,876	41,385
Rubber and Plastic	7,305,773	8,225,041	28	5,156,737	325,039

4.1.4 Empirical results

Recall that the super-efficiency DEA method measures the performance of each firm relative to the best-practice frontier formed by the remaining firms in the sample. Hence, a firm's input-output vector can be inside, outside, or on the frontier, leading to an efficiency score less than, greater than, or equal to unity. Scale efficiency accounts for VRS technology, and shows the room to exploit the scale of the firm. In addition, if the Malmquist index or any of its components has a value less than one, it represents deterioration in performance. On the contrary, if its value is greater than one, it indicates improvement or growth in performance.

Table 4.3 presents the means of efficiency and productivity over the period 2005-2013 in two groups of indices: one in levels including technical efficiency (TE), scale efficiency (SE), and TFP; and the other group consisting of pure technical efficiency change (PECH), scale efficiency change (SECH), technical change (TECHCH), and Malmquist index or TFP change (TFPCH). Note that TFP change is measured by the product of pure efficiency change, scale efficiency change, and technological change. Similarly, TFP level is estimated by the product of technical efficiency, scale efficiency, and technical index. One assumption is made that all the changes in 2005 compared with those before 2005 are unchanged. In other words, pure efficiency change, scale efficiency change, and technical index are assumed equal to one in 2005.

Table 4.3 **– Means of efficiency and productivity over the sample period 2005-2013**

Sample/Industry	TE	SE	TFP	PECH	SECH	TECHCH	TFPCH (Malm Index)
Total	0.94	0.91	0.86	1.11	1.05	1.01	1.17
Exporters	1.05	0.87	0.91	1.13	1.01	0.99	1.14
Non-exporters	0.92	0.92	0.85	1.11	1.05	1.01	1.18
Wood and Furniture	0.96	0.91	0.88	1.14	1.06	1.00	1.21
Exporters	0.99	0.91	0.89	1.10	1.00	0.99	1.10
Non-exporters	0.94	0.91	0.86	1.11	1.06	1.01	1.18
Rubber and Plastic	0.93	0.91	0.86	1.14	1.03	1.01	1.19
Exporters	1.33	0.69	0.92	1.23	1.06	1.00	1.31
Non-exporters	0.88	0.93	0.83	1.12	1.02	1.01	1.17

As shown in table 4.3, for the whole sample, the Malmquist productivity index increased on average about 17% per year over the period 2005-2013. The increase in productivity results mainly from the rise in pure efficiency change (whole sample 11%, wood and furniture products 14%, and rubber and plastic products 14%). This can be proved by the correlation coefficients among the Malmquist index and its components as presented in the table 4.4. The correlation coefficient between productivity growth and efficiency change is high and positive (0.68). It explains that efficiency change has a primary and positive impact on the productivity progress. In addition, the productivity growth of the wood and furniture industry is slightly higher than that of the rubber and plastic industry (21% and 19%, respectively). The superiority in the productivity growth of the wood and furniture industry is due to higher growth in scale efficiency. Likewise, on average, firms producing wood and furniture products achieved moderately higher technical efficiency than their counterpart manufacturing rubber and plastic products (0.96 and 0.93, respectively). This can be explained by the average size of these two industries. As shown in table 4.1, the wood and furniture industry had substantially smaller values of output and inputs than the industry rubber and plastic industry. Therefore, it is probable that firms operating in the wood and furniture industry are more flexible and adaptable, and hence their ability to improve efficiency and productivity growth is better over time.

Comparing between exporters and non-exporters, table 4.3 reports greater annual TFP growth of firms serving only the domestic market for the whole sample (non-exporters: 18%

vs. exporters: 14%) despite the exporting firms obtaining higher technical efficiency and improving their efficiency more over time. This is due to the other source of productivity growth, scale efficiency change, improving more among non-exporters. Similarly, in the wood and furniture industry, the growth in TFP of non-exporters was greater than exporting businesses (18% and 10%, respectively) although exporters gained higher technical efficiency. This is also explained by the better performance in scale efficiency growth of non-exporting businesses. However, in the rubber and plastic industry, the story is different. Exporters performed impressively in terms of TFP growth, technical efficiency, and scale efficiency change compared to their counterparts. For the technical index, the result shows that minor differences between exporters and non-exporters and the index is close to one.

Table 4.4 **– Correlations of pure efficiency change (PECH), scale efficiency change (SECH), technical change (TECHCH), and Total Factor Productivity change (TFPCH) or Malmquist index (MALM)**

Correlations	PECH	SECH	TECHCH	TFPCH /MALM
PECH	1			
SECH	-0.3596	1		
TECHCH	-0.1516	-0.1384	1	
TFPCH/MALM	0.6816	-0.0108	0.0703	1

Overall, TFP progressed over the period 2005-2013, reaching its peak in 2007 (figure 4.1a). Note that the survey in 2007 provided information for 2006. In this year, the whole economy was in an economic boom. This fact might have affected the productivity of the firms. Additionally, the trends of pure efficiency growth, technical index and productivity index also confirm the relation between pure efficiency change and productivity change. Even though the other two sources of productivity growth (scale efficiency change and the technical index) fluctuated over the period 2005-2013, efficiency growth and productivity growth still exhibit the same tendency. There exists a moderately negative relationship between pure efficiency change and scale efficiency change implied by the negative correlation coefficient between them (-0.36, table 4.4). Considering the fact that the two efficiency scores moved in the opposite directions only in year 2011, where pure technical efficiency improved but scale efficiency deteriorated, it is likely that the learning effect was stronger than the scale optimisation while both efficiencies improved in most years (figure 4.1a).

Regarding the trends in technical efficiency in figure 4.1b, firms exhibited different trends in two manufacturing industries. For the wood and furniture industry, although exporters achieved moderately higher technical efficiencies than non-exporters did, both of them followed a similar trend, improving over time. Yet in the rubber and plastic industry, the efficiency scores of exporting businesses fluctuated considerably despite their great efficiencies over the period. Those exporters achieved their highest efficiencies in 2007, the economic boom year, and decreased after that due to the financial crisis in 2008-2009. They also obtained exceptional efficiencies compared to non-exporting businesses operating in the same industry, and even to exporters in wood and manufacturing industry. Non-exporters producing rubber and plastic products had a quite stable rise in efficiency scores over 2005-2013. However, they operated less efficiently than non-exporters manufacturing wood and furniture products.

Figures 4.1c and 4.1d present the trends in scale efficiency and technology index. Basically, all firms followed alike pattern of stability except exporters in the rubber and plastic industry. For the scale efficiencies, these exporting firms operate significantly lower in scale compared to others although they surge over time. For the technical index, regardless of export status, the index of the wood and furniture industry regressed in 2009, progressed back in 2011, and then regressed again in 2013. This fluctuation shows some impacts on the pattern of TFP in the figure 4.1e. The exporters in the rubber and plastic sector had a progression in frontier shift (or technological change) and a considerably higher score in technical efficiency in 2009, leading to a peak in TFP in 2009. However, their technical index and TFP reduced after 2009. This is likely because of the influence of the financial crisis in 2009. On the other hand, non-exporters manufacturing rubber and plastic products had a steady rise in productivity in 2005-2011 and then dropped in 2013. This may be interpreted as a decrease in price due to the increase in domestic supply. The timbers used in wood and furniture production are mostly imported because the limited domestic source of timber comes from plantation forests. And the Vietnamese furniture market has been dominated by multinational and foreign investment companies. Interestingly, productivity in the wood and furniture industry peaked and was over the frontier in 2011 despite exporters performing better than non-exporters. After that, their productivity fell. This might also be due to the issue of demand and supply. Likewise, other types of materials in rubber and plastic production are also imported from other countries. This probably impacts the price, quantity, and productivity of firms.

In short, on average, TFP progressed over the sample period with its peak in 2007. The growth of TFP primarily stemmed from pure efficiency change. However, when observing separate industries and export status, there are some interesting findings. Exporters attained higher technical efficiencies but lower growth in TFP than non-exporters did, even though their pure efficiency growth was slightly higher. The inferior productivity growth of exporters was driven by the regression of the technological change. Moreover, exporters operating in the rubber and plastic industry performed substantially better than their counterparts in terms of technical efficiency and TFP. They climbed the peak in 2009 but fell after that. This trend may be due to the aftermath of the post-financial crisis and the problem of supply-demand. Especially, exporters in this industry obtained higher technical efficiencies than exporters in wood and manufacturing industry.

Figure 4.1a – **Mean values of PECH, SECH, TECHCH and TFPCH of all firms in the sample**

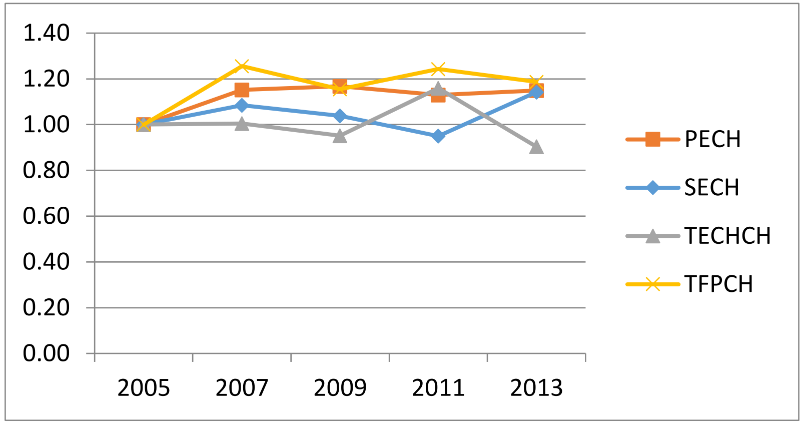


Figure 4.1b – **Mean values of TE of exporters and non-exporters in two industries (Wood and Furniture (WF), and Rubber and Plastic (RP)**

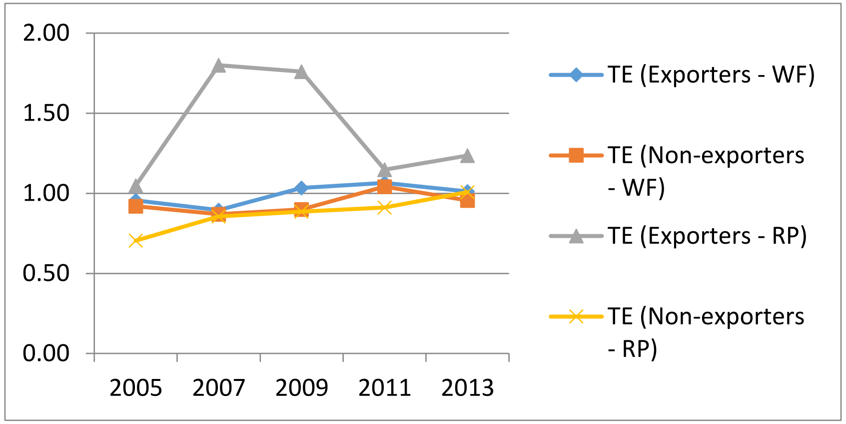


Figure 4.1c – **Mean values of SE of exporters and non-exporters in two industries**

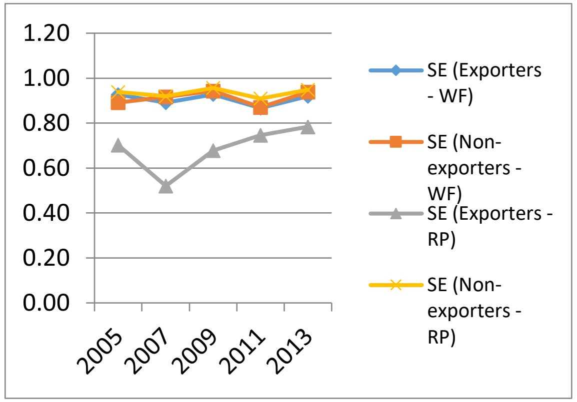


Figure 4.1d – **Mean values of TECHCH of exporters and non-exporters in two industries**

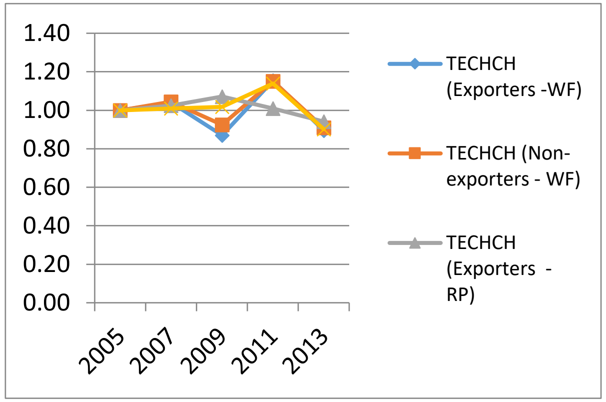
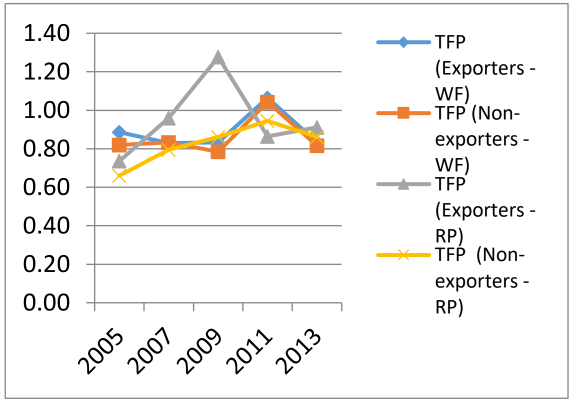


Figure 4.1e– **Mean values of TFP of exporters and non-exporters in two industries**



4.2 Empirical results of the endogenous switching regression model

4.2.1 Descriptive analysis: firm characteristics and export participation

As can be seen from table 4.5, the sample firms are classified into different size groups. The size here follows the definition by World Bank. Micro, small, and medium sizes refer to the firms with the number of employees less than 10, from 10 to 49, and from 50 and above, respectively. More than 50% of the firms are micro-sized and just over 7% of firms are medium-sized. This is reflective of the distribution in the wood and furniture industry due to its large proportions. However, the rubber and plastic industry has a slightly different distribution. Compared with the wood and furniture industry, the rubber and plastic industry has larger proportions of small and medium-sized firms and a smaller proportion of micro-sized firms. This is in line with our expectation because producing rubber and plastic products requires a larger scale operation in general than producing wood and furniture products. In addition, more than 57% of medium-sized firms became exporters. Also, exporter proportion increases with firm size (micro: around 2%, and small: about 12%). This characteristic is in clear agreement with previous empirical results (Clerides et al., 1998; Bernard & Jensen, 2004).

Table 4.5 **– Firms by size (micro: number of employees less than 10, small: 10-49 employees, medium: from 50 employees above)**

Firm size	Rubber and Plastic	Wood and Furniture	Total	Exporters
Micro	77	381	458	9
	40.53%	56.44%	52.95%	1.97%
Small	88	251	339	41
	46.32%	37.19%	39.19%	12.09%
Medium	25	43	68	39
	13.16%	6.37%	7.86%	57.35%
Total	190	675	865	89
	100%	100%	100%	10.29%

Table 4.6 shows different firm ownership structures. A noticeable result is that around 65% of firms are household businesses. In particular, almost 73% of firms in the wood and furniture industry are household businesses. Most firms in this category of enterprise are regarded as not satisfying the conditions of the Enterprise Law. In other words, they are

unregistered enterprises or belong to the informal sector of the economy. This category of firms accounts for the largest number in both industries. However, in the rubber and plastic industry, limited liability companies also make up quite a significant proportion (more than 35%). The partnership and joint stock companies have the lowest proportion in the sample but the highest exporter proportion. Despite being the largest proportion of the household businesses, they rarely became exporters (only 3.38%). Combining the observations from tables 4.5 and 4.6 leads to the conclusion that over 50% of the firms in the sample are small-sized household businesses. However, more than half of exporters are medium-sized and under categories of joint stock and partnership.

***Table 4.6* – Firms by ownership structure**

Firm ownership	Rubber and Plastic	Wood and Furniture	Total	Exporters
Household business	70	492	562	19
	36.84%	72.89%	64.97%	3.38%
Private (sole proprietorship)	24	67	91	20
	12.63%	9.93%	10.52%	21.98%
Partnership	3	7	10	3
	1.58%	1.04%	1.16%	30%
Collective/Cooperative	20	21	41	7
	10.53%	3.11%	4.74%	17.07%
Limited Liability company	68	79	147	35
	35.79%	11.7%	16.99%	23.81%
Joint stock company	5	9	14	5
	2.63%	1.33%	1.62%	35.71%
Total	190	675	865	89
	100%	100%	100%	10.29%

Table 4.7 summarises the proportions of exporters in the two industries in different years. A firm is classified as an exporter if the firm’s revenue includes export income. On average, only about 10% of the firms in the sample engaged in exporting business over the years. This small proportion could be explained by the sizes of most firms in the survey. Small firms would be less likely to be exporters. This is consistent with the size analysis above. Unsurprisingly, the proportion of exporters in the two industries is also low, around 8%-10%. However, this proportion in both industries increases after 2009. Another interesting result is that the percentage of export participation of wood and furniture

products is stable over 2005-2009 while the exporter percentage of rubber and plastic products decreases.

Table 4.7 **– Distribution of exporters**

Sample	2005		2007		2009		2011		2013	
	No. of firms	% of exporters	No. of firms	% of exporters	No. of firms	% of exporters	No. of firms	% of exporters	No. of firms	% of exporters
Total	173	11%	173	10%	173	9%	173	10%	173	11%
Wood and Furniture	135	10%	135	10%	135	10%	135	11%	135	12%
Rubber and Plastic	38	13%	38	8%	38	5%	38	8%	38	8%

Information on the changes of export status of the firms is given in table 4.8. I divide the sample period into two sub-periods, namely 2005-2009 and 2009-2013. The reason for this division is that there was a financial crisis in 2008-2009 and hence there may be a notable result in this year. In fact, the number of new exporters (7) is less than the number of quitters (10) over 2005-2009, and most of them belong to the wood and furniture industry. Additionally, the number of firms exiting from the exporting business in 2009 is quite large compared to quitters in 2013 (10 and 3, respectively). The number of new exporters over the two sub-periods is similar but the number of permanent exporters over 2009-2013 is slightly higher than permanent exporters over 2005-2009. This could be explained by improvements after the financial crisis. In addition, the number of new entries into exporting and quitters of the wood and furniture over the period 2005-2009 are equal, thus explaining the stable trend of its exporter distribution. On the contrary, the rubber and plastic industry has no new exporters but three firms quitting the export business. This is the cause of the reduction in the exporter percentage over 2005-2009. However, due to the small number of firms changing their export status, these findings need to be interpreted with caution.

Table 4.8 – **Changes in export status of the sample firms.**

	2005-2009	**2009-2013**
Exporters in both years	9	13
Wood and furniture	7	11
Rubber and plastic	2	2
Switching from non-exporter to exporter	7	6
Wood and furniture	7	5
Rubber and plastic	0	1
Switching from exporter to non-exporter	10	3
Wood and furniture	7	3
Rubber and plastic	3	0
Non-exporters in both years	147	151
Wood and furniture	114	116
Rubber and plastic	33	35
Total	**173**	**173**

4.2.2 Exporter premium: comparison between exporters and non-exporters

To compare exporters and non-exporters, export premiums are estimated for some basic characteristics of the firms: output value, value added, total labour, average wage, capital intensity, labour productivity, capital productivity, technical efficiency, scale efficiency, and TFP. Definitions of these variables are provided in table 3.2 in the methodology chapter.

Table 4.9 reports the percentage of export premium of the sample firms over the period 2005-2013. The results indicate that exporters are significantly larger in terms of total assets and total employees than non-exporters. Exporters also have greater value in output, value added and capital. With regard to firm performance, exporting firms have lower capital intensity, but higher capital productivity. In other words, exporters use more labour-intensive production technology and hence generate higher value added per unit of capital invested. This result is consistent with the competitive advantage of Vietnam in its low labour cost. Therefore, export-oriented industries are labour-intensive. In addition, exporting firms achieve higher technical efficiency but lower scale efficiency than their counterparts do. However, the difference in TFP is not statistically significant.

Table 4.9 **– Export premium of the sample firms over 2005-2013 (in %)**
*Note: ***, **, and * denote significance level at 1%, 5%, and 10%, respectively*

Variable	**Export status**	**Standard Errors**
Output value	109.43	(0.128)***
Value added	122.11	(0.118)***
Total labour	134.60	(0.110)***
Average Wage	2.14	(0.081)
Total assets	55.89	(0.142)***
Capital	51.68	(0.152)***
Capital intensity	-35.34	(0.138)***
Labour productivity	-5.32	(0.092)
Capital productivity	46.43	(0.126)***
Technical efficiency	10.74	(0.058)*
Scale efficiency	-6.40	(0.017)***
TFP	-0.35	(0.040)

*** p<0.01, ** p<0.05, * p<0.1

4.2.3 Empirical results of the endogenous switching regression model

Table 4.10 presents the estimates of technical efficiency, scale efficiency, technology index, and TFP equations for exporters and non-exporters. In the case of the technical efficiency equation, an increase in capital intensity has a negative effect on technical efficiency for both exporters and non-exporters but this effect is stronger on exporters. It is, however, in line with the export premium analysis. Firms can improve technical efficiency if they become less capital-intensive or more labour-intensive. The influence of average wage on technical efficiency for both exporters and non-exporters is quite similar. Average wage represents the quality of the labour. Therefore, unsurprisingly, its increase contributes to an improvement in the efficiency for all firms regardless of their export status although its effect for exporters is slightly higher. In addition, the location of the firms in the main cities (i.e. Ha Noi and Ho Chi Minh) also positively affects non-exporters' technical efficiency while this effect is insignificant for exporting businesses. Firms located in the main cities may receive more support because there are many industrial parks and export-processing zones with preferential policies in big cities. Moreover, the principal cities also provide good infrastructure and communication technology, closeness to markets, and other supportive policies. According to the coefficients for the size dummies (with the micro group as the base category), the size of a firm appears to have a negative effect on its technical efficiency. This implies that increasing labour input results in an output growth at a rate that is lower than the rate of increase in labour input.

For the scale efficiency equation, only the effect of the main cities is statistically significant for both exporters and non-exporters. However, this effect on scale efficiency is negative although the size of the effect is quite modest. Besides, for the exporter group, medium-sized firms on average show a lower scale of efficiency than micro-sized firms. This implies that the technically optimal productive scale (TOPS) is quite small, and medium-sized exporting firms exhibit decreasing returns to scale. This finding implies some difficulties in the nation’s strategy to increase exports through increased production scales. At least for the two industries studied in the present thesis, increasing the scale would lead to lower productivity. Since this result is peculiar to the current production technology, efforts to transform that technology would be needed to achieve an increase in the scale of production and hence exports, without sacrificing productivity.

Regarding the technology index (TECHCH) equation, the use of more capital-intensive technology has a modestly positive contribution to the frontier effect in exporters. Small-sized businesses enhanced their technology more than micro-sized firms. Small firms may have advantages in capital and labour to apply a new technology. They are also dynamic and adaptable to changes in economic conditions. Besides, all variables have a negligible effect on technical change among non-exporters.

For the TFP equation, the effects of capital intensity, average wage and main city location are quite similar to those in the technical efficiency equation. Firms using less capital intensity would make an improvement in productivity for all firms regardless of export status. An increase in quality of labour leads to an increase in TFP for both exporters and non-exporters, with the size of the increase being larger for exporters than for non-exporters. Moreover, being located in the main cities has a positive effect on TFP for non-exporters, while its effect for exporters is negative but insignificant. The effects of capital intensity on TFP and technical efficiency are the opposite of those on technological change. The use of labour-intensive technology improves a firm’s technical efficiency and productivity but causes its technology index to deteriorate. This has a significantly negative effect on the TFP of exporters and a significantly positive effect on the TFP of non-exporters. This implies that using more capital per unit of labour raises a firm’s technical index but reduces its technical efficiency. Moreover, this effect of capital intensity on firm technical efficiency dominates the effect on technology change. As a result, increasing capital intensity also has a negative impact on firm TFP.

As for endogenous selection into the export market, Wald tests on the joint significance of the two parameters for the selection term (r1 and r0 in Table 4.8) indicate that selection is endogenous only for technical efficiency, but not for scale efficiency and TFP. This implies that the error term in the selection model is only correlated with the error terms in the technical efficiency equations for exporters and non-exporters. The rho_1 and rho_0 in the table refer respectively to the correlation coefficient between the error term in the selection equation (u) and the error term in the exporter equation (ε^1) and the correlation between u and the error term in the non-exporter equation (ε^0). These correlation coefficients have the same signs as the corresponding covariances. The coefficients for the selection term in equations (3.27) and (3.30) are the covariance between u and ε^1 and negative of the covariance between u and ε^0, respectively; note the negative sign in front of the coefficient in equation (3.30). Hence, the positive signs of rho_1 and rho_0 in the technical efficiency equations imply that the selectivity term has a positive effect on the technical efficiency of exporters but a negative effect for non-exporters. This in turn means that a firm that elects to be an exporter performs better in achieving higher technical efficiency than a randomly-selected firm would do in an exporting business. On the other hand, a firm that elects to be a non-exporter performs worse on average than a randomly-selected firm would do in a non-exporting business. However, only the negative effect on the technical efficiency of non-exporters is statistically significant. This suggests that some unobservable factor that is common to the firms that do not participate in the exporting market drags them down in their efforts to improve their technical efficiency. These findings may have some implications for supporting export polices not only from the government but from the firm level. The study provides evidence on the superior efficiency of exporters over non-exporters. This could provoke some government policies to support SMEs approaching new markets. However, exporters experienced less productivity growth than their non-exporting counterparts. This relates to the scale optimization. Exporters lack scale efficiency or the scale is larger than the optimal scale. The SMEs in the sample used traditional and old production technologies, and hence optimal scale size was quite small. Therefore, exporting businesses need to modernize the production technology to increase the optimal scale and accordingly boost firms' scale efficiency and productivity. Moreover, non-exporters could improve their technical efficiency by optimising the use of inputs such as labour, material, and capital.

Table 4.10 **– Endogenous switching regression**

	TE (VRS)		**SE**		**TECHCH**		**TFP**	
Main equations	**Exporter**	**Non-exporter**	**Exporter**	**Non-exporter**	**Exporter**	**Non-exporter**	**Exporter**	**Non-exporter**
Capital Intensity	-0.145***	-0.0645**	-0.00878	-0.00923	0.0362**	0.00680	-0.0971***	-0.0617***
	(0.0436)	(0.0252)	(0.0130)	(0.00660)	(0.0157)	(0.00703)	(0.0351)	(0.0113)
Average Wage	0.219***	0.122***	0.0167	0.0218**	-0.0308	-0.0108	0.169***	0.135***
	(0.0532)	(0.0363)	(0.0208)	(0.00964)	(0.0187)	(0.00809)	(0.0393)	(0.0166)
Main cities	0.0899	0.124***	-0.0788*	-0.0230**	-0.00981	0.0146	-0.0536	0.0780***
	(0.0816)	(0.0426)	(0.0414)	(0.0111)	(0.0302)	(0.0136)	(0.0561)	(0.0242)
Small	-0.210**	-0.0624	0.0430	0.0115	0.164**	0.0231	-0.0389	-0.0338
	(0.104)	(0.0567)	(0.0491)	(0.00816)	(0.0760)	(0.0174)	(0.0967)	(0.0518)
Medium	-0.393**	-0.128	-0.0134	-0.0593**	0.129	0.00787	-0.279*	-0.160
	(0.181)	(0.128)	(0.0603)	(0.0284)	(0.0898)	(0.0421)	(0.155)	(0.101)
Export selection equation								
Capital Intensity	0.000907		-0.0104		0.0210		0.0323	
	(0.160)		(0.170)		(0.141)		(0.144)	
Average Wage	0.231		0.234		0.239		0.215	
	(0.209)		(0.204)		(0.203)		(0.192)	
Small	0.178		0.214		0.163		0.201	
	(0.368)		(0.388)		(0.356)		(0.363)	
Medium	0.787		0.816		0.717		0.842	
	(0.571)		(0.541)		(0.549)		(0.555)	
Main cities	0.458*		0.496*		0.433*		0.464*	
	(0.266)		(0.289)		(0.257)		(0.266)	
Previous export status	0.888***		0.903***		0.994***		0.878***	
	(0.301)		(0.269)		(0.301)		(0.279)	
r1								

_cons	0.0141	-0.534	-0.267	-0.197
	(0.517)	(2.568)	(0.438)	(0.325)
r0				
_cons	0.123***	-0.263	0.177	0.0616
	(0.0387)	(0.212)	(0.157)	(0.0699)
rho_1	0.014	-0.489	-0.261	-0.194
	(0.517)	(1.955)	(0.408)	(0.313)
rho_0	0.123	-0.257	0.175	0.615
	(0.038)	(0.198)	(0.153)	(0.07)
N	**865**	**865**	**865**	**865**
Wald test of indep. equa.	**Wald**	**Wald**	**Wald**	**Wald**
Prob>chi2	**0.00130**	**0.207**	**0.204**	**0.279**

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

However, the failures to reject the null hypothesis of exogenous selection in the cases of scale efficiency and TFP imply that both exporters and non-exporters perform no better or worse than a randomly-selected firm would do. The lack of evidence regarding selection bias in scale efficiency and TFP equations may be due to the limitations of the data. The sample focuses on the private sector and hence excludes large firms which form the biggest proportion of exporters. In fact, the percentage of exporters in the sample is only about 8%-10%.

The selection model reports an interesting result relating to previous export status that represents the sunk-entry-cost effect. The previous export status has a significant impact on the decision by firms to export. Because of the sunk costs, exporters are less likely to exit the export business. In other words, export status in the previous year probably determines current export status. However, other variables insignificantly affect the export decision. It may be due to the inconsiderable number of firms that changed their export status compared to the number of non-exporters keeping their status over the years, as reported in table 4.8.

The expected technical efficiency for exporters and non-exporters can be found in table 4.11. Rows (1) and (2) give the unconditional expected technical efficiency for exporters and non-exporters, evaluated at the sample mean values of exporters and non-exporters respectively. Rows (3)-(6) present the conditional expected technical efficiency. Row (3), which is based on equation (3.27), provides the expected technical efficiency at the sample mean levels of the variables for exporters who choose to export their products to international markets while row (6), which is based on equation (3.30), gives the expected efficiency for non-exporters that decide not to export, evaluated at the sample mean values of the variables for non-exporters. Rows (4) and (5), which are based on equations (3.29) and (3.28) respectively, provide the counterfactual expectations. Row (4) reports the expected technical efficiency that the firms which self-selected into the exporting business would achieve if they served only the domestic market. Likewise, row (5) shows the technical efficiency level non-exporters would be expected to achieve if they decided to export.

The unconditional efficiency differential is in favour of non-exporters with the score of 0.92. However, the average conditional technical efficiency of exporters (row 3) is higher than the average conditional efficiency of non-exporters (row 6) (1.05 and 0.92 respectively).

Relating to the selection effect, potential efficiency of exporters if they only serve the domestic market (row 4) is also greater than non-exporting firms if selected into international market (row 5). The strongest differential is the between the conditional efficiency in row (3) and conditional efficiency in row (5). The predicted mean efficiency of exporters (row 3) is substantially higher than the predicted mean efficiency of non-exporters if they choose to participate in the export markets (1.05 and 0.81 respectively). Therefore, the findings suggest that exporters should keep exporting but that non-exporters may not benefit from the decision to start exporting. This may in part be a result of the existence of unobservable factors that impact the export decision.

Another measure of export premium could be obtained as follows:

$$E(lny_{it}^1|I=1,X_{it},\bar{X}_i,\bar{Z}_i) - E(lny_{it}^0\big|I=1,X_{it},\bar{X}_i,\bar{Z}_i) = X_{it}'(\beta_1-\beta_0) + (\alpha_1-\alpha_0)\bar{X}_i + (\sigma_{1u}-\sigma_{0u})\frac{\phi(Z_{it})}{\Phi(Z_{it})}$$

The above measure computes the difference in efficiency of exporters between what they achieve in exporting and what they would achieve by not exporting. The first term, $X_{it}'(\beta_1-\beta_0)$, represents the advantage/disadvantage of exporting effects in in the observable characteristics of a firm. The second term, $(\alpha_1-\alpha_0)\bar{X}_i$, measures the advantage/disadvantage in the effects of unobservable firm heterogeneity. Lastly, the third term, $(\sigma_{1u}-\sigma_{0u})\frac{\phi(Z_{it})}{\Phi(Z_{it})}$, captures the effect of selectivity. The export premium would be 0.24 (row 3 – row 5). This implies that if exporters do not get involved in exporting business, they would give up the chance to achieve higher efficiency. The result is in line with the previous export premium analysis. Again, exporters should retain their export status.

***Table 4.11* – Expected technical efficiency from switching regression model, evaluated at the sample mean levels of the variables.**

Note: Standard deviations are given within parentheses

Unconditional efficiency	
All firms	
1. Exporters' efficiency	0.83
	(0.25)
2. Non-exporter's efficiency	0.92
	(0.11)
Conditional efficiency	
Exporters	
3. If involved in exporting	1.05
	(0.28)
4. If uninvolved in exporting	0.93
	(0.10)
Conditional efficiency	
Non-exporters	
5. If involved in exporting	0.81
	(0.23)
6. If uninvolved in exporting	0.92
	(0.11)

This research may have three limitations. The first is the sample. The study only focuses on two industries: wood and furniture, and rubber and plastic. Even though they are the most export-oriented industries in the survey data, the proportion of exporters is quite modest, around 10% of the total of firms in the sample. The second is characteristics of the survey data which highlight household businesses in the micro-size. Because household businesses are unregistered firms, they face many difficulties and lack support from government policies. Therefore, their ability to export is quite moderate. Lastly, there is lack of trusted available sources of data to provide a better analysis of the role of Vietnamese SMEs in manufacturing sector and in exporting markets. These limitations result in the caution expressed here in interpreting the results.

CHAPTER 5 - CONCLUSION

This study has investigated the sources of productivity growth including technical efficiency change, scale efficiency change, and technological progress. It has also explained the factors that impact firm efficiency/productivity along while controlling non-random selection of exporters. The evidence from this study intimates that the productivity of the sample firms on average increased annually by 17% over the period 2005-2013. In addition, TFP growth is driven by pure efficiency growth. Compared to non-exporters, exporters use more labour, more capital, and obtain more outputs, more value added, and more capital productivity. Exporters also utilise labour-intensive technology to align with Vietnam's competitive advantage. Moreover, they achieve higher technical efficiency than their non-exporting business counterparts. This result is even substantially higher in the rubber and plastic industry. However, productivity growth of exporters is less than of non-exporters. The reason for this inferior productivity is exporters lack scale efficiency or the optimal scale is too large to be scale efficient. Therefore, exporters should modernise the production technology to boost their scale efficiency and productivity. In addition, around 60% of exporters are joint stock companies or partnerships, and medium-sized. Nevertheless, when controlling for the selectivity bias of the export decision, the findings suggest that in terms of technical efficiency, exporters should keep their export status and non-exporters should not enter the export market. Furthermore, previous export status is the important factor to influence the decision to export. The evidence in the study could promote some both government and firm policies to enter export markets. These results should be interpreted with caution due to the limitations of sample size and the high proportion of micro-sized household businesses.

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