PERFORMANCE OF SMALL AND MEDIUM ENTERPRISES AND THE IMPACT OF ENVIRONMENTAL VARIABLES: EVIDENCE FROM VIETNAM

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This thesis is developed from a real life application of performance evaluation of small- and medium-sized enterprises (SMEs) in Vietnam. The thesis presents two main methodological developments on evaluation of dichotomous environment variable impacts on technical efficiency. Taking into account the selection bias the thesis proposes a revised frontier separation approach for the seminal Data Envelopment Analysis (DEA) model which was developed by Charnes, Cooper, and Rhodes (1981). The revised frontier separation approach is based on a nearest neighbour propensity score matching pairing treated SMEs with their counterfactuals on the propensity score.

The thesis develops order-m frontier conditioning on propensity score from the conditional order-m approach proposed by Cazals, Florens, and Simar (2002), advocated by Daraio and Simar (2005). By this development, the thesis allows the application of the conditional order-m approach with a **dichotomous environment variable** taking into account the existence of the self-selection problem of impact evaluation. Monte Carlo style simulations have been built to examine the effectiveness of the aforementioned developments.

Methodological developments of the thesis are applied in empirical studies to evaluate the **impact of training programmes** on the performance of food processing SMEs and the **impact of exporting** on technical efficiency of textile and garment SMEs of Vietnam. The analysis shows that training programmes have no significant impact on the technical efficiency of food processing SMEs. Moreover, the analysis confirms the conclusion of the export literature that exporters are self selected into the sector. The thesis finds no significant impact from exporting activities on technical efficiency of textile and garment SMEs. However, large bias has been eliminated by the proposed approach. Results of empirical studies contribute to the understanding of the impact of different environmental variables on the performance of SMEs. It helps policy makers to design proper policy supporting the development of Vietnamese SMEs.

This thesis is dedicated to my daughters

The thesis is finished under the supervision by:

Dr. Gary Simpson

Prof. Dr. Emmanuel Thanassoulis

And examined by the examination committee, which includes:

Dr. Ozren Depric	*Aston University*
Dr. Mika Kortelainen	*Manchester University*

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Abbreviations

ASMED	Agency for SME Development
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
CIEM	Central Institute for Economic Management
COLS	Corected Ordinary Least Squares
CRS	Constant Returns to Scale
DANIDA	Danish International Development Agency
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
FDH	Free Disposal Hull
FDI	Foreign Direct Investment
FIE	Foreign Invested Enterprises
GDP	Gross Domestic Product
GSO	General Statistics Office
GTZ	Deutsche Gesellschaft für Technische Zusammenarbeit
HACCP	Hazard Analysis Critical Control Point
IFC	International Finance Corporation
ILO	International Labour Organization
ILSSA	Institute of Labour Science and Social Affairs
ISIC	International Standard Industrial Classification
MISE	Mean Integrated Square Error
MLE	Maximum Likelihood Estimation
MOLS	Modified Ordinal Least Square

MPI	Ministry of Planning and Investment
MSE	Mean Square Error
ODA	Official Development Assistance
OLS	Ordinal Least Squares
PPS	Production Possibility Set
ROA	Return on Assets
ROI	Return on Investment
ROS	Return on Sales
SFA	Stochastic Frontier Analysis
SME	Small and Medium-Sized Enterprise
SOE	State-Owned Enterprise
TFP	Total Factor Productivity
UNIDO	United Nations Industrial Development Organization
USD	United State Dollar
VND	Vietnamese Dong
VRS	Variable Returns to Scale

Chapter 1. Introduction

1.1. Research Context

The recent literature on small- and medium-sized enterprises (SMEs) emphasizes the significant contribution of SMEs to an economy. The contribution to an economy by SMEs is not limited to developing countries, where rare financial resources curb the size of enterprises, but also in developed economies, including leading economies of the world such as the U.S., Japan, and Europe. SMEs play a more important role in developing economies. Studies on SMEs in developing countries show that SMEs have greater economic benefits than large firms in terms of employment generation and growth (Hallberg, 1999). SMEs are flexible in adapting to local needs, technology and available resources. They are more efficient than large enterprises in terms of capital investment per job created. SMEs usually use unskilled workers whose supply is in excess in developing countries. By creating employment opportunities for the unskilled labour, they could increase income and reduce poverty in those countries. Therefore, development of SMEs is believed to be a way to transform the structure of the economy to support growth and reduce poverty in developing countries. Thus promoting the development of SMEs has often become a popular development strategy in developing countries.

For transition economies, where market-based economies are being built upon the legacy of centrally planned economies, SMEs play the key role. In economic development, there are two factors that dominate the development of an economy - labour and capital. With abundant labour resources and lack of capital, it is a straight logic that a developing economy's performance will be better off if an adequate share of its resources is used for technologies of medium capital intensity. They should not invest all of their capital to few workers working in modern capital-intensive industries.

The importance of SMEs in the development of national economies makes public policies supporting their development necessary. Public policies facilitating the development of SMEs are usually more microeconomic in their nature, helping SMEs to build up their competitiveness and efficiency. Exporting promotion through marketing and providing information is one of the policies conducted by governments to promote development by SMEs. Technology upgrading and technology supplying is also aimed at by public policies. Besides, access to credit, vocational training for workers, specially designed training for entrepreneurs and support for inter-firm cooperation involving SMEs or taking advantage of economies of scale are mostly used by policy-makers worldwide. A macroeconomic policy that is usually concerned by economists in facilitating the development of SMEs is exchange rate management. SMEs are usually sensitive to the external shocks and do not have large reserves. Therefore, guarding against external shocks to affect SMEs is a task of the government.

The importance of SMEs in the development of national economies also makes researchers pay more attention on their performance. The number of studies on productivity, both total factor productivity and partial productivity of labour, on innovation, growth, technology progress and technical efficiency of SMEs, increases rapidly. Studies on the impact of the operating environment and governmental supporting policies on performance of SMEs are also encouraged and received large attention by researchers.

In Vietnam, the contribution of SMEs to the country's economy has been significant. According to official statistics, in 1999, 91 percent of Vietnam's enterprises were categorized as SMEs by capital criteria, or 97 percent by the labour size criteria. By the year 2000, the contribution of SMEs to GDP was more than 50 percent. In the industrial sector, SMEs produced 20 percent of gross output annually. Vietnamese SMEs create about 49 percent of total employment in all kinds of firms (CIEM, 2004a). However, they are facing a growing number of problems such as limited investment opportunities, lack of capital, fierce competition from domestic manufacturing sector as well as from imports. On top of that, technical improvement in these enterprises has been very slow. These observations apply to SMEs in other developing countries too, and one way for

SMEs to deal with these problems is to improve their technical efficiency. Improving technical efficiency could be a vital means for SMEs to grow and expand in a liberalised and competitive environment. Therefore, evaluation of the efficiency of SMEs and factors influencing SMEs' technical efficiency is becoming an interesting and attractive topic. This thesis is one of many efforts aiming at the build-up of technical efficiency and impacts of environmental factors on the technical efficiency of Vietnamese SMEs.

1.2. Motivation and Scope of the Study

This thesis is the result of my own journey into three fields of interesting knowledge, which are all far from my starting point as a macroeconomic researcher. One relates to nonparametric frontier analysis, from CCR and BCC DEA models to conditional order-m frontier. Another is the policy impact evaluation in which the problem of selection bias is recognised and solved. The last field is the knowledge on operations of an active sector in an economy, SMEs.

My motivation in pursuing this research originates from the big question of economic development of the transition economy of Vietnam, where about 20 percent of the population is still under poverty threshold and where SMEs are playing an important role. The study is aimed at understanding the performance of SMEs in a transition economy context. The study goes further by investigating environmental variable impacts on SMEs technical efficiency.

The initial idea of the thesis was to evaluate the performance of Vietnamese SMEs and compare those receiving policy interventions such as export subsidies (treatments) with those not receiving policy treatments in order to quantify the impact of policy treatment on the performance of enterprises. As doing PhD is an evolutionary process, the outcome is quite different from its initial plan, and so it happened in this research. The existence of the self-selection problem at the heart of the evaluation of treatment impact on technical efficiency has resulted in the development of a research methodology.

The literature on the use of **dichotomous environmental variables** to assess the impact of interventions on technical efficiency is not large even though studies on the impact of exogenous variables[1] on technical efficiency are abundant. The impact of external variables on technical efficiency in general has been studied since the initial development of DEA techniques. Studies on effects of external variables on technical efficiencies can be classified into five main groups: (i) *frontier separation approach*; (ii) *all-in-one approach*; (iii) *two-stage approach*; (iv) *multi-stage approach*; and (v) *conditional frontier approach*.

Among these approaches, there are two approaches that were widely used to deal with dichotomous external variables. The first is the frontier separation approach. In the frontier separation approach, which was developed by Charnes, Cooper, and Rhodes (1981), efficient frontiers are established for subsamples which are created by stratifying the data set according to a single categorical variable which characterizes the different external environment such as ownership structure, or location and the entire data set (Fried, Schmidt, and Yaisawarng, 1999). Then the impact of external variables will be determined by comparing the subsample and overall efficiencies scores of individual DMUs, which are evaluated on both frontiers namely that of the sub-sample and of the whole dataset. The main weakness of this approach is that it does not address the potential bias from the existence of the self-selection problem[2] in the context of evaluating the impact of treatment.

The second is the two-stage approach, where in the first stage, technical efficiency is estimated by DEA. Then the DEA efficiency is regressed on contextual variables so as to adjust it for such variables. This approach is seen as a solution for the existence of noise

[1] In this study we use interchangely the terms: exogenous variable, external variable, environmental variable and nondiscretionary variable to imply a variable that is not controlled by DMUs but influences directly or indirectly the technical performance of those DMUs. In some places we use the term contextual variable with the same meaning.

[2] Self-selection problem implies the case where individuals, or enterprises in our study, select themselves into a group. This causes bias since the probability to be withdrawn and become a sample observation is not as designed and makes it difficult to determine the causation. Please see section 4.2 of chapter 4 for more detailed discussions.

as well as impact of variables that are not included in the initial DEA estimation. It was first introduced by Ray (1991) to analyse the impact of school inputs and other socio-economic factors on public schools. This approach faces the same problem of ignoring the self-selection behaviour of analysed DMUs. Also the approach suffers from a serious problem that limits its application in the current studies. The two-stage approach violates the regression assumption conducted in the second stage where serial correlation between estimated efficiencies exists and efficiency scores are estimated by mathematical programming without clear probability distributions describing data-generating process and therefore *"there is some doubt about what is being estimated"* in the second stage (Simar and Wilson, 2007). Moreover, there is also possible correlation between the DEA inputs and/or outputs with independent variables used in the regression stage (Thanassoulis et al., 2008).

In addition the above two famous approaches to dichotomous external variables, in all-in-one approach study by Banker and Morey (1986b) also deals with dichotomous external variables. Banker and Morey (1986b) revised the envelopment formulation to include a [0, 1] variable into the framework. More recently in a working paper De Witte and Kortelainen (2009) integrate into the conditional frontier a tailored mixed kernel function to examine the impact of continuous and discrete environmental variables, which can be used to study the impact of dichotomous external variable.

All in all, the choice of method by researchers for analysing the impact of dichotomous external variables is limited. With the existence of self-selection behaviour, the frontier separation approach should be revised to be able to evaluate the impact of a dichotomous external variable on technical efficiency. The thesis will develop a model based on the separation approach engrafted with the propensity score to deal with self-selection problem in evaluating the impact of dichotomous variable. More importantly, besides the revision of the frontier separation approach, the thesis develops another model from the novel approach of conditional frontier to make it possible to be used in evaluating the impact of a dichotomous external variable on technical efficiency. Both theoretical models proposed by the thesis will be supported by simulations and empirical studies.

1.3. Structure of the Thesis and Guide to Subsequent Chapters

To explore the performance of SMEs and investigate impacts of external variables on technical efficiency of SMEs, the thesis is constructed as follows. Chapter 2 will discuss the development of SMEs in Vietnam and describe the role of the government in the development process of SMEs. The fact that Vietnam has just renounced her centrally planning mechanism, as directed by socialist ideology in which private ownership is limited, is the starting point of the chapter. This chapter will briefly present the economic environment for the development of SMEs. It will analyse the current situation of this sector and its role in the economy of Vietnam. A general assessment of the performance of the SMEs sector will also be presented in this chapter. An important section of this chapter is devoted to discussing the role of the government in supporting the development of the SMEs sector. Institutions for the support of the government to SMEs will be discussed. Important policies supporting SME development will also be analysed in this chapter.

Chapter 3 is dedicated for the overview of literature on performance measurement and external variable impact evaluation. The chapter will briefly survey the formation and major developments of performance measure in terms of technical efficiency. This chapter will focus most of its contents on the discussion of nonparametric approaches to assess the impact of external variables on technical efficiency, which is the research direction of the thesis. Five major approaches to evaluating the impact of an external variable on technical efficiency will be reviewed in this chapter. It will reveal the possibilities and weaknesses of these methods, as a starting point for the development of the approaches used in the thesis.

Chapter 4 of the thesis presents one important theoretical model of the thesis. The chapter will begin by discussing the basic problem of policy evaluation. It then goes on to establish a theoretical model by revising the traditional frontier approach taking into account selection bias problem. Its advantages over traditional frontier separation approaches are demonstrated by Monte Carlo simulations. The results of simulations in this chapter are the foundation for empirical analyses conducted in chapter 5 of the thesis.

Chapter 5 contains an empirical analysis that is an application of the theoretical approach proposed and proved in Chapter 4 of the thesis. This chapter deals with the evaluation of impact of training programmes on the performance of SMEs in the food processing industry.

A further methodological contribution of the study is presented in Chapter 6 of the thesis. The chapter is devoted to building a model of order-m frontier conditioning on propensity score. The model enables the use of conditional frontier approach to evaluate the impact of dichotomous external variables. Validity of the proposed approach is examined by Monte Carlo simulations, and the results of the simulations are also presented in the chapter.

Chapter 7 of the thesis is devoted to an empirical study on the impact of exporting on technical efficiency of textile and garment SMEs. This empirical study is enabled by the methodological development presented in Chapter 6 of the thesis.

Finally, Chapter 8 will conclude the thesis by summarising main developments and contributions of the analysis. This chapter ends with a reference on perceived limitations of the study and possible topics for future research.

Chapter 2. Development of SMEs in Vietnam and the Role of Government

2.1. Introduction

SMEs play an important role in developing economies. SMEs in developing countries are believed to create greater benefits to the economy than large firms through their expansion and employment generation (Hallberg, 1999). In the case of the transition economy of Vietnam, the dynamic SMEs in particular and non-state enterprise sector in general is to help restructuring and slimming state enterprises and expanding non-farm employment (Havie, 2001). The contribution of SMEs to Vietnam's economy has been significant. In 2005, SMEs contributed 46 percent of GDP and around 40 percent of total employees of all registered enterprises of the country (Nguyen, 2008).

Along with the development of SMEs and opening the economy to the world, the government of Vietnam has conducted policy reforms to support the development of the economy. There are many policy incentives conducted to facilitate the development of the private sector. During the last few years, the Government of Vietnam has implemented deregulation policies that were expected to have positive impacts on the growth of the national economy.

One of the large moves of the Vietnamese Government is to implement a new Enterprise Law in 2000. This new law was to simplify the license application by removing 145 sublicense procedures (Far Eastern Economic Review, 2001). The response from domestic investors was very positive to the enactment of the new Enterprise Law. In fact the number of newly established enterprises increased by nearly 90,000 in only 4 years, from 2000 to 2004. Thank to the new law, number of joint-stock companies increased tenfold compared to the total registered joint-stock companies in the previous 9 year in the same period. Total registered capital from newly established companies reached approximately USD 10 billion. It became more important capital resources than foreign direct investment (FDI) (CIEM, 2004b). The government also applies an assistance system to the enterprises through different programs, e.g. credit assistance, assistance to export through trade promotion agency, assistance in obtaining land and premises, assistance through industrial expansion program and SMEs promotion program.

This chapter will provide a brief description of the development of SMEs in the context of the recent development of the Vietnamese economy. The first section of the chapter is devoted to the description of the economic environment for the development of SMEs in Vietnam. The second section focuses on the current situation of SMEs. The third section describes efforts of the Vietnamese government in supporting the development and improving the productivity and efficiency of SMEs.

2.2. Economic Environment for the Development of SMEs in Vietnam

During its transition to a market-based economy, Vietnam has achieved a rapid economic growth and impressive achievement in poverty reduction (Dollar and Kraay, 2004). The economic reform known as “doi moi” launched in 1986 has made the Vietnamese economy one of the fastest growing economies in the world with the average GDP growth rate of over 7 percent per annum. With a favourable economic and political environment for development of SMEs, the numbers of SMEs established have increased rapidly in the past few years. The fact that Vietnamese domestic enterprises are dominated by SMEs and SMEs are most important employers as well as contributors to the economy is the answer for a right policy option made by the government.

Looking back to the recent history, SMEs, especially private SMEs, in Vietnam have overcome many difficulties in their development. After the end of Vietnam War in 1975, efforts to eliminate capitalism in the south of the country resulted in dissolving private sector. Large-scale private enterprises were not allowed to exist and had to have merged to either state-owned enterprises or cooperatives. The government controls the whole economy by managing the system of production plans and product distribution. The major players in production included state owned enterprises, cooperatives and households. Prices were set by the government with the bureaucratic assistance from the State Planning Committee (Vu, 1994). This pricing system offers low procurement prices to cooperatives and households. Wages in urban areas were kept low, and producers lacked of incentives for improving productivity and increasing production outputs since there were no rewards for such an effort (Beresford, 2001). Foreign trade was small and monopolized by the state owned enterprises. In that condition, there was no room for the development of private SMEs.

In 1986 after suffering a long economic stagnation, the Sixth Communist Party Congress decided to establish a market-oriented economy in Vietnam. Fforde and De Vylder (1996) believed that the move towards a market economy in Vietnam is due to the pressure from bottom up with “fence breaking” activities[3] and the “three plans” system[4]. Influence from hyperinflation during the late 1980s reinforces the determination to move forward a market economy, reducing support to SOEs sector, eliminating official prices, and opening the economy to foreign investment and trade. In 1987, the law on foreign investment was passed. The law allowed the establishment of 100 percent foreign invested enterprises with significant tax holidays and 100 percent profit repatriation. Vietnam proved to be a good investment place and by 1996 the amount of FDI surged up to USD 8.5 billion, constituting one third of total investment of the country (Beresford, 2001).

Efforts to establish the ground for a market economy resulted in good outcomes. In 1988, the Resolution 10 by the Politburo created a huge incentive to farmers and

[3] The attempts of state-owned enterprises and agricultural cooperatives to operate outside the plan without seeking permission.

[4] Responding to “fence-breaking” activities by industrial producers, the government adopt the “three plans” system. Plan I represented the traditional system where inputs and outputs are assigned from the government. Plan II allowed enterprises to use inputs procured at market prices to produce assigned outputs and sell those output at market prices. In Plan III state enterprises could produce products unrelated to their original production assignments and could sell their products on markets and retain up to 90 percent of profits earned (O'CONNOR, D. 1998. Rural industrial development in Vietnam and China: A study in contrasts. *MOCT-MOST: Economic Policy in Transitional Economies,* 8**,** 7-43.).

indirectly contributed to shifting Vietnam from a net importer of rice to the third largest rice exporter of the world. The Resolution has abandoned the procurement contracts applied to agricultural products and decided that all farming outputs could be traded at market prices. In 1989, the exchange rate was floated by abolishing official prices determined by the Central Bank. Positive interest rates were applied, and therefore direct subsidies to SOEs have been eliminated. In 1990, the Company Law and Private Enterprises Law were enacted to officially recognize the existence of private enterprises. The results of all macroeconomic reforms were very positive. Hyperinflation with three digit in 1988 has been reduced to only 36 percent in 1990 and to one digit in 1993.

As a result of radical changes in policies, Vietnam enjoyed a new phase of economic development of high growth rate, which only ends in the eve of the East Asian financial crisis. Between 1989 and 1995, the economy grew at an average rate of 7.7 percent per annum in terms of real GDP. The Asian financial crisis caused the economy to grow at a lower rate of around 6 percent per annum from 1997 to 1999. The economy gained its momentum shortly after the crisis with average growth rate of 7.5 percent in the period from 2000 to 2005. Vietnam's economy became the second fastest growing economy in the region after China.

During 20 years of reforms, Vietnam has obtained great achievement in terms of economic development. GDP in real terms has expanded 3.6 times from VND 109.2 trillion in 1996 to VND 393 trillion in 2005.[5] More importantly GDP per capita increased 5.4 times, from just USD 86 in 1988 to USD 638 in 2005 (GSO, 2006). The country has been praised by the World Bank for its "*striking progress against poverty*" (World Bank, 2000).

[5] In current USD, GDP increased from USD 25 billion to USD 53 billion, respectively.

Figure 1. Economic Reforms, Growth, and Inflation, 1986-2005

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Source: GSO (various years), (CIEM, 2001, CIEM, 2002, CIEM, 2003, CIEM, 2004a, CIEM, 2004c, CIEM, 2004b, CIEM, 2005, CIEM, 2006)

During the period of rapid economic growth, the main engine of the economy has shifted from agriculture to industry. Contribution of agriculture to GDP has declined from 40.5 percent to 21 percent during the period 1991-2005. The GDP share of the industry sector increased from 24 percent to 41 percent in the same period. This change shows the radical transformation of the economic structure of the Vietnamese economy. The industrial sector also contributed largely to the rapid growth rate of the economy. During the period from 1999 to 2005, the industrial sector grew impressively at an average of 9.8 percent. The services sector grew at an average of 6 percent, meanwhile the agricultural sector kept its growth at a steady rate of 4 percent (CIEM, 2001, CIEM, 2003, CIEM, 2006). The higher growth rates of the industry and services sectors explain the increasing share of those sectors of GDP (see figure 2). As a result, the gross industrial outputs increased 9.6 times from VND 43.5 trillion to VND 416.9 trillion.[6]

[6] In 1994 constant price.

Figure 2. Sectoral shares of GDP, 1986-2005

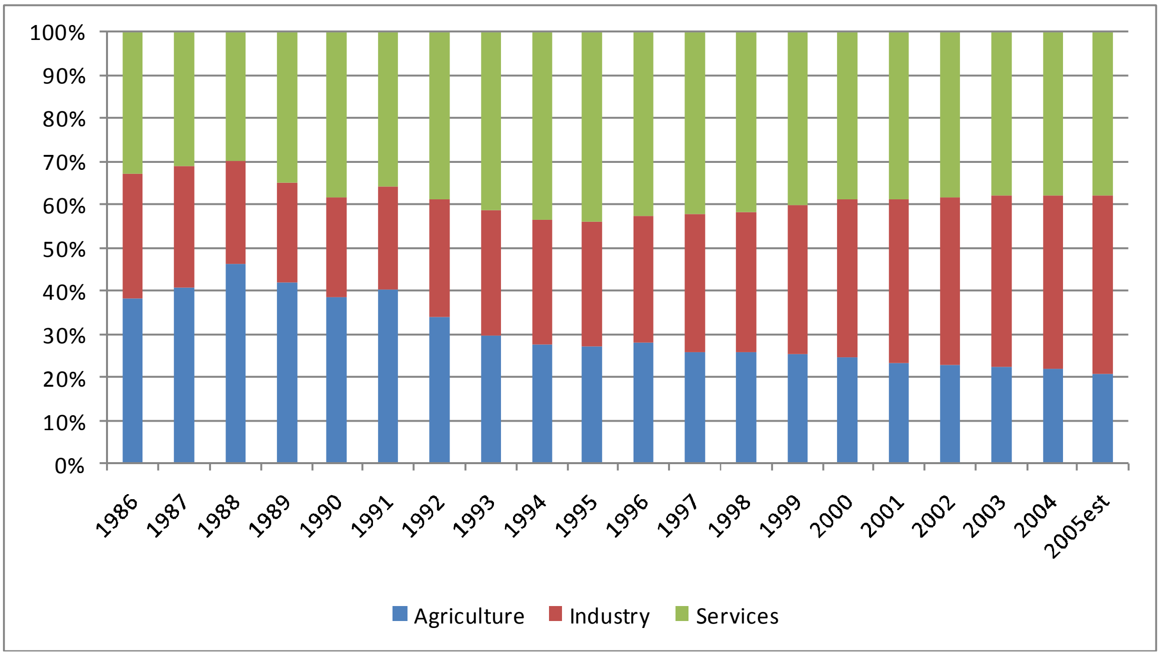
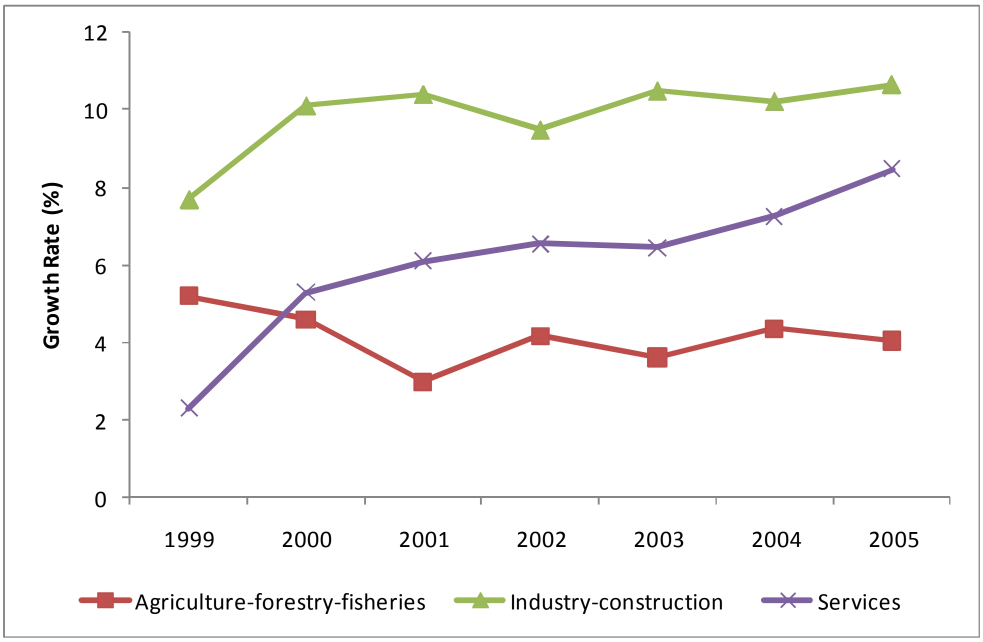


Figure 3. Sectoral growth rates, 1999-2005



There was another important change in the structure of the Vietnamese economy. The period of the 1990s has witnessed the rise of non-state sector and the foreign invested sector. This trend continued in early 2000s when the contribution of manufacturing SOEs reduced from 51.7 percent in 2000 to 32 percent in 2005. The reduction of SOEs in manufacturing was captured by domestic private enterprises and foreign invested enterprises (FIEs). Both sectors developed with a sharp rise belonging to the foreign invested sector, from 26.5 percent in 2000 to more than 40 percent in 2005 (see Table 1).

Table 1. Ownership in manufacturing, 2000-2005

	2000	2001	2002	2003	2004	2005

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Source: GSO Enterprises Consensus Surveys 2001, 2002, 2003, 2004, 2005, 2006

The incentives in the agriculture sector along with devaluation of the exchange rate in 1989 and the opening of the economy to the outside world led to a surge in exports. The rate of export growth is always high after the reform, at an average of about 30 percent per annum. Total imports and exports volume has increased 23 times from USD 3 billion in 1986 to USD 69.4 billions in 2005. High growth of the economy increased domestic savings. Along with foreign capital inflows, it has supported a large increase in investment, from 11.7 percent in 1989 to nearly 26 percent of GDP in 1995. In absolute terms total investment increased 14 times from VND 15.3 trillion in 1986 to VND 212 trillion 2005 (GSO, 2006). By opening the economy to foreign investment, Vietnam has received a huge amount of foreign capital. From 1988 when foreign investment was allowed under the foreign investment law, which was seen as a liberal law by the region standards to 2005, total registered capital of foreign invested enterprises increased by 20 times, from USD 0.3 billion to USD 6.3 billions. The surge of total investment to the domestic economy continues, and it was 35.3 percent of GDP in 2006 (Tumbarello et al., 2007).

The growth of state investment was always at the rate of 10 to 15 percent per annum. Therefore, the increase in total investment was supported by high growth of private investment, both domestic and foreign. Growth rate of domestic private investment was always higher than 18 percent since 1990, with a surge in 2002 to 2004 at 31, 47 and 47.5 percent respectively. The growth rate reduced to 18-19 percent per year in the period of 2005-2007. Foreign investment growth reached a peak in 1995 and then reduced due to the Asian financial crisis. It gained increasing momentum again since 2005 (CIEM, 2008).

The increase in private investment both domestic and foreign has changed radically the investment structure in recent years. The share of state investment in total investment has reduced from 59 percent in 2000 to 35 percent in 2006. At the same time, domestic investment has increased by 15 percentage points, from 23 percent to 38 percent in 2006. The share of FDI has reduced 2 percentage points from 18 percent in 2000 to 16 percent in 2006 due to the rapid growth of the domestic investment (CIEM, 2008) (See Figure 4).

Figure 4. Share of investment, 1996-2006

Source: CIEM (2008)

One feature of growth in Vietnam in the earlier period of development is that the growth extended in all sectors of the economy. More importantly, all people enjoyed the growth thanks to the equal distribution system maintained by the government. The labour force in Vietnam is also a favourable factor for the development of enterprises. After the Vietnam War, there was a baby boom in the country, and this leads to very young population these days in the country.

With such economic environment and the revision of company and enterprise laws to lessen the barriers for the establishment of new enterprises, the enterprise sector in general and SMEs in Vietnam in particular have grown rapidly. In the end of 2008, the total of enterprises having been established since 2000 is about 350.000. About 40.000 enterprises were dissolved by the end of 2008. At the moment it is reported by the General Taxation Agency that there are 270.000 enterprises fulfilling their taxation responsibility, equal 77 percent of total number of enterprises registered (CIEM, 2008).

Table 2. Performance of the economy, 1989-2005

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Source: GSO (www.gso.gov.vn)

2.3. Current Situation of SMEs

The economic reforms in the 1980s have encouraged millions of Vietnamese individuals to join the business world by establishing enterprises and expanding their current business to outside markets. Nowadays, a large number of SMEs characterize the Vietnamese economy. SMEs are officially defined by the decree 90/2001/ND-CP of the government as enterprises with registered capital of under VND 10 billion (about USD 625,000) and fewer than 300 employees. So, the Vietnamese government uses both labour and capital as criteria for defining SMEs. This follows international practice. In terms of labour, the practice is followed strictly, however in terms of capital, the threshold is much lower (see the following table). It reflects the fact that labour is abundant and the economy needs more capital.

Table 3. Definition of SMEs in Some Countries

Location	***Definition and/or criteria for SME***

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Source: Nhat (2007)

By this definition in 2002 99.9 percent of 2.7 million business establishments (including registered enterprises and non-registered household businesses) in Vietnam were small and medium size. They created 8.3 million jobs, and engaged 77 percent of all non-agricultural labour force in 2002 (MPI, 2006). In terms of registered business, SMEs accounted for 94.4 percent in 2000, when the new Enterprises Law was enacted.

Since this enactment of the Enterprises Law, the number of newly registered enterprises has increased rapidly. The number of newly registered enterprises from 2000 to 2004 is 3.5 times higher than the total of enterprises registered in 9 previous years (MPI, 2006). In terms of enterprise size, the number of SMEs has more than doubled from nearly 40,000 in 2000 to nearly 110,000 in 2005 (see Table 4). Not only increasing in number, the SMEs sector plays an increasingly important role in the economy. They account for 96.8 percent of total registered enterprises of the economy in 2005. This is increased from 94.4 percent of total registered enterprises in 2000. They created jobs for more than 2.5 million workers, doubled from 2000 number. More importantly, they are cost effective in generating off farm employment for the economy. As estimated by the World Bank, each job created by SMEs requires an investment of about USD 800. Meanwhile, a state-owned enterprise (SOE) requires USD 18,000 to create a new job. This is also what the World Bank observed from other countries (World Bank, 1998).

The Vietnamese SMEs have similar characteristics with SMEs in other countries. A small enterprise in Vietnam employs about 19 persons, which are very close to the average of 20 in Europe. A medium enterprise creates an average of 112 jobs while it is 95 in Europe. The main difference is micro enterprises which is very small, an average of less than 2 employees in Vietnam, and large enterprises, which employ an average 773 employees per enterprise in Vietnam and 1020 employees per enterprise in Europe (MPI, 2006).

The capital mobilized by SMEs also has increased impressively. The average growth rate of total assets owned by SMEs is 25.5 percent over the period 2000-2005. Total assets of SMEs increase from VND 294 trillion in 2000 to VND 911 trillion in 2005[7], i.e. roughly tripled in this period. There is also a good signal for Vietnam that is the size of enterprises in terms of capital has been increasing in the past few years. On average total asset used by one enterprise have increased from VND 7.4 billion in 2000 to VND 8.3 billion in 2005[8]. SMEs account for 34 percent of total assets owned by all registered enterprises in 2005, increasing from 26.7 percent to 2000 (see Table 4).

Table 4. SMEs in Vietnam, 2000-2005

	2000	2001	2002	2003	2004	2005

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Source: GSO Enterprises Consensus Surveys 2001, 2002, 2003, 2004, 2005, 2006

SMEs in Vietnam consist primarily of non-state enterprises. Both SOEs and FIEs account for only 3 percent each in total SMEs of the country. The statistics also show that while the ratio of SMEs in private enterprises remain the same at 99 percent in 2000 and 2004, the ratio of SMEs in SOEs reduced from 75 percent in 2000 to 64 percent in 2004.

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[7] Equivalent to USD 20.8 billion in 2000 and 57.4 billion in 2005, respectively. Exchange rates in this study are taken from INTERNATIONAL MONETARY FUN (IMF) 2000. Vietnam: Statistical Appendix and Background Notes. *IMF Staff Country Report No. 00/116*. and INTERNATIONAL MONETARY FUN (IMF) 2000. Vietnam: Statistical Appendix and Background Notes. *IMF Staff Country Report No. 00/116*. if nor otherwise indicated

[8] Equivalent to USD 525,000 in 2000 and USD 523,000 in 2005 at the current exchange rates, respectively.

There was a small reduction in the ratio of SMEs in FIEs, which was 80 percent in 2000 and 77 percent in 2004.

Most of SMEs are household businesses involved in low skill, low value adding, low technology and finance constrained activities (Harvie, 2007). Figure 5 shows that, there is an increase in the ratio of manufacturing SMEs, but most of SMEs operates in trade and services. These industries require less capital and are easy to set up as a business. The chart also shows that the number of SMEs working in agriculture and fishing remarkably decreased during the last five years. In 2004, less than 3 percent SMEs remained in agriculture compared to 8 percent in 2000. This is not because of the growth rate of newly registered enterprises is lower than the other industries, but it shows a real reduction in the number of SMEs in agriculture. Both current and potential entrepreneurs see agriculture as not creating enough benefits.

Figure 5. Share and growth of industries, 2000-2004

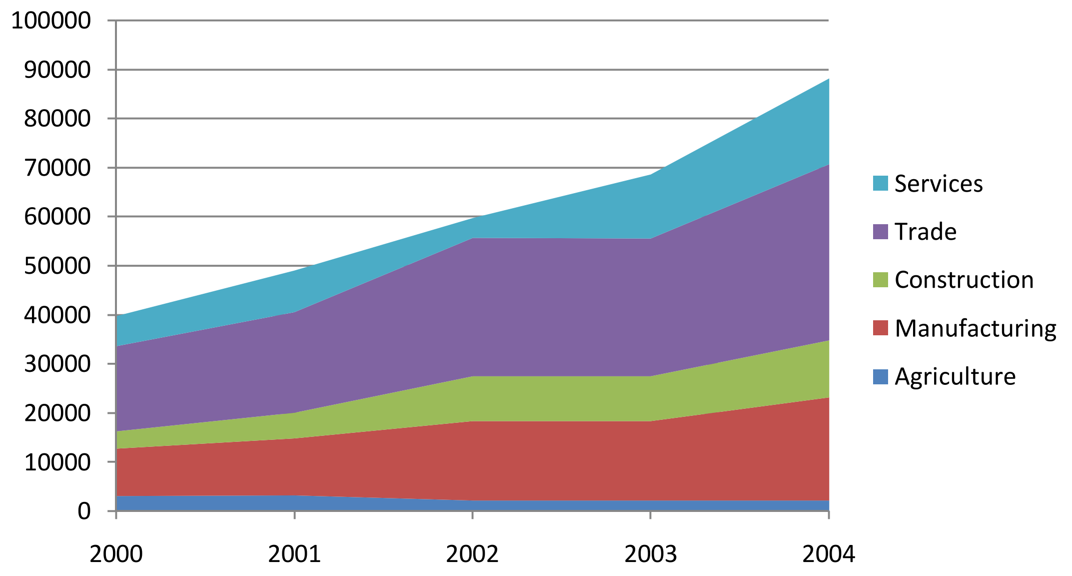
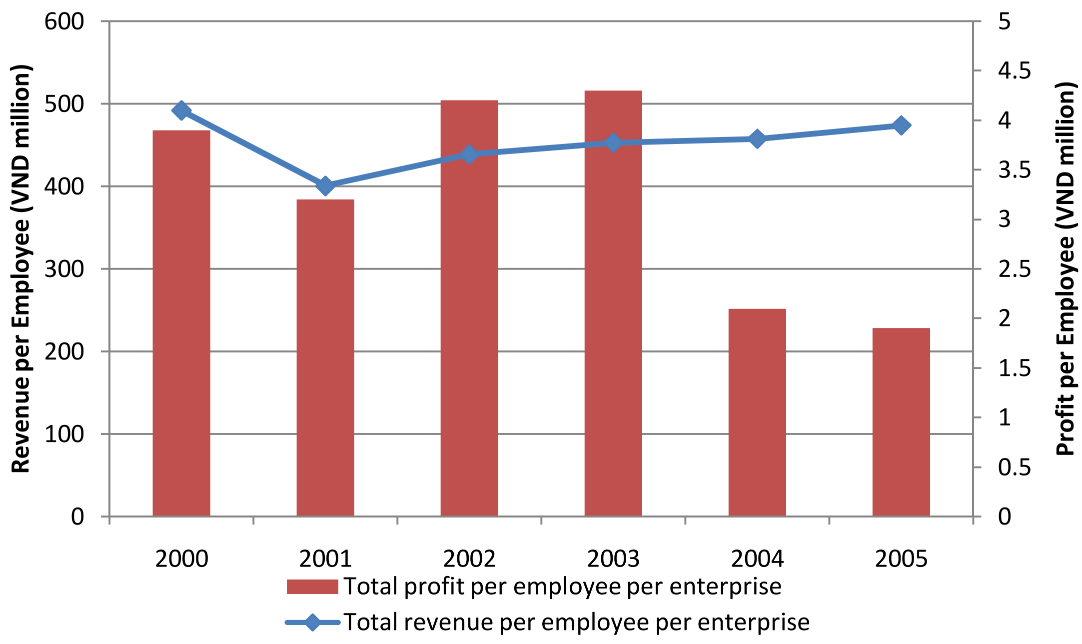


Figure 6. Performance of SMEs, 2000-2005



Making strong impression on the growth of numbers of enterprises as well as number of jobs created, SMEs in Vietnam have not operated well enough. Labour productivity in terms of revenue generated per person has fallen from VND 491.5 million in 2000 to VND 473.5 million in 2005.[9] Total profit per person also reduced dramatically over the same period, from VND 3.9 million to VND 1.9 million (see Figure 6).[10] The average rate of shrinking of profit per person is 9 percent over the period 2000-2005, which is an alarming signal for SMEs entrepreneurs.

Harvie (2007) summarises impediments to development of SMEs in Vietnam, including: access to land, access to finance, troublesome regulations, access to technology, access to market, access to information, access to skilled human resources, access to information… to name but a few. According to the surveys conducted in 2002 and 2005 by the Institute of Labour Science and Social Affairs (ILSSA) in the Ministry of Labour, Invalids and Social Affairs (MOLISA) and University of Copenhagen (Denmark), most important constrains to growth as perceived by entrepreneurs include the shortage of

[9] About USD 35,000 in 2000 and USD 30,000, respectively.

[10] About USD 276 in 2000 and USD 120 in 2005, respectively.

capital and credit, the harsh competition in the markets, products not satisfying needs of buyers and lack of access to production sites. All of the aforementioned constraints are related closely with the rapid increase in the number of SMEs. Moreover, during the past decades Vietnam has consistently conducted its liberalisation policy. The result is a more open economy with many bilateral and multilateral trade agreements that have been concluded and implemented. In addition, the existence of FIEs creates a huge pressure on domestic enterprises in terms of both mobilising skilled labour forces and selling domestic products. In the long term with the fierce competition on the market and the "creative destruction" process, it certainly will result in a competitive SMEs sector in Vietnam. However, at the moment SMEs are facing huge difficulties in development.

Figure 7. Important Constraint to Growth as Perceived by the Enterprise

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Source: Rand and Tarp (2007)
Note: Number of answers from surveyed enterprises

Access to land is a significant problem for SMEs in Vietnam. To access land SMEs have three options (i) leasing from the government, or (ii) purchasing land-using right from land transfers, or (iii) renting from industrial zones for SMEs. According to the Ministry of Planning and Investment (MPI, 2006), there are about 200 industrial zones for SMEs having been established in 36 cities and provinces. These small numbers of industrial zones cannot meet the huge demand from SMEs. Moreover, the rent in industrial zones is too high for an SME to be located in the zone (MPI, 2006).

In cities and provinces where most SMEs are operating land is very expensive due to inappropriate land policies by the government[11]. Leasing land from the government is difficult and it is a source for corruption. Land planning information is not widely and efficiently disseminated to people and enterprises, making the risk of acquiring an out of planning piece of land higher.

The problem in accessing land is part of the credit problem of SMEs since land is an important mortgage. The Ministry of Planning and Investment in 1999 reported that about 80 percent of SMEs have lack of capital for production and/or business. The situation has not improved yet. Harvie (2007) pointed out several difficulties in accessing finance by SMEs in Vietnam. The nature of difficulty in accessing finance by SMEs is the fact that a level playing field has not been established. There are still policies that are favourable to SOEs. The majority of external resources such as ODA (Official Development Assistance) and FDI have been allocated to the state sector. SOEs also can have cheaper credit in comparison to private enterprises in general. Collateral for bank loans applies to non-state enterprises while it does not for SOEs.

In terms of human capital, employees in SMEs have low skill since they have not received appropriate training while their education level is low. There is a trend that difficulties in recruiting skilled labour increased in the past few years. About 50 percent of medium size enterprises have more difficulty in recruiting labour that meets desirable standards (Rand et al., 2008). Most of manufacturing SMEs in Vietnam recruits labour through relatives and friends.

On the other hand, smaller enterprises do not have difficulties in looking for suitable employment. A report by Rand et al. (2008) shows that only 10 percent of micro enterprises have employment problems. One reason is that owners of micro enterprises

[11] Some reports that land price in Vietnam is one of the highest in the world.

usually are self-employed. Their businesses also do not require high skills and therefore they can easily find suitable employees.

The development strategy for SMEs drafted by the Ministry of Planning and Investment (MPI) in 2006 pointed out that SMEs have low competitiveness partly due to their outdated technology and equipment. Estimation by MPI shows that the majority of Vietnamese enterprises are using technology of 3 or 4 generations behind the average level of the world.

2.4. Role of Government in Developing SMEs

SMEs play an important role in the economy, accounting for nearly 100 percent of the total number of enterprises in both developed and developing countries, generating more than 50 percent of jobs in the economies (see Table 5). Therefore, policies to support the development of SMEs are common in all countries, especially in developing countries. Policies to support the development of SMEs have been an important aspect of industrial policy changing structure of the economy towards a modern economy. At the same time the development of SMEs is seen as a policy package in order to eradicate hunger and reduce poverty (Harvie and Lee, 2005).

The importance of SMEs in the transition economy of Vietnam implies that they should not face constraints in their establishment, production and business. The government of Vietnam has been trying to ensure that SMEs as well as other business organizations could operate efficiently with low administrative compliance and transaction costs. Many policies supporting SMEs are to remedy the weaknesses or disadvantages of SMEs suffered from the direct competition of large enterprises (Harvie and Lee, 2005).

Harvie (2007) pointed out that the government of Vietnam should act at both the macro and micro level to support SMEs development. At macroeconomic level, the main role of the government is to maintain the stability of the economy. To support the development of enterprises a favourable environment for business should be obtained. The discrimination between SOEs and non-state enterprises, between FIEs and domestic enterprises should be eliminated. Legislation on the business registration should be improved so that new enterprises can be established more easily and cheaply, and be protected in their registered names and brands.

Table 5. Role of SMEs in Some Developed and East Asian Economies

(Source: Fawzy, 2002)

The 5 years development plan for SMEs drafted by MPI in 2006 declared that there is a comprehensive SMEs support system operating in Vietnam. It consists of state management agencies and socio-economic organizations. Many supporting activities for the development of SMEs have been undertaken by those agencies and organizations. The SMEs Promotion Council provides consultation to the central government and directly to the Prime Minister. The Council consists of leaders of Ministries, business associations and researchers in different organizations. The Council is chaired by the Ministry of Planning and Investment, and supported by the Agency for SME Development (ASMED). Others ministries, such as Finance, Natural Resources and Environment, Industry and Trade, Science and Technology, and the State Bank of Vietnam, play very active supporting roles.

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SMEs are also supported by local governments. There are three Technical Assistance Centres for SMEs established in the three largest cities, including Hanoi, Ho Chi Minh City, and Danang. A Trade Promotion Agency was established by the Ministry of Industry and Trade to support domestic enterprises, which consist of mainly SMEs, to access foreign markets by providing consultation and information on the market situation, organizing trade fairs and exhibitions abroad, and other supporting activities to boost exports. A development assistance fund has been established whose main tasks are to assist domestic enterprises to realise investment projects and export contracts using state financial support. SMEs are also supported by business associations, which in 2006 were about 200. These associations represent the rights of their enterprise members in dialog with the government. International donors play important roles in development of SMEs by providing support to increase productivity, efficiency and profitability of SMEs.

There are various activities conducted by a supporting system to assist the development of SMEs. Training programs for business start-up, management, and employees have been conducted with the support of international organizations such as ILO, UNIDO, GTZ, IFC, DANIDA, The ASMED has their own designed training courses for SMEs to assist SMEs to develop business strategies and expand export markets. The training courses conducted by ASMED are not only for existing SMEs but also for potential entrepreneurs. The ASMED training program was in pilot phase in period 2004-2005 and has continued in the period 2006-2008. Training programs have been running in sharing cost mode, in which the government contributed VND 119.4 billion[12]. The number of courses run under this project is 3,589 and estimated number of attendants to training course is 107,670.[13]

Training courses on the formulation of product standards, quality management and machinery/equipment inspection have been conducted by the Directorate for Standards and Quality. In most provinces, SMEs can access training and grants for implementing quality control (ISO 9000, HACCP, etc.) through the provincial Department of Science and Technology. Besides, SMEs in each province may enjoy assistance from specific programs on improving plant varieties, livestock breeds, forest tree varieties or biotechnology programs.

[12] Equivalent to about USD 7 million at 2005 exchange rate.

[13] *http://www.business.gov.vn/asmed.aspx?id=66&LangType=1033, accessed in August 2009*

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accessed in August 2009)

Export promotion programs are always an important part in SMEs promotion packages conducted by state agencies and international donors. The Trade Promotion Agency runs the National Focal Trade Promotion Program to encourage domestic enterprises to penetrate into foreign markets following the general guidance from the export development strategy. Provincial governments also have their own export promotion programs for SMEs in their territory. It is reported that there are 30 cities and provinces where trade promotion activities are carried out (MPI, 2006).

Government agencies and provincial governments have implemented other support activities. Credit Guarantee Funds for SMEs have been established in several provinces to support SMEs in accessing finance. The government is pushing forward the e-government program, to provide enterprises with legal information at cheaper cost and a convenient way. The IT infrastructure is also being invested heavily in order to provide enterprises an efficient way to do business. Provincial government, ministries and other government agencies have implemented various information dissemination activities targeting enterprises, such as leaflets, brochures, direct information delivery upon request, website.

The Ministry of Planning and Investment has positive evaluation on the impacts of government supporting policies to the development of SMEs in Vietnam (MPI, 2006). However, to measure the exact impact of government policies to the productivity, efficiency, profitability and strength of SMEs, more careful quantitative research is needed. This thesis is conducted partly to shed light on the impacts of government policies on technical efficiency of SMEs in Vietnam. We believe that it will be an important contribution of the study to understand the way the government can improve efficiency of SMEs in a transitional economy, besides contributing to the methodology used to investigate those impacts.

Chapter 3. Literature review

3.1. Introduction

The previous chapter has described the general context of SMEs development. It shows that even thought rapid development of SMEs was witnessed in Vietnam, SMEs suffer from weaknesses. That is the reason for the intervention of the government to facilitate the development of SMEs. However, impact of government policy intervention on technical performance of SMEs has never been evaluated in Vietnam. In this chapter we discuss approaches that have been used in the past for evaluating the influence of external i.e. contextual variables on the technical efficiency of DMUs. However, before going into details of these approaches a review of the development of performance evaluation methods under the name of non-parametric frontier analysis will be conducted. The chapter focuses on the external variables and their impacts on the performance of units.

3.2. Efficiency Measurement

3.2.1 Overview

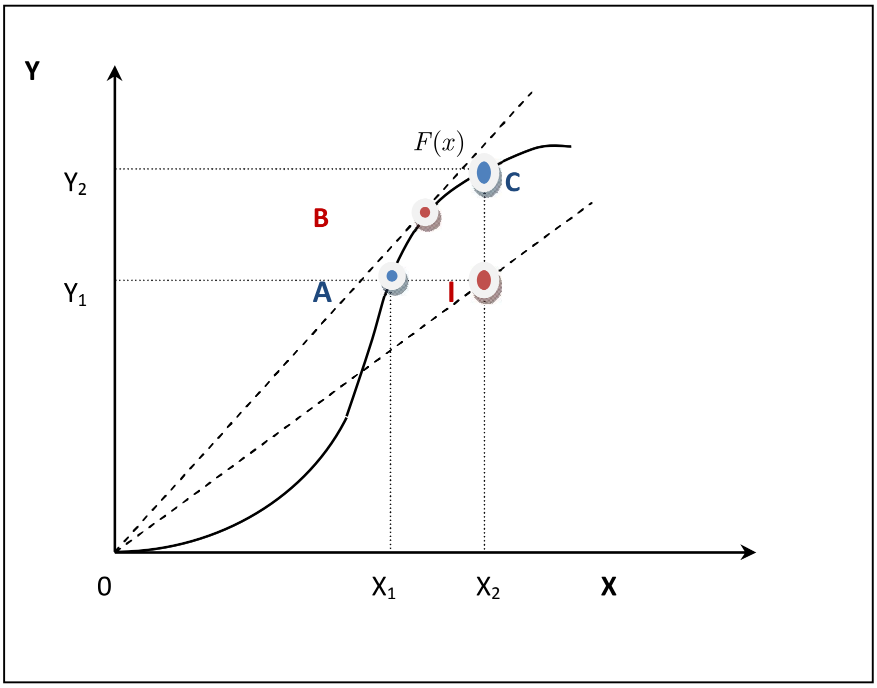
Performance measurement is the process to gauge performance in order to improve the quality and quantity of operations of organizations. Performance improvement cannot be realized without performance measurement (Browne et al., 1997). Performance measurement can be understood differently by different people. It can be observed from the financial perspective, which is the traditional approach to measuring the performance of organizations. From this perspective, the performance of an organization can be measured by financial indexes such as ROI (Return on Investment), ROA (Return on Assets (Equity)), ROS (Return on Sales). Performance of an organization can be observed from the external perspective, where market or industry share or customer satisfaction, retention and acquisition are the main aspects to be screened. Performance of an organization can also be analysed from the internal operation perspective. From this perspective, one of the most popular indicators is productivity. Productivity means the ability to convert input(s) into output(s). Productivity can be affected by production technology progress, by efficiency in the production process, or by the production environment where productive operations occur (Lovell, 1993).

A closely related concept to productivity is efficiency. Measuring the efficiency requires setting the outputs of a production unit against the inputs it uses. Efficient production units would be those that produce a certain level of output with the minimum level of inputs. On the other hand, they would be the ones that produce the maximum level of outputs at a given level of inputs. Efficient production units play the important role of production benchmarks, so that all other production units in the same industry could be compared to them and find their level of efficiency. Efficient production units establish an empirical production frontier, which can also be seen as an efficient frontier for the rest of the observations.

The concepts of productivity and technical efficiency can be differentiated by using the following figure, in which we describe a simple production technology with only one input and one output. In Figure 8 production frontier is defined by $0F(x)$, which illustrates the relationship between input and output in a particular industry. The production unit I is technically inefficient since it is operating under the production frontier. Meanwhile production units A, B and C are technically efficient since they are operating on the production frontier.

Productivity of production units is measured by the slope of the line connecting the origin to the data point of those production units. For example, the productivity of the unit I will be the slop of the ray 0I, which is Y_1/X_2 . Meanwhile technical efficiency is the distance between the inefficient unit and its efficient counterpart. In our figure, unit I is inefficient and the level of its efficiency can be measured by comparing with efficient units, either following output or input orientation. The output-oriented efficiency of unit **I** can be estimated by the distance between its output and output of efficient unit C, where both units using the same level of input. Output-oriented efficiency of unit I in this case is Y_1/Y_2 . On the other hand, input-oriented efficiency of unit **I** is X_2/X_1 , where unit **I** is directly compared to unit A. Both units produce the same level of output using different levels of input, and unit A is efficient.

Figure 8. Productivity and Technical Efficiency



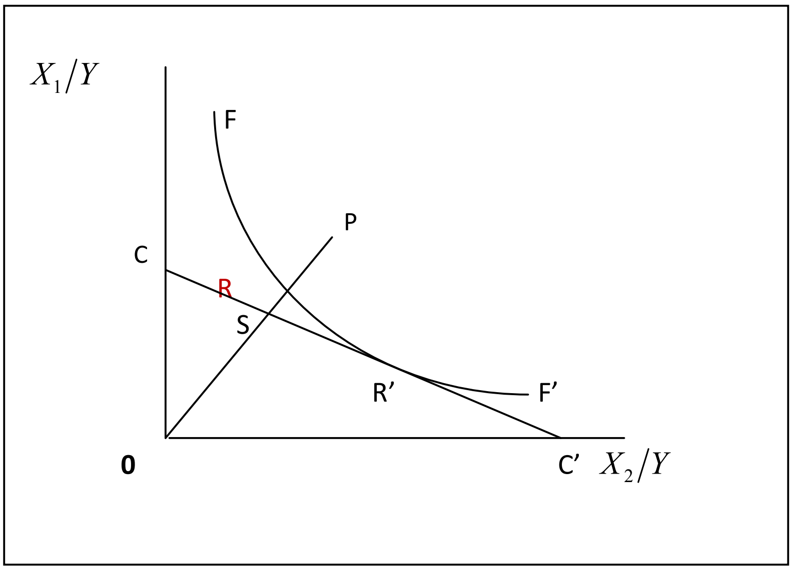
It is the distance between an observed producer and the empirical production frontier that has an interest for managers and policy makers. Managers of production units want to know their comparative efficiency to know their level of competitiveness, while government policy makers are interested in the efficiency level of production units to design policy supporting schemes or competition policies. Productivity and efficiency studies are now conducted in virtually every country. They are also conducted literally in every industry, both for profit and not-for-profit. Attention by researchers in building an empirical production frontier, from the performance of production units was started by the work of Debreu (1951), Koopmans (1951), and Farrell (1957).

The formal concept of efficiency in production is mentioned in Koopmans' paper (1951) in which he uses Pareto's equality concept to define the production efficiency as a situation in which, an increase in one or more outputs is impossible without an increase in at least one of the inputs or a decrease in at least one of the outputs. Koopmans (1951, pp. 60) defined that an efficient point in the commodity space is efficient *"whenever an increase in one of its coordinates can be achieved only at the cost of a decrease in some other coordinate"*. Debreu (1951) offered the first measure of efficiency of the economy with a coefficient of resource utilization. His coefficient is a radial measure of efficiency where it is the *"distance from the actually given complex of physical resources to the set of optimal complexes"* (Debreu, 1951, pp. 274).

However, the most substantial contributions to the development of efficiency measurement are attributed to Farrell (1957). In his paper, Farrell suggested that efficiency could be decomposed into technical efficiency and allocative efficiency. Technical efficiency is defined as **the ability of a firm to produce a maximum of outputs from a given set of inputs**. Meanwhile allocative efficiency is related to price levels, where inputs are used in optimal proportions in terms of costs. These two components are combined to give the overall efficiency of a firm. Farrell's idea of efficiency can be explained in terms of the following Figure 9. In his example, Farrell assumed that the firms involved use two inputs $X_1 \text{ and } X_2$ to produce one output Y (in other words, the production curve has normalized output to a unit). With his further assumption of constant returns to scale technology, Farrell was able to define the unit isoquant of the fully efficient firm. This unit isoquant FF' captures the minimum combination of inputs needed to produce a unit of output. The curve FF' establishes a de facto production frontier, where any combination of inputs needed per unit of output along the curve is seen as efficient technically.

If P is the combination of inputs the observed firm needed to produce a unit of output, then the measurement of technical efficiency is feasible by comparing the combination of inputs used by the observed firm to the projection point on the FF' curve. In the case of the observed firm with the combination of inputs P, technical efficiency of this firm is defined by the ratio OR/OP. And the distance RP represents the possible proportional reduction of inputs without any reduction of output produced by the observed firm.

Figure 9. Technical and allocative efficiency



Farrell argued further that if market prices are known and the input price ratio can be represented by the line CC' which is the locus of input levels that yield the minimum feasible cost of inputs to secure a unit of output. Then allocative efficiency of the observed firm operating at P is defined as OS/OR. The distance SR represents the possible reduction of production costs, which is made feasible by moving from the technically but not allocatively efficient combination of inputs R to the technically and allocatively efficient combination R'. And the overall efficiency of the observed firm is defined as the ratio OS/OP, which is the product of technical and allocative efficiency, $(OR/OP)(OS/OR)$, of the observed firm. Farrell's measures of efficiency are radial measures of efficiency.

The measures of technical, allocative and overall efficiency are made possible by the assumption that the production function of the full efficiency firm is known. However, this is not the case in reality. The methodology to estimate a production function is the very aspect that made the development of efficiency measurement to follow a non-parametric approach, or empirical function as suggested by Farrell in his seminal paper.

Historically, efficiency measurement discussed in Farrell (1957) was revitalized by the work of Charnes et al. (1978) and Färe and Lovell (1978) for non-parametric approaches and Aigner et al. (1977) and Meeusen and van den Broeck (1977) for parametric approaches with the introduction of stochastic frontier analysis. The works by Charnes et al. (1978) and Färe and Lovell (1978) are named deterministic frontier analysis since they attribute all the difference in production of an observed unit to the production frontier to technical inefficiency. Meanwhile the works by Aigner et al. (1977) and Meeusen and van den Broeck (1977) built a background for stochastic frontier analysis (SFA) since they attribute only a part of the difference in production of an observed unit to the production frontier to technical inefficiency. The remainder part of the difference is accounted for by the random noise originating from the production process.

It should be noted that there is a subtle difference between productivity and technical efficiency concepts. Productivity and technical efficiency are two related concepts, but should be differentiated. Thanassoulis (2001, pp.24) defines that *"technical (input) efficiency of a Decision Making Unit (DMU) is the maximum proportion any one of its efficiently contracted input levels is of the observed level of that input"*. This definition of technical efficiency follows the definition of Debreu technical efficiency. In other words, technical efficiency is the radial distance between the quantity of input and output that is used and produced by a production unit and the efficient frontier created by a group of production units in the same industry. Meanwhile, the productivity of a DMU as defined by (Lovell, 1993) is the ratio between its output and its inputs.

The following subsections give a brief review of the measurement of efficiency. Starting with deterministic methods, parametric approach to efficiency measurement developed to stochastic frontier analysis, which eliminated disadvantages of deterministic parametric methods in not accommodating random noise and in having a possibility for specification error in the formulation of production forms. The development of panel data allows estimation of technical efficiency, which is consistent in the presence of external variables. Then the other branch of efficiency measurement, non-parametric frontier, will be reviewed.

3.2.2 Parametric approach to technical efficiency measurement

Deterministic frontier

After the work by Farrell on efficiency measurement, there were a large number of authors who followed his idea to develop efficiency measurement methods in a parametric framework. Those authors started with the measurement of technical efficiency as a difference between the observed output and the theoretical output determined by a theoretical production function. Technical efficiency then is defined by the following formula:

$$(1) \qquad TE_i = \frac{y_i}{f(x_i, \beta)}$$

Where $i = 1,...,n$ are indexes of n production firms, TE_i is technical efficiency of the i-th firm, y_i is the observed output of the i-th firm, x_i is the inputs vector used by the i-th firm. $f(\bullet)$ is the production function in which theoretical output is determined, depending on two factors: inputs x_i and technological parameter β. It is obvious from this definition that $0 < TE_i \leq 1$. With the assumption of a Cobb-Douglas production function (in log form) and the assumption that all difference between observed and the theoretical potential output is attributed to technical inefficiency only, as proposed by Aigner and Chu (1968), the production frontier can be written as follows:

$$(2) \qquad \ln(y_i) = f(x_i, \beta) - u_i$$

Where notation is the same as above, and u_i is a non-negative variable presenting production inefficiency. Following the formulation above the estimate of technical efficiency of the i-th firm is:

$$(3) \qquad TE_i = \frac{y_i}{\exp\{f(x_i, \beta)\}} = \exp(-u_i)$$

Technical efficiency as defined above can be estimated using goal programming or econometric techniques. Aigner and Chu (1968), Timmer (1971), Forsund and Hjalmarsson (1979), Nishimizu and Page (1982) to name but a few followed goal programming techniques to derive the deterministic production function and estimate technical efficiency. In the aforementioned approach utilised by Aigner and Chu (1968), the parameters of the model were derived by using linear programming to solve the minimization problem of $\sum_{i=1}^{n} u_i \quad \text{s.t.} \quad u_i \geq 0$.

The development in econometrics theory and application allowed researchers to estimate technical efficiency using econometric techniques. Afriat (1972) developed a framework in which u_i were assumed to have gamma distribution and parameters in his model, which is similar to Aigner and Chu (1968) and can be estimated by the maximum likelihood method. Richmond (1974) specified a framework in which the parameters in Aigner and Chu (1968) were estimated by a new method, later named as **modified ordinary least squares** (MOLS). The method proposed by Richmond (1974) made an assumption about the distribution of the technical inefficiency component u_i. Most popular distributions were assumed including half normal, exponential, truncated normal and gamma. Another method, which is later named **corrected ordinary least square** (COLS) was also developed by Gabrielsen (1975) where the frontier estimated by ordinary least square (OLS) was shifted upward so that all corrected residual are nonpositive and at least one is zero. Different deterministic production frontiers as mentioned above, i.e. MLE, MOLS, COLS, are presented in Figure 10 in reference to the OLS estimation of production function.

Figure 10. Parametric frontier approaches

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Source: Lovell (1993)

COLS, MOLS, and MLE models are criticized by Lovell (1993) for inheriting disadvantages of both parametric and nonparametric models. They make no accommodation for noise and see all deviations from production frontier as technical inefficiency. They, therefore, share the same disadvantage with the nonparametric approach. Meanwhile, they establish production frontiers on certain functions, and face the problem of misspecification of production functional forms.

Stochastic Frontier Analysis

The stochastic production frontier is so named because a stochastic component is added to the function to account for the random noise originating from sampling error, measurement error, and specification error as usual in the economic analysis. In 1977 Aigner et al. (1977) and Meeusen and van den Broeck (1977) simultaneously proposed the stochastic frontier model. They added an error term v_i to the Aigner and Chu (1968) production function. With a Cobb-Douglas production form as provided in the aforementioned framework, the stochastic frontier model can be written as follows:

$$\ln(y_i) = f(x_i, \beta) + v_i - u_i \quad (4)$$

The error term v_i is assumed to be independent and identically distributed (i.i.d.), meanwhile the inefficiency component u_i is a nonnegative one-sided error that can take different distributions. The most frequently assumed distributions for the inefficiency term are half-normal, exponential, and truncated. Aigner et al. (1977) and Meeusen and van den Broeck (1977), however, could not decompose technical inefficiency from the composed error term $v_i + u_i$, and so they were not able to estimate technical efficiency for each firm. Rather they could estimate the mean technical efficiency over all firms in the sample. Individual technical efficiency of a firm could only be estimated by Jondow et al. (1982). They showed that with the half-normal distribution assumption of the technical inefficiency component, the expected value of u_i conditional on the composed error term is:

$$(5) \qquad E\left(u_i \middle| \varepsilon_i\right) = \frac{\sigma\lambda}{\left(1+\lambda^2\right)}\left[\frac{\phi\left(\varepsilon_i\lambda/\sigma\right)}{\Phi\left(-\varepsilon_i\lambda/\sigma\right)} - \frac{\varepsilon_i\lambda}{\sigma}\right]$$

Where $\varepsilon_i = v_i - u_i$, $\phi(\bullet)$ is the density of the standard normal distribution, $\Phi(\bullet)$ is the cumulative density function, $\lambda = \sigma_u/\sigma_v$, and $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$. The point estimate of u_i as presented above will be inserted to equation 3 to obtain the estimated of TE_i.

When each firm in the sample is observed more than once, we have panel data model, which is proved to have many advantages over the cross-sectional stochastic frontier model as noted above. Schmidt and Sickles (1984) specified such a production frontier as

$$(6) \qquad y_{it} = f\left(x_{it}, \beta\right) + v_{it} - u_i$$

Where $t = 1,\ldots,T$ is the time index. In the composed error term, technical inefficiency does not vary over time, while the noise term does. Schmidt and Sickles (1984) pointed out that with panel data, the assumption of distribution form of technical inefficiency component is not needed and all the parameters of the production frontier model can be estimated using normal fix-effects or random-effects model for panel data. Also the assumption that technical inefficiency component and input variables of the frontier model are independent is not necessary for the panel data, therefore we can introduce time-invariant variable to the model. The estimate of inefficiency term is still consistent according to Schmidt and Sickles (1984), therefore it opens the door for the study of impact of external variables on technical inefficiency (efficiency).

The Schmidt and Sickles (1984) model of time-invariant inefficiency can be modified to accommodate time varying inefficiency. Such a model was proposed by Cornwell et al. (1990). They replaced the one-sided firm effects of equation 6 with quadratic functions of time. The model can be presented as:

$$(7) \qquad Y_{it} = f\left(x_{it}, \beta_{0t}\right) + v_{it} - u_{it}$$

$$(8) \qquad Y_{it} = f\left(x_{it}, \beta_{it}\right) + v_{it}$$

Where β_{0t} is the common production frontier intercept to all cross-sectional productive units in period t. While $\beta_{it} = \beta_{0t} - u_{it}$ is the intercept of unit i in period t. The technical inefficiency component then of a firm i at the time period t is

$$(9) \qquad u_{it} = \Phi_{1i} + \Phi_{2i} t + \Phi_{3i} t^2$$

Where Φs are cross-section producer specific parameters. Battese and Coelli (1992) assumed that technical inefficiency follows an exponential function of time, instead of the original quadratic function of time considered by Schmidt and Sickles (1984), and have shown that only one additional parameter has to be estimated as in the following formulation:

$$(10) \qquad u_{it} = \delta(t) u_i = \left[\exp\left(-\eta\left(t-T\right)\right)\right] u_i$$

Where $u_i s$ are assumed to be i.i.d with truncated-normal distribution.

3.2.3 Non-parametric approach to technical efficiency measurement

Farrell in his paper (Farrell, 1957) developed a production possibility set based on a piece-wise convex hull of input-output vectors. This approach was followed by only a handful of researchers. In 1978 it was reformulated by Charnes et al. (1978) in which they propose a mathematic programming model and coined the term **data envelopment analysis** (DEA). Charnes et al. (1978) developed performance measures for DMUs with special reference to public programs by building an "**envelopment frontier**". It measures the relative efficiencies of DMUs, given multiple inputs and outputs consumed and produced by DMUs. They proposed a relative performance of weighted outputs to weighted inputs in which production is under constant returns to scale.

Starting with the ratio form of the measurement of technical efficiency where we would like to have the ratio of all outputs over all inputs as a measure of technical efficiency, Charnes et al. (1978) formulation of the multiple inputs and multiple outputs case can be seen as a reduction to a virtual single output and virtual single input, by which the measurement of technical efficiency via ratio form is made possible. We have $\text{Efficiency} = \frac{\text{output}}{\text{input}}$ in a single input and a single output case. While in the case of a DMU which has multiple inputs and outputs, the real world case, efficiency can be measured as: $\text{Efficiency} = \frac{\text{Virtual output}}{\text{Virtual input}}$

Where virtual output and virtual input are weighted sum of outputs and weighted sum of inputs, respectively, produced and used by that DMU.

$$\text{Virtual Input} = \sum_{i=1}^{m} v_i x_i$$

$$\text{Virtual Output} = \sum_{r=1}^{s} u_r y_r$$

where:

x_i: amount of input i

y_r: amount of output r

v_i: the weight given to input i

u_r: the weight given to output r

m: number of input

s: number of output

In the case of comparing efficiency between a set of DMUs this is a difficult task since we have to define a set of weights. The approach proposed by Charnes et al. (1978) that originated the nonparametric measurement of efficiency is to solve the following model:

$$\max \quad \theta = \frac{\sum_{r=1}^{s} u_r y_{rj_o}}{\sum_{i=1}^{m} v_i x_{ij_o}}$$

$$\text{subject to:} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad j = 1,...,n \tag{11}$$

$$u_r, v_i \geq 0. \quad \forall r, i$$

In the above model the efficiency of unit j_0 is defined and maximized with constraints that efficiencies of other units in the set subject to an upper bound of 1 (or 100 percent). The model also finds solutions for input and output weights, v_i and u_r, used for calculating efficiency. They are chosen so that the efficiency of the targeted unit j_0 is maximised. The unit j_0 will be either efficient with its efficiency equals 1 or inefficient when its efficiency is less than 1.

The model (11) is a fractional linear model and is transformed into linear form. With its linear form, linear programming methods can be used and the linear programming model of Charnes et al. (1978) (CCR model) is presented as follows: [14]

[14] There are changes in notation since it is a different linear program, that is transformed from the original problem to avoid the problem of infinitive number of solutions. Detailed analysis can be found in

$$
\begin{aligned}
(12) \qquad & \max \quad \theta = \sum_{r=1}^{s} \mu_r y_{ro} \\
& \text{subject to} \quad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1,\ldots,n \\
& \qquad \sum_{i=1}^{m} v_i x_{io} = 1 \\
& \qquad \mu_{r,} v_i \ge \varepsilon \succ 0. \quad \forall r, i
\end{aligned}
$$

This is also called the multiplier form of the linear programming problem. The duality of linear programming allows one to derive the so called envelopment form of this problem (Cooper et al., 2006):

$$
\begin{aligned}
(13) \qquad & \min \quad \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
& \text{subject to} \quad \sum_{j=1}^{n} x_{ij} \lambda_j = \theta x_{ijo} - s_i^-, \qquad i = 1,\ldots,m \\
& \qquad \sum_{j=1}^{n} y_{rj} \lambda_j = y_{rjo} + s_i^+. \qquad r = 1,\ldots,s \\
& \qquad 0 \le \lambda_j, s_i^-, s_r^+. \quad \forall j, i, r \quad j = 1 \ldots n \\
& \qquad \varepsilon \text{ is a vanishingly small positive number}
\end{aligned}
$$

The nonparametric approach to efficiency analysis presented above is attractive due to its minimal data requirements and considerable flexibility. Moreover, additional information obtained from DEA models beyond the efficiency measure is also useful. Thanassoulis, Dyson and Foster (1987) stated that DEA can be efficiently used for initially differentiating efficient and inefficient DMUs. More importantly, DEA can be used to identify aspects, which can be further investigated for improving operations of units. Therefore, DEA can also be used for setting performance targets, which can be achieved by inefficient units and identifying aspects that can be strengthened by efficient units in order to further improve their efficiency.

COOPER, W. W., SEIFORD, L. M. & TONE, K. 2006. *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*, Springer Verlag.

DEA is seen as owning advantages over the traditional use of regression analysis for performance measurement. Thanassoulis (1993) compared DEA with regression analysis as alternative methods for performance assessment. He showed that DEA and regression analysis differ fundamentally in estimating the marginal input or output values. DEA compares each DMU with only the "best" DMUs of the sample while regression analysis estimates the average level of performance for DMUs. On the other hand, traditional DEA analysis has the limitation of being non-parametric, so statistical tests are not possible. Moreover, prediction by regression analysis on future performance under assumption that inefficiencies cannot be eliminated is more accurate (Thanassoulis, 1993).

Empirically, for DEA to be discriminating on efficiency, Thanassoulis et. al (1987) suggested that numbers of inputs and outputs should be as small as possible relative to the number of DMUs, subject to reflecting the function performed by the units being assessed. In search for better application of DEA, Thanassoulis and Dyson (1992) suggested a model using DEA for estimating performance targets, where inefficient units are shown the way to improve efficiency when they have varying preferences over inputs and outputs that are to improve.

There are several limitations with the Charnes, Cooper, and Rhodes (1978) model. They assumed constant returns to scale, which is not always the case in reality. The model suffers from the fact that efficiency of productive organisations changes when their size changes. This assumption is relaxed in Banker et. al. (1984), which makes the method even more popular and is introduced below. Several improvements in practical aspects of DEA applications, including the replacement of the constant returns to scale assumption by variable returns to scale, are reported in Boussofiance, Dyson and Thanassoulis (1991). The practical aspects of choosing inputs and outputs for a DEA model are also considered in their paper. The use of DEA in managing performance using DEA is also reported, where possible uses of DEA include using peer groups, target setting, identifying efficient operating practices, and identifying efficient strategies, monitoring efficiency changes over time and resource allocation.

The model of variable returns to scale as proposed by Banker et. al. (1984) and named in literature of nonparametric efficiency measurement as BCC is as follows:

$$\begin{aligned}
&\min \quad \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
&\text{subject to} \quad \sum_{j=1}^{n} x_{ij}\lambda_j = \theta x_{ijo} - s_i^-, \qquad i = 1,\ldots,m \\
&\sum_{j=1}^{n} y_{rj}\lambda_j = y_{rjo} + s_i^+. \qquad r = 1,\ldots,s \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&0 \le \lambda_j, s_i^-, s_r^+. \quad \forall j, i, r \quad j = 1 \ldots n \\
&\varepsilon \text{ is a vanishingly small positive number}
\end{aligned} \tag{14}$$

Under variable returns to scale, the technical efficiency now can be decomposed into pure technical efficiency and scale efficiency and can be expressed as follows:

*BCC efficiency = CCR efficiency * Scale Efficiency*

The convexity of the production frontier of DEA is relaxed by Deprins et al. (1984) by introducing FDH (Free Disposal Hull). FDH is a general DEA model, in which DEA estimators are estimated with a free disposability assumption. The maximization orientation of the DEA model was also developed even free from orientation as in the additive model proposed by Ali and Seiford (1993).

DEA models have also been developed to accommodate efficiency in the presence of prices. The models identify the optimal combination of inputs given the input prices. This development made DEA even more popular with economists.

One serious disadvantage of non-parametric approaches compared to the parametric ones is their deterministic nature. This makes the generalisation of results of a sample obtained from DEA to the population of units difficult. In other words, DEA is seen as a non-statistical method. Several authors have tried to overcome this problem by using bootstrapping techniques. Ferrier and Hirschberg (1997) were first to use a bootstrapping technique to introduce a stochastic element into the Farrell measure of technical efficiency. In this approach efficiency scores obtained through DEA techniques were bootstrapped to derive confidence intervals and level of bias. However, the Ferrier and Hirschberg bootstrapping technique is criticised by Simar and Wilson (1999). Simar and Wilson (1999) showed by a simple example that estimates by Ferrier and Hirschberg bootstrapping techniques are inconsistent. They instead introduce their own bootstrapping method for technical efficiency scores, which have become a standard method for studies aiming at building a confidence interval for the estimated DEA efficiency scores (Simar and Wilson, 1998).

Another issue related to deterministic non-parametric measures of technical efficiency is that the efficient production frontier can be seriously affected by outliers. When outliers are on the frontier, they will affect the accuracy of estimates of technical efficiency for other units, since they become reference sets for the whole sample. In an effort to deal with the robust extreme value in frontier analysis, Cazals et al. (2002) developed a framework which does not envelop all the data points. Using a probabilistic formulation, Cazals et al. (2002) showed that by withdrawing m random DMUs the partial frontier efficiencies are robust to extreme value. Daraio and Simar (2005) develop this approach for the multivariate case, along with the use of conditional frontier for explaining the impact of external variables, which are factors able to affect the production but are neither inputs or outputs nor controlled by DMUs

Concerning the choice of parametric and non-parametric approaches to technical efficiency analysis, Lovell (1993, pp. 19) stated that: "*neither approach strictly dominates the other*". This thesis, however, is biased in terms of its approach to deal with its main research questions. It utilises the **non-parametric approach** as its main engine for the investigation of the impacts of dichotomous nondiscretionary variables on technical efficiency. The choice of a non-parametric approach is made assuming advantages of non-parametric approach over the parametric ones. Thanassoulis (1993) concluded the following advantages of DEA over the parametric regression analysis:

- There is no need for the stipulation of a mathematical form for the production function.

- It measures performance against efficient rather than average performance. Therefore, the comparison is more meaningful than the average comparison by regression.
- It is an advantage of DEA in dealing with multiple inputs and multiple outputs in performance measurement. It is also an advantage over regression analysis by identifying the nature of returns to scale and the sources of inefficiency.
- DEA offers more accurate estimates of relative efficiency, and of marginal values of inputs or outputs. It offers efficient rather than average marginal values of inputs and outputs, which is obviously more information content in terms of efficiency comparison than regression analysis. DEA allows for variable marginal values for different input-output mixes.
- Marginal values estimated by DEA are not faced with the problem of multi-colinearity or strong correlations between explanatory variables, which can be very serious issues of regression analysis.
- Since it is a boundary method, DEA offers more appropriate individual targets where outputs or inputs cannot vary independently of one another.

The limitations of non-parametric approaches have been overcome thanks to recent developments in DEA literature. Its extreme sensitivity to outliers has been controlled efficiently by the partial frontier order-m approach proposed by Cazals et al. (2002) and developed by Daraio and Simar (2005). Its non-statistical characteristics are remedied by bootstrapping methods proposed by Simar and Wilson (1998). Therefore, it is natural given the chosen approach to focus on non-parametric approach in analysing external variable impacts in the following section.

3.3. Nonparametric Approaches in Analysing Exogenous Variable Impacts

Technical efficiency is measured for the two reasons. Firstly, it plays as an objective performance indicator for ranking productive units operating in the same industry. Secondly, the question that interests all researchers after a measurement of technical efficiency levels is how various exogenous factors influence the technical efficiency of operating units (DMUs) (Lovell, 1993). This is in fact an important and interesting question since it will give researchers and policy makers the power to change the current situation of technical efficiency of a DMU. It is one of the factors that make the analysis necessary. Exogenous variables also commonly referred to as non-discretionary or uncontrollable, environmental variables are factors that DMUs have no control over. They can be classified into two types: variables which have direct influence on the production hence the technical inefficiency, and variables that are able to influence production indirectly. Exogenous variables that have direct influence on technical inefficiency, called by Thanassoulis et al. (2008) as *internal factors*, can be used in defining the production possibility set (PPS). Exogenous variables with indirect influence on technical inefficiency such as program or policy governing the units, ownership status of units, etc., which are called *external factors* by Thanassoulis et al. (2008). Both types of variable can have a very important impact on the production process and hence technical inefficiency but cannot necessarily be used in defining the PPS.

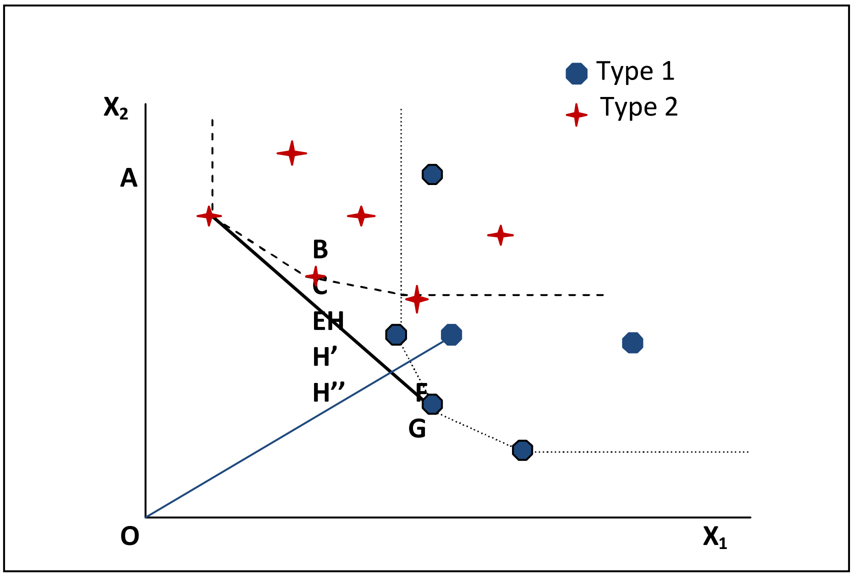
During more than 30 years of development of nonparametric measurement of technical efficiency, there are various approaches that have been put forward for examining the effect of exogenous (contextual or environmental) variables on the technical efficiency of DMUs. Generally speaking, approaches to identifying the impacts of exogenous variables on technical efficiency of DMUs can be classified in five groups. The first four groups are coined by Fried et al. (1999) and the fifth group is a newly developed approach. The first family of models, which is also the oldest non-parametric approach to exogenous variable impacts on technical efficiency, is the frontier separation approach. The approach was proposed by Charnes, Cooper, and Rhodes in their 1981 paper on the 'Follow Through Program'. The second family of models is the all-in-one approach which is used in Banker and Morey (1986a), Banker and Morey (1986b) and Ruggiero (1996). The next family of the models is the two-stage approach that is the combination of non-parametric techniques conducted in estimating technical efficiency first and a second stage parametric technique, which is used to identify the relationship of the technical efficiency to different environmental factors. The multi-stage approach is another family of models for analysing the impacts of environmental variables on technical efficiency in which information about the environmental variables is obtained from the first stage and the model is improved by including this information in subsequent steps (see Ruggiero (1998), Fried et al. (1999), Muñiz (2002). Finally, recently, there is a novel approach proposed firstly by Cazals et al. (2002) and applied by Daraio and Simar (2005) and generalized in Daraio and Simar (2007a). The idea of the approach is to incorporate environmental variables into a conditional frontier, which is established in a probabilistic formulation of the production process. The following sections will discuss in detail these approaches.

3.3.1 Frontier separation approach

The frontier separation approach was first used by Charnes et al. (1981). In this approach exogenous variables can influence the production process indirectly, which are usually perceived as environmental factors for the production of DMUs. In Charnes et al. (1981), it is the Program Follow Through conducted in education as the exogenous variable[15]. The impact of a single categorical variable - Program Follow through - on technical efficiency is estimated by stratifying the entire dataset according to the single categorical variable then performs efficiency assessment within the different groups. There are three steps involve in the approach. At first managerial efficiency of unit within each group of DMUs is estimated using DEA. Then the efficient targets of each inefficient DMU are estimated and the DMU is **projected** so that all the resultant observations will be on the frontier of the group of DMUs concerned. Lastly the efficient targets are pooled across all groups and evaluated by final DEA model. The efficiency at this stage is termed Programme as being attributable to the programme of the DMU rather than its management. The approach by Charnes et al. (1981) can be illustrated in the following figure, where there are two types of schools: type 1 including schools attending Follow Through program, and type 2 including schools not attending Follow Through program.

[15] Program Follow Through is a large scale social experiment applied to public schools in the US. It was conducted from 1966-1977 aiming at helping disadvantaged children in their pre-school education to obtain significant cognitive and non-cognitive gains.

Figure 11. Input-Oriented Frontier Separation Approach



The frontier separation approach starts by grouping type 1 and type 2 schools, in which observations E, F, G form the efficient frontier for type 1 schools and observations A, B, C form the efficient frontier for type 2 schools. In this context, H is a school of type one, and its managerial efficiency score will be estimated by comparing it with its projected school, H', which is located in the efficient surface of type 1 group, and it is OH'/OH. In frontier separation approach all the schools (observations) will be projected on the efficient surfaces of their own groups respectively. Then all the **projected** observations are pooled to form a sample of schools which has the envelopment surface created by A, F and G in the above figure. This pooled data is used by Charnes et al. (1981) to determine the "program efficiency", which is OH''/OH'.

The Charnes et al. (1981) approach has spawned a sequence of DEA models, which add various statistical tests with the aim of separating program efficiency i.e. the influence of exogenous variables. Byrnes et al. (1986) followed the Charnes et al. (1981) approach by using two sample mean and Wilcoxon test to determine the impact of ownership on the performance of water utilities. Following this approach, Grosskopf and Valdmanis (1987) applied the Mann-Whitney test to confirm that the two samples of for-profit hospitals and not-for-profit hospitals have different distributions of their programme efficiencies. The use of the Mann-Whitney test is also followed by Brockett and Golany (1996).

The program efficiency as defined by Charnes et al. (1981) is also derived by decomposing overall efficiency, which is the approach proposed by Fizel and Nunnikhoven (1992) and Portela and Thanassoulis (2001). Their approach derived between-group (or program) efficiency by solving two DEA models. The first DEA model is to estimate within-group (or managerial) efficiency for each group of DMUs. The second is to estimate "overall efficiency", which is the performance of each DMU in the pooled dataset. The program efficiency is then derived from the following formula:

Overall Efficiency = Managerial Efficiency x Program Efficiency

In the analysis framework of Figure 11, the formula for estimating program efficiency of DMU (school) H will be:

$$\text{Program Efficiency} = \frac{\text{Overall Efficiency}}{\text{Managerial Efficiency}}$$

$$\Leftrightarrow$$

$$OH''/OH' = \frac{OH''/OH}{OH'/OH}$$

Conceptually the Charnes et al. (1981) approach is preferred since it compares only the efficient parts of the PPS boundaries of two DMU groups (Thanassoulis et al., 2008). But the Fizel and Nunnikhoven (1992) and Portela and Thanassoulis (2001) approaches are less time-consuming and more direct which is advantage for simulation as we proceed further in this study.

Up to now the frontier separation approach and the two-stage approach as presented later have been the only approaches that are possible to deal with the impact of exogenous variables that take the dichotomous form in DEA. However, the frontier separation approach faces some problems. Firstly, this approach assumes that evaluated DMUs are different only because of the influence of the program they belong to. It does not take into account the selection bias in which DMUs may choose to participate to a program or policy at their discretion. The self-selection into a program or policy in fact can bias the estimated level of influence of a program or policy. This issue will be discussed in more detail in the following chapter of the thesis. Secondly, the result of the frontier separation approach can be biased if the groups have different size, which is an often-accounted real life fact in program or policy impact evaluation. It is obvious from the DEA literature that the discrimination power of the DEA model is changed when its sample size changes. The different sample sizes also invalidate the statistical tests (Wilcoxon, Mann-Whitney) usually used in comparison with the frontier separation approach (Simpson, 2007). Simpson (2007) argues that the process of projecting inefficient DMUs to the efficient frontiers to eliminate the managerial inefficiency depends on how the efficient DMUs of the two programmes (in the context of frontier separation approach) are distributed. However this projection process is not equally effective since programme with fewer DMUs will be biased with more managerial inefficiency. The Mann-Whitney test that follows therefore is biased.

3.3.2 All-in-One approach

The second approach is the all-in-one approach, which allows both non-discretionary and categorical external variables to define the PPS. The exogenous variables are incorporated directly into the definition of the production possibility set and are treated in the model in such a way that they are kept in their current level while non exogenous (i.e. traditional) inputs or outputs reduce or increase in the input or output oriented framework respectively. The non-discretionary variables influence the position of the frontier through the reference set constraints. The first model of all-in-one approach was proposed by Banker and Morey (1986a), which applies for variable returns to scale production technology with input orientation:

$$\min \quad \theta$$

$$\text{subject to:} \quad \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \quad r = 1,...,s$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \quad i = 1,...,m \tag{15}$$

$$\sum_{j=1}^{n} \lambda_j z_{kj} \leq z_{ko}, \quad k = 1,...,t$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0$$

where: n is the number of DMUs in the data set
s is the number of of outputs
m is the number of controllable inputs
t is the number of uncontrollable inputs
y_r, x_i, z_k are outputs, controllable inputs and uncontrollable inputs, respectively

The above model is very similar to the original BCC DEA model under variable returns to scale, except for the constraint on the uncontrollable inputs z. Even thought the uncontrollable inputs are fixed and do not directly enter the estimation of the efficiency score θ, they can affect indirectly efficiency scores through their influence on the parameters λ_j. Particularly, it requires the virtual reference unit to utilise no more of the uncontrollable inputs than the DMU under evaluation. The Banker and Morey (1986a) model is extended by Golany and Roll (1993) to accommodate simultaneously both non-discretionary inputs and outputs and partially controlled factors. The Banker and Morey (1986a) model however does not restrict the reference set enough to reflect the impact of exogenous variables on the performance of the DMU under assessment. In particular, by assuming convexity of the uncontrollable inputs, Banker and Morey model may underestimate the level of technical performance of DMUs (Ruggiero, 1996, Ruggiero, 1998). Muñiz (2002) pointed out that the Banker and Morey (1986a) model leads to two doubtful results: (i) the production frontier is exactly the same as the one in which all inputs have been considered as controllable, and (ii) when some inputs are considered as non-controllable as proposed in Banker and Morey (1986a) model, the inefficient DMUs will have their efficiency scores lower in comparison to the original BCC model. Yet the Pareto efficient units do not have their efficiencies affected through the presence of uncontrollable factors.

Ruggiero (1996) proposed another all-in-one model which shares the same logic as the Banker and Morey (1986a) model when the evaluated DMU will be compared only to DMUs that are in the same or hasher production environment on the basis of the exogenous variable. DMUs with a more favourable environment in comparison with the evaluated DMU will be excluded from the reference set. The Ruggiero (1996) model for input oriented under variable returns to scale assessments is as follows:

$$
\begin{aligned}
&\min\ \theta \\
&\text{Subject to:} \quad && \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, && r = 1,\ldots,s \\
& && \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, && i = 1,\ldots,m \\
& && \lambda_j = 0 \quad \text{if} \quad z_{kj} < z_{ko}, && k = 1,\ldots,t \\
& && \sum_{j=1}^{n} \lambda_j = 1 \\
& && \lambda_j \geq 0
\end{aligned}
\tag{16}
$$

where:
n is the number of DMUs in the data set
s is the number of of outputs
m is the number of controllable inputs
t is the number of uncontrollable inputs
y_r, x_i, z_k are outputs, controllable inputs and uncontrollable (non-discretionary) inputs, respectively
z_{ko} is the non-discretionary variable z_k of the evaluated DMU_o and the larger the z value is, the harsher the production environment

As in the Banker and Morey (1986a) model, the Ruggiero (1996) model faces the same weakness. It requires prior knowledge of whether the environmental variables should be included into the model as input or output. Therefore it could not be used in cases where direction of impacts is unclear. Moreover Ruggiero (1998) shows that the Ruggiero (1996) model will increase the possibility of a DMU falling into reference set as the number of exogenous variables added into the consideration increases. This happens because comparison between the analysed DMU and another DMU will be abandoned if the DMU being assessed has at least one less favourable exogenous variable, regardless of the fact that other exogenous variables of the assessed unit may be in its favour. These weaknesses of the all-in-one approach are overcome by the alternative two-stage approach as presented next.

3.3.3 Two-stage approach

The next family of models is the two-stage approach that is the combination of a non-parametric technique used for estimating technical efficiencies and a parametric technique, which is used in identifying the relationship of the technical efficiency to different environmental factors. In the first stage, technical efficiency is determined by DEA. Then the DEA estimators are regressed in the second stage on the uncontrollable factors. This approach is seen as a solution to the existence of noise and in capturing the impact of variables, which are not included in the DEA estimation.

Ray (1991) was the first to apply the two-stage approach in the context of DEA. Ray (1991) believed that exogenous factors should not be included in the DEA model for estimating efficiency scores. Rather they should be analysed afterwards by regression analysis. In the regression stage, efficiency scores estimated by DEA will be the dependent variable, while exogenous variables play the role of independent variables. An adjustment is made by adding the largest positive residual to the intercept to arrive at predicted efficiency scores and make sure that predicted efficiency scores always larger than DEA-estimated efficiency scores. Ray (1991) model is as follows:

$$\theta = \alpha + \beta_1 z_1 + \beta_2 z_2 + ... + \beta_s z_s + \varepsilon \quad (17)$$

where: θ is DEA-estimated efficiency score
z are external variables
β_s are parameters for the impact of external variable z_s on θ
ε is the random noise

The difference between adjusted predicted efficiency scores obtained from regression analysis and DEA-estimated efficiency scores is interpreted by Ray (1991) as the "*extent of managerial efficiency not caused by external factors*." The issue with the Ray (1991) model is that predicted efficiency scores obtained from regression analysis may be larger than 1. Moreover the dependent variable in the regression analysis is bound between 0 and 1 or 0 and 100. Therefore McCarty and Yaisawarng (1993) proposed to use a truncated regression – Tobit model – in the second stage of the analysis.

The two-stage approach is used widely in many empirical studies (e.g. see Simar and Wilson (2007)). The advantage of the two-stage approach is that it reveals both direction and significance of impact of exogenous variables on technical efficiency. Researchers are free from determination of direction of impact of external variables on technical efficiency. The two-stage approach can be applied to continuous, categorical, or dichotomous data.

The disadvantage of most second-stage approaches is that information from the slacks of DEA are not exploited, which may cause bias to estimators in the regression in the second-stage. Fried et al. (1993) try to solve this weakness by using a seemingly unrelated regression (SUR) in the second stage of analysis, in which radial and non-radial slacks and surpluses are dependent variables. One problem of the two-stage approach is the possible correlation of the explanatory variables in the regression analysis and inputs and/or outputs used for the estimation of DEA efficiency scores in the first stage. Also the approach suffers from a serious problem, which is the violation of the regression assumption in the second stage. Since efficiency scores are arrived by mathematical programming in the first stage, they do not have a clear data-generating process, and there are a serial correlation between estimated efficiencies (Simar and

Wilson, 2007). Moreover, there is also possible correlation between the DEA inputs and/or outputs with independent variables used in the regression stage (Thanassoulis et al., 2008). Therefore bootstrapping technique is needed in the second stage of analysis.

3.3.4 Multiple-stage approach

The multi-stage approach is another family of models for analysing the impacts of environmental variables on technical efficiency. The regression analysis in the two-stage approach helps to adjust the efficiency scores of the inefficient DMUs only, while keeping the reference set unchanged. The three-stage model is proposed by Ruggiero (1998) to overcome this weakness in the two-stage approach. Following Ray (1991), Ruggiero (1998) used only discretionary inputs and outputs in the first stage, where efficiency scores are estimated by DEA by comparing to the efficient frontier without consideration of exogenous variables. Then a regression of efficiency scores against exogenous variables was taken as in the two-stage approach. However, the purpose of the regression is to build an overall environmental index for exogenous variables, which is a scalar indicator for multi exogenous variable. The index is estimated as a sum of all parameters of exogenous variables derived from the regression:

$$Z = \sum_{i=1}^{s} \beta_i z_i \tag{18}$$

where: Z is overall index of exogenous variables

z_i is exogenous variable *i*th

β_i is the parameter of the *i*th exogenous variable derived from the following regression:

$$\theta = \alpha + \beta_1 z_1 + \beta_2 z_2 + \ldots + \beta_s z_s + \varepsilon$$

(regression in the two-stage approach)

After the index is estimated, it will be incorporated into the following linear program (input-oriented, variable returns to scale) as a constraint to derive adjusted efficiency score and reference set for each DMU in analysis.

$$
\begin{aligned}
&\min \ \theta \\
&\text{subject to:} \quad \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \qquad r = 1,\ldots,s \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \qquad i = 1,\ldots,m \\
&\lambda_j = 0 \quad \text{if} \quad Z_j \leq Z_o \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq 0
\end{aligned} \tag{19}
$$

where: n is the number of DMUs in the data set
s is the number of outputs
m is the number of controllable inputs
y_r, x_i are outputs, controllable inputs and uncontrollable input, respectively
Z is the overall index of exogenous variables

An alternative three-stage model for analysing the impacts of environmental variables to technical efficiency is proposed by Muñiz (2002). In this model, information from slacks and surpluses in DEA models is taken into account. The Muñiz (2002) model is similar to the two-stage model and the Ruggiero (1998) model where in the first stage, only discretionary inputs and outputs are considered in the DEA estimation of technical efficiency. The total slack for each DMUs arrived at during the first stage will be, along with exogenous variables, included in a linear program to calculate "slack that each producer (DMU) would obtain for each variable if it were technically efficient" (Muñiz, 2002). With the estimated slack as mentioned above, the original slack obtained in the first stage will be decomposed into: (i) the true technical inefficiency, and (ii) influence of exogenous variables, in the third stage.

Fried et al. (1999) proposed a four-step procedure to separate the managerial effect from the effects of external variables on technical efficiency. This multi-step procedure is as follows: (i) estimate traditional DEA efficiency scores; (ii) total slacks or surpluses including both radial and non-radial slacks or surpluses are now dependent variables in regressions, in which independent variables are variables characterizing the operation environments. Slacks or surpluses of each input or output are regressed sequentially; (iii) parameters from the aforementioned regressions are used to predict the "allowable" slacks or surpluses for each input or output. These predictions are used to adjust original inputs and outputs so that influence of external environment is accounted for; (iv) DEA model is run again to isolate the managerial effects on efficiency scores.

As described in Fried et al. (1999), this approach can be seen as an extension of the two-stage approach, and has the following advantages: (i) estimation of managerial efficiency with conventional interpretation; (ii) heritage of the advantage of the two-stage approach in not requiring in advance the direction of the impact of external variables; (iii) statistical test of the influence of external variables on efficiency scores can be conducted; (iv) information from slacks and surpluses generated in the first-stage analysis is exploited.

The two- and multiple-stage approaches are based on the assumption that environmental variables would only influence technical efficiency level, but not input and output levels. This assumption is generally not applicable in several cases where environmental variables not only influence technical efficiency levels but also inputs and outputs used for production.

3.3.5 Conditional frontier approach

Recently, there is a novel approach proposed firstly by Cazals et al. (2002) and applied by Daraio and Simar (2005) and generalized in Daraio and Simar (2007a). The idea of the approach is to incorporate environmental variables into a so-called conditional frontier, which is established through a probabilistic formulation of the production process. The production process in Cazals et al. (2002) can be described by a joint probability measure of inputs and outputs. The efficiency measure therefore can also be presented in the probability framework and environmental variables can be incorporated into the framework by letting the production process be conditional on the environmental variables.

In the probabilistic framework, the support of a product combination where a productive unit operates can be written as follows:

$$(20) \qquad H_{XY}\left(x, y \middle| z\right) = \Pr\left(X \leq x, Y \geq y \middle| Z = z\right)$$

where x is the input vector including p components, $x \in \Re_{+}^{p}$, and y is the output vector including q components, $y \in \Re_{+}^{q}$, and z is external variable. ψ is (unconditional) production set established by x and y, $\psi = \left\{(x, y) \middle| x \in \Re_{+}^{p}, y \in \Re_{+}^{q}\right\}$. The aforementioned support defines the conditional production set ψ^{z}. Where

$$(21) \qquad \psi^{z} = \left\{(x, y') \in \Re^{p+q} \middle| y' \leq y^{\partial,z}(x), (x, y) \in \psi\right\}$$

In which $y^{\partial,z}(x) = \theta\left(x, y \middle| z\right) y$ and $(x, y) \in \psi$. The aforementioned joint probability of (x, y) is decomposed into survival function for the output and density function for input. The condition $Z = z$ requires the use of Kernel function $K\left((z - z_i)/h\right)$, where $K(\bullet)$ is a kernel function of compact support such as Epanechnikov, rectangular or quadratic kernel, and h is the bandwidth of the kernel (Daraio and Simar, 2005).[16]

The aforementioned *conditional frontier* as named by Cazals et al. (2002) overcomes the issue of prior knowledge on directional effects of the environmental variables. However, the model is built to deal with the continuous environmental variables only. It also heavily relies on the bandwidth to estimate the nonparametric kernel functions for selecting the appropriate reference set. The approach used by Daraio and Simar (2005) used the cross-validation k-nearest neighbour technique for estimating the bandwidth, in which the influence of external variables on the production process is not taken into account. Recently, De Witte and Kortelainen (2009) proposed to use conditional frontier with mixed kernel function to deal with both continuous and discrete external variables. They look into the impact of variables external variables on the performance of pupils in the UK. It is large improvement from Daraio and Simar (2005) and can be modified with

[16] Please see detailed discussions about conditional frontier approach in Chapter 5.

deal with self-selection problem and dichotomous external variable, which will be dealt with in this thesis.

3.4. Conclusion

The choice for a researcher to analyse the case where external variables enter the context as a dichotomous variable (variable presented as 0 and 1), such as joining a supporting program of the government in our case, is limited. Most of the above mentioned approaches are designed for continuous variables and so are not suitable for zero-one external variables. It is unambiguous from the literature that only two possible approaches can be applied to dichotomous external variables of this kind. Firstly it is the frontier separation approach as proposed by Charnes et al. (1981), which divides the observations into two samples corresponding to their programs. Secondly the two-stage approach can be applied by adding the dichotomous external variable as an explanatory variable in the second stage regression.

The common problem faced when using the aforementioned approaches to examine the impacts of policies from the government is that all of them do not take into account the selection bias. Selection bias in general happens when a sample is not drawn according to some prearranged specification. In other words, observations within a given group have different probabilities of belonging to that due to their different characteristics. The results, if allowance is not made for this, are likely to be biased. As highlighted by Wei and Charles (2006) that *"if no adjustment is applied, estimates based on the sample are likely to be biased"*. In analysing the influence of external variables on technical efficiency, the case of policy impact can be subject to selection bias. This is due to the fact that treated DMUs - DMUs who enjoy preferred treatment by joining in some programs - can have characteristics which make them having different probability to join the program. At the same time, these characteristics can influence efficiency levels of evaluated DMUs.

The literature on impact of external variables to efficiency scores shows that the choice for approaches used for analysing dichotomous external variables in DEA is very limited. Moreover, with the selection bias there is real need for new methods to the issues of impact of dichotomous external variable to efficiency scores. It is the very task of the thesis to develop a new method to deal with the mentioned problem. Chapter 4 and 6 of the thesis will propose these methods in details.

Chapter 4. Frontier Separation Approach and Propensity Score

4.1. Introduction

This chapter discusses a research strategy in which the main problem of the thesis will be investigated. The research methodologies developed in this thesis will establish a solid ground for the empirical analyses presented in the subsequent chapters. The chapter begins with a review of the problem of policy evaluation, which is the very nature of the investigation of the thesis. It then goes on with the set up of a theoretical model, in which the central problem of the thesis is highlighted and solved theoretically. To prove the ability of the theoretic model as well as its advantages in solving the specific problem a simulation will be built. The strategy in this part is to set up a Monte Carlo type of simulation, which will be utilised to generate artificial data for the research, and then the theoretic model will be applied and tested for its validity. Methodological issues in production function setting, selection bias combination, and propensity score projection will be clarified in this chapter. The results of the analysis will also be presented in this chapter. A summary of issues and problems solved will conclude the chapter.

4.2. Policy Evaluation and Classical Problem of Selection Bias

The main theme of the thesis is to examine the impacts of external variables on the technical efficiency of SMEs. Particularly we are interested in analysing the impact of government policies on the performance of SMEs. Let us assume that enterprises participate in a program supported by the government in order to improve their export performance. This obviously has some effects on the general performance of the enterprises. If we would like to evaluate the impact of the program then the best way is to compare two potential outcomes, one with the treatment (Y_1) and the other without treatment (Y_0). Then the difference between the performance of treated enterprises and non-treated enterprises $\Delta_i = Y_{i1} - Y_{i0}$ will tell us whether the program works or not.

However, there is a serious problem with this kind of comparison. We can only observe one specific enterprise in one situation, either treated or non-treated. In other words we cannot observe both Y_0 and Y_1 for the same enterprise. The unobservable potential outcome is called the counterfactual outcome. Suppose that $D=1$ means the enterprise is treated, and $D=0$ means otherwise, then the observed response for the treatment will be formulated as follows:

$$(22) \qquad Y_i = D_i Y_{i1} + (1 - D_i) Y_{i0}$$

This fundamental problem of evaluation exercise is treated by Heckman et al. (1998) as a missing data problem and cannot be solved at individual level. Instead, an average of treatment effect of the population is seen as an alternative solution. There are two parameters that are of most interest to researchers. Firstly, the population average treatment effect (ATE) which is the difference between the expected outcomes with treatment and without treatment:

$$(23) \qquad \Delta_{ATE} = E(\Delta) = E(Y_1) - E(Y_0)$$

Heckman et al. (1997) points out that this estimate might not be relevant in evaluating impact of programs, since it includes individuals in the estimation, which were not targeted by the program (Y_0). The parameter of interest according to Heckman et al. (1997) is the average treatment effect on the treated (ATT). This estimate considers only individuals who actually participated in the program or policy. The treatment effect in this approach is the difference between the expected outcomes of those who have actually been treated with and without treatment. It could be established as follows:

$$(24) \qquad \Delta_{ATT} = E(\Delta \mid D=1) = E(Y_1 \mid D=1) - E(Y_0 \mid D=1)$$

As we know, the mean $E(Y_1 \mid D=1)$ can be estimated from the observations of participants of the program. However, since the mean $E(Y_0 \mid D=1)$ could not be observed in this case, the outcome of non-participants $E(Y_0 \mid D=0)$, which is observed, is often used as approximation for $E(Y_0 \mid D=1)$. In the case of randomized experiments, there is no selection bias occurred since $E(Y_0 \mid D=1) = E(Y_0 \mid D=0)$ (Heckman et al., 1997) . Most of the data for social science are not experimental data, therefore we face the problem of selection bias since: $E(Y_0 \mid D=1) \neq E(Y_0 \mid D=0)$. Particularly, we have difference in outcome:

(25) $$E(Y_1 \mid D=1) - E(Y_0 \mid D=0) = E(Y_1 - Y_0 \mid D=1) + \{E(Y_0 \mid D=1) - E(Y_0 \mid D=0)\}$$

which consists of actual average treatment effect on the treated and the selection bias. According to Caliendo (2006), "*selection bias exists because treated and non-treated units are selected groups. They would have different outcomes even in the absence of the program impact.*"

Lee (2005) describes the problem of selection bias by an example on the impact of standardized tests on the academic achievement of student in two regions R_1 and R_2. Supposed that the region R_1 applies standardised test meanwhile R_2 does not. Lee assumes further that there are no true effects of the standardised tests on academic achievement of students, but the population of R_1 has a higher average income than R_2. It is logically supposed that students with higher income parents enjoy more education outside school, and that results in higher academic achievement. Therefore it is the higher average income and thus higher outside school education, not the standardised tests, that results in higher academic achievement in R_1 than in R_2. Unambiguously the two regions are heterogeneous in terms of incomes and that make the comparison of the two regions for the impact of standardised tests are incomparable. In the context of the thesis, we can imagine an example in which an enterprise with highly active management board is more likely to participate in a government supporting program and also is more likely to have higher technical efficiency. In this case we also face the problem of selection bias when comparing this specific enterprise with another enterprise that does not participate in the government supporting program.

The gold standard for evaluating causal effects in this case is a randomized experiment. Particularly in the Lee (2005) example, students of the same level of intelligence and social and education conditions are **randomly** divided into treated and control group exposed to the standardized tests. Then their results are compared for the impact of standardized tests. The randomized experiment however is not always possible ethically or politically or economically. In this case a **matching** is a feasible solution for observational studies. The idea is to find for each treated observation i with characteristics X_i a control observation j of similar characteristics so that comparability in terms of observed covariates can be achieved and a direct comparison can be conducted. The impact factor of interest can be measured from this comparison.

Matching will help to produce pairs of treated and control observations, which have homogenous distribution of the observed covariates. Matching will also cancel out the bias in the treatment effects resulting from the observed covariates. However, when treated and control observations are different in several characteristics, which is a common problem in reality, covariate matching as mentioned above faces so-called curse of dimensionality issue. In which the possible matches increase exponentially with the number of observed covariates used for matching. Caliendo (2006) estimated for his research on labour market policies that with 38 discrete and 6 continuous covariates used for matching, covariate matching will produce a possible over 278 million cell matches. Therefore **exact covariate matching** is impossible in this case.

To avoid the curse of dimensionality and deal with biases in observational studies as mentioned above, Rosenbaum and Rubin (1983) proposed **propensity score matching**. In this seminal paper they introduced propensity score, which is the possibility to be treated given a set of covariates presenting characteristics of observations. They show that propensity is a single dimensional vector, which can be used as a summary of multi-dimensional space created by observed covariates. While they asserted that observed covariates are finest balancing score, propensity score can be seen as a coarsest balancing score. It is the very scalar vector that allows researchers to directly compare the treated and the non-treated (control) group. It is where the conditional distribution of the covariates X given a function of $b(X)$ is the same for the treated and control observation.

The Rosenbaum and Rubin (1983) method is based on several assumptions. The most important one is the assumption that the treatment follows some form of exogeneity (Caliendo, 2006). This assumption is first articulated by Rosenbaum and Rubin (1983) who coined the term "*unconfoundedness*". This assumption is also referred to as selection on observables (Heckman and Robb, 1985) or condition independence assumption (CIA) (Lechner, 1999). The conditional independence of outcome and treatment given some covariates assumption is written under notation of Dawid (1979) as follows:

$$Y_0, Y_1 \perp D \mid X \qquad \text{(Assumption 1. Unconfoundedness)}$$

Where $\perp$ denotes independence, Y_1, Y_0 are the outcomes with and without treatment, D is treatment and X are covariates that are not influenced by treatment. *This unconfoundedness assumption ensures that units that satisfy the assumption will have the same distribution for their outcomes, regardless of being treated or non-treated*. In the other words, the assumption means that given covariates X the selection into treatment is random (Ichino, 2007). This assumption combined with the second assumption of overlap as presented below is referred it as "ignorable treatment assignment" or "strong ignorability" by Rosenbaum and Rubin (1983). The second assumption ensures that all treated units have a counterpart in the non-treated population. This is also called support region and it makes sure that from X a perfect predictor cannot be determined, i.e. $\Pr\left(D=1 \mid X\right)$ will not take $0 \text{ or } 1$ for certain, since if it is the case matching is impossible.

$$0 < \Pr\left(D=1 \mid X\right) < 1 \qquad \text{(Assumption 2. Overlap)}$$

The idea behind matching is to identify for each observed outcome a counterfactual outcome in the opposite group, which has the similar covariates value. If both above assumptions are satisfied then the marginal distribution of the counterfactuals is:

$$F_0(Y_0 \mid D = 1, X) \text{ and } F_1(Y_1 \mid D = 0, X)$$

However, the joint distribution of (Y_0, Y_1), $\mathrm{F}(Y_0, Y_1 | D, X)$ could not be found without making further assumptions about the structure of outcome and participation equations (Heckman et al., 1998). Under the strong ignorability the mean treatment effect on the treated can be estimated as follows:

$$\begin{aligned} \Delta_{ATT} &= E(Y_1 - Y_0 \mid X, D = 1) \\ &= E\left\{Y_1 - E\left(Y_0 \middle| X, D = 1\right) \middle| X, D = 1\right\} \\ &= E\left\{Y_1 - E\left(Y_0 \middle| X, D = 0\right) \middle| X, D = 1\right\} \end{aligned} \tag{26}$$

where the first term is arrived from the treatment group, and the second term is constructed by using: $E(Y_0 | X, D=1)$ = $E(Y_0 | X, D=0)$, for each treated observation we can find a counterfactual from control group.

The propensity score for an individual is defined as conditional probability of receiving treatment given a vector of observed covariates (Rosenbaum and Rubin, 1983; D'Agostino, 1998). With the characteristics of balancing score, propensity score can be used to reduce the bias in observational studies. This section describes the possible uses of propensity scores, and then going into details of the use of the propensity score for matching.

Since the work of Rosenbaum and Rubin (1983), there has been an increasing number of researches focus on adjusting differences based on propensity score. The use of propensity score was discussed intensively in purely statistics theory papers (e.g., Rosenbaum and Rubin (1984), Rosenbaum and Rubin (1985), Imbens (2000), Imbens (2004)). Imbens (2004) identified that propensity score can be used in 4 different ways for estimating causal effects, including: (i) weighting observation by propensity score to create balanced treated and control units; (ii) stratifying or subclassifying (or blocking-on-the-propensity-score as named by Rosenbaum and Rubin (1983)) the sample into subsamples based on propensity score; (iii) regressing on the propensity score; and (iv) matching on the propensity score. These methods can also be combined in order to reduce bias using propensity score. D'Agostino (1998), however, identified that propensity can be used in only 3 different ways in reducing bias: matching, stratification, and regression. And the main methods are defined by Caliendo (2006) as matching and regression.

The use of the propensity score for analysing causal effects is also based on the two most important assumptions of the matching method mentioned in the above section. In applications of propensity score matching, the "ignorable treatment assignment" is proved by Heckman et al. (1998) *as too strong* if the (population) average treatment effect is of interest. Instead, it is sufficient to assume that:

$$E\left[Y(d)\middle|D,X\right]=E\left[Y(d)\middle|X\right] \quad \text{for } d=0,1$$ (Assumption 3. Mean independence)

This assumption can be rewritten as in Caliendo (2006, pp. 32):

(27) $$E\left(Y_0\middle|X,D=1\right)=E\left(Y_0\middle|X,D=0\right)$$

and

(28) $$E\left(Y_1\middle|X,D=1\right)=E\left(Y_1\middle|X,D=0\right)$$

The important implication of the unconfoundedness assumption is that we do not need to condition on all covariates. Instead conditioning solely on the propensity score can reduce bias dues to observable covariates (Rosenbaum and Rubin, 1983; Imbens, 2004). Thus, weighting, regression, stratification, and matching on the propensity score produces unbiased estimates of the treatment effects when treatment is in some form of exogeneity.

4.3. Theoretical Model

This section will present the production process with its properties using set theory. This is followed by the presentation of the nonparametric approach to technical efficiency of production units. The probability approach to production process will be briefly presented as a background for the development of theoretical approach for this thesis. The last section contains the background for the contribution of the thesis to the current literature on impact evaluation in the context of technical efficiency analysis.

4.3.1 Production Process

Production can be understood as a process to transform inputs into outputs. In this chapter the transformation process of production of a production unit will be presented using set theory. Following Lovell (1993) we define a production unit as an institution which uses p inputs

$$x = \left(x_1, \ldots, x_p\right) \in \Re_+^p \tag{29}$$

to produce q outputs

$$y = \left(y_1, \ldots, y_q\right) \in \Re_+^q . \tag{30}$$

Then the production technology can be presented by the following equation:

$$\psi = \left\{(x, y) \middle| x \in \Re_+^p, y \in \Re_+^q, (x, y) \text{ is feasible}\right\}. \tag{31}$$

Production processes can be analysed from the input requirement side or from the output correspondence side. The production set as described here can be presented as an input requirement set in which the input requirement set consists of all input vectors that make the production of output vector $y \in \Re_+^q$ feasible.

$$L(y) = \left\{x \middle| (x, y) \in \psi\right\} \tag{32}$$

On the other hand a given input vector can be used to produce an output correspondence set, which includes all possible output vectors.

$$P(x) = \left\{y \middle| (x, y) \in \psi\right\} \tag{33}$$

Therefore, the production set can be retrieved from the input requirement set as follows:

(34) $$\psi = \left\{ (x, y) \middle| x \in L(y)), y \in \Re_{+}^{q} \right\}$$

Equivalently, it can also be achieved from the output correspondence set as:

(35) $$\psi = \left\{ (x, y) \middle| x \in \Re_{+}^{p}, y \in P(x) \right\}$$

The production set we present above satisfies several economic axioms, namely no-free lunch, free disposability, bounded, convexity (see Coelli et al. (2005) or Daraio and Simar (2007a) for more details).

The production of a production unit is also characterised by properties on the behavioural relationship between input and output. Particularly a production unit can have constant returns to scale production function, in which for efficient units a given percent rise in inputs leads to the same percent rise in outputs. Meanwhile increasing returns to scale characterises a production technology in which output rise by a higher percentage than inputs in the foregoing scenario and decreasing returns to scale means outputs rise by a smaller percentage than inputs. Mathematically different types of production technology as aforementioned can be stated as follows:

Constant returns to scale:

(36) $\forall (x, y)$ with $x \in \Re_{+}^{p}$ are characterised by $L(\alpha y) = \alpha L(y), \alpha > 0$

Increasing returns to scale:

(37) $\forall (x, y)$ with $x \in \Re_{+}^{p}$ implies that $L(\alpha y) > \alpha L(y), \alpha > 1$

Decreasing returns to scale:

(38) $\forall (x, y)$ with $x \in \Re_{+}^{p}$ implies that $L(\alpha y) < \alpha L(y), \alpha > 1$

4.3.2 *Efficient boundaries and technical efficiency*

We have just described the production process and its characteristics in the previous section. By using activity analysis we can also describe the efficient frontier, which envelops all combinations of inputs, and outputs that are observed from production units in the same industry. Building an efficient frontier is the first step in measuring the efficiency of a production unit. Following the above presentation of production processes, the input efficient boundary can be stated as follows:

(39) $$\partial L(y) = \{x | x \in L(y), \lambda x \notin L(y), \forall \lambda, 0 < \lambda < 1\}$$

Similarly, the output efficient boundary can be presented as below:

(39) $$\partial P(x) = \{y | y \in P(y), \theta x \notin P(y), \forall \theta > 1\}$$

Equivalently we can define the efficient subsets for input space and output space as follows:

(40) $$\mathit{eff}\ L(y) = \{x | x \in L(y), x' \notin L(y), x' \leq x\}$$

and satisfies: $\mathit{eff}\ L(y) \subseteq \partial L(y) \subseteq L(y)$

And $\mathit{eff}\ P(x) = \{y | y \in P(x), y' \notin P(x), y' \geq y\}$

and satisfies: $\mathit{eff}\ P(x) \subseteq \partial P(x) \subseteq P(x)$

In the other words a DMU is output-orientation efficient if it is on the boundary of the output correspondence set and a DMU is seen as efficient in input space if it is on the boundary of the input requirement set. Then for a production unit operating at level (x_0, y_0) the Debreu-Farrell input-oriented measure of efficiency can be defined as follows:

(41) $$TE_x(x_0, y_0) = \min(\lambda | \lambda x_0 \in L(y_0))$$

We will have $TE_x(x_0, y_0) = 1$ if $x_0 \in \partial L(y)$.

The Debreu-Farrell output-oriented measure of efficiency is:

$$TE_y(x_0, y_0) = \max\left(\theta \middle| \theta y_0 \in P(x_0)\right) \tag{42}$$

The $TE_y(x_0, y_0) = 1$ if we have $y_0 \in \partial P(x)$

4.3.3 DEA Efficiency

The classical nonparametric efficient frontier is a frontier of a convex production set. The frontier was invented by Charnes et al. (1978), who coined the term Data Envelopment Analysis (DEA) for the approach to identifying the convex efficient frontier. The DEA estimation of technical efficiency could be presented as a measurement of ratio between given inputs of a set (x, y) to the boundary input for the same set of outputs. As presented by Daraio and Simar (2007a) we will have production levels of production units that dominate other units in the same industry and create the famous DEA production frontier:

$$\hat{\psi}_{DEA} = \left\{ \begin{array}{l} (x, y) \in \Re_{+}^{p+q} \middle| y \leq \sum_{i=1}^{n} \gamma_i Y_i; x \geq \sum_{i=1}^{n} \gamma_i X_i, \text{ for } (\gamma_1, ..., \gamma_n) \\ \\ \text{s.t.} \qquad \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, ..., n \end{array} \right\} \tag{43}$$

Where (X_i, Y_i) are observations in a convex hull of $\chi = \{(X_i, Y_i), i = 1, ..., n\}$ covering unit (x, y).

The above formula allows the variable returns to scale production technology, where outputs under efficient production change by a different proportional to the change in inputs. Other types of returns to scale can be achieved by changing the constraint $\sum_{i=1}^{n} \gamma_i = 1$. If $\sum_{i=1}^{n} \gamma_i = 1$ is dropped from the formula we will have a presentation of a constant returns to scale technology as described earlier. While setting $\sum_{i=1}^{n}\gamma_i \geq 1$ or ≤ 1 we allow respectively for non-decreasing or non-increasing returns to scale, respectively.

With variable returns to scale production technology, the input-oriented technical efficiency score for a production unit operating at the level (x_0, y_0) will be:

$$\hat{\lambda}_{DEA}(x_0, y_0) = \min\{\lambda | y_0 \leq \sum_{i=1}^{n}\gamma_i Y_i; \lambda x_0 \geq \sum_{i=1}^{n}\gamma_i X_i; \lambda \geq 0; \sum_{i=1}^{n}\gamma_i = 1; \gamma_i \geq 0; i = 1,...,n \tag{44}$$

with the input-oriented technical efficiency score $\hat{\lambda}_{DEA}$, to achieve the output level (y_0) the projection of (x_0, y_0) on the efficient boundary is $\hat{\lambda}_{DEA} * x_0$. Therefore the difference between x_0 and $\hat{\lambda}_{DEA} * x_0$ is the radial distance which measures the efficiency of a production unit in producing a given level of output (y_0).

Similarly, the output-oriented approach to technical efficiency will arrive at the DEA efficiency by solving the optimization problem:

$$\hat{\theta}_{DEA}(x_0, y_0) = \max\{\theta | \theta y_0 \leq \sum_{i=1}^{n}\gamma_i Y_i; x_0 \geq \sum_{i=1}^{n}\gamma_i X_i; \theta \geq 0; \sum_{i=1}^{n}\gamma_i = 1; \gamma_i \geq 0; i = 1,...,n \tag{44}$$

4.3.4 FDH Efficiency

The convexity constraint for the production technology as applied in DEA approach sometimes cannot be justified in the empirical operation of production units. For this reason, Deprins et al. (1984) proposed an efficiency estimator which relies only on the free disposability assumption of the production technology. They constructed a "free disposal hull" (FDH) of the data, which can be visualized along with a respective DEA frontier in Figure 12. In this figure, an output-oriented DEA frontier is presented by the solid line, while its FDH counterpart is presented by the dashed line. Without the convexity constraint of the production technology, the FDH frontier has a staircase shape, in which a production unit A is projected to a lower FDH frontier than a convex DEA frontier. Therefore, we expect a higher efficiency score of a unit in FDH framework than the one in DEA framework.

Figure 12. FDH and DEA output frontier

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Source: Fried and Lovell (2008)

The FDH estimator of the production set Ψ is defined as the union of individual productions under the free disposability of inputs and outputs. It can be written as follows:

$$\hat{\psi}_{FDH} = \left\{ (x, y) \in \Re_{+}^{p+q} \middle| y \leq Y_i ; x \geq X_i , (X_i, Y_i) \in \chi \right\} \quad (44)$$

Where (X_i, Y_i) are observations in a convex hull of $\chi = \left\{ (X_i, Y_i), i = 1, ..., n \right\}$ covering unit (x, y) as defined in the previous section. Under FDH framework, the input requirement set is:

$$\widehat{C}(y) = \left\{ x \in \Re_{+}^{p} \middle| (x, y) \in \hat{\psi}_{FDH} \right\} \quad (45)$$

The input oriented efficient boundary is:

(46) $$\partial\widehat{C}(y)=\left\{x \middle| x\in\widehat{C}(y),\theta x\notin\widehat{C}(y)\forall 0<\theta<1\right\}$$

The input-oriented efficiency score for a given point in FDH nonconvex frontier is given by:

(47) $$\hat{\lambda}_{FDH}(x_0,y_0)=\min\left\{\lambda \middle| y_0\le Y_i;\lambda x_0\ge X_i,(X_i,Y_i)\in\chi\right\}.$$

The output correspondence of the FDH estimator is:

(48) $$\hat{P}(x)=\left\{y\in\Re_+^q \middle| (x,y)\in\hat{\psi}_{FDH}\right\}$$

The output-oriented efficient boundary is:

(49) $$\partial\widehat{P}(x)=\left\{y \middle| y\in\widehat{P}(x),\lambda y\notin\widehat{P}(x)\forall\lambda>1\right\}$$

and the efficiency score in the output orientation framework for a given point in FDH nonconvex frontier is given by:

(50) $$\hat{\theta}_{FDH}(x_0,y_0)=\max\left\{\theta \middle| \theta y_0\le Y_i;x_0\ge X_i;(X_i,Y_i)\in\chi\right\}.$$

4.4. Dichotomous External Variable Impact on Technical Efficiency: Revised Frontier Separation Approach

As mentioned earlier the frontier separation approach which was proposed by Charnes et al. (1981) is the first model to deal with the policy (program) impact on DEA technical efficiency. It remains as a basic and important tool for an analyst to conduct the evaluation of impact environmental variable on technical efficiency. There are several developments in incorporating environmental factors into the DEA analysis context. However, most of the developments deal with variables, which enter directly into the production process, or in other words, enter directly in the transformation of inputs into outputs. Therefore the main literature development on environmental variable evaluation in the DEA context is devoted to incorporating environmental variables directly into DEA models. In this approach the analyst has to have prior knowledge about the direction of the environmental variable impact. More importantly, this approach cannot be applied to the situation in which environmental factors exist in the form of dichotomous variables, or in other words, ‘yes’ or ‘no’ cases as in policy treatment.

It should be noted that Charnes et al. (1981) conducted a simple covariate matching procedure where Non-Follow Through schools were selected to created a matched comparison sets of supposedly comparable students. By doing that Charnes et al. (1981) become pioneers in combining program evaluation methods with nonparametric production frontier analysis. Charnes et al. (1981) approach however suffers from weaknesses. It will encounter the curse of dimensionality if it is applied to a large pool of data where several covariates should be used to find the matched observations to ensure the comparability of the sample. Also Charnes et al. (1981) approach assumes implicitly that the program can influence the most efficient units, thus the frontier. It is a strong assumption since the inefficiency of units under the frontiers is attributed to managerial inefficiency. The program impact therefore will be assumed to be non-existence with these units. The aforementioned weaknesses of Charnes et al. (1981) approach will be addressed partly in this chapter. Particularly the propensity score matching will help to avoid the curse of dimensionality, while ensure the quality of the matched sample. The later issue will be addressed in chapter 6 where a order-m frontier conditioning on propensity score is proposed since it is the nature of the Charnes et al. (1981) approach.

Beside the frontier separation approach, there is another approach that was developed in the past to take into account environmental factors including dichotomous variables, which is a two-step method. This method is applied by firstly estimating an efficiency score using nonparametric models and then using a regression model to capture the relationship of the efficiency variable with environmental factors. The two-step method is criticized by several authors (Simar and Wilson, 2007) for lacking knowledge on the data generating process during the course of technical efficiency estimation.

Recently there are studies using parametric approach and propensity score matching to deal with selection bias in examining the impact of dichotomous external variables. Mayen et al. (2010) compare productivity and technical efficiency of organic and conventional dairy farms. Using Durbin-Wu-Hausman test, they found that the organic dummy is endogenous, in other words there is a sign of self-selection into organic production. To deal with self-selection into organic farming Mayen et al. (2010) used propensity score matching. By comparing organic and matched conventional farms, they found that organic farms are 13% less productive, however there is little difference in technical efficiency between between the two groups. Mayen et al. (2010) wrongly claimed that their paper is the first study using propensity score matching in dealing with self-selection in productivity analysis. In 2004 Girma et al. (2004) introduced propensity score matching in studying productivity of exporting enterprises.

Affuso (2010) evaluates a *Soil Productivity Improvement program* run for farmers in Tanzania. Using propensity score matching to create a balanced sample of treated and control observations and a stochastic frontier model he found that farmers who participated in the program are on average 9.2% more efficient than farmers who did not. Using a spatial autoregressive stochastic frontier analysis he also discovered that there is a spatial spillover effect, which benefited the farmers who did not take part to the program.

Bravo-Ureta et al. (2010) use propensity score matching to establish a matched sample of treated and control farms to study the impact of MARENA, a natural resource management program. By estimating and comparing technical efficiency using fixed effects coefficients they concluded that technical efficiencies of MARENA beneficiaries are consistently higher than for the control farmers

All of the above studies use propensity score matching with a parametric approach to productivity and technical efficiency analysis. They therefore have the disadvantages of a parametric frontier approach mentioned in chapter 3. In this chapter we focus our investigation on the frontier separation approach as the baseline for our proposed approach. We propose to revise the frontier separation approach to improve its performance under the existence of selection bias. The strategy therefore is to use **propensity score** to derive a counterfactual sample that can be compared with the treated sample without worry of selection bias. As mentioned in section 2 of the chapter, there are several options to use propensity scores to arrive at such a counterfactual sample. We follow the nearest neighbour matching algorithm to derive matched pairs of treated and control observations for several reasons. The nearest neighbour matching allows investigators to form matched pairs without dropping treated observations. Also by using matching without replacement we arrive at an equivalent number of observations in the counterfactual sample. This is crucial for DEA analysis, since it is known that there is bias against the smaller group when comparing two groups of DMUS in DEA analysis through frontier separation (Simpson, 2005).

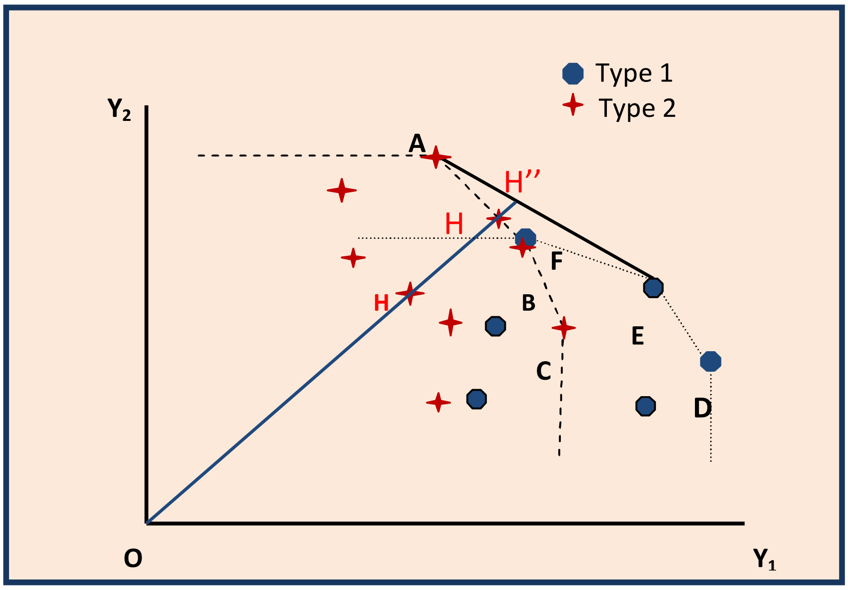
The propensity score matching method will be used along with the frontier separation approach to improve the quality of impact evaluation by eliminating the bias associated with treatment assignment. The traditional approach to program efficiency can be found in (Charnes et al., 1981) where efficiency of schools under the Follow Through program were examined in comparison with those without the program. Section 3.3.1 presented in details the approach for input orientation model. For the purpose of this chapter we reproduce briefly the approach with output orientation model. The Figure 13 illustrates how the frontier separation approach work for the output-oriented technology. The program efficiency in this case is estimated by the following formula:

$$\text{Program Efficiency} = \frac{\text{Overall Efficiency}}{\text{Managerial Efficiency}}$$

Or

$$\left(OH'' / OH' \right) = \frac{\left(OH'' / OH \right)}{\left(OH' / OH \right)}$$

Figure 13. Frontier separation approach – output oriented



In this study we apply the weakly inefficiency version Charnes et al. (1981) separation approach for estimating program efficiency. The approach, also used in Thanassoulis and Portela (2002), helps to reduce the estimation burden, and more importantly it can be intergrated easily in building the simulation code without negative impact on the quality of the analysis.

We build our model on the assumption of an output oriented production frontier and constant returns to scale production technology. However the results of the model can be applied with the input oriented and variable returns to scale production. Our model is built on the assumption of the production process as described in section 4.3.1 to arrive the estimation of technical efficiency as presented in section 4.3.3, i.e. following DEA technique in efficiency measurement.

To evaluate the impact of a dichotomous external variable on technical efficiency, we focus on the average impact of the policy on all treated enterprises rather than on individual enterprises. Suppose that $D=1$ means the enterprise is treated, and $D=0$ means otherwise, then the policy impact (treatment effect) could be established as follows:

(51) $$\Delta_{\hat{\theta}} = E(\Delta_{\hat{\theta}} \mid D=1) = E(\hat{\theta}_{PT} \mid D=1) - E(\hat{\theta}_{PC} \mid D=1)$$

Where the subscript PT is denoted for policy treated enterprises while PC is policy non-treated enterprises; $\hat{\theta}$ is estimated output-oriented DEA efficiency scores; $\hat{\theta}_{PT}$ and $\hat{\theta}_{PC}$ are estimated output-oriented DEA efficiency scores of policy treated and non-treated enterprises, respectively. Under the traditional frontier separation approach, Charnes et al. (1981) proposed first to eliminate the management efficiency from the performance of DMUs before going on to identify the policy impact, reflected in program efficiency. In the same manner, Thanassoulis and Portela (2002) proposed a shortcut to derive program efficiency by decomposing overall efficiency to managerial efficiency and program efficiency. Our proposed approach follows Thanassoulis and Portela (2002) with a matching by propensity score to cancel out the selection bias. With this clarification, components of the treatment effect formula as presented above can be explained as follows.

Management efficiency of each matched **treated** DMU will be:

(52) $$\hat{\theta}_T(x_0, y_0) = \max\left\{\theta \middle| \left(\theta y_0 \le \sum_{i=1}^{n} \gamma_i Y_{iT}; x_0 \ge \sum_{i=1}^{n} \gamma_i X_{iT}; \theta \ge 0; i = 1,...,t \middle| D = 1\right)\right\}$$

Where Y_{iT} is the output of matched treated DMUs and X_{iT} is the inputs of these DMUs. And t is the number of treated DMUs.

Meanwhile management efficiency of each matched **control** DMU will be:

(53) $$\hat{\theta}_C = \max\left\{\theta \middle| \left(\theta y_0 \le \sum_{i=1}^{n} \gamma_i Y_{iC}; x_0 \ge \sum_{i=1}^{n} \gamma_i X_{iC}; \theta \ge 0; \gamma_i \ge 0; i = 1,...,c \middle| D = 1\right)\right\}$$

Where Y_{iC} are the outputs of matched control DMUs and X_{iC} is the inputs of these DMUs. And c is the number of control DMUs.[17]

Each **matched** DMU will have an overall efficiency, which is estimated as follows:

$$(53) \qquad \hat{\theta}\left(x_0, y_0\right) = \max\left\{\theta \left| \left(\theta y_0 \leq \sum_{i=1}^{n} \gamma_i Y_i; x_0 \geq \sum_{i=1}^{n} \gamma_i X_i; \theta \geq 0; i = 1,\ldots,n \middle| D = 1\right)\right.\right\}$$

where $n = t + c$ and the estimated program efficiency for each **matched treated** DMU is: $\hat{\theta}_{Pi} = \frac{\hat{\theta}_{Ti}}{\hat{\theta}_i}$, $i = 1,\ldots,t$ for treated DMU where $\hat{\theta}_{Ti}$ and $\hat{\theta}_i$ are estimated from equation (55) and (57) above respectively. The estimated program efficiency for each matched control DMU is: $\hat{\theta}_{Pi} = \frac{\hat{\theta}_{Ci}}{\hat{\theta}_i}$, $i = 1,\ldots,c$ for control DMU where $\hat{\theta}_{Ci}$ and $\hat{\theta}_i$ are estimated from equation (56) and (57) above respectively.

The above section presents the methodology development to revise the classical frontier separation approach to cope with selection bias in an evaluation exercise. Before applying the proposed method to empirically examine the impact of a government policy on technical efficiency of SMEs in Vietnam, it should be tested. The following section will discuss a Monte Carlo type simulation, which helps to theoretically prove the validity of the proposed method. We will present in details the simulation design and the results of the simulation. A demonstration for a theoretical impact of 5 percent from environmental variable on technical efficiency will be discussed to show how the method works and how it improves the estimation of policy impact.

[17] $D = 1$ in the equation (56) implies that they are counterfactuals of treated observations, which are not observed but are created by matching observations from control DMUs. In other words, $D = 1$ stands for matched controls, which establish the counterfactuals for treated DMUs.

4.5. Simulation Design

Simulation has been used widely in both efficiency measurement and propensity score matching analysis in the past few years. In the field of efficiency measurement, Bowlin et al. (1984), Gong and Sickles (1989), Banker et al. (1993) have used this method to compare the efficiency measures obtained with parametric and non-parametric approaches. Monte Carlo simulation was also used in at least two papers by Yu (1998) and Cordero et al. (2008) to examine the effectiveness of different approaches in analysing the impact of external variables on technical efficiency. Yu (1998) made a comparison between a one-stage procedure in which non-discretionary variable is incorporated directly into the estimation of the production function, and a two-stage procedure, in which efficiency scores are regressed against variables which are believed to influence the efficiency of DMUs. The paper focused mainly on the differences between parametric and non-parametric approaches. Cordero et al. (2008) used Monte Carlo simulation as a vehicle to compare the difference between one-stage, two-stage, three-stage and four-stage approaches in dealing with non-discretionary variables in DEA models.

A common procedure in Monte Carlo experiments for DEA analysis is as follows. At first, a production function is defined, which is usually Cobb-Douglas or translog production function. However, other forms of production function are also used, such as CRESH (constant ratio of elasticity of substitution homothetic) as used by Yu (1998). It is essential to assume that DMUs are homogenous and have the same production function. After all the nonparametric approach to technical efficiency is based on the assumption that DMUs are operating in the same industry, producing products that are the same so that comparison can be made between them. Inputs of production are generated from a random distribution. Outputs of DMUs are delivered from the production function given the inputs. At this point, true inefficiency is introduced according to a distribution assumption. Subject to this true inefficiency, the observed inputs and outputs are used to estimate efficiency scores. To test the quality of alternative approaches to impact evaluation, estimated impacts are compared with true impacts generated from simulation.

Simulation is a popular method to study the effectiveness of propensity score matching in singling out the impact of treatment on subjects (Zhao, 2004, Brookhart et al., 2006, Zhao, 2008, Austin, 2007, Austin, 2009, Austin et al., 2007). In simulation for propensity score matching, the most important function is the treatment assignment function, which determines the treatment incident depending on the propensity score. Given the selection problem which is the main reason for the existence of propensity score matching method the Monte Carlo simulation is usually designed as follows. Firstly, independent variables are generated with a random distribution. Secondly, a treatment indicator is determined given the selection function. True propensity scores are generated within this procedure and are the main variable for the determination of the treatment indicator. Particularly, the treatment indicator taking the value [0, 1] is determined randomly conditional on the propensity score. Propensity score to be treated, in its turn, depends on several variables, which in our simulation are X_p and X_1 (see Figure 14). Thirdly, the outcomes are generated given the independent variables and treatment. Then the results of causal effects of treatment will be estimated by and compared between different approaches.

To study the effectiveness of propensity matching in separating the impact of non-discretionary variables to the technical efficiency of DMUs, our Monte Carlo experiment consists of two main designs. The first design is intended for the technical efficiency simulation where a production technology is assumed. Beside the production frontier simulation, treatment assignment design is formulated so that assignment of treatment is conditional on several variables. The relation of variables within the treatment assignment simulation and production frontier can be seen as follows:

Figure 14. Monte Carlo propensity simulation design

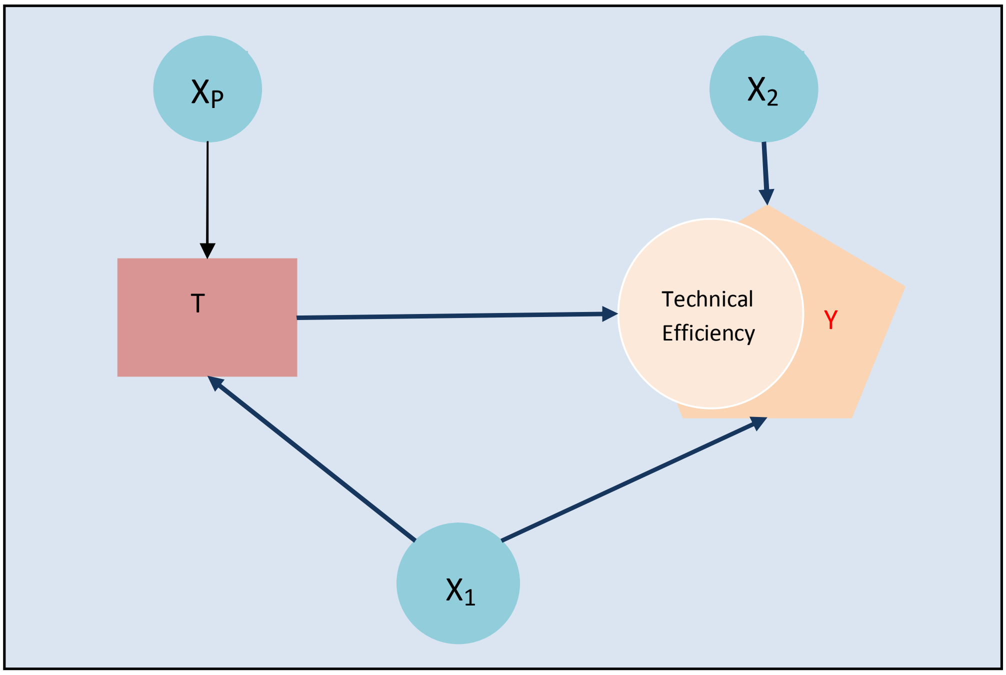


Figure 14 shows that DMUs in the simulation use two inputs, X_1 and X_2, to produce one output, Y. There is policy (dichotomous environmental) variable, T, that influences the technical performance of DMUs in the model. The possibility to attend the policy treatment T is determined by two variables, X_p and X_1. The simulation can be presented in the following equations.

(54) $$Y = f(X)\exp(w)$$

(55) $$w = \alpha T - \sigma + \varepsilon \ , \ T = \{0 \ or \ 1\}$$

(56) $$P = f\left(X_1, X_P\right)$$

(57) $$T = I\left(P\right)$$

For simplicity of the estimation without the loss of generality of the model, we assume that a DMU uses two inputs for producing one output. In this simulation, X_1 and X_2 are inputs for the production and are normally distributed, which enter directly to the production function, $f(X) \equiv f(X_1, X_2)$, to determine the level of output. There is aggregate deviation from the production frontier, which is the main target of our analysis. This aggregate deviation component of a DMU is affected by the environment factor – T – at *the level of α, which is in our specific study is the level of policy impact*, an inefficiency level of a individual DMU, σ, and a random disturbance, ε, which captures statistical noises.

Each individual DMU has a propensity to be treated, or in other words to attend a treatment and therefore expose to impact from the environmental factor T, which is taking the value of 1 for attending the policy treatment or 0 for not attending the policy treatment. We assume that propensity to attend the policy treatment is dependent to two variables, X_1 and X_P, in which X_1 is a direct input to production, and X_P is a variable that affects propensity but not production. The treatment variable T is dependent to the propensity to be treated and determined by $T = I(P\ )$, where $I(\bullet)$ is an indicator function.

We use a simple production function for projecting outputs of DMUs given inputs. Particularly, we use a Cobb-Douglas production function, which will be fitted in two analysis scenarios corresponding to status of returns of scale. The first analysis scenario is to set up under constant return to scale and evaluates the ability of the proposed methodology in distinguishing the impact of an environment factor. Variable returns to scale will be considered in the second scenario and is in fact increasing returns to scale pattern. We assume that, in constant returns to scale, the Cobb-Douglas production function will take the following form:

$$f(X) \equiv \beta X_1^a X_2^{1-a} \qquad (58)$$

Where in this research, $a = 1 - a = 0.5$.

The increasing returns to scale Cobb-Douglas production function follows the formulation:

(59) $$f(X) \equiv \beta X_1^a X_2^b$$

Where $a+b>1$ and in this research we apply $a=b=0.75$.

Concerning treatment assignment, we first simulate the true propensity for each observation, P_i. The propensity scores P_i are simulated following a logit specification: $\frac{\exp(A_i)}{1+\exp(A_i)}$, where $A_i = f(X_{1i}, X_{Pi})$. The treatment indicator T_i is drawn from a Bernoulli distribution with parameter P_i. It is also formulated so that 30% of the simulated data is treated.

Following the simulation procedure of data for DEA, the inefficiency of each DMU is generated with a half normal distribution. Specifically, inefficiency is generated from the distribution: $\sigma \sim (0, 0.36)$ as used in Yu (1998). It is also generated to ensure that there are 20% of the DMUs on the frontier. In other words, these DMUs have 100% efficiency scores. In the last step of the simulation design for this study, observed outputs are generated given the simulated inputs, the impact of the non-discretionary variable, and the inefficiency level. Since the purpose of the study is to test the ability to single out the impact of dichotomous exogenous variable on technical efficiency, we build the simulation based on the assumption that the true efficiency scores of DMUs will increase by 0%, 5%, 10%, 15% and 25% by attending the treatment $(\text{i.e. } \alpha = 0.00;\ 0.05;\ 0.10;\ 0.15; \text{ and } 0.25)$. Following Yu (1998) we assume that the noise component is drawn randomly and independently from a normal distribution $\varepsilon \sim N(0, 0.15^2)$. There are four sample sizes, $N = 100,\ 200,\ 300,\ 500$, to be used for the generation of data for analysis. In each sample, different treatment effects are assumed to happen, so that they change the true levels of inputs and output. With different impact levels of discretionary variables, a corresponding observed level of outputs will be obtained for testing the effectiveness of the method proposed. To form the Monte Carlo style simulation and increase the confidence for conclusions withdrawn from the simulation a repetition of 100 times for each sample will be conducted.

Since the simulation code is written for both revised frontier separation approach and the order-m frontier conditioning on propensity score, the stochastic noise included in the efficient frontier output. This is justified by the practical code writing but not theoretical consideration since for the deterministic frontier analysis used in this chapter, all deviation from frontier is seen as inefficiency. This however will not affect the validity of the approach, but proves that the proposed approach can work with data at the present of stochastic noise.

In this simulation, the true efficiency is ratio between true output which is defined by the Cobb-Douglas production function with observed input X_1 and X_2. True impact of external variable on technical efficiency will be the difference between efficiency estimated with observed output generated at present of inefficiency, impact, and stochastic noise components and the efficiency estimated with observed output generated at present of inefficiency and impact component.[18] For the convenience of code writing and simulation running as mentioned above, stochastic noise is included in the impact estimation. But the analysis result of the chapter remains valid since the stochastic noise is generated following a normal distribution with expected value of zero.

The matching process will follow to form the matched sample for analysis. This matched sample is defined by the estimated propensity score. There are several methods in literature used to estimate the propensity score to participate in a treatment. The most frequently used parametric methods include logit and probit regression. Caliendo (2006) argued that logit and probit models usually produce the same results for the binary treatment case. In our simulation we use the logit specification in generating true propensity, therefore logit regression is proposed to use. However, to prove the capability of the proposed method, independent variables included in the logit model for estimating propensity score are expanded not only the two variables used in generating true propensity score, X_1 and X_P but also the variable X_2 as an

[18] Please refer to the code at points 3.2, 3.4, and 4.0, Appendix V, to know more details about how true efficiency and true impact are calculated.

explanatory variable. The parametric approaches to propensity score have the advantages of easy to compute in the era of high speed computer. They can handle nonlinear relationship between dependent and independent variables. Also normal distribution of error term is not assumed. However, both probit and logistic regression approaches to propensity score require much more data to be stable.

In addition to the aforementioned parametric methods for estimating propensity score, there are nonparametric and semi-parametric approaches. Hahn (1998) and Hirano, Imbens, and Ridder (2003) used semi-parametric approach to propensity score. Nonparametric approach to propensity score is presented in Li and Racine (2007) in which kernel function is used to estimate probability function. Our approach in this chapter is a semi-parametric where propensity score is estimated using a parametric approach. In the second step a nonparametric analysis is used to examine the impact of the dichotomous external variable. As mentioned in chapter 8 about the further development of research, nonparametric approach to propensity score is natural further step of this study to make the approach purely nonparametric. However, due to space and time of the study we applied a more traditional method of logistic regression in estimating propensity score used for matching.

4.6. A Demonstration of Frontier Separation Conditional on Propensity Score Approach

In this section we will present a demonstration case for the frontier separation conditional on propensity score approach, and in the last part of the chapter, we will present the results of the Monte Carlo simulation for this approach. To go on with the analysis, we assume an impact of 5 percent $(\alpha = 0.05)$ from the policy treatment. That is to say we assume all else being equal the treatment raises the relative efficiency of a unit by 5 percentage points. We consider a sample of 300 observations, where 30 percent of them are treated and 20 percent are efficient by construction. The inefficiencies are assumed to be half-normal $\sigma \sim N(0, 0.36)$, while random noise is believed to follow a normal distribution, $\varepsilon \sim N(0, 0.15^2)$ and the technology is assumed to exhibit constant returns to scale (CRS). However, we also present results for variable return to scale technology, so that a more exact evaluation of the approach can be made. It should be noted that the results presented here are to demonstrate how the frontier separation conditional on propensity score can be conducted. More general evaluations will be made of the Monte Carlo simulation, in section 7 of this chapter.

Following the procedures described in the part on simulation design, summarized in Appendix I, the generated sample which follows constant returns to scale technology, where policy impact of 5 percentage points is applied to treated observations, has following characteristics:

Table 6. Statistical characteristics of demonstration sample

Variable	Denotation	Mean	Standard deviation	Min	Max
Size of the sample	**200**				
Number of treated observations	**65**				
Number of control observations	**135**				
Input 1	X1	10.09	1.94	4.92	14.49
Input 2	X2	10.02	2.03	4.28	14.55
Variable affecting propensity to treatment	Xp	10.07	2.02	4.05	15.21
True propensity	P	0.52	0.27	0.03	0.96
Treatment	Tr	0.33	0.47	0	1
Output on frontier	Y	9.95	1.41	6.10	13.89
Inefficiency	W	0.23	0.23	0	0.94
Output presenting the presence of inefficiency, treatment impact, and random noise	Yutv	8.19	2.12	2.73	14.09
True efficiency	effTrue	0.82	0.17	0.39	1
Efficiency as estimated by DEA model	DEAeff	0.78	0.16	0.38	1
Efficiency as estimated by FDH model	FDHeff	0.86	0.16	0.41	1

The generated sample has 65 observations that received treatment (treated observations) and 135 observations that did not receive treatment (control observations). Thus, roughly 32.5 percent of observations fall into the treatment group compared with 30 percent as designed. To start the analysis firstly an estimation of the propensity score is needed. The balancing checks as outlined below are then applied to the propensity score before the propensity score being used for determining the matched fair for each treated observation from the control observations. The propensity score can be estimated following logit or probit regression. Since we designed to generate the true propensity using logit specification, logit regression will be used in this analysis for the estimation of propensity score to receive policy treatment.[19]

There is a lively discussion in the evaluation literature about which variables should be included in the estimation of the propensity score. While Augurzky and Schmidt (2000) and Bryson et al. (2002) support the view that there should be a careful choice of variables included in the estimation of propensity score, Heckman et al. (1997), Rubin and Thomas (1996), Ho et al. (2007) recommend to use all variables, which are suggested from the theory and empirical findings of previous studies that they may influence the propensity to receive policy treatment, into the propensity score model even if it is not statistically significant.[20]

By adding X_2 as an explanatory variable for receiving treatment even though it is not designed to have impact on propensity to treatment, we give our support to the second viewpoint above. The specification of propensity score estimation function is then presented as follows:

$$\widehat{\Pr} = \gamma + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_P + \varepsilon \tag{60}$$

Propensity estimation following logit regression is as follows:

Pr =	-9.474 +	0.388 X_1 +	0.106 X_2 +	0.357 X_P [21]
	(1.778)***	(0.096)***	(0.081)	(0.091)***

[19] Further discussion about the choice of model for propensity score estimation will be presented in the Chapter 6, where an empirical analysis of the impact of training policy on SMEs is discussed.

[20] More on this issue is discussed in the Chapter 6.

[21] Standard deviation is put in bracket; *: significant at 10%; **: significant at 5%; ***: significant at 1%

To test for the balancing property of the propensity score for nearest neighbour matching, we use both a visual aid as a tool provided by Ho et al. (2004) and the procedure discussed by Becker and Ichino (2002). As noted in section 4 nearest neighbour matching without replacement is a suitable method since it avoids the trimming of treated observations and bias in comparing unbalanced groups of observations as mentioned in Simpson (2005). As shown in the following paragraphs nearest neighbour matching is possible to ensure the balance between treated and control group. Figure 15 is a quantile-quantile (Q-Q) plot, which is a probability plot, comparing the probability distribution of each independent variable in the treated and untreated group. It is established by plotting quantiles of independent variables in treated and untreated group against each other. If the distributions of an independent variable in a treated group and in an untreated (control) group are similar, the points in the Q-Q plot will approximately lie on the 45^0 line. As showed in Figure 15, for variables X_p and X_1, before matching there is bias to treated group where in fact means of X_p and X_1 in treated group are larger than means of X_p and X_1 in untreated (control) group (see Table 9 for more details). The variables X_p and X_1 in treated and untreated groups have more similar distributions after matching as shown in the right-hand side panels in Figure 15. However, the balance improvement in variable X_2 obtained from matching is marginal, as showed Figure 15 and Table 9 also. In Figure, histograms of propensity scores show that, while the distribution of treated observation propensity scores is kept the same since we do not discard any treated observation from the matching procedure, the distribution of untreated observation propensity scores is improved and becomes similar to the distribution of treated observation propensity scores.

Figure 15. Distribution of independent variables before and after matching

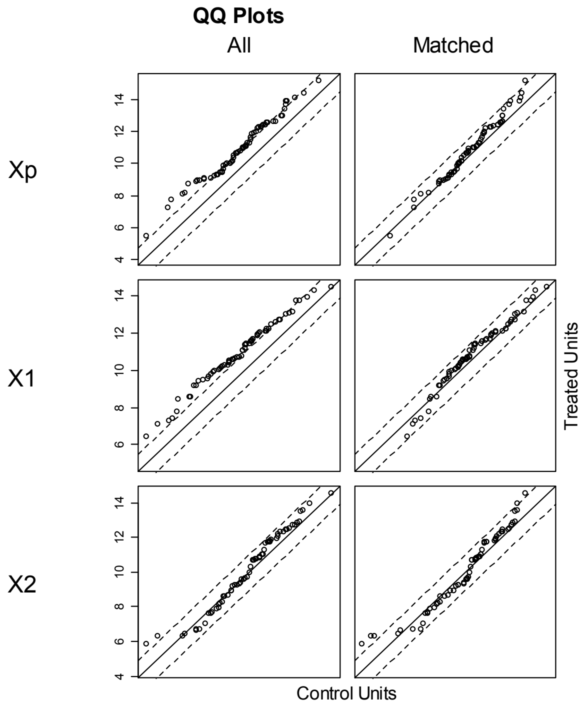
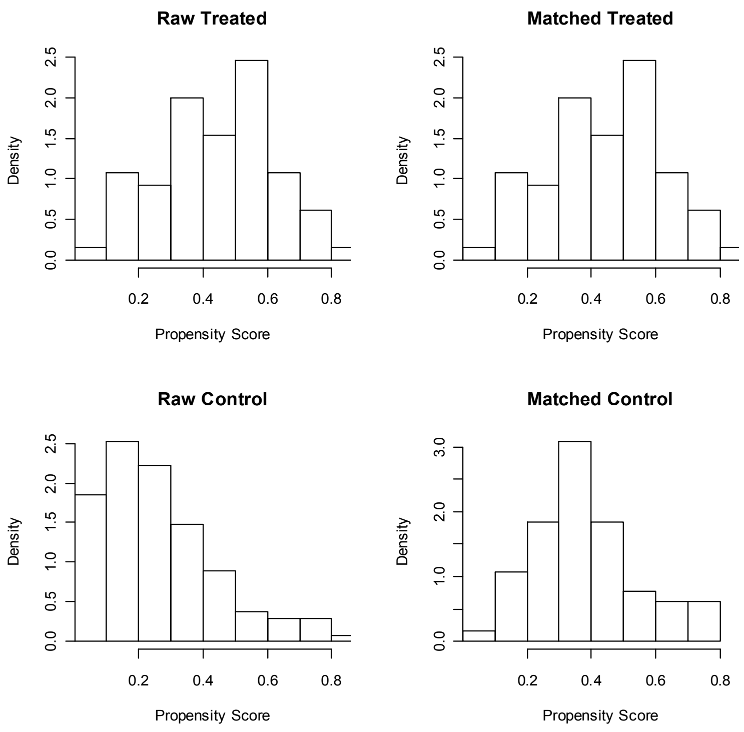


Figure 16. Propensity score distribution of treated and control units before and after matching



In addition to visualisation of variables and propensity scores distributions as discussed above, testing procedures as used by Becker and Ichino (2002) also show that the estimated propensity score satisfies the balancing property. By splitting the sample into 5 equally spaced intervals of the propensity score (inferior blocks), tests with the null hypothesis that the mean difference between treated and control group in terms of sample variables equals 0 are being conducted. The results of the tests show that we cannot reject the null hypothesis. The test for optimal inferior blocks of propensity score is presented in the Table 7. And test for the balancing property of sample variables: X_1, X_2, X_p according to propensity score are presented in Table 8.

Table 7. Testing for the optimal interior block of propensity score

Inferior of block of propensity score	Treated obs.	Control obs.	Total obs.	Degree of Freedom	Ho hypothesis	t value	Decision
0	59	8	67	65	$\mu_1 = \mu_0$	-2.0667	Accepted
0.2	50	19	69	67	$\mu_1 = \mu_0$	-1.3525	Accepted
0.4	17	27	44	42	$\mu_1 = \mu_0$	-2.161	Accepted
0.6	8	11	19	17	$\mu_1 = \mu_0$	0.2725	Accepted
0.8	1	0	1		no treated observation		
Total	***135***	***65***	***200***				

Table 8. Testing for balancing property of sample variables

Inferior of block of propensity score	Treated obs.	Control obs.	Total obs.	Degree of Freedom	Ho hypothesis	t value for X1	t value for X2	t value for Xp	Decision
0	59	8	67	65	$\mu_1 = \mu_0$	-1.2383	0.3839	-0.5582	Accepted
0.2	50	19	69	67	$\mu_1 = \mu_0$	0.4094	-0.3455	-0.8795	Accepted
0.4	17	27	44	42	$\mu_1 = \mu_0$	-0.8207	-0.2689	-0.0337	Accepted
0.6	8	11	19	17	$\mu_1 = \mu_0$	0.5036	-0.1345	-0.1746	Accepted
0.8	1	0	1		no treated obs.				
Total	***135***	***65***	***200***						

As results of the matching operation, we have a matched sample where the unconfoundedness assumption $Y_0, Y_1 \perp D | X$ holds. The following tables show the balance improvement of sample variables X_1, X_2, X_P and propensity score between treated and control groups by matching.

Table 9. Statistics before and after matching

	Statistics before matching			**Statistics after matching**			**Balance Improvement (%)**
	Means Treated	***Means Control***	***Mean Diff.***	***Means Treated***	***Means Control***	***Mean Diff.***	
Propensity score	0.444	0.268	0.177	0.444	0.386	0.058	67.13
X_p	10.896	9.666	1.230	10.896	10.565	0.331	73.12
X_1	10.919	9.693	1.226	10.919	10.644	0.274	77.62
X_2	10.160	9.953	0.208	10.160	9.997	0.164	21.21

Table 10 shows the results for the frontier separation approach before and after matching. The estimated results show that both DEA and FDH models generate a good estimation of true efficiency. The frontier separation conditional on propensity score produces a closer estimation of true policy impact on the treated observations than the traditional separation approach. The revised approach produces a reduction of 28% of bias compared to the traditional approach. However, we can only give conclusions about the dominance of the revised approach over the traditional approach after reference to the Monte Carlo simulation results, which are presented in the next section of the chapter.

Table 10. Analysis results

Variable	**Mean**
Number of treated observations	65
Number of control observations	135
Total number of observation	200
Number of observations after matching	130
True overall efficiency of all observations	0.82

Variable	Mean
FDH estimated overall efficiency of all observations	0.86
DEA estimated overall efficiency of all observations	0.78
Traditional FSA program efficiency of the treated group	0.98
Traditional FSA program efficiency of the control group	0.97
Revised FSA[22]program efficiency of the treated group	0.98
Revised FSA program efficiency of the control group	0.96
True impact from external variable	**0.0342**
Estimated impact by traditional FSA	**0.0139**
Estimated impact by revised FSA	**0.0237**
Bias reduction by revised FSA (%)	**27.99**

4.7. Results of Monte Carlo Simulation for Frontier Separation Conditional on Propensity Score Approach

In the previous section we have a demonstration of how a revised frontier separation approach is conducted and gives better results than the traditional frontier separation approach as proposed by Charnes et al. (1981) after eliminating the selection bias from the analysis. In this section, the advantage of the revised frontier separation approach by means of propensity score matching will be given through a Monte Carlo simulation. We have run 4000 repetitions of estimation of different specifications of the frontier function and different treatment impacts. In particular, as described in section 5 about the simulation design, the simulation is built with the assumption that treatment effects will be 0%, 5%, 10%, 15% and 25% $\left(\text{i.e. } \alpha = 0.00;\ 0.05;\ 0.10;\ 0.15; \text{ and } 0.25\right)$.There are four sample sizes, $N = 100,\ 200,\ 300,\ 500$, to be used for the generation of data for

[22] We use the term revised FSA to imply our proposed model that revises traditional FSA by applying proposensity score matching and arriving an equal samples of treated and non-treated DMUs before conducting further analysis.

analysis. We consider both types of production technology, i.e. constant and variable returns to scale.[23]

To compare the performance of traditional and revised frontier separation approaches, we use two indicators. The first indicator is the bias reduction as a ratio of the difference between the treatment effect estimated by the traditional and the revised frontier separation approach to the true treatment impact. The second indicator is the mean square error (MSE), which is square of mean difference between the estimated treatment effect and the true treatment impact. This indicator shows how close the estimated treatment effect is to the true treatment impact. The closer to zero the indicator is the better.

The figures placed in the following section show the performance of the traditional frontier separation approach (FSA) and revised FSA. In Figure 17 the average estimated and true treatment effects are projected for different values of α in the CRS production technology for samples with the same size of 100 observations and of sample repetition of 100 times. The figure shows that the revised FSA produced a closer estimation of the treatment effect to true treatment effect than the traditional FSA. Figure 18 showing the average MSE of the two approaches with regards to different values of α confirming the advantage of the revised FSA to the traditional one. The detailed estimations of different designed treatment effects with sample size of 100 observations, repetition 100 times, are presented in the Table 11. We can see that the bias reduced by the revised FSA is significant, e.g. it reduces bias by an average of 42% with the estimation of treatment effect for $\alpha = 0.05$, 25% for $\alpha = 0.1$, and 10% for $\alpha = 0.25$.[24]

[23] See section 4.5: Simulation Design for more details about the specifications of the simulation.

[24] Detailed statistics for all simulation designs can be found in the Appendix IV of the thesis. Detailed tables provide 15 estimated indicators for each simulation. Here we only describe some examples which are enough to prove the advantage of the proposed approach. Figures are the main forms of presentation since they help to easily visualize the results of the analysis.

Figure 17. True and estimated treatment effects with CRS technology, N=100

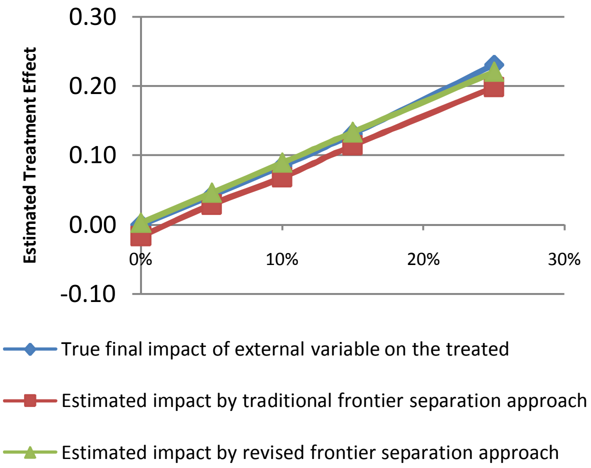


Figure 18. MSE with CRS technology, N=100

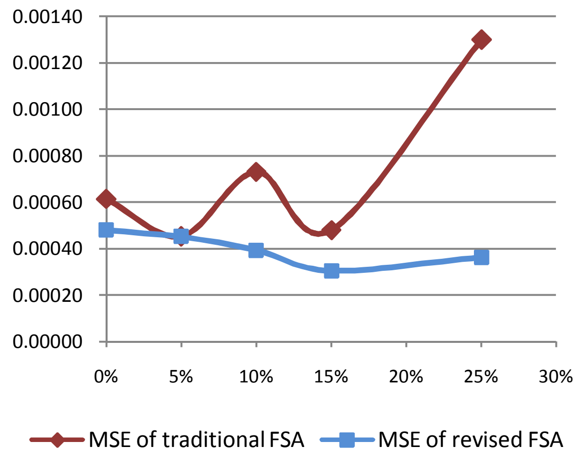


Table 11. Monte Carlo simulation with 100 obs., 100 repetitions, CRS technology

	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
Sample 100 observations, 100 repetitions	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
True impact of external variable	-0.00053	0.00039	0.04250	0.00047	0.08501	0.00052	0.13057	0.00068	0.23038	0.00102
Estimated impact by traditional FSA	-0.01697	0.00192	0.02908	0.00172	0.06797	0.00224	0.11436	0.00167	0.19834	0.00177
Estimated impact by revised FSA	0.00271	0.00221	0.04638	0.00211	0.08946	0.00212	0.13327	0.00187	0.22066	0.00185
MSE of traditional FSA	0.00061	0.00009	0.00045	0.00007	0.00073	0.00012	0.00048	0.00007	0.00130	0.00012
MSE of revised FSA	0.00048	0.00008	0.00045	0.00007	0.00039	0.00005	0.00030	0.00005	0.00036	0.00005
Bias reduction by revised FSA (percentage)	-2741.28	10007.06	41.69	3.43	25.16	1.93	14.54	1.10	9.66	0.68

With the VRS production technology, traditional FSA shows a weaker performance compared to the revised FSA. Particularly, Figure 19 and Figure 20 present the performance of revised FSA in comparison with the traditional FSA. It shows the superiority of the revised FSA to the traditional FSA in estimating the treatment effects of external variable when the production technology takes the form of variable returns to scale. The detailed information on estimated treatment effects as well as MSE of traditional and revised FSA can be seen in the Table 12 below.

Figure 19. True and estimated treatment effects with VRS technology, N=100

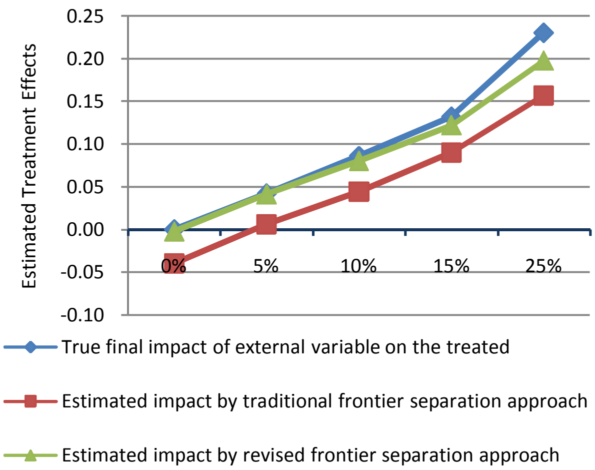


Figure 20. MSE with VRS technology, N=100

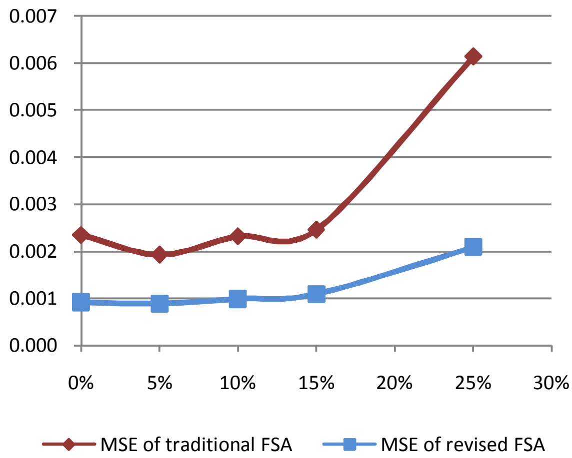


Table 12. Monte Carlo simulation with 100 obs., 100 repetitions, VRS technology

Sample 100 observations, 100 repetitions	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
True impact of external variable	0.00003	0.00044	0.04223	0.00050	0.08613	0.00052	0.13252	0.00060	0.23060	0.00090
Estimated impact by traditional FSA	-0.03978	0.00283	0.00609	0.00269	0.04459	0.00256	0.09005	0.00274	0.15700	0.00292
Estimated impact by revised FSA	-0.00200	0.00312	0.04120	0.00313	0.08025	0.00320	0.12203	0.00328	0.19773	0.00336
MSE of traditional FSA	0.00235	0.00032	0.00193	0.00022	0.00232	0.00022	0.00246	0.00024	0.00614	0.00044
MSE of revised FSA	0.00092	0.00016	0.00089	0.00011	0.00099	0.00014	0.00109	0.00014	0.00209	0.00030
Bias reduction by revised FSA (percentage)	1037.98	644.19	85.01	5.47	41.36	2.88	24.24	1.61	17.67	1.04

Similarly results of simulations with $(\alpha = 0.00;\ 0.05;\ 0.10;\ 0.15; \text{ and } 0.25)$ and sample sizes of $N = 200,\ 300,\ 500$ for both CRS and VRS production technology are presented in the figures from 10 to 21. It is clear from these figures that, for some simulations with $(\alpha = 0.05;\ 0.10)$ and CRS production technology, traditional FSA can be compared with revised FSA in terms of MSE. The revised FSA however is better than traditional FSA in producing estimated treatment effects that are closer to true treatment impacts in CRS production technology. The revised FSA is superior to traditional FSA in estimating treatment effects with models of VRS production technology.

The difference between traditional and revised FSA can be clearly seen in the simulation design where policy has no impact at all to technical efficiency of productive units $(\alpha = 0.00)$. In fact, traditional FSA always produces a significant negative impact from environmental factor on technical efficiency. The negative impacts from environment factor projected by FSA range from -1% to -4% (see the Table 13 for more details).

Table 13. True and estimated impacts of environmental variable on technical efficiency with $(\alpha = 0.00)$, repetitions: 100 times

Sample size	Production technology	True impact	Estimated impact, traditional FSA	Estimated impact, revised FSA
N=100	CRS	-0.00053	-0.01697	0.00271
	VRS	0.00003	-0.03978	-0.00200
N=200	CRS	-0.00020	-0.01319	-0.00054
	VRS	-0.00023	-0.02883	-0.00127
N=300	CRS	-0.00038	-0.01274	-0.00106
	VRS	0.00016	-0.02268	0.00081
N=500	CRS	0.00009	-0.00988	0.00019
	VRS	-0.00024	-0.02208	-0.00238

Results from simulation designs with $(\alpha = 0.00)$ show an issue of DEA method related to the establishment of the production frontier. By design, the control DMUs account for 70 percent of total number of DMUs. This in turn affects the possibility of a control DMU to be located on the production frontier. Since all of the variables in the simulation are generated randomly with the same distribution for both treated and control groups, the larger the number of one group, the higher the possibility that that group has its DMUs on the production frontier. In our case, since the control group by design has more DMUs, then the possibility that an efficient DMU belonging to this group is higher. It implies that frontier separation approach or other DEA based approach to impact evaluation in general can only differentiate the impact if external variable impact is higher than the impact of higher probability of being on production frontier by control DMUs to the estimation of impact. This issue has been analysed in Simpson (2007) when discussing the failure of the test for programmatic efficiency for two groups with different size of sample.

Figure 21. True and estimated treatment effects with CRS technology, N=200

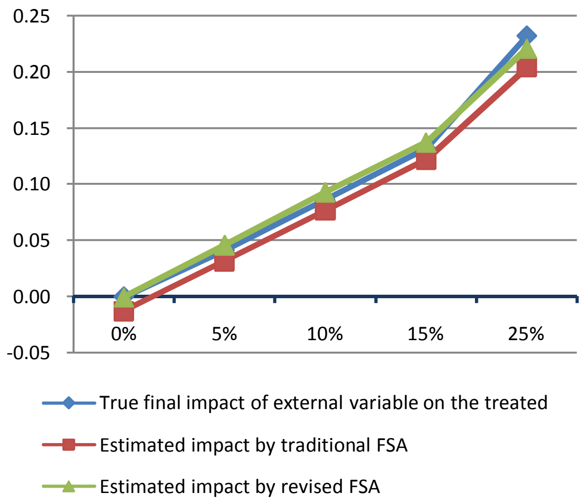


Figure 22. MSE with CRS technology, N=200

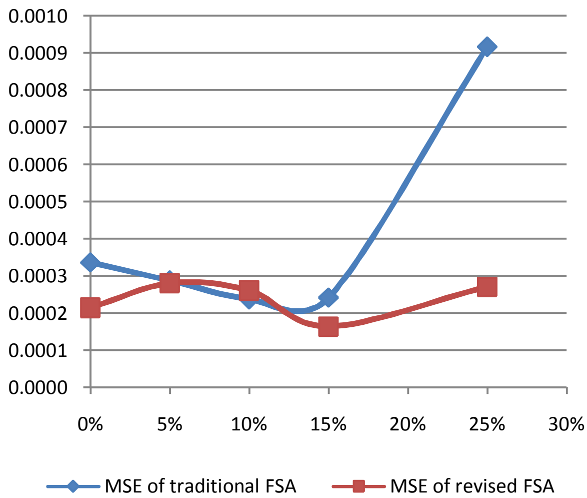


Figure 23. True and estimated treatment effects with VRS technology, N=200

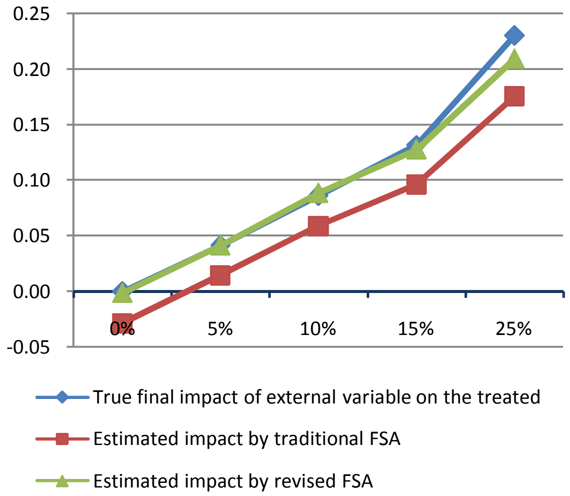


Figure 24. MSE with VRS technology, N=200

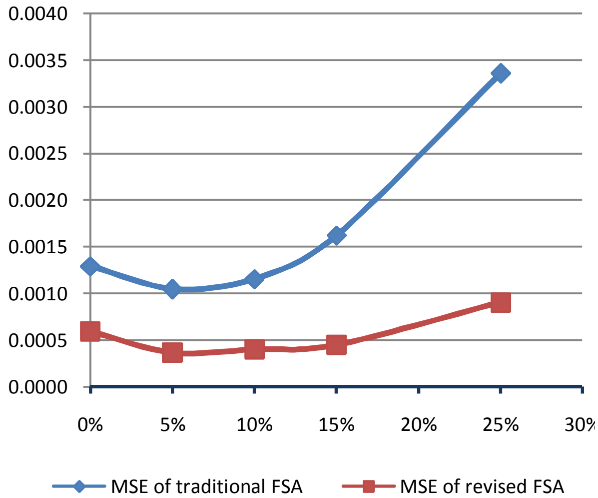


Figure 25. True and estimated treatment effects with CRS technology, N=300

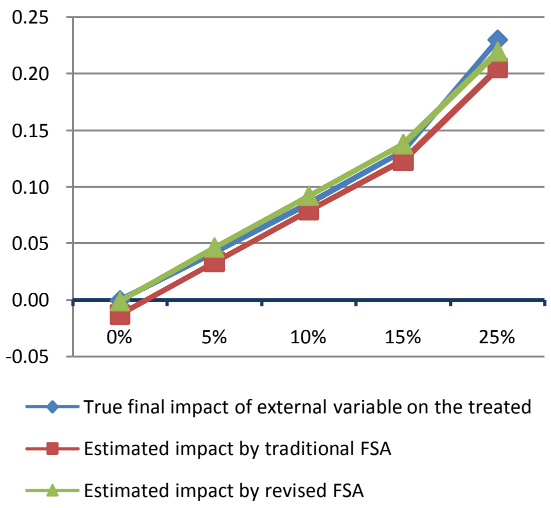


Figure 26. MSE with CRS technology, N=300

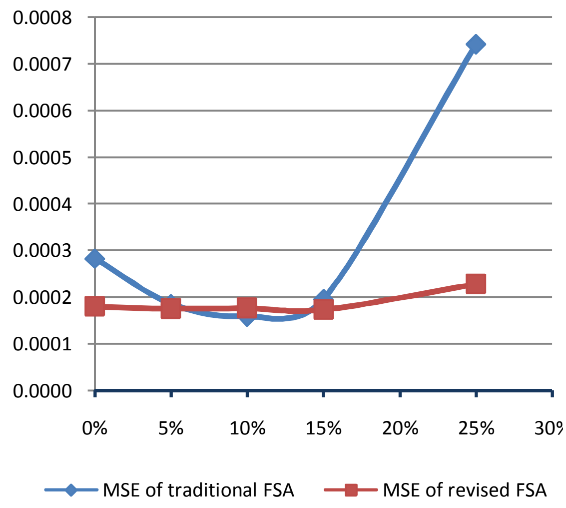


Figure 27. True and estimated treatment effects with VRS technology, N=300

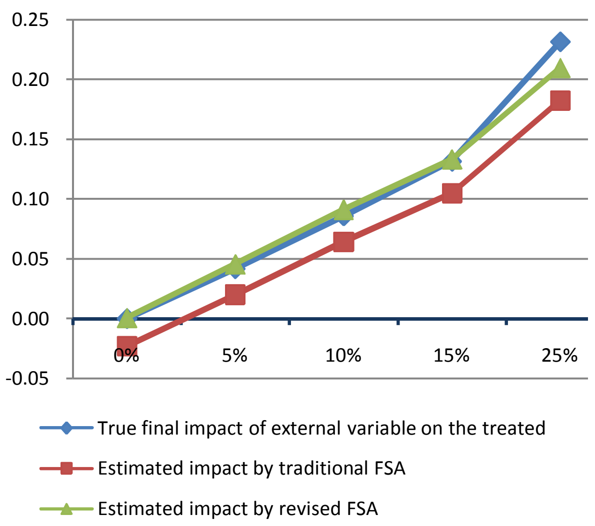


Figure 28. MSE with VRS technology, N=300

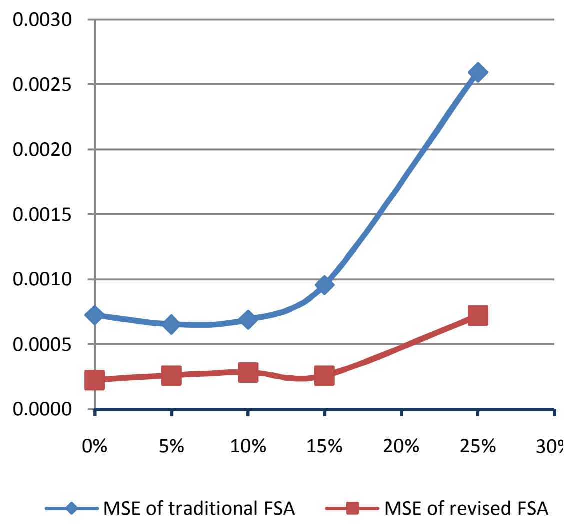


Figure 29. True and estimated treatment effects with CRS technology, N=500

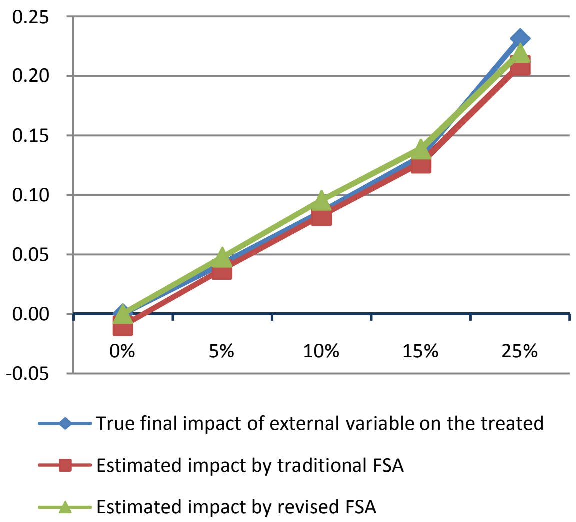


Figure 30. MSE with CRS technology, N=500

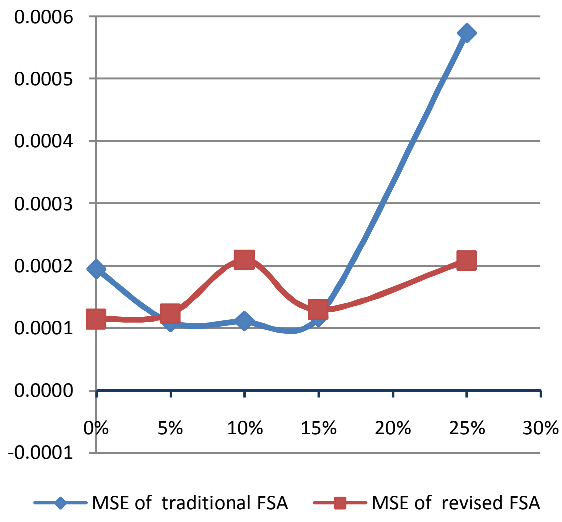


Figure 31. True and estimated treatment effects with VRS technology, N=500

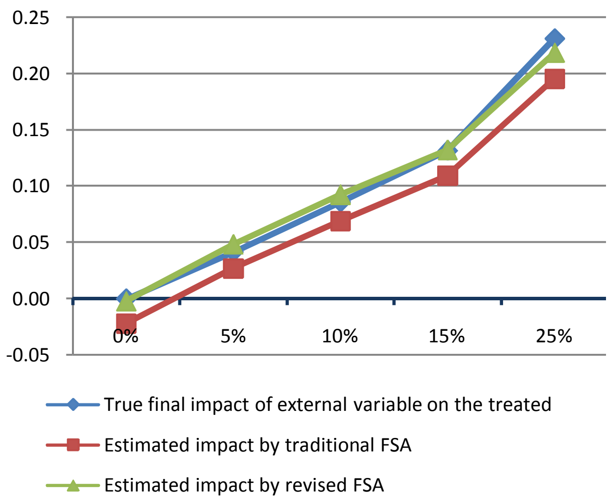
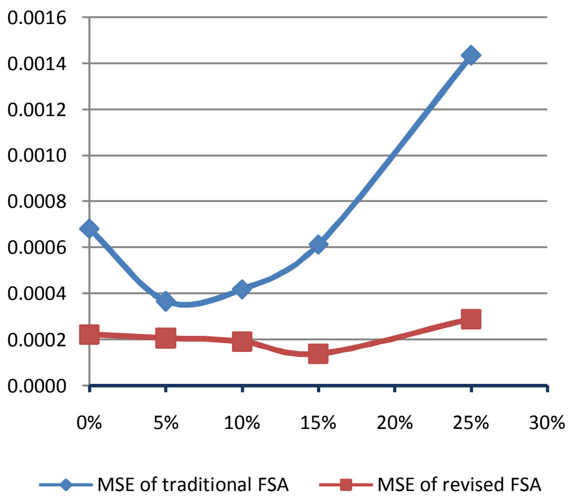


Figure 32. MSE with VRS technology, N=500



4.8. Conclusion

This chapter described one approach to evaluate the impact of an environmental variable on technical efficiency, in which the environmental variable takes the form of a dichotomous variable and selection bias exists. We propose a revised FSA, which takes into account the existence of selection bias and combines matching algorithms with the FSA to deal with this problem. A detailed demonstration how the proposed approach works in distinguishing the treatment effect of a dichotomous environmental variable is presented in the chapter. Monte Carlo simulations are run to evaluate the performance of the proposed approach. Simulations with different original external impacts of 0%, 5%, 10%, 15% and 25% are formulated and conducted with four different sample sizes: $N = 100,\ 200,\ 300,\ 500$. A nearest neighbour matching without replacement algorithm is used for matching treated and control observations.

The results from the Monte-Carlo simulations show that the proposed approach is able to estimate average treatment effects close to the true average treatment effects produced from models. The revised FSA is superior to traditional FSA in estimating treatment effects for both CRS and VRS production technologies. The proposed approach performs better in both reducing the bias originated from the treatment and overcoming impact of higher probability of being on production frontier by control DMUs when they are more numerous than the treated ones.

The simulation conducted in this chapter reveals the problem of DEA based approach to separating the impact of external variable in the context where the number of control DMUs are much higher than number of treated DMUs or the other way round. Moreover, a separation frontier may not be a good approach since by separating observations into two groups for analysis and estimating within group technical efficiency, one may argue that we are considering production units with different technology frontier and they may not be compatible for a direct comparison.

Chapter 5. Evaluation of the Impact of a Training Program on the Technical Efficiency of Food Processing SMEs

5.1. Introduction

As presented in Chapter II of the thesis, the development of SMEs becomes the key for the development of Vietnam's economy. Therefore, there have been various policy programs to support the development and enhance the productivity and efficiency of SMEs. There is a wide variety of policies supporting the development of SMEs. Along with a macroeconomic environment favourable for the development of enterprises, the government has introduced a range of policies in order to assist the development of SMEs. These policies include assistance to access to land, credit, market expansion and training, among others.

This chapter aims to evaluate the impact of the training policy instituted by the government to enhance performance of SMEs in Vietnam. By using the revised frontier separation approach as proposed in Chapter 4 of the thesis, we will be able to control for the selection bias caused by several factors so as to arrive at the true impact of the training policy. We choose to analyse the impact of the training policy on the food processing industry, which is a fast growing industry in Vietnam. The chapter is constructed as follows. Section 2 of the chapter will be devoted to literature review of previous studies on the impact of training on enterprise performance. Section 3 describes briefly our analysis objective, the food processing industry. The next section will present the methodology and data used for the research. Results and analysis will be presented in section 4 of the Chapter. Section 5 will conclude the Chapter.

5.2. Training Program and Enterprise Performance

The reasoning for the government's support to training of SMEs' entrepreneurs and employees is based on the fact that one of the most important factors for economic development is the human capital from both macro and micro economic perspectives. Lucas (1993) claimed accumulation of human capital, which takes place in education and training systems as well as in the course of production and trading, as the main engine of growth for the miracle development of East Asian economies. While Koch and McGrath (1996) showed that competitive advantage achievement and maintenance through productivity is attributed to human capital of employees in an enterprise.

However, employees in SMEs are much less likely to be exposed to training than employees in larger enterprises (Westhead and Storey, 1997). This is due to several reasons. The perception of management boards of SMEs that training is costly is one obstacle for the training for employees (Hankinson, 1994). It is more difficult for SMEs since SMEs have smaller budgets relative to larger firms and do not have dedicated human resource staff for training (Bryan, 2006). More importantly, there is a perception that training does not help to enhance performance (Fernald et al., 1999). This perception is supported by several studies on the impact of training to SMEs performance, both productivity and finance, as mentioned below. An additional obstacle faced by SMEs in providing training to their staff is poaching by larger enterprises and other counterparts (Hankinson, 1994). Since SMEs have shallow organizational hierarchies which play as a professional progress ladder of employees, management training is seen as providing skills beyond the need of SMEs (Bryan, 2006).

Explanations for lower incentive for providing training to employees in SMEs is grouped by Westhead and Storey (1997) as follows. Firstly, SMEs' entrepreneurs are not aware of the benefits of training and therefore do not commit resources for training to obtain the optimal human capital for their employees. This can be called as the "ignorance" reason for the phenomenon. Secondly, SMEs' owners may be aware of the benefits that can be originated from training for their firms' performance. However, they provide training to their employees that is less than optimal level based of the perception that training cost may be larger than the returns enterprises can obtain from it. This is the "market-forces" explanation of lower incentive for training in SMEs.

From the government's point of view, if training is not provided or is provided inadequately to employees of SMEs because of the ignorance of owners, there is a justification for policy intervention by the government. The government could provide entrepreneurs with training information, as well as evaluation of the impact of training on performance of SMEs by improving knowledge and skills of employees. The government could also provide direct training subsidies to SMEs. Huang (2001) suggested that intensive examination of the impact of training programs on the performance of enterprises should be carried out to determine the type and extent of training assistance needed from the government to SMEs.

Despite extensive literature on SMEs, very little attention has been paid to examining the effectiveness of training on business performance. Moreover, the results of meagre studies on the relationship between training and business performance of SMEs are controversial. Therefore there exists a perception within SME entrepreneurs about the ineffectiveness of training on business performance. Studying 1,604 SMEs in the UK in 1991, among which 768 SMEs survived by 1997, Cosh et al. (2000) found a positive relationship between training and SMEs performance in terms of employment growth for the year 1997. Devins and Johnson (2003) examined the effectiveness of the European Social Fund (EFS) Objective 4 programme which assists employees to develop their skills during the period 1998 -2000. They found that a third of the SMEs surveyed reported a very significant impact on their sales as a result of the programme.

Jayawarna et al. (2007) recently studied training of both types, formal and informal, and discovered that formal training has a positive relationship with performance of enterprises by targeting activities that contribute more significantly to the performance of enterprises. At the mean time, informal training is less likely targeted to activities that contribute significantly to performance of enterprises and therefore it is not effective. Chi et al (2008) also found a positive relationship between training to do investment abroad (outgoing FDI) and the performance of 816 Taiwanese SMEs.

Positive relationship between training and performance, however, is not dominant in the literature. Marshall et al. (1993) evaluated the impact of Business Growth Training project by the government, which from 1989 to 1991 provided financial resources to conduct training in SMEs in Britain, and suggested that management training does not improve business performance. The weak link between training provided and firm performance was reported by Wynarczyk et al. (1993) for rapid-growth SMEs in the UK. A survey of studies on the relationship between training and performance of SMEs by Westhead and Storey (1997) also confirmed that the relationship is not well established.

In fact, training in SMEs may vary in types of skills or knowledge delivered, modes of delivery, as well as duration (Westhead and Storey, 1997). Moreover, the definition of performance is not consistent among studies. For most of the previous studies, performance of SMEs is measured in terms of turnover, employee growth, and survival (De Kok, 2002). A review by Thang and Buyens (2008) showed that 94 percent of studies examined use financial indicators to measure the performance of SMEs. The use of productivity or technical efficiency as performance indicator for SMEs is absent from studies we have reviewed, yet they should capture the impact of training, which is targeted at improving financial performance. In this chapter we will for the first time examine the impact of training on comparative technical efficiency of SMEs in food processing industry. This will compare firms with training and firms without, controlling for selection bias, so as to isolate the impact of training on performance.

5.3. The Food Processing Industry in Vietnam

Food processing can be defined as the process of transformation of agricultural commodities in preparation for human consumption (Minot, 1998). Several activities are included under food processing as defined above, that are cleaning, grading, and storage, as well as various types of cooking, milling, canning, and freezing. Food processing plays an important role in the development in developing countries, also reflects the economic development while people tend to consume ready processed, high quality food when their living standard is being improved. The sector is relative labour intensive, therefore it is a meaningful sector for a developing country where there is abundance of labour forces. It importantly contributes to the improvement of rural population, since its plants are usually located in rural area, creating jobs for rural populations (Minot, 1998). Such job creation is also helped because its inputs are from agriculture, which is directly related to rural population.

The food processing sector has several distinctive characteristics, which affect their production behaviour as well as their cost allocation. Input supplies for the food processing industry are highly seasonal. Therefore, food processors usually rely on storage capacity to maintain their production off-season. Alternatively they may have to produce other products to survive in periods out of agricultural harvest. It influences importantly productivity and profitability of food processors. Food processing sector inputs are affected heavily by weather conditions, and therefore can fluctuate substantially on year-to-year basis. The quality of inputs also can vary largely due to their perishability. The value per volume of raw material for the food processing industry is usually low, therefore processors usually build large size plants. This results in the fact that plants are usually located near producing areas, which are mostly rural areas where labour skills are low. Moreover, since their products have direct implication for consumer health, operations of food processors are heavily regulated by the government, making their cost of operation higher (Minot, 1998).

With a large population, increasing urbanisation and improvement in living standards thank to rapid economic growth, the demand for quality food is increasing rapidly in Vietnam. It is a motivation for the food processing industry to expand rapidly. In the past few years this sector has expanded at the rate of 20-30 percent per annum. The consumption habits of the consumers have been changing substantially due to the increase of disposable income making the processed food a potential profit making industry. It is not a surprise that world giant food producers are present in Vietnam markets. Among them are South Korean giant Lotte Confectionary, Japanese Sojitz Corporation, Unilever, Nestle…

The rapid growth of the food processing sector is supported by a high growth in consumption demand for processed food by the population. As estimated by Business

Monitor International (2009), the growth rates of food consumption are 13.12 percent in 2006, 13.49 percent in 2007 and estimated 14.58 percent in 2008 (see Table 14 for details). The growth of food consumption is actually very much higher than the GDP rate of growth. The accession to the WTO in 2007 provides the food processing sector and other sectors of the economy an opportunity to expand to foreign markets. At the same time, it creates competition pressure on food processors in domestic markets, since international integration process opens the domestic market door to foreign competitors.

Table 14. Domestic Food Consumption of Vietnam

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Note: e - estimated figure; f - forecasted figure

Source: Business Monitor International (2009)

An enterprises consensus survey by the General Statistics Office (GSO) in 2007 showed that, there are more than 4,000 food processors operating in the country[25]. Among them are around 260 large seafood-processing plants, who are the main foreign exchange generators of the economy, producing 250,000 tons of seafood annually; 65 large-size fruit and vegetable-processing plants, 27 instant noodles manufacturing plants, 23 confectionary manufacturers (Business Monitor International, 2009). The remaining enterprises are mostly small and medium sized enterprises.

[25] GSO, 2007, Enterprise Consensus Servey, estimated by the author.

With the presence of large scale food processing plants and foreign manufacturers, food processing SMEs face many difficulties in production. They have to compete in both fronts, quality inputs for their production and markets for their outputs. These along with the special characteristics of the food processing industry, i.e. seasonal production with large volume inputs stored, large production site, high quality requirement, low labour skill due to being located in rural areas, makes the difficulties faced by food processing SMEs even larger. Therefore there are several support schemes that have been launched by the government. Among others is training support provided by different institutions to SMEs. They are not aimed at supporting only food processing enterprises. Rather they are aimed at SMEs in all industries. The access to support, however, depends on the responsiveness of the entrepreneurs as well as the planned location of the support scheme.

As mentioned in Chapter 2, training support to SMEs is provided in different types. Training programs for business start-up, management, and employees have been conducted with the support of international organizations such as ILO, UNIDO, GTZ, IFC, DANIDA. The Agency for SMEs Development (ASMED) has their own designed training courses for SMEs to assist SMEs to develop business strategies and expand export markets. The training courses conducted by ASMED are not only for existing SMEs but also potential entrepreneurs. Training courses on the formulation of product standards, quality management and machinery/equipment inspection have been conducted by the Directorate for Standards and Quality. In most provinces, SMEs can access training and grants for implementing quality control (ISO 9000, HACCP, etc.) through the provincial Department of Science and Technology.

The SMEs survey by ILSSA of the Ministry of Labour, Invalids, and Social Affair, under the supervision CIEM and the Copenhagen University as discussed in the section on data for analysis shows that most of the enterprises surveyed appreciate the training support scheme. However, a detailed analysis is needed to understand better the impact of the policy on the performance of those enterprises. The next section of this chapter discusses in detail the research methodology and data used for this analysis.

5.4. Research Methodology and Data

5.4.1 Research Methodology

In this chapter we apply the methodology presented in Chapter 4 for the estimation of impacts of training policy on the performance of SMEs in the food processing industry in Vietnam. In particular, the revised frontier separation approach will be used as the main engine for the analysis. The strength of this method is that it is able to measure the level of impact of training on the technical efficiency of enterprises. At the same time it isolates the true impact from the selection bias caused from the difference in characteristics of enterprises used in the comparison.

Detailed discussion about the methodology based on propensity scores was given in chapter 4 of the thesis. The procedure includes the separation of enterprises into two samples according to whether or not they attended training. Normal comparison of average performance indicators, regardless whether they are financial indicators, productivity indexes, or technical efficiencies, of the two samples does not give us the true impact of a training program on performance. This is due to the possibility that enterprises select themselves into treatment. E.g. those generally more efficient may be more prone to self select to train. Therefore normal comparison will give biased results.

One solution to this problem is to compare only enterprises that are similar to each other in all observed characteristics, and are different only in training attendance. The procedure to determine two similar enterprises, one is treated and the other is not treated is called matching. Heckman et al. (1997) (pp.606) give a concise and clear definition and procedure to conduct matching as: "*Matching methods pair programme participants with members of a non-experimental control group who have similar observed attributes and estimate treatment impacts by subtracting mean outcomes of matched comparison group members from the mean outcomes of matched participants*".

Before the seminal paper by Rosenbaum and Rubin (1983) covariate matching was the main engine for matching similar observations. However, Rosenbaum and Rubin (1983) proved that by using a scalar vector of propensity scores matching can be done without worry about the curse of dimensionality faced in covariate matching. The probability, or propensity score, that an observation is treated is not known. However, it can be estimated by using binary choice models (Smith, 1997, Caliendo, 2006).

The linear probability model is the simplest binary choice model where the probability of the event occurring is the result from linear regression of a set of explanatory variables. The main advantage of linear probability models is that they are much easier to fit (Dougherty, 2007). However, it has shortcomings that are well known among econometricians. In the linear probability model with one dependent and one independent variable we have following expression:

$$Y_i = \beta_1 + \beta_2 X_i + u_i \tag{61}$$

Where i is observation index, Y_i is dependent variable, taking value 1 if the event occurs, 0 if event does not occur. X_i is independent variable, and u_i is a disturbance term. Since the outcome variable Y_i takes only value 0 and 1, when Y_i=1 the disturbance term is: $u_i = 1 - \beta_1 - \beta_2 X_i$. On the other hand when Y_i=0 the disturbance term is: $u_i = -\beta_1 - \beta_2 X_i$. The disturbance term in this case can take only two values, therefore standard errors and test statistics are invalid..

Another issue is that the population variance of the disturbance term is correlated with the explanatory variables, resulting in the heteroscedasticity problem of linear probability models (Fosu, 1984). Moreover, linear probability models may predict probabilities of more than 1 or less than 0, outside the [0, 1] bound of probabilities (Smith, 1997). Therefore other binary choice models are favoured over linear probability models for the estimation of propensity scores in analyses.

Other binary choice models are logit models and probit models, which are non-linear regression. According to Caliendo (2006) logit and probit models usually produce the same results for the binary treatment case, which is also the case in this analysis. Therefore the choice of probit or logit model for the estimation is not important.

Beside the choice of model for the estimation of propensity scores, Caliendo (2006) in his empirical guidance for the implementation of matching, points to another issue that researchers should take into consideration. That is variables to be included in the propensity score estimation model. As presented in Chapter 4 of the thesis, one of the key assumptions of the matching method is the conditional independence assumption (CIA), which requires that the outcome variable should be independent of treatment. Matching strategy works by obtaining this independence via conditioning on propensity scores. Variables that are used for estimating propensity scores therefore must be chosen to meet this condition. Heckman et al. (1997) show that if important variables are omitted from the estimation of propensity scores then the resulting estimates can be seriously biased. Smith and Todd (2005) believed that a sound knowledge of economic theory, previous empirical studies, and institution settings are needed to guide researchers in building up the model. The most important variables which should be included in the model are variables that influence simultaneously both the participation decision and the outcome (Caliendo, 2006).

5.4.2 Data for Analysis

The analysis is conducted with the data collected under the project Business Sector Programme Support (BSPS) funded by DANIDA and managed by CIEM. The survey was conducted by ILSSA of the Ministry of Labour, Invalids, and Social Affairs, under the supervision of CIEM and Copenhagen University in 2007. This survey covered 2,492 manufacturing enterprises in 3 cities (Hanoi, Hai Phong, and Ho Chi Minh City) and 7 provinces (Ha Tay, Phu Tho, Nghe An, Quang Nam, Khanh Hoa, Lam Dong and Long An). The sample was taken from the population of manufacturing enterprises in these cities and provinces. SMEs included in the survey consist of household enterprises, cooperatives, partnerships, private enterprises, limited liability companies and share-holding companies.

The survey samples are based on two sources of information (Rand et al., 2008). The Establishment Census 2002 (GSO, 2004) is used to obtain information about household enterprises, the type of enterprises not being regulated by the Enterprise Law. The

Industrial Survey 2004-2005 (GSO, 2007) provides information about enterprises registered at province level under the Enterprises Law, which include private, collectives, partnerships, private limited enterprises and joint stock enterprises. Table 15 presents the population of enterprises in cities and provinces where the survey was conducted, from which the sample was drawn.

Table 15. Population of non-state manufacturing enterprises in surveyed provinces and cities

	Household enterprise	Private/sole proprietorship	Partnership/ Collective/ Cooperative	Limited liability company	Joint stock company

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Sources: GSO, 2007; GSO, 2004, quoted in Rand et al.(2008)

The most important factor that has many significant impacts on the analysis of SMEs from this survey is that the number of micro size enterprises dominates the sample. 66.7 percent of enterprises in the survey are micro firm with 1 to 9 employees. It follows the population structure of SMEs in Vietnam where micro firms account for a larger share of all enterprises. Most of the micro firms are established as household establishments. Medium size enterprises account for only 6.3 percent of the sample. And limited liability companies are the second most popular forms of enterprises in the survey. Household establishment is the most popular business type in the survey. They account for nearly 70 percent of the total surveyed enterprises, against 95 percent of the population as presented in the above table. These characteristics along with micro size characteristics will be taken into account in all analyses using this dataset. Table 16 and 17 present the ownership and location versus size and legal business types of surveyed enterprises.

Table 16. Ownership and size structure of surveyed enterprises

	Micro	Small	Medium	Total	Percent
Household establishment	1,491	235	6	1,732	***(69.5)***
Private/sole proprietorship	76	96	19	191	***(7.7)***
Partnership/Collective/Cooperative	18	63	18	99	***(4.0)***
Limited liability company	74	254	99	427	***(17.1)***
Joint stock company	4	24	15	43	***(1.7)***
Total	1,663	672	157	2,492	***(100.0)***
Percent	***(66.7)***	***(27.0)***	***(6.3)***	***(100.0)***	

Table 17. Location and Legal structure of surveyed enterprises

	Household enterprises	Private/sole proprietorship	Partnership/ Collective/ Cooperative	Limited liability company	Joint stock company	Total
Ha Noi	119	26	19	102	13	279
Phu Tho	222	4	4	10	2	242
Ha Tay	312	14	10	43	2	381
Hai Phong	92	25	35	33	9	194
Nghe An	288	22	6	28	5	349
Quang Nam	130	7	6	9	2	154
Khanh Hoa	56	14	1	12	3	86
Lam Dong	65	8	0	8	0	81
HCMC	352	50	17	176	7	602
Long An	96	21	1	6	0	124
Sample total	**1732**	**191**	**99**	**427**	**43**	**2492**

Survey of Manufacturing SMEs in Vietnam
2007

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Number of Surveyed SMEs

81
86
124
154
194
242
279
349
381
602
No data

Source: Author creation from the dataset

The following tables present surveyed enterprises by sector, legal status and size. The tables are built based on the International Standard Industrial Classification (ISIC). As can be seen from the tables, three most popular sectors in the survey include the food processing sector (ISIC 15), fabricated metal product (ISIC 28) and manufacturing of wood products (ISIC 20)[26] [27]. More than four-fifths of the enterprises in the food processing sector are household enterprises, which are not registered under the Enterprise Law. The same proportion of food processing enterprises belongs to micro-size enterprises. These factors should be taken into account when evaluating the performance of food processing enterprises and the impact of training policy on the performance of these enterprises.

Table 18. Legal type and sector distribution of surveyed enterprises

ISIC	Household enterprise	Private/sole proprietorship	Partnership/ Collective/ Cooperative	Limited liability company	Joint stock company	Total	Percent
15	570	36	10	67	13	**696**	*27.9*
16	6	0	0	2	0	**8**	*0.3*
17	69	8	2	36	0	**115**	*4.6*
18	47	8	5	38	2	**100**	*4*
19	39	3	3	4	1	**50**	*2*
20	232	20	15	27	2	**296**	*11.9*
21	21	8	7	28	5	**69**	*2.8*
22	21	7	2	28	1	**59**	*2.4*
24	23	1	2	18	2	**46**	*1.8*
25	51	19	18	40	4	**132**	*5.3*
26	117	5	8	17	3	**150**	*6*
27	13	7	4	3	1	**28**	*1.1*
28	315	37	17	49	3	**421**	*16.9*
29-32	38	7	2	32	2	**81**	*3.3*
34	19	2	0	8	1	**30**	*1.2*
35	1	3	1	2	0	**7**	*0.3*
33+36	141	19	3	28	3	**194**	*7.8*
37	9	1	0	0	0	**10**	*0.4*
Total	**1,732**	**191**	**99**	**427**	**43**	**2,492**	*100*
Percent	*69.5*	*7.7*	*4*	*17.1*	*1.7*	*100*	

[26] See the Appendix III for the notation of sectors according to International Standard Industrial Classification (ISIC).

[27] Since there is no enterprises in the sector of refined petroleum, ISIC 23, it is eliminated from the above listing.

Table 19. Size and sector distribution of the surveyed enterprises

ISIC	Micro	Small	Medium	Total	*Percent*
15	577	94	25	696	***(27.9)***
16	5	3	0	8	***(0.3)***
17	53	50	12	115	***(4.6)***
18	36	48	16	100	***(4.0)***
19	31	17	2	50	***(2.0)***
20	200	82	14	296	***(11.9)***
21	17	37	15	69	***(2.8)***
22	28	29	2	59	***(2.4)***
24	21	20	5	46	***(1.8)***
25	57	57	18	132	***(5.3)***
26	91	47	12	150	***(6.0)***
27	13	12	3	28	***(1.1)***
28	329	84	8	421	***(16.9)***
29-32	43	32	6	81	***(3.3)***
34	17	7	6	30	***(1.2)***
35	2	4	1	7	***(0.3)***
33+36	134	48	12	194	***(7.8)***
37	9	1	0	10	***(0.4)***
Total	1,663	672	157	2,492	***(100.0)***
Percent	***(66.7)***	***(27.0)***	***(6.3)***	***(100.0)***	

5.5. Analysis

In this section we take a closer look at 644 food processing SMEs, which is the final number of food processing SMEs that we shall analyse after a data cleaning process of 696 in the aforementioned survey. Among the 644 enterprises, only 22 enterprises attended training courses organized by governmental agencies as assistance to improve the performance of SMEs. This is a typical form of a policy evaluation in which the number of treated observations is much less than the number of non-treated observations (controls). Our main exercise is to evaluate the impact of the training program on the efficiency of food processing enterprises. This is done by comparing the technical efficiency of treated observations with their **counterfactuals**. The counterfactual of a treated observation is not observed but can be created by a matched observation from those not treated. The matching is by means of propensity scores (Rosenbaum and Rubin, 1983, Heckman et al., 1997, Heckman et al., 1998). In the following box, the necessary steps to evaluate the impact of the training policy on technical efficiency of food processing enterprises by the revised frontier separation approach is presented.

Box 3. Steps to evaluate the impact of training policy on technical efficiency of food processing enterprises

Step 1. Choose variables that are included in the estimation of the propensity score to attend a training program supported by the government.

Step 2. Estimate the propensity scores using a logit regression model.

Step 3. Find pairs of treated and non-treated observations by propensity score matching for training attendance.

Step 4. DEA is applied to the population of matched enterprises to estimate the overall technical efficiencies of food processing enterprises. DEA is also used separately for two matched samples of treated and non-treated food processing enterprises to estimate the within-sample-efficiencies.

Step 5. Program efficiencies are estimated based on the overall technical efficiencies and within-sample-efficiencies following the Thanassoulis and Portela (2002) approach. They are then compared to find the impact of training policy on technical efficiency.

The general guidance for including variables in propensity score estimation (Caliendo, 2006) suggests that all important variables should be included in the estimation since their omission can seriously increase the bias of the score estimated (Heckman et al., 1997). In a more critical manner Rubin and Thomas (1996) recommend to use all variables in the propensity score model even if they are not statistically significant. Ho et al. (2007) also confirm that all variables that affect both the treatment assignment and the outcome variable should be included in the matching process. They argue that all variables that would have been included in the analysis of the impact without the matching process should also be taken into account in the matching process. Only variables that are not related to the outcome or not proper will be excluded from the model.

The study by Cosh et al. (1998) on the determinants of training found positive links between the propensity to conduct training and innovation activities conducted in the past, size of the unit in terms of labour, growth rate of employment in the past and the existence of difficulties in recruiting labour. Their study also showed that management training has higher probability to happen in firms with higher innovation efforts, higher growth objectives, firms experiencing difficulties in recruiting managers, and firms with larger size. The conventional wisdom also shows that higher education level of enterprise managers may lead to higher probability to attend and/or organise training.

In this research we follow the guidance to include variables which are seen as related to the attendance of training programs. Table 20 describes variables used in propensity score estimation.

Table 20.Variables used in analysis

Variable	Meaning
treat	It is training incidence, the dependent variable in the regression, which is a dichotomous variable taking value of 0 or 1.
entype	Legal form of enterprises, which is a discrete variable taking value from 1 to 5, in respect to household enterprises, private/sole proprietorship, partnership/cooperative, limited liability company, joint stock company
tuoi	The age of enterprise since its establishment
newproduct	New product, as a proxy for the innovation of the enterprise
exportdum	Dummy variable showing export status of the enterprise.
nomcap	Nominal capital of the enterprises, one of three most important inputs for the production of enterprises.
wage	Total wage paid to employees, as an input for production
nominput	Materials for the production, in nominal value, another important input for the production of enterprise
nomrev	It is the output of the enterprise in the form of nominal revenue

We use variables presenting the type of enterprises with the assumption that structural organization has impact on the decision to attend training programs. Age of enterprises is also included in the estimation with the assumption that the older the enterprise in its market, the more experience they have in getting support from the government and the higher the possibility to get information about the support from the government. All other variables which will be used for efficiency estimation will also be included in propensity estimation, following the suggestion from Ho et al. (2007). These are capital of the enterprises, total wage paid to employees, and material inputs used for production of enterprises. We also include a variable under the assumption that attendance into a training program depends on innovation of the enterprise. Innovation of enterprises is proxied by the ability to introduce new product into the market. At the same time, knowledge learning from exporting activities is assumed to have an impact on the decision to attend training program. These variables stand for the capacity of the management board, with the common understanding that an active board of management will react quickly to all possibilities that can enhance its enterprise competitiveness and ability.

Statistics of the variables used in matching process are presented in Table 21. From the table we know that there is very small number of enterprises participating in the training program supported by the government.[28]The treated enterprises are mostly registered enterprises under the enterprises law, meanwhile the non-treated sample has more observations, which are not registered under the enterprises law.[29]

[28] The mean of variable "treat" is only 0.03, meaning that only 3 percent of enterprises participated in training program.

[29] The mean of legal form for treated enterprises is 2.36, compared with 1.31 of non-treated enterprises, which is close to household enterprises.

Table 21. Basic statistics of the variables

Variable	Mean			Std. Dev.			Min			Max		
	Pop.*	Treated	Non-treated	Pop.*	Treated	Non-treated	Pop.*	Treated	Non-treated	Pop.*	Treated	Non-treated
observation	644	22	622	--	--	--	--	--	--	--	--	--
treat	0.03	1	0	0.18	0	0	0	1	0	1	1	0
entype	1.35	2.36	1.31	0.94	1.47	1	1	1	1	5	5	5
tuoi	14.23	17.14	14.13	10.85	12.6	10.78	1	2	1	76	47	76
newproduct	0.028	0.27	0.02	0.16	0.46	0.14	0	0	0	1	1	1
exportdum	0.02	0.18	0.02	0.15	0.39	0.13	0	0	0	1	1	1
wage	106,064.20	468,672	93,238.86	252,353.50	691,409.10	212,013.40	1800	5,000	1,800	2,700,000	2,700,000	1,683,087
nomcap	2,408,548	13,100,000	2,030,196	8,285,854	22,500,000	7,059,919	1000	51,000	1,000	93,500,000	80,900,000	93,500,000
nominput	2,340,923	2,570,848	2,332,791	27,500,000	4,102,695	28,000,000	6700	35,360	6,700	681,000,000	14,400,000	681,000,000
nomrev	2,613,151	3,413,731	2,584,835	27,800,000	5,066,739	28,200,000	12910	59,500	12,910	685,000,000	17,000,000	685,000,000

*Note: *: Population of observations surveyed, which is then divided into treated sample and non-treated sample according to training attendance*

Treated enterprises also have been established longer than non-treated enterprises. There also exists the large difference in the innovation initiative by treated and non-treated enterprises. While non-treated enterprises are close to the population mean on innovation variable, treated enterprises have the mean of innovation variable very much higher than the population mean. Education level of the treated enterprises owners is also higher than the one of non-treated enterprises owners. There are also big differences in other variables between treated and non-treated enterprises, and all of them are biased to treated enterprises.

The differences in variables of treated and non-treated enterprises imply the existence of bias among these two types of enterprises. For example, mean of capital of treated enterprises is VND 13.1 billion while non-treated enterprises have an average capital of VND 2 billion. The difference in capital invested in these two types of enterprise is more than 6 times, implying that treated enterprises have a huge advantage in term of capital over non-treated enterprises. The same conclusion can be made concerning average wage paid by treated and non-treated enterprises to their employees. Treated enterprises are more than 4 times larger than non-treated enterprises in terms of wage. It reinforces the need for a balancing method before undertaking further analysis. We therefore conduct propensity score matching as a method to balance the prior differences between treated and non treated firms. The basic idea (see Rosenbaum and Rubin, 1983) is to filter from a large number of control units those units that are comparable with treated units in all relevant characteristics. Matching is a common technique used in identifying for each treated unit a control unit based on necessary-to-be-controlled covariates. The idea is straightforward but it is difficult to identify units that are similar on all important characteristics. Matching on covariates faces the problem of dimensionality as an increase in the number of variables reduces the possibility to find an exact match exponentially. This difficulty is solved by using propensity score as the single scalar variable which captures the differences in many background covariates. By using propensity score in place of the direct covariates, Rosenbaum and Rubin (1983) proved that it is capable of eliminating biases.

We apply here the logit regression following the rationale presented in the above section. The logit regression finds a very strong relationship between enterprise legal form, age of enterprises, innovation of the enterprises and training attendance. It also shows that size of enterprises in terms of capital has a positive relationship with training attendance. The results of the logit regression are presented in the following table.

Table 22. Logistic regression used in propensity score model

Independent variables	**Est. Coefficient**	**Std. Dev**
Intercept	-5.25797300***	0.60882470
entype	0.46821140**	0.23799290
tuoi	0.04331530***	0.01631420
newproduct	2.11486300***	0.74607390
exportdum	2.23260700*	1.18155000
nomcap	0.00000005*	0.00000003
wage	0.00000094	0.00000113
nominput	-0.00000023	0.00000015
Number of observations	644	
Log likelihood	-71.90	

*Notes: *: significant at 10 percent; **: significant at 5 percent;*

****: significant at 1 percent*

There are several matching algorithms usually used in practice, of which the most popular are nearest neighbour matching, radius matching, and kernel matching. We apply the nearest neighbour matching, which is the straightest forward of the aforementioned matching estimators. It also ensures that there is no treated observation being trimmed from the dataset. The method makes sure that each treated observation will find a non-treated one to make a pair. Table 23 shows the summary statistics of matched sample. Comparing with summary statistics of the whole sample presented in Table 21, there are significant improvements of data for analysis presented in Table 23. Means of variables in treated and untreated groups are getting closer, while deviation is significantly smaller.

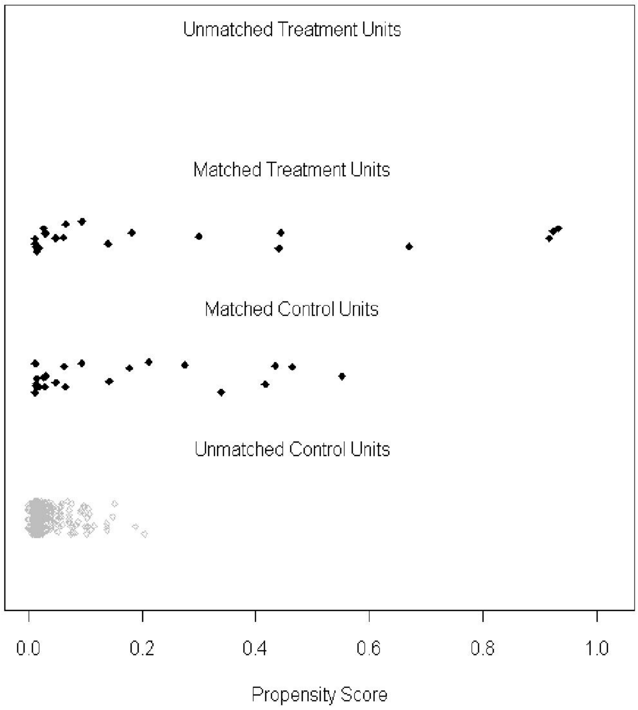
Table 23. Statistics before and after matching

Variable	Statistics before matching			Statistics after matching			Balance improvement (%)
	Mean Treated	Mean Control	Mean Difference	Mean Treated	Mean Control	Mean Difference	Mean Difference
propensity score	0.245	0.027	0.219	0.245	0.157	0.088	59.78
entype	2.364	1.314	1.050	2.364	2.182	0.182	82.69
tuoi	17.140	14.130	3.005	17.140	24.550	-7.409	-146.6
newproduct	0.273	0.019	0.253	0.273	0.182	0.091	64.13
exportdum	0.182	0.018	0.164	0.182	0.091	0.091	44.61
nomcap	13,110,000	2,030,000	11,080,000	13,110,000	3,994,000	9,112,000	17.73
wage	468,700	93,240	375,400	468,700	236,700	232,000	38.22
nominput	2,571,000	2,333,000	238,100	2,571,000	1,092,000	1,478,000	-521.06

Column balance improvement in Table 23 gives a detailed picture on the improvement resulting from the matching procedure, where imbalance is the mean difference between treated and untreated groups, and improvement is the percentage of mean difference that is reduced by matching. It shows that the balance between the treated and non-treated observations' variables is improved substantially. The highest improvement thanks to the matching exercise is observed in the legal form of the enterprises, innovation variable, and exporting status with 82, 64, and 44 percent respectively. Means of propensity scores of treated and non-treated groups also have smaller difference after matching. However, not all variables have balance improvements by matching. Mean difference of enterprise age between treated and non-treated group increases significantly after matching. Increase in mean difference is also observed in material inputs used by treated and non-treated enterprises

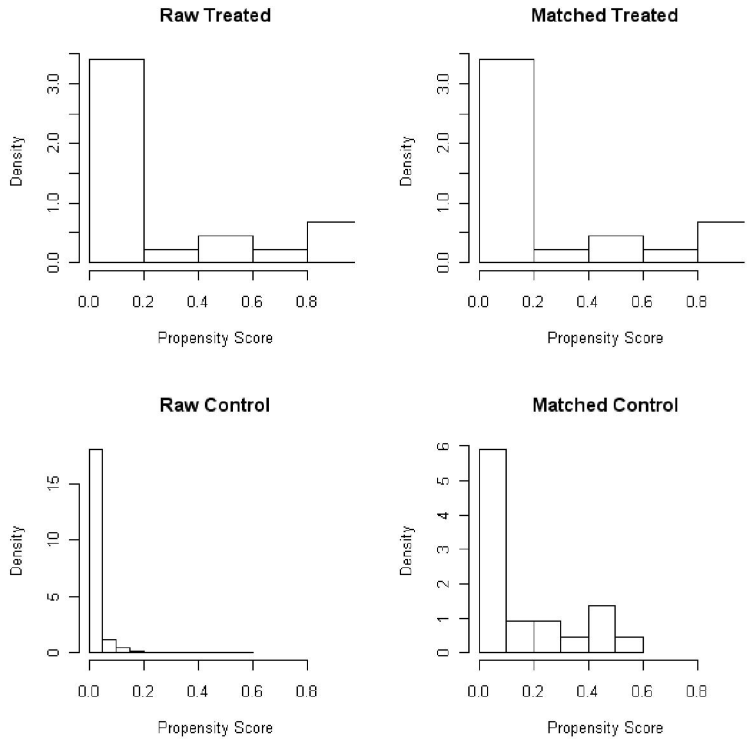
The quality of the matching can also be seen in Figure 33 and Figure 34. Figure 33 shows that all the treated enterprises are matched, and the distribution of propensity scores of treated and non-treated enterprises in the matched sample. Propensity scores of treated units range widely, while ones of untreated units are limited at about 60 percent. Unmatched control units are in the propensity score range from 0 to 20 percent. Figure 34 further clarifies the improvement of propensity of treated and non-treated enterprises after the matching. The figure shows that treated and non-treated enterprises have a more similar distribution of propensity scores than the distribution before the matching. [30]

Figure 33. Propensity Scores of Matched and Unmatched Treatment and Control Units



[30] These figures are produced by a plugin to R, called MatchIt, which is created by HO, D., IMAI, K., KING, G. & STUART, E. 2005b. MatchIt: Nonparametric Preprocessing for Parametric Casual Inference. *URL http://gking.harvard.edu/matchit. R package version*, 2.2-5.

Figure 34. Distribution of Propensity Score Before and After Matching



As discussed in Chapter 4, Thanassoulis and Portela (2002) approach to frontier separation approach will be used to analyse the program efficiency and impact of external variable. We apply the input oriented BCC DEA model for the analysis. Since all analysed enterprises are small and medium, they do not have the power to impose price to customers, instead they have to accept the market price. Their outputs sold therefore depend to market demand, which is out of their control. Input orientation is our choice for the DEA model of technical efficiency. Size of SMEs in consideration varies significantly in both capital and labour benchmark. In this study we assume that there exists variable returns to scale from operations of enterprises. The DEA model used for estimating overall and within program efficiencies therefore takes following form:

$$
\begin{aligned}
\min \quad & \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
\text{subject to} \quad & \sum_{j=1}^{n} x_{ij}\lambda_j = \theta x_{ijo} - s_i^-, \qquad i = 1,\ldots,m \\
& \sum_{j=1}^{n} y_{rj}\lambda_j = y_{rjo} + s_i^+. \qquad r = 1,\ldots,s \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& 0 \le \lambda_j, s_i^-, s_r^+. \quad \forall j,i,r \quad j = 1\ldots n \\
& \varepsilon \text{ is a vanishingly small positive number}
\end{aligned}
$$

Concerning the inputs and outputs variables to be used in DEA analysis, following guidance from Thanassoulis (2001), input variables should exclusively and exhaustively influence the outputs chosen. In our studies input variables include total capital stock of enterprises, employee payment or wage, and materials. Output variable will be total revenue. This choice of inputs and output is consistent with previous studies on the technical efficiency of SMEs (Yang, 2006, Reverte and Guzman, 2008, Halkos and Tzeremes, 2010).

Estimation of program efficiency for treated and non-treated group following the traditional frontier separation approach is summarised in Table 24. We can see that there is no treated DMU on the production frontier – all of treated DMUs have overall technical efficiency less than 100 percent. It is a special case where one group of DMUs forms the production frontier of the whole industry. This results in the fact that within-program efficiency of non-treated group is exactly the same with overall technical efficiency as we can see from Table 24. As a result, program efficiency of non-treated DMUs is equal 100 percent for all DMUs. Program efficiency is estimated by following formula:

$$
\textit{Program Efficiency} = \frac{\textit{Overall Efficiency}}{\textit{Managerial Efficiency}}
$$

Where managerial efficiency is also called within-program efficiency. Table 24 shows **all treated** enterprises, and all non-treated enterprises on **production frontier**, but not all non-treated enterprises that are not fully efficient.

Table 24. Efficiencies estimated by traditional frontier separation approach

DMU	Treatment	Overall Efficiency	Managerial Efficiency	Program Efficiency
1051	*1*	0.49	1.00	0.49
1059	*1*	0.53	1.00	0.53
1467	*1*	0.48	1.00	0.48
1487	*1*	0.73	1.00	0.73
2175	*1*	0.61	1.00	0.61
2216	*1*	0.31	0.96	0.33
2941	*1*	0.36	0.94	0.38
2984	*1*	0.36	0.95	0.38
2997	*1*	0.34	0.97	0.36
3024	*1*	0.19	0.94	0.20
3243	*1*	0.71	1.00	0.71
3773	*1*	0.96	1.00	0.96
3851	*1*	0.95	1.00	0.95
3921	*1*	0.51	0.93	0.54
4200	*1*	0.52	1.00	0.52
4250	*1*	0.56	1.00	0.56
4262	*1*	0.88	1.00	0.88
4407	*1*	0.50	1.00	0.50
4472	*1*	0.91	1.00	0.91
5174	*1*	0.12	1.00	0.12
6238	*1*	0.23	0.86	0.26
6517	*1*	0.26	0.73	0.36
158	0	0.45	0.45	1.00
250	0	1.00	1.00	1.00
1056	0	1.00	1.00	1.00
1067	0	0.31	0.31	1.00
2267	0	1.00	1.00	1.00
2272	0	0.50	0.50	1.00
2308	0	1.00	1.00	1.00
2401	0	1.00	1.00	1.00
2714	0	0.56	0.56	1.00
2716	0	0.55	0.55	1.00
2719	0	1.00	1.00	1.00
3514	0	1.00	1.00	1.00
3614	0	1.00	1.00	1.00
3686	0	1.00	1.00	1.00
3691	0	0.68	0.68	1.00
3872	0	1.00	1.00	1.00
3874	0	1.00	1.00	1.00
4002	0	1.00	1.00	1.00
4118	0	1.00	1.00	1.00
4465	0	1.00	1.00	1.00
4664	0	1.00	1.00	1.00
4761	0	1.00	1.00	1.00
4826	0	1.00	1.00	1.00

DMU	Treatment	Overall Efficiency	Managerial Efficiency	Program Efficiency
4902	0	1.00	1.00	1.00
4903	0	0.83	0.83	1.00
4920	0	1.00	1.00	1.00
4992	0	0.92	0.92	1.00
5002	0	1.00	1.00	1.00
5066	0	1.00	1.00	1.00
5115	0	0.89	0.89	1.00
6254	0	0.48	0.48	1.00
...	...	...	...	...
6513	0	0.59	0.59	1.00

Notes: Treatment = 1: DMU belongs to treated group;

Treatment = 0: DMU belongs to non-treated group

Not all non-treated DMUs is presented in this table

Efficiencies estimated following the revised frontier separation approach are presented in Table 25. By applying matching procedure, we establish a sample of enterprises in two groups – treated and non-treated - which are comparable to each other without worry about selection bias. Table 25 shows efficiencies of all treated and non-treated DMUs remained after matching. By matching there are treated DMUs on production frontier.

Table 25. Efficiencies estimated by revised frontier separation approach

DMU	Treatment	Overall Efficiency	Managerial Efficiency	Program Efficiency
1051	**1**	1.00	1.00	1.00
1059	**1**	1.00	1.00	1.00
1467	**1**	0.97	1.00	0.97
1487	**1**	1.00	1.00	1.00
2175	**1**	1.00	1.00	1.00
2216	**1**	0.95	0.96	0.99
2941	**1**	0.89	0.94	0.94
2984	**1**	0.90	0.95	0.95
2997	**1**	0.91	0.97	0.95
3024	**1**	0.94	0.94	1.00
3243	**1**	1.00	1.00	1.00
3773	**1**	1.00	1.00	1.00
3851	**1**	1.00	1.00	1.00
3921	**1**	0.73	0.93	0.78

DMU	Treatment	Overall Efficiency	Managerial Efficiency	Program Efficiency
4200	**1**	1.00	1.00	1.00
4250	**1**	0.99	1.00	0.99
4262	**1**	1.00	1.00	1.00
4407	**1**	0.92	1.00	0.92
4472	**1**	1.00	1.00	1.00
5174	**1**	1.00	1.00	1.00
6238	**1**	0.85	0.86	0.98
6517	**1**	0.73	0.73	1.00
2188	0	0.82	0.83	0.99
2261	0	0.66	0.71	0.94
2272	0	1.00	1.00	1.00
2404	0	1.00	1.00	1.00
2991	0	0.74	0.90	0.82
3011	0	0.92	0.95	0.97
3116	0	1.00	1.00	1.00
3160	0	0.96	0.98	0.98
3181	0	0.92	0.94	0.98
3222	0	0.78	0.87	0.90
3574	0	1.00	1.00	1.00
3842	0	0.83	0.86	0.96
3890	0	1.00	1.00	1.00
3901	0	0.77	0.95	0.81
4021	0	0.91	0.91	1.00
4218	0	1.00	1.00	1.00
4751	0	0.95	0.99	0.96
5160	0	1.00	1.00	1.00
6110	0	1.00	1.00	1.00
6260	0	1.00	1.00	1.00
6269	0	0.88	1.00	0.88
6394	0	1.00	1.00	1.00

Notes: Treatment = 1: DMU belongs to treated group;

Treatment = 0: DMU belongs to non-treated group

Comparison of efficiencies estimated by traditional and revised frontier separation approach (FSA) shows that serious selection bias exists since food processing enterprises select themselves into training programs supported by the government. Estimated impact of training program on technical efficiency of food processing enterprises with full data shows a huge negative impact. Mean difference between treated and non-treated group with **traditional FSA** is **-46.5 percentage points**, which is seen as the result of the training program (see Table 26). There is also a possibility that a part of the difference is due to the different sample sizes of treated and control groups.

Table 26. Analysis results

Variable	Mean
Traditional frontier separation approach	
Number of treated observations	22
Number of control observations	622
Total number of observation	644
Overall efficiency	0.557
Within-program efficiency of treated group	0.967
Within-program efficiency of non-treated group	0.559
Program efficiency of treated group	0.535
Program efficiency of non-treated group	1
Revised frontier separation approach	
Number of treated observations	22
Number of control observations	22
Total number of observation	44
Overall efficiency	0.930
Within-program efficiency of treated group	0.967
Within-program efficiency of non-treated group	0.949

Variable	Mean
Program efficiency of treated group	0.976
Program efficiency of non-treated group	0.963
Estimated impact by traditional FSA	**-0.465**
Estimated impact by revised FSA	**0.012**

The matching procedure gives us a different picture, which is seen as a result of eliminating selection biases present in the full dataset. The revised FSA shows that training programs organised by governmental agencies and international donors have a positive impact on efficiency of Vietnamese food processing SMEs. To confirm the result of the analysis, we use the Mann-Whitney rank test to test the distribution of the two samples. The null hypothesis is that the two samples have come from the same population. It means that treated and control groups do not differ from each other. In other words, the treatment effect cannot be determined from the analysis.

We follow the procedure proposed by Brockett and Golany (1996). It includes the following steps:

1. Production units are divided into two groups according to the treatment. DEA is run separately for each group.
2. Inefficient production units in each group are projected to the efficient frontier. By doing so, the effect of managerial inefficiencies within each group is eliminated.
3. Combine both groups of production units in their projected efficient level of production, then running DEA to estimate efficiency scores. The inefficient levels of production in this step are seen as a result of programme difference.
4. The Mann-Whitney rank test is applied to test if the two groups have difference in efficiency.

The Mann-Whitney rank test is applied for both the full data program efficiency and the matched data program efficiency. The results of the test are presented in Table 27:

Table 27.The Mann-Whitney rank test results

Empirical study	Observations		Mean rank		Sum of Ranks		Z	P	Null Hypothesis
	N1	N2	N1	N2	N1	N2			
Traditional FSA	622	22	333.50	11.50	207437	253	-25.35	0	**Reject**
Revised FSA	22	22	21.09	23.91	464	526	-.778	211	**Accept**

Note: N1 is number of control enterprises; N2 is number of treated enterprises

With traditional FSA, the test rejects the null hypothesis that two samples have come from the same population. Therefore the impact of **-46.5 percentage points** from attending training programs is confirmed. As analysed this is false result due to selection bias and by different sample size bias as pointed out by Simpson (2005) which can be eliminated by applying revised FSA.

Results from the Mann-Whitney test presented in Table 27 also show that with revised FSA, we cannot reject the null hypothesis that two samples have come from the same population. In other words, no difference in efficiency is observed by enterprises that attend the training and those that do not. This conclusion is contrast with the conclusion we drew from traditional FSA. So if matching is not applied, normal analysis by applying frontier separation approach will give a biased answer to the question on the impact of training program to efficiency of enterprises.

Note that our findings here suggest that there is a positive impact on technical efficiency attributable to treatment (educational programmes). However, this is statistically not significant as the Mann-Whitney test demonstrates.

5.6. Conclusion

The first section of this Chapter presented a brief review of the relationship between training and performance of SMEs. The literature is unclear about whether there is a link between training and performance of SMEs. Cosh et al. (2000) found a positive relationship between training and SMEs performance in terms of employment growth for 1997. Devins and Johnson (2003) in their study of the effectiveness of the European Social Fund (EFS) Objective 4 programme found that a third of the SMEs surveyed reported a very significant impact on their sales from labour training programmes. The positive links are also found by Jayawarna et al. (2007), Chi et al. (2008). However there is evidence that a positive relationship between training and performance is not dominant. The weak link between training provided and firm performance was reported by Wynarczyk et al. (1993), Westhead and Storey (1997), Marshall et al. (1993).

For most of the above studies, performance of SMEs is measured in terms of turnover, employee growth, and survival(De Kok, 2002). There is no study to our knowledge taking into consideration the impact of training on the technical efficiency of SMEs. We therefore start the journey to examine the impact of training on technical efficiency of food manufacturing SMEs in a transition economy. In this study we are aware of the selection bias that may lead to a biased conclusion about the training impact. Therefore, we have developed a new approach which is applied on the traditional frontier separation analysis put forth by Charnes et al. (1981). The theoretical presentation was laid out in Chapter 4 of the thesis.

The main engine of the approach is the matching on propensity scores to attend training. A scalar of propensity score replaces multiple covariates in matching, which helps to avoid the curse of dimensionality. In this chapter the propensity scores to attend training are estimated by a logit regression. Matching is then conducted following the nearest neighbour algorithm. The result is more balanced variables for analysis. Improvement of balance is observed in all characteristics of considered enterprises.

The revised frontier separation approach applied to match sample gives a more reliable impact of training on technical efficiency. The comparison with the revised frontier separation approach shows that the original frontier separation approach is unable to deal with the selection bias. In the context of this study, the original frontier separation approach gives a surprise result of **-46.5 percentage points** negative impact on technical efficiency from training. The further Mann-Whitney rank test does also confirm that two samples have different distribution, meaning that negative impact is true. This is purely the outcome of the much larger sample of non treated units. Its efficient units tend to outperform the efficient units of the treated sample but this is purely by chance. By applying the revised frontier separation approach and matching treated and non treated units on propensity to be treated we arrive at comparable ex ante units. Comparing these units post treatment we arrive at an impact of **+1.2 percentage points** on technical efficiency from treatment (training). The Mann-Whitney rank test afterward shows that this impact is not statistically significant. Therefore, our conclusion from the study is that there is no significant impact from training to technical efficiency found in food processing SMEs in Vietnam.

Even though we cannot confirm a positive impact from training on technical efficiency in food processing SMEs, the revised FSA allows us to conclude that attending training program does not reduce efficiency of food processing SMEs as it does from traditional FSA and it may have a small positive effect, even if not statistically significant.

Chapter 6. Conditional Efficiency and Propensity Score

6.1. Introduction

This chapter discusses the research strategy along with the concept of conditional efficiency, in which the main issue of the thesis, i.e. the impact of exporting on technical efficiency of Vietnamese food processing firms, will be investigated. The research methodology established in this chapter will become ground for the empirical analysis in Chapter 7 where the impact of export activities on technical efficiency is considered.

This chapter extends the conditional frontier approach proposed by Cazals et al. (2002) and advocated by Daraio and Simar (2005) to use in evaluating the impact from dichotomous variable. As presented in chapter 3, traditional nonparametric approaches have been used widely to examine the impact of external variables on technical efficiency. However, there are severe limitations that should be carefully considered in those approaches. Particularly the impact of external variables is examined in the context of approaches to technical efficiency, which are sensitive to outliers and extreme values. More importantly external variables are introduced into non-parametric models of technical efficiency by unsatisfactory techniques such as allowing environmental variables affecting directly the measurement of the efficiency (see Daraio and Simar, 2007).

Conditional frontier model as proposed by Cazals et al. (2002) and Daraio and Simar (2005) overcomes most of the drawbacks of previous approaches (Daraio and Simar, 2007) in this context. However, researchers interested on evaluating the impact of dichotomous external variables on technical efficiency still find that they have very limited options in term of research methodology. The original conditional frontier model by Cazals et al. (2002) and Daraio and Simar (2005) does not deal with external variable taking value [0, 1]. In Chapters 4 and 5 we proposed to revise the frontier separation approach to examine the impact of dichotomous external variables on technical efficiency, taking into account the existence of selection bias. In this chapter we further develop conditional frontier approach to evaluate impact of dichotomous variable on technical efficiency. The proposed approach here is intended to carry the advantage of robust conditional frontier approach in dealing with extreme values and outliers to dealing with selection bias.

In the following section, the chapter presents the consistency between matching and conditional efficiency. In other words, conditional efficiency on an external variable is an application of matching methodology. Based on this observation, two different strategies are proposed to analyse the particular variant of external variables, external factor in the form of a dichotomous variable. Monte Carlo simulations follow the proposed approach to prove the usability of the approach. A summary of issues and problems solved will conclude the chapter.

6.2. Probability Presentation of Production Process and Efficient Boundaries

The conditional frontier approach to technical efficiency proposed by Cazalset al. (2002) is developed from a probabilistic approach of production processes. The formulation of a production process by the mean of a probabilistic approach provides a convenient presentation and more importantly it helps to introduce a robust nonparametric framework for technical efficiency analysis. In a probabilistic framework the production of an organization which is evaluated can be presented by a joint probability function:

$$H_{XY}\left(x,y\right)=\Pr\left(X\leq x,Y\geq y\right) \quad (62)$$

Where $\left(X,Y\right)\in\Re^{p}\times\Re^{q}$ and is the support of the probability $H_{XY}\left(x,y\right)$. Daraio and Simar (2007a) (pp.66) defined the joint probability $H_{XY}\left(x,y\right)$ as: *"the probability for a unit operating at the level* $\left(x,y\right)$ *to be dominated"*. It means that there are other productive units while using as much input as utilised by the unit producing input-output level of (x, y) can produce output level at least at(y). Simar and Wilson (2008) noted that this is not a standard distribution function, since the input part in the formula is cumulative distribution function with an inequality, meanwhile the output part is a survival function. In the output oriented framework, the aforementioned function can be decomposed as

$$H_{XY}(x, y) = \Pr(Y \geq y | X \leq x)\Pr(X \leq x) \\ = S_{Y|X}(y|x)F_Y(x) \tag{63}$$

Where $S_{Y|X}(y|x) = \Pr(Y \geq y | X \leq x)$ is the conditional survival function of(Y), $F_X(x)$ is the distribution function of(X). Both satisfy the assumption: $S_{Y|X}(y|x) > 0$ and $F_X(x) > 0$. The output-oriented technical efficiency is presented as follows:

$$\theta(x, y) = \sup\{\theta | S_{Y|X}(\theta y | x) > 0\} \\ = \sup\{\theta | H_{XY}(x, \theta y) > 0\} \tag{64}$$

The output technical efficiency as presented in equation 68 can be defined as *"the proportionate increase in outputs required for the same unit to have zero probability of being dominated, holding input levels fixed"* (Simar and Wilson, 2008, pp. 434). Output technical efficiency score can be estimated by plugging in the empirical estimator of conditional survivor function of (Y) into the equation (68). The empirical estimator of technical efficiency score is:

$$\widehat{\theta}_n(x, y) = \sup\{\theta | \widehat{S}_{Y|X,n}(\theta y | x) > 0\} \tag{65}$$

Where the empirical estimator of conditional survivor function of $(Y)$is:

$$\widehat{S}_{Y|X,n}(y|x) = \frac{\widehat{H}_{XY,n}(x, y)}{\widehat{H}_{X,n}(x)} = \frac{\widehat{H}_{XY,n}(x, y)}{\widehat{H}_{XY,n}(x, 0)} \tag{66}$$

And the empirical distribution function $\widehat{H}_{XY,n}(x,y)$ for the theoretical distribution function $H_{XY}(x,y)$ could be estimated by the following formulation:

$$(67) \qquad \widehat{H}_{XY,n}(x,y)=\frac{1}{n}\sum_{i=1}^{n}I(x_i\le x, y_i\ge y)$$

Where $I(\bullet)$ is an indicator function and $(x_i,y_i)\in\psi_n$.

Cazals et al. (2002) showed that the estimated output-oriented technical efficiency as mentioned above coincides with the FDH estimators of the Debreu-Farrell efficiency scores given by the following formula:[31]

$$(68) \qquad \begin{aligned}\tilde{\theta}_{FDH}(x,y) &= \sup\left\{\theta \middle| (x,\theta y)\in\hat{\psi}_{FDH}\right\}\\ &= \sup\left\{\theta \middle| \widehat{F}_{X|Y,n}(\theta y|x)>0\right\}\\ &= \max_{i|X_i\le x}\left\{\min_{j=1,\dots,p}\left(\frac{Y_i^j}{y^j}\right)\right\}\end{aligned}$$

Where j denotes the j^{th} component of a vector.

The DEA estimator of technical efficiency scores also can be introduced by convexifying the FDH estimator as proposed by Daraio and Simar (2007). The DEA estimator of input oriented technical efficiency can be produced for each data point (x_i,y_i).

$$(69) \qquad \hat{\theta}_{DEA}(x,y)=\max\left\{\theta \middle| \theta y\le\sum_{i=1}^{n}\gamma_i y_i^{\partial,FDH}; x\ge\sum_{i=1}^{n}\gamma_i x_i; \sum_{i=1}^{n}\gamma_i=1; \gamma_i\ge 0, i=1,\dots,n\right\}$$

Where $\hat{y}_i^{\partial,FDH}=\hat{\theta}_{FDH}(x_i,y_i)y_i$ is the efficient output level of y_i projected on the FDH efficient frontier in output oriented framework (see Daraio and Simar (2007b) for more details).

[31] For probabilistic approach to input-oriented efficiency, please see Daraio and Simar (2008) for detailed presentation.

6.3. Robust Partial and Conditional Robust Efficiency Frontier

With probabilistic approach to production process, Cazals et al. (2002) outlined a robust partial frontier approach to deal with outliers and extreme values in data. They also introduced conditional frontier to incorporate exogenous variables in non-convex nonparametric framework. Daraio and Simar (2005) and Daraio and Simar (2007b) expanded Cazals et al. (2002) approach to cover multivariate cases with and without convex production technology.

The most outstanding problem with nonparametric approaches to technical efficiency analysis is that they are sensitive to outliers and atypical observations as they could significantly influence the production frontier and therefore efficiency measurement of other DMUs working under this frontier. This is the main reason for Cazals et al. (2002) to propose a partial frontier, which is established from *m* randomly chosen DMUs using as much inputs as the analysed DMU to produce at least the output level of the analysed DMU. Thus instead of comparing their performance with a full frontier, a DMU now compares their performance of a less extreme frontier, formed from the expected value of *m* random DMUs. The order-*m* efficiency score as coined by Cazals et al. (2002) with output-oriented production is defined as:

$$\theta_m(x,y) = E_{Y|X}\left(\tilde{\theta}_m(x,y)\middle| X \le x\right) \tag{70}$$

Where $\tilde{\theta}_m(x,y) = \max\{\theta | (x,\theta y) \in \tilde{\psi}_m(x)\}$ and $E_{Y|X}$ is the expectation given $S_{Y|X}(y|x)$.

Since now a DMU is comparing its performance against an average frontier, there is a case where its performance on average is superior to its order-m frontier, i.e. $\theta_m(x,y) > 1$, which cannot be observed by traditional nonparametric models.

The nonparametric estimator of output oriented efficiency score is arrived by plugging the empirical estimator of conditional survivor function, $\hat{S}_{Y|X,n}(y|x)$, into above function:

(71)
$$\begin{aligned}\hat{\theta}_{m,n}(x,y) &= \hat{E}\left(\tilde{\theta}_{m,n}(x,y) \middle| X \le x\right)\\ &= \int_0^\infty \left[1-\left(1-\widehat{S}_{Y|X,n}(uy|x)\right)^m\right]du\\ &= \widehat{\theta_n}(x,y) - \int_0^{\widehat{\theta_n}(x,y)} \left(1-\widehat{S}_{Y|X,n}(uy|x)\right)^m du\end{aligned}$$

Probabilistic approach to production process also allows Cazals et al. (2002) to develop conditional frontier approach to incorporate an environmental variable into consideration. The conditional frontier approach by Cazals et al. (2002) applies to continuous environmental variables, which are not controlled by DMUs, but can influence the production process of DMUs. This approach is further developed by Daraio and Simar (2005) to cover the multivariate setup. The key idea to introduce environmental variables into probabilistic nonparametric model is to condition the production process to a given value of an environmental variable. In this case the support of (X, Y) will be:

(72)
$$H_{XY}(x,y|z) = \Pr\left(X \le x, Y \ge y \middle| Z = z\right).$$

This joint distribution function can be decomposed as a combination of a conditional cumulative distribution of X and a conditional survival function of Y:

(73)
$$\begin{aligned}H_{X,Y|Z}(x,y|z) &= \Pr\left(Y \ge y \middle| X \le x, Z = z\right)\Pr\left(X \le x \middle| Z = z\right)\\ &= S_{Y|X,Z}(y|x,z)F_{X|Z}(x|z)\end{aligned}$$

Empirical estimator of conditional output-oriented efficiency score can be expressed as $\hat{\theta}(x,y|z) = \sup\left\{\theta \middle| \widehat{S}_{Y|X,Z}(\theta y|x,z)\right\}$, and it can be estimated by plugging in the formulae of empirical survivor function, which is defined by Daraio and Simar (2008) as follows:

(74)
$$\widehat{S}_{Y|X,Z,n}(y|x,z) = \frac{\sum_{i=1}^{n} I\left(X_i \le x, Y_i \ge y\right)K\left(z, z_i, h\right)}{\sum_{i=1}^{n} I\left(X_i \le x\right)K\left(z, z_i, h\right)}$$

Where K is the kernel and h is bandwidth of appropriate size of the external variable z. As with the unconditional efficiency approach, conditional order-m frontier can be built to deal with outliers and extreme values in conditional efficiency framework. Again instead of a full frontier with the existence of external variable, a partial frontier can be established by drawing randomly *m* DMUs for with $Y \geq y, X \leq x$ and the expected value of these draws can be used to measure the efficiency score $\theta_m(x, y|z)$. The nonparametric estimator of conditional output order-m efficiency score is:

$$\begin{aligned} \hat{\theta}_m(x, y|z) &= \int_0^\infty \left[1 - \left(1 - \hat{S}_{Y|X,Z,n}(uy|x, z)\right)^m\right] du \\ &= \widehat{\theta}_n(x, y) - \int_0^{\widehat{\theta}_n(x,y)} \left(1 - \hat{S}_{Y|X,Z,n}(uy|x, z)\right)^m du \end{aligned} \tag{75}$$

The above order-m technical efficiency can also be estimated using a simple Monte-Carlo algorithm (see Daraio and Simar(2007a) for more details).

6.4. Conditional Efficiency and Matching

6.4.1 Order-m Efficiency Conditional on Propensity Score

To examine the impact of an environmental variable on technical efficiency in the framework of conditional frontier, Daraio and Simar (2007a) suggested a decomposition of conditional efficiency of production units into unconditional efficiency estimated by full or partial frontier approach, a directional impact index, which indicates the direction of the environmental factor effect, and an index measuring the exploitation of environmental factor effect of individual production unit – producer intensity index as named by them. These indexes are enabled by comparing the unconditional efficiency and conditional efficiency estimated in the presence of environmental factors.

The unconditional efficiency is the efficiency scores of full frontier which is $\theta_m(x, y) = E_{Y|X}\left(\tilde{\theta}_m(x, y)\middle| X \leq x\right)$ and the conditional frontier is:

$$(76) \qquad \hat{\theta}_m(x, y|z) = \int_0^\infty \left[1 - \left(1 - \hat{S}_{Y|X,Z,n}(uy|x,z)\right)^m\right] du$$

In which conditional efficiency scores are estimated given Z=z. This equality relation in fact can only be conducted in the efficiency estimation with a smoothing density. The empirical conditional survival function therefore takes the form (Daraio and Simar, 2007a):

$$(77) \qquad \hat{S}_{Y|X,Z,n}(y|x,z) = \frac{\sum_{i=1}^{n} I(X_i \le x, Y_i \ge y) K(z, z_i, h)}{\sum_{i=1}^{n} I(X_i \le x) K(z, z_i, h)}$$

Where $K(\bullet)$ is a kernel function and h is the bandwidth of the kernel. Daraio and Simar (2005) pointed out that the kernel that can be used in the empirical conditional survivor function of Y should have compact support. With an unbounded support kernel such as Gaussian kernel, $\hat{S}_{Y|X,Z,n}(y|x,z)$ is not different from $\hat{S}_{Y|X,n}(y|x)$, and therefore we have $\hat{\theta}(x, y|z) = \hat{\theta}(x, y)$. It means that we cannot detect any influence of environmental variable by using unbounded kernel.

The conditional frontier approach to technical efficiency can be seen as a special case of the matching methodology, where production units with similar characteristics (influenced at the similar level of environmental factor) are pooled together to establish a frontier and their efficiencies are estimated against this frontier. The bandwidth h of kernel function is the criteria that determined the "similarity" of analysed production units.

In the conditional efficiency approach, an unconditional efficiency is the efficiency with the influence of environmental factor and conditional efficiency is the efficiency which is "purified" from the environmental factor effect. This is because by conditioning on an external variable, conditional efficiency scores are estimated by reference to an average frontier established by DMUs which are similarly influenced by the environmental variable. The similarity in terms of environment variable between DMUs is defined by the smoothing bandwidth, h. The ratio between conditional and unconditional efficiency as used by Daraio and Simar (2005, Daraio and Simar, 2007a) is therefore able to indicate the impact of an environmental factor on individual production units.

Seeing the conditional efficiency in this way enables us to utilise this approach to evaluate the impact of environmental dichotomous variable, i.e. evaluation of policy impact in our empirical studies. More importantly, we can use propensity score matching methodology in this evaluation. Particularly, the presentation of the output order-m efficiency conditional on propensity score can be described as follows:

$$\hat{\theta}_m\left(x, y \middle| \Pr_z\right) = \int_0^\infty \left[1 - \left(1 - \hat{S}_{Y|X,\Pr_Z,n}\left(uy \middle| x, \Pr_z\right)\right)^m\right] du \tag{78}$$

Where $\hat{S}_{Y|X,Z,n}\left(y \middle| x, z\right) = \dfrac{\sum_{i=1}^{n} I\left(X_i \leq x, Y_i \geq y\right) K\left(\Pr_z, \Pr_{z_i}, h\right)}{\sum_{i=1}^{n} I\left(X_i \leq x\right) K\left(\Pr_z, \Pr_{z_i}, h\right)}$

Where $K(\bullet)$ is a kernel function and h is the bandwidth of the kernel.

The use of propensity score in formula (82) help to reduce the dimension in which the number of variables that might influence of impact is reduced to a scalar of propensity score. The dimension reduction is obtained using parametric assumptions in the first stage using logistic regression. In this approach, the estimated efficiency scores are adjusted by by difference in propensity to attend the treatment. By doing so, the bias caused by self-selection of a productive unit into a policy treatment is eliminated. In other words, we have $E\left(\widehat{\theta_m^T} \middle| \Pr_z, Tr = 0\right) = E\left(\widehat{\theta_m^C} \middle| \Pr_z, Tr = 1\right)$ satisfies the unconfoundedness condition of treatment effect evaluation problem presented in the previous chapter. Propensity score in this case is called a balancing score (Rosenbaum and Rubin, 1983).

In this analysis, the average treatment effect on the treated is of interest. It is pointed out by Heckman et al. (1998) that this effect is the proper indicator to look at in an impact evaluation since it reflects the intended impact of policy. The average treatment effect on the treated in this case is estimated by the following formula:

$$\begin{aligned} \Delta_{ATT} &= E\left(\hat{\theta}_m^{T=1} - \hat{\theta}_m^{T=0} \middle| \Pr_z, Tr = 1\right) \\ &= E\left(\hat{\theta}_m^{T=1} \middle| \Pr_z, Tr = 1\right) - E_{\Pr_z}\left[E\left(\hat{\theta}_m^{T=0} \middle| \Pr_z, Tr = 0\right) \middle| Tr = 1\right] \end{aligned} \tag{79}$$

Where the first term can be estimated from the treated observations efficiency scores, and the second term is estimated from the mean efficiency scores of control observations.

6.4.2 Propensity Score Matching on the Outcome (Efficiency Scores)

As discussed in Chapter 4, evaluating a dichotomous environmental variable impact such as policy impact in our empirical case study can be done in several ways. Matching on propensity score is an efficient way to eliminate overt bias (Lee, 2005) and propensity score is the coarsest balancing score (Rosenbaum and Rubin, 1983). Efficiency scores as we note in this study can be seen as outcome of the management performance and being influenced by environmental variables. In this case we can directly match the outcome – efficiency scores – of treated productive units with the outcome of control group to isolate the impact of the environmental variables.

Matching on propensity score is initiated by Rosenbaum and Rubin (1983) to filter from a large number of control units those units that are comparable with treated units in all relevant characteristics. Matching is a common technique used in identifying for each treated unit a control unit based on necessary-to-be-controlled covariates. The idea is straightforward but it is difficult to identify units that are similar on all important characteristics. Matching on covariates face the problem of dimensionality as an increase in the number of variables increases the matching cell exponentially. This difficulty is solved by using propensity score as the single scalar variable which captures the differences in many background covariates. By using propensity score in replacing for direct covariates adjustment, Rosenbaum and Rubin (1983) proved that it is capable of eliminating biases due to self-selection as pointed out in Heckman et al. (1998) or Caliendo (2006).

A matching method has three advantages compared to conventional selection models and instrument variable estimators as identified by Li (2004): (i) no separability of outcome or choice equations are required; (ii) information in exogenous and endogenous variables is exploited efficiently; (iii) there is no limitation on the functional forms of outcome equations. Criticisms of matching methods are that matching does not solve the problem of correlation between error terms in outcome and selection equations but assumes away from the problem. If the probability of participation can be predicted perfectly then the method cannot be applied. Another problem is that if a perfect prediction of participation is obtained, i.e. $P(X) = 1 \text{ or } 0$, then matching is impossible since we cannot construct a counterfactual.

There are several different types of matching estimators, of which the most popular are nearest neighbour matching, radius matching, and kernel matching.

a. Nearest-Neighbour-Matching

The most straightforward of the aforementioned matching estimators is nearest neighbour matching. Let $Y_0(i)$ denote the set of control unit potentially matched to the treated unit i. Under nearest neighbour matching, this set is given by:

$$Y_0(i) = \min_j \| P_i - P_j \| \tag{80}$$

By applying the above equation a control unit with propensity score of P_j that is closest to propensity score of treated unit i will be chosen as a match for the treated unit i. There are two variants of nearest neighbour matching estimator that are nearest neighbour matching with replacement and without replacement. In the nearest neighbour matching with replacement a control unit can play the role of a match more than once, while in the nearest neighbour matching without replacement a control unit will be used as a match only once.

b. Calliper and radius matching

In nearest neighbour matching, the quality of the match can be questioned if the closest neighbour is too far away from the treated unit. This problem can be overcome by imposing a limit for the difference to be accepted. This conditional matching is called calliper matching, and the condition is under the form:

$$\left\| P_i - P_j \right\| \prec \varepsilon; \quad j \in n_0 \qquad (81)$$

Where n_0 is the number of treated units and ε is the specified tolerance level.

A variant of calliper matching that is named radius matching. In radius matching, all of the comparison units within the calliper are used rather than the only nearest neighbour unit within the calliper.

c. Kernel matching

Kernel matching is a non-parametric matching estimator that utilizes all members of the control group to establish a match for each treated unit. In kernel matching the average value is assigned a higher weight on the unit that is close in terms of propensity score and lower weight on unit, which has farther distance in terms of propensity score to the treated unit. Kernel matching uses the following weight:

$$w_{n_0}(i,j) = \frac{K_{ij}}{\sum_{k \in I_0} K_{ik}} \qquad (82)$$

Where $K_{ik} = K\left[\Pr_i, \Pr_k, h_{n_0}\right]$ is a kernel, and h_{n_0} is a bandwidth parameter. A list of kernel functions is presented in the following table:

Table 28. Kernel functions

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Source: DiNardo and Tobias(2001)

Once a matched control group has been defined, the difference between the means of treated group and matched controls will be calculated by following formula:

(83) $$\widehat{\Delta} = \frac{1}{N_T}\sum_{i\in T} Y_i^T - \frac{1}{N_T}\sum_{j\in C} w_j Y_j^C$$

Where NT is the number of the treated units, T is treated and C is control group observations. The variance of the estimator is calculated as follows:

(84) $$V\left(\widehat{\Delta}\right) = \frac{1}{N_T} V\left(Y_i^T\right) + \frac{1}{N_T^2} w_j^2 V\left(Y_j^C\right)$$

In kernel matching, the estimators are estimated by the following formula:

(85) $$\widehat{\Delta} = \frac{1}{N_T}\sum_{i\in T}\left\{ Y_{1i} - \frac{\sum_{j\in C} Y_{0j} K\left(\frac{\widehat{p}(\mathbf{w}_j) - \widehat{p}(\mathbf{w}_i)}{h_n}\right)}{\sum_{k\in C} K\left(\frac{\widehat{p}(\mathbf{w}_j) - \widehat{p}(\mathbf{w}_i)}{h_n}\right)} \right\}$$

Where $K(\bullet)$ is a kernel function and h_n is a bandwidth parameter of the kernel function.

In this study, along with estimation of the treatment effect based on order-m conditioning on propensity score we propose a kernel matching as a traditional approach to evaluate policy impact (dichotomous environment variable) on efficiency. This approach has the advantage of taking into account all control group outcomes for estimating the counterfactual for each treated unit. It avoids the deterministic decision that we have to make in conducting radius matching. It helps to improve the quality of the match which is questionable in the closest neighbour matching where the nearest neighbour may be too far away from the treated unit, or the nearest neighbour is not the only one which is very close to the treated unit. The approach is also convenient in that all technical efficiency scores estimated by any technique can be used without worrying about the problem of integration into the function as in the proposed conditional order-m approach. It should be noted that, in opposite to the order-m conditioning on propensity score approach, the traditional kernel matching approach of efficiency scores assumes implicitly that the efficient frontier is not affected by the impact, but the distribution of efficiency scores is. The details of two approaches for conditioning on propensity score will be presented in the next section on simulation design.

6.5. Simulation Design

6.5.1 General Settings

Monte-Carlo simulations again are used to test the ability of the proposed models to evaluate the impact of a dichotomous environmental variable on the technical efficiency of production units. We use the same specification and codes of the Chapter 4 simulation in generating data for analysis. Particularly data generation is conducted based on the equations 58, 59, 60, 61 of Chapter 4:

$$Y = f(X)\exp(w)$$

$$w = \alpha T - \sigma + \varepsilon \ , \quad T = \{0 \ or \ 1\}$$

$$P = f\left(X_1, X_P\right)$$

$$T = I(P)$$

In which $f(X) \equiv f(X_1, X_2)$ is the production function, taking the form of Cobb-Douglas and there are two types of technology apply: CRS and VRS. The true propensity score is generated following logit relationship of X_1 and X_p. The treatment indicator T_i is drawn from a Bernoulli distribution, correlated with the true propensity score P_i and there is average of 30% of observations that are treated. Inefficiency is generated from the distribution: $\sigma \sim (0, 0.36)$ as used in Yu (1998), with 20% of the DMUs on the frontier$(\sigma = 0)$. The simulation based on the assumption that environmental variable impacts on technical efficiency score are respectively $\alpha = 0.00;\ 0.05;\ 0.10;\ 0.15;\text{ and } 0.25$. Random noise level is drawn from a normal distribution $\varepsilon \sim N(0, 0.15^2)$, following Yu (1998). There are four sample sizes, $N = 100,\ 200,\ 300,\ 500$, each simulation is repeated 100 times.[32] [33] [34]

[32] I would like to thank Cinzia Daraio and Kriftof De Witte for generously prodiving their codes used in their papers: DARAIO, C. & SIMAR, L. 2007b. Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach. *Journal of Productivity Analysis,* 28**,** 13-32. and DE WITTE, K. & KORTELAINEN, M. 2009. Blaming the exogenous environment? Conditional efficiency estimation with continuous and discrete exogenous variables. *Available at SSRN: http://ssrn.com/abstract=1323344.* Their sharing makes my works more efficient since I could spend more time for analysing the data.

[33] The sample size is limited to 500 observations and the repetition is choosed at 100 times with the belief that it is good enough to produce significant results for the analysis following statistical laws. However, these numbers are choosed also from practical side of the work. The codes are written in R language and including many loops inside. Therefore it required a lot of calculation power of the computer used for simulation. In the system of Window XP, R version 2.11.1, 4 MB ram, Intel quad-core processor working at 2.4 Ghz speed, one simulation with 500 observations and repetition of 100 times can only be finished after **3 days**. The time constrain limited us from conducting more senarios of analysis.

[34] Time constrain also prevented us from conducting a comprehensive study with different sizes of the parameter *m*. As pointed out in DARAIO, C. & SIMAR, L. 2005. Introducing environmental variables in nonparametric frontier models: a probabilistic approach. *Journal of Productivity Analysis,* 24**,** 93-121. and DARAIO, C. & SIMAR, L. 2007a. *Advanced robust and nonparametric methods in efficiency analysis: methodology and applications*, Springer Verlag, DARAIO, C. & SIMAR, L. 2005. Introducing Environmental Variables in Nonparametric Frontier Models: A Probabilistic Approach. *Journal of Productivity Analysis,* 24**,** 93-121. the value of *m* in order-m frontier can influence the technical efficiency scores. With *m* is infinitive the order-m frontier approachs FDH frontier (Dariao and Simar, 2007a). Therefore we expect of different estimated impacts with different *m* value. A comprehensive survey of the influence of *m* value

6.5.2 Data-Driven Bandwidth Selection

In the conditional efficiency approach, kernel function is used as smoothing function to produce a nonparametric density for the analysis. The univariate kernel density estimator is a nonparametric estimator constructed with a symmetric weight function $K(u)$ chosen in such a way as to produce a smooth functional estimator.

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{X_j - x}{h} \right) \tag{86}$$

The Kernel function can be any of ones presented in Table 28. As suggested by Cazals et al. (2002) kernel functions used in the conditional efficiency approaches should have compact support, i.e. $K(u) = 0 \ if \ |u| > 1$. Kernel functions such as Gaussian kernel, which has unbounded support, will not be used. Kernel functions that can be used include uniform, triangle, Epanechnikov or quadratic. Following Cazals et al. (2002), Daraio and Simar (2005), Daraio and Simar (2007a), Epanechnikov kernel is used in the analysis.

In nonparametric estimation, however, the choice of kernel function is not as important as the choice of bandwidth (or window width) h (Racine, 2008) which is as important as the choice of specification in parametric estimation (Daraio and Simar, 2007a). While the kernel function determines differentiability and smoothness properties on the resulting estimates, bandwidth defines the finite-sample behaviour of the estimation. Both the bias and variance of the nonparametric estimation depend on the bandwidth (Racine, 2008). Bandwidth controls the amount of smoothness of kernel estimators.

In general there are four approaches to bandwidth selection (Racine, 2008): (i) reference rule-of-thumb, (2) plug-in methods, (3) cross-validation methods, and (4) bootstrap methods. Cross-validation methods are preferred since they are fully automatic and data-driven, working to minimise the global error measure of the

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should be taken in a further development study. In this study, we taken the default value of *m* set in the Wilson's FEAR fackage for R language in which our codes are writen as the a given value of *m* for our study.

estimation or maximise the log likelihood function of leave-one-out kernel (Li and Racine, 2007). The least squares cross-validation approach to bandwidth selection operates in such a way that minimises the mean integrated square error (MISE) of the resulting estimate. Meanwhile the likelihood cross-validation determines h by maximise the leave-one-out log likelihood function:

$$CV(h)=\sum_{i=1}^{n}\log\widehat{f}_{-i}\left(x\right) \tag{87}$$

Where $\widehat{f}_{-i}\left(x\right)$ is the leave-one-out kernel estimator of the density $f\left(X_i\right)$. The kernel estimator $\widehat{f}_{-i}\left(x\right)$ uses all points except X_i to construct the density estimate and takes the form:

$$\widehat{f}_{-i}\left(x\right)=\frac{1}{\left(n-1\right)h}\sum_{j=1,j\neq i}^{n}K\left(\frac{X_j-x}{h}\right) \tag{88}$$

The least square cross-validation approach to bandwidth h selection is sensitive to the presence of rounded data and to small-scale effects in the data. It tends to introduce spurious noise in the density estimate (Racine, 2008). Therefore, Daraio and Simar (2007a) suggested to use the likelihood cross-validation as data-driven approach for choosing bandwidth h. In this study we also utilise the likelihood cross-validation as the main engine in determining the bandwidth h for our conditional efficiency estimation and propensity score matching.

6.6. Simulation Results

We present in the following paragraphs results of simulations in which the true treatment impacts on the treated are compared with its estimators. The average treatment effect estimators include the propensity score conditional order-m efficiency scores and kernel matching average treatment effects of efficiency scores estimated by FDH and DEA approach. The following tables show good results of estimators except the estimated average treatment effects of the convex frontier.

With $(\alpha = 0.00)$ all estimations are close to true impact, with the exception of the estimated propensity score conditional order-m efficiency scores with sample size of 300 and VRS technology and both VRS and CRS production technology with sample size of 500. However, in comparison with results from traditional FSA model presented in table 9 of chapter 4, all results of simulations with the propensity score conditional order-m average treatment effects (ATT), DEA and FDH matching average treatment effects are very much better. The Figure 35 and Figure 36 showing the mean square error also confirm the conclusion that estimated treatment effects are not far from true impact. There is large improvement in MSE with both VRS and CRS production technology when the sample size is large.

Table 29. True and estimated impacts of environmental variable on technical efficiency with $(\alpha = 0.00)$, repetitions: 100 times

Sample size	**Production technology**	**True impact**	**Estimated impact, conditional order-m**	**Estimated impact, DEA matching ATT**	**Estimated impact, FDH matching ATT**
	CRS	-0.00053	-0.00403	-0.00339	-0.00730
100	VRS	0.00003	-0.00044	-0.00421	-0.00672
	CRS	-0.0002	0.00124	-0.00142	-0.00573
200	VRS	-0.00023	0.00683	0.00078	-0.00271
	CRS	-0.00038	0.00109	-0.00284	-0.00595
300	VRS	0.00016	0.00932	0.00222	-0.00232
	CRS	0.00009	0.00787	0.00202	-0.00113
500	VRS	-0.00024	0.00812	0.00015	-0.00348

Figure 35. MSE with CRS technology,
$(\alpha = 0.00)$

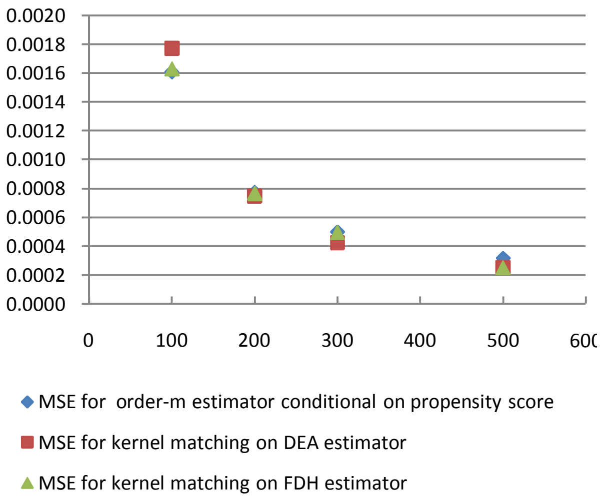
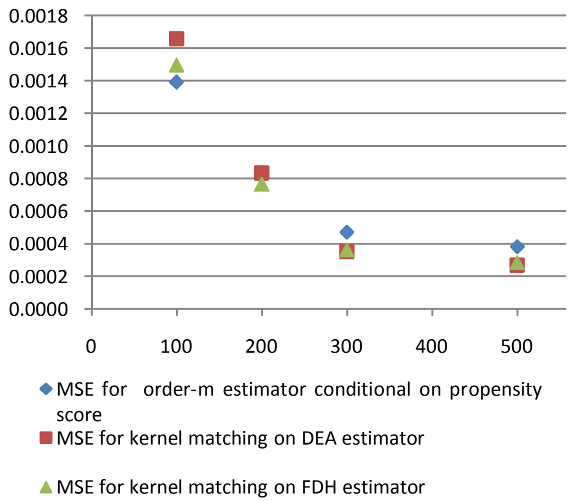


Figure 36. MSE with VRS technology,
$(\alpha = 0.00)$



With $(\alpha = 0.05)$ ATT of propensity score conditional order-m and DEA matching approaches are very good estimators of the true impact, while FDH matching estimator shows a large deviation from the true impact. This conclusion is applied to both VRS and CRS production technology. And these estimators are very much better than the traditional FSA estimator in the case of VRS production technology. Figure 37 and Figure 38 respectively show the MSE of estimated ATT from the true impact. There is pattern of improvement when the sample size increases from 100 observations to 500 observations. MSEs are similar in both VRS and CRS production technology, showing a reliable estimators produced by the proposed approaches regardless type of production technology.

Table 30. True and estimated impacts of environmental variable on technical efficiency with $(\alpha = 0.05)$, repetitions: 100 times

Sample size	Production technology	True impact	Estimated impact, conditional order-m	Estimated impact, DEA matching ATT	Estimated impact, FDH matching ATT
	CRS	0.0425	0.0328	0.0437	0.0243
100	VRS	0.0422	0.0325	0.0342	0.0162
	CRS	0.0414	0.0356	0.0388	0.0228
200	VRS	0.0413	0.0392	0.0364	0.0189
	CRS	0.0414	0.0363	0.0355	0.0219
300	VRS	0.0418	0.0425	0.0362	0.0207
	CRS	0.0420	0.0447	0.0404	0.0282
500	VRS	0.0415	0.0505	0.0407	0.0253

Figure 37. MSE with CRS technology, $(\alpha = 0.05)$

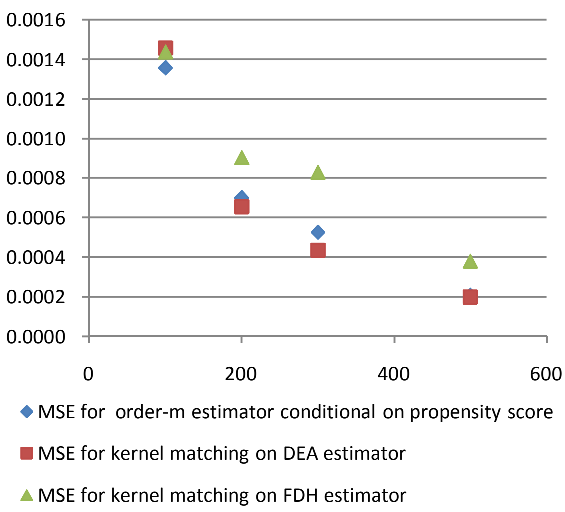
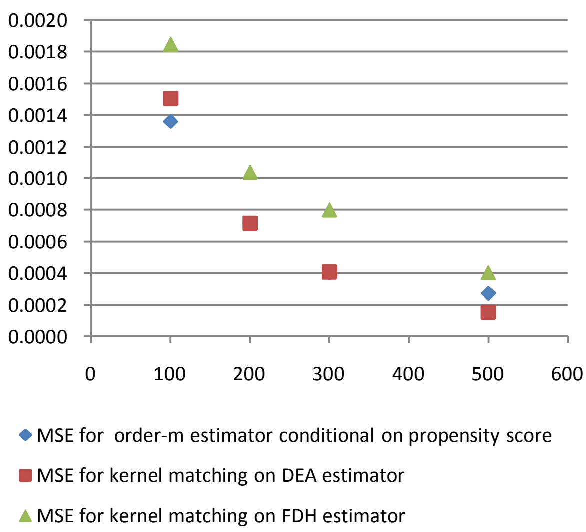


Figure 38. MSE with VRS technology, $(\alpha = 0.05)$



Results from simulations with $(\alpha = 0.10)$ show that the estimator by propensity score conditional order-m approach improves significantly along with the increase in sample size. It approaches the true impact in both VRS and CRS production technology simulations, in which estimator in VRS technology shows a better improvement. It is clear from Table 31 that while the ATT estimator of DEA matching approach is very stable and close to the true impact. This conclusion is applied to estimations for both VRS and CRS technology, which are in fact very close to each other. Among the three proposed approaches, FDH matching estimator is the worst estimator which is very far from true impact. Figure 39 and Figure 40 show the MSE for estimations of CRS and VRS technology. They confirm the above conclusions and show that with sample sizes from 200 to 500, estimated average treatment effects of conditional order-m and DEA matching approaches are very close the true impact.

Table 31. True and estimated impacts of environmental variable on technical efficiency with $(\alpha = 0.10)$, repetitions: 100 times

Sample Size	Production technology	True impact	Estimated impact, conditional order-m	Estimated impact, DEA matching ATT	Estimated impact, FDH matching ATT
100	CRS	0.08501	0.05890	0.07776	0.04644
	VRS	0.08613	0.06284	0.07063	0.04098
200	CRS	0.08606	0.06403	0.07150	0.04661
	VRS	0.08603	0.07420	0.07578	0.04624
300	CRS	0.08549	0.07316	0.07456	0.05183
	VRS	0.08586	0.07876	0.07352	0.04749
500	CRS	0.08584	0.07838	0.07548	0.05592
	VRS	0.08566	0.08216	0.07109	0.04886

Figure 39. MSE with CRS technology, $(\alpha = 0.10)$

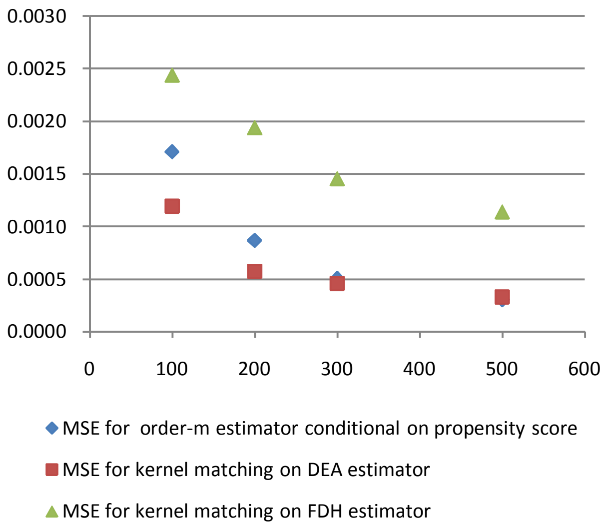
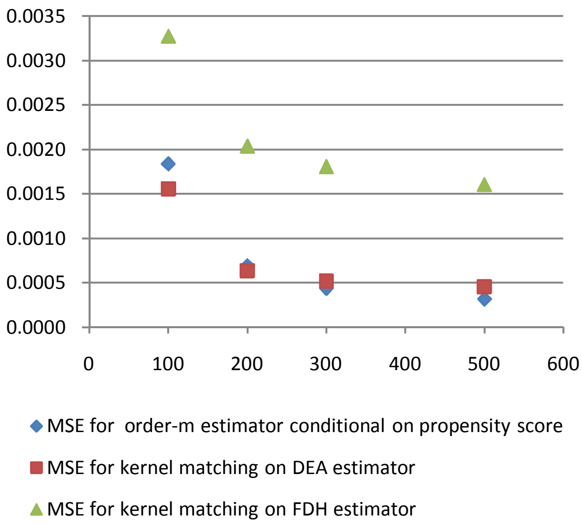
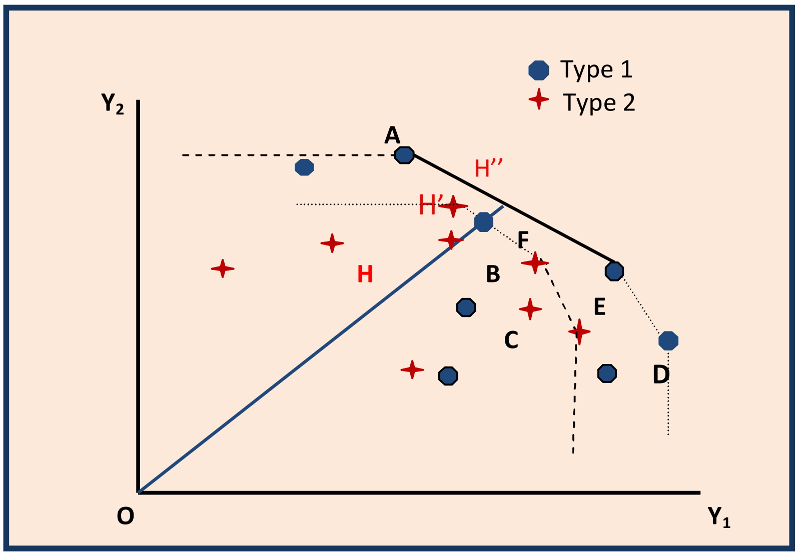


Figure 40. MSE with VRS technology, $(\alpha = 0.10)$



With $(\alpha = 0.15)$ and $(\alpha = 0.25)$ there is a domination of one group over the other with regard to FSA. In other words, the within group frontier of treated observations is superior and covers the within group frontier of control observations. This case can be visualised by Figure 41 where type 1 can be seen as treated group which is dominant in the FSA framework, and type 2 is control group. This happens when the designed impact α is large enough to dominate the presence of random noise and the inefficiency level of a productive unit.

Figure 41. FSA with one dominant group



Results from simulations with $(\alpha = 0.15)$ and $(\alpha = 0.25)$ and different sample sizes are presented in Table 32 and Table 33. From these tables, it is clear that under the domination of frontier of treated observations over frontier of control observations the estimated impacts from propensity score conditional order-m approach have a large difference among different sample sizes. The worst estimation of ATT for the propensity score conditional order-m approach is the estimation with sample size of 100 observations, while the best estimation of ATT is for the sample size of 500 observations. Figures on MSE between estimated and true impacts also show the improvement of estimation along with the increase in sample size. In both designs $(\alpha = 0.15)$ and $(\alpha = 0.25)$, estimated ATTs from DEA matching approach are very stable over the sample size and production technology. The estimated ATTs by the DEA matching approach can show about 75% of the true impact, while the estimator of the FDH matching approach continues to be estimating poorly true impact.

Table 32. True and estimated impacts of environmental variable on technical efficiency with $(\alpha = 0.15)$, repetitions: 100 times

	Production technology	**True impact**	**Estimated impact, conditional order-m**	**Estimated impact, DEA matching ATT**	**Estimated impact, FDH matching ATT**
100	CRS	0.13057	0.08292	0.10724	0.06672
	VRS	0.13252	0.08789	0.10398	0.06096
200	CRS	0.13181	0.09856	0.11208	0.07931
	VRS	0.13144	0.09844	0.10210	0.06496
300	CRS	0.13156	0.10376	0.10783	0.08001
	VRS	0.13163	0.10895	0.10561	0.07397
500	CRS	0.13232	0.11477	0.11091	0.08841
	VRS	0.13158	0.11633	0.10454	0.07694

Figure 42. MSE with CRS technology, $(\alpha = 0.15)$

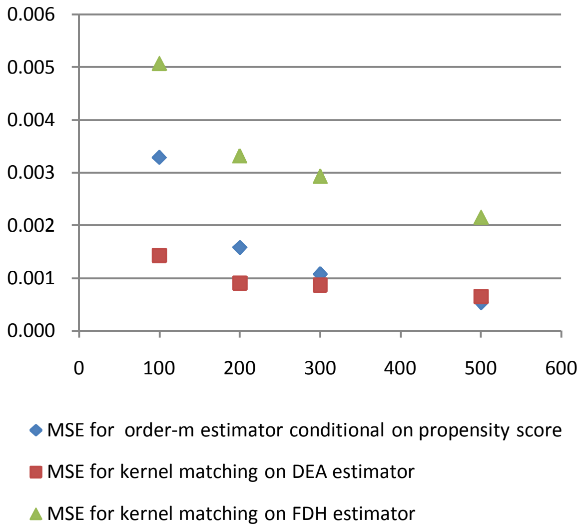


Figure 43. MSE with VRS technology, $(\alpha = 0.15)$

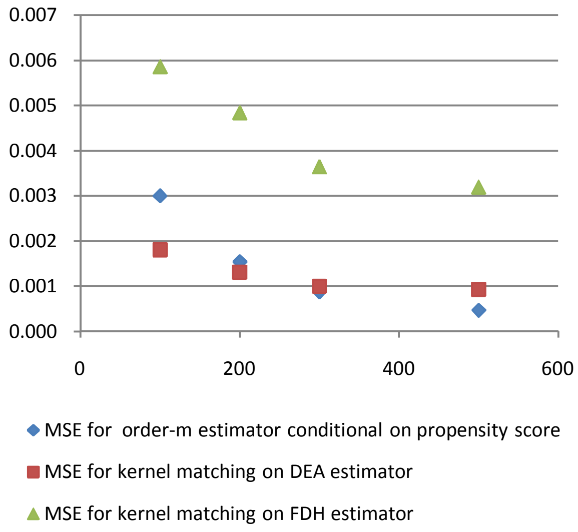


Table 33. True and estimated impacts of environmental variable on technical efficiency with $(\alpha = 0.25)$, repetitions: 100 times

	Production technology	True impact	Estimated impact, conditional order-m	Estimated impact, DEA matching ATT	Estimated impact, FDH matching ATT
100	CRS	0.23060	0.14424	0.17144	0.11135
	VRS	0.23060	0.14424	0.17144	0.11135
200	CRS	0.23201	0.15928	0.17625	0.13524
	VRS	0.23000	0.15862	0.16363	0.11905
300	CRS	0.23027	0.16715	0.17250	0.14100
	VRS	0.23145	0.17228	0.17272	0.13150
500	CRS	0.23159	0.18083	0.17518	0.14997
	VRS	0.23128	0.18648	0.17067	0.14141

Figure 44. MSE with CRS technology, $(\alpha = 0.25)$

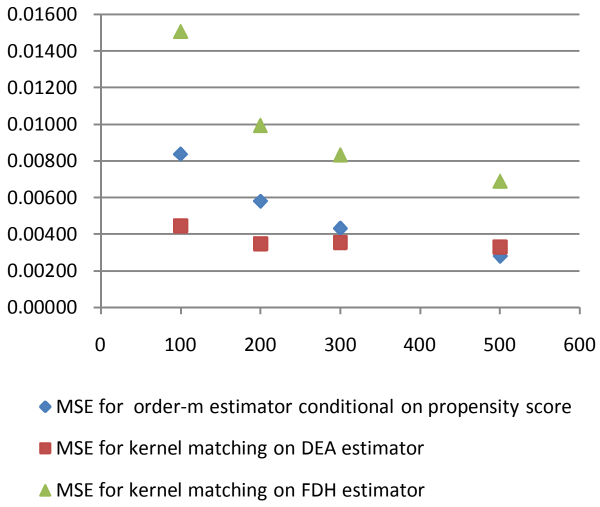
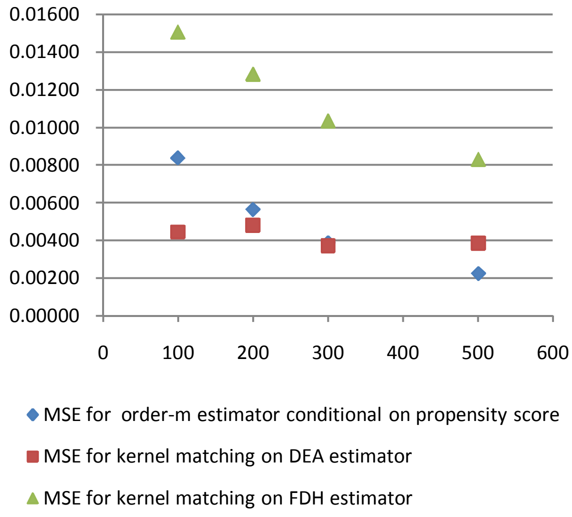


Figure 45. MSE with VRS technology, $(\alpha = 0.25)$



6.7. Conclusion

In this chapter we introduce two approaches, which can be classified according to stages of analysis as one stage and two-stage, i.e. propensity score conditional order-m approach and propensity score matching ATT approach respectively. Propensity score conditional order-m approach is based on the novel conditional efficiency approach proposed by Cazals et al. (2002) and advocated by Daraio and Simar (2005). We proved that the conditional efficiency score as proposed by Cazals et al. (2002) is a covariate matching procedure. Therefore, efficiency score estimation based on a propensity score conditional order-m approach is possible as a way to eliminate selection bias. This approach falls into one stage family of environmental variable impact analysis.

We show that by seeing efficiency score as outcome of management performance, we can also apply the popular propensity score matching procedure invented by Rosenbaum and Rubin (1983). Kernel matching algorithms in which all control observations are used to build counterfactuals for each treated observation is used in the simulation. The compact support kernel function Epanechnikov is used in the simulation. A data-driven bandwidth selection following Daraio and Simar (2005) and Daraio and Simar (2007a) is suggested, where bandwidth is determined such that the leave-one-out log likelihood function is maximised. This approach can be categorised as two stage approach to environment variable impact evaluation in which efficiency scores are estimated by different estimators in the first stage and treatment effects are determined using matching on propensity score in the second stage.

Monte Carlo type simulations are established with different configurations to test and compare the ability of these approaches in distinguishing the impact of a dichotomous environmental variable. Impacts of 0%, 5%, 10%, 15% and 25% are analysed along with four different sample sizes: 100 observations, 200 observations, 300 observations, and 500 observations. Each simulation is repeated by 100 times. Moreover, both CRS and VRS production technologies are simulated to examine the impact of type of production technology to the capacity of proposed approaches.

Results from simulation show that propensity score conditional order-m approach and DEA matching approach give very good estimations of the true impacts. They all overcome the problem of significant impacts estimated at the design simulation with $(\alpha = 0.00)$ as with traditional FSA presented chapter 4 of the thesis. The estimator improves along with the increase in sample size. These estimators are better when there is no dominant group in term of within group frontier. While that propensity score conditional order-m approach shows a significant fluctuation of estimated ATT over sample size, the DEA matching approach produces very stable estimators over different sample sizes in both VRS and CRS production technology. Incompatible with the two mentioned approaches, the FDH matching approach produces not very good results as showed by simulations.

The two proposed approaches enable the use of the novel conditional efficiency approach in analysing the impact of a dichotomous environmental variable on technical efficiency. They widen the choice for the analyst in the field of environmental impact evaluation. The simulations confirm the capability of these approaches.

Chapter 7. Impact of Exporting on Technical Efficiency of Textile and Garment SMEs

7.1. Introduction

In chapter 6 we present simulations in which the impact of a dichotomous environmental variable on technical efficiency is diagnosed by the novel approach of conditional order-m efficiency. By proposing the application of propensity score along with conditional order-m we are able to gauge the impact of a dichotomous environmental variable on technical efficiency. The simulations showed that the proposed approach can assist in the task to identify the impact of dichotomous environmental variable on technical efficiency. They show that order-m efficiency conditioning on propensity score is superior to the revised FSA as proposed in Chapter 4 of the thesis in dealing with zero impact from dichotomous environmental variable as simulated in Chapter 6.[35] They prove that order-m efficiency conditioning on propensity score surpasses regular propensity score matching in producing a better estimate of dichotomous environmental variable impact.

This chapter presents an empirical study applying the methodology presented in chapter 6 to a segment of the Vietnamese economy. In particular the task of this chapter is to examine the impact of exporting on the technical efficiency of SMEs in the textile and garment industry. By using the proposed method we can answer the question whether a good enterprise enters exporting, whether exporting improves an enterprise's performance and if so, then by how much.

In conducting this study, a normal comparison between exporting and all other non-exporting enterprises in the sample is not enough and may yield biased results. This is

[35] Please refer to Table 13 and Table 29 to see the performance of the proposed revised FSA and order-m frontier conditioning on propensity score approach.

because enterprises can self-select to export and their self-selection depends on several different factors. It is necessary therefore that we should conduct the comparison taking into account these differences between enterprises that may predispose them to self-select to export. That is where the contribution of the proposed approach comes into play and proves to be effective in the simulation presented in chapter 6.

This chapter is structured as follows. The next section will present literature on the impact of exporting on the performance of enterprises. Section 3 of the chapter will discuss the data on the textile industry used in this study. Section 4 will present the analysis. The last section will conclude this chapter.

7.2. Exporting and its Impact on Performance of Enterprises

7.2.1 Enterprise Performance and Exporting

Exporting is believed to bring a chance for a developing country to improve its economy. Higher openness is always seen as a good signal for policy makers, whose belief is that, by having larger share in the world markets, the country's economy could gain from economies of scale. More importantly, harsh competition in the world markets and 'learning by exporting' will help to enhance the productivity of domestic exporters (Xiaolan, 2005). The past experience of Vietnam proves that this belief has its roots from the development of the economy. Vietnam obtained its rapid growth rate thanks to two engines: foreign investment and international trade. Vietnamese exports grew by an average of 17.6 percent over the period 2001-2005 (CIEM, 2006). Main export items of the country include crude oil, coffee, coal, rubber, tea, rice and cashew nuts. While the country is the second largest and third world largest exporter in rice and coffee, respectively, crude oil export is the main contributor of the state budget. With low technology standards and labour intensive production, Vietnamese enterprises export mostly raw materials and agricultural products, where they obtain their somewhat comparative advantage in the world markets.

According to Wagner (2007) there are two alternative hypothesis about the reason explaining higher performance of exporters versus non-exporters. The first hypothesis is that more productive enterprises tend to select themselves into export markets. This self-selection behaviour happens because there exist additional costs when entering foreign markets. The extra costs can include transportation costs, distributions and marketing costs, cost to train workers skills to satisfy management and quality requirements of foreign markets. These costs become a barrier that enterprises must overcome to become exporters and less productive enterprises fail to pass. Theoretical models by Dixit(1989, 1989b)and Krugman (1989) support this view and suggest that sunk costs in entering export market may play important role in the formation of decisions to enter exporting by enterprises. Roberts and Tybout (1997) develop a dynamic model accounting for profit heterogeneity and sunk entry costs to explain the export decision of Colombian enterprises. They find that sunk costs are large and differences in enterprise characteristics contribute significantly to the probability to export of an enterprise. Bernard and Jensen (1999) examine the possible impact of export on performance and emphasize the heterogeneity of enterprise characteristics with regard to export decisions. They find that exporters have more workers, higher wages, higher productivity, more capital intensive, and more modern technology than their non-exporting counterparts.

Another hypothesis points to the role of exporting in helping/forcing enterprises to obtain better performance. Exporting activities can contribute to performance improvement of domestic enterprises by different channels. They include: (i) economies of scale, obtained by the expansion of international markets for the domestic products; (ii) efficiency improvement through “learning by doing”, resource reallocation from less efficient to more efficient industries and enterprises; (iii) improvement of technology by spillover from foreign contacts and encouragement of R&D (Xiaolan, 2005). Lopez (2003) points to another channel where the source of technology and knowledge are obtained by exporters when they purchase of new machinery to produce exporting products. The study on 77 developing countries by Coe, Helpman and Hoffmaister (1997) support this view. Their finding is that an increase of TFP by 0.28 percent can be obtained by 1 percent increase in the imports of machinery and equipment to GDP ratio.

Literature on the impact of exporting on performance of enterprises focuses on the increase of *productivity* as a result of entering the exporting sector of an enterprise. *Labour productivity* is the variable most often used in these studies. The surge of research on the impact of exporting on productivity originated by studies of Bernard and Jensen (1995, 1999), in which longitudinal data for enterprises are used. Bernard and Jensen (1995) test the hypothesis whether the difference of exporters and non-exporters within the same industry and whether exporters perform better than non-exporters. As the first step in Bernard and Jensen approach, unconditional productivity differential is derived by looking at the difference in average labour productivity or average total factor productivity (TFP) of exporters and non-exporters. Exporters as reported by Bernard and Jensen (1995) were substantially larger than non-exporters in plant size, capital per employee, wage payment, labour productivity. In other words, the good firms enter the exporting sector. The self-selection hypothesis is also supported by many studies (Delgado et al., 2002, Clerides et al., 1998, Bernard and Wagner, 1997, Kraay, 1999)

However the evidence about learning by exporting is mixed. By using longitudinal data, Bernard and Jensen (1995) discover that plants that exit from exporting have worse performance compared to remaining exporter and non-exporter. Therefore "*there is no guarantee that current exporters will continue to outperform other establishments in the future*" (Bernard and Jensen, 1995, pp. 111). Clerides, Lach and Tybout (1998) use longitudinal plant level data for Colombia and Morocco to examine the learning by exporting impact on productivity via proxies of average variable cost in the most export oriented industries in these two countries. Their results confirm the pattern that exporting firms are more efficient than non-exporting firms. However, their econometric analysis fits their "no-learning-by-exporting scenario".

Bernard and Jensen (1999) analyse United States manufacturing firm data over the period 1984-92 and realise that there is no productivity improvement after firms enter exporting. The learning by exporting hypothesis is therefore denied by their study. Studying firm level data of Korea and Taiwan Aw, Chung and Roberts (2000) find mixed results for different industries in the two countries. They examine the development of

TFP between exporters and non-exporters in 5 manufacturing industries. For Taiwanese textiles, plastics and electronics and electrical machinery industries, exporters have faster productivity growth. This finding supports the learning by exporting hypothesis. Meanwhile, they cannot find the evidence of higher productivity of exporters in Taiwanese apparel and transportation equipment industries. For the case of Korea, they cannot find any evidence supporting learning by exporting hypothesis from the same 5 manufacturing industries.

In contrast to the above studies, Aw and Hwang (1995) study 2832 enterprises in Taiwanese electronics industry, using a translog production function, and find that enterprises are self-selecting into the exporting sector. But at the same time they find that the evidence of learning by exporting exists, in other words enterprises joining the exporting sector obtain higher productivity. Using data on 2105 Chinese industrial enterprises, Kraay (1999) is able to find evidence of learning by exporting. Past exports result in significant improvement of productivity. One interesting finding of Kraay (1999) is that learning by exporting is trivial and occasionally negative for export starters. Meanwhile by applying a nonparametric analysis to TFP differences 1766 Spanish manufacturing firms in the period 1991-96 Delgado, Farinas, and Ruano (2002) find weak evidence supporting learning by exporting hypothesis among export starters.

A comprehensive survey of 54 empirical studies conducted after 1995 covering 34 countries on the relationship between export and productivity by Wagner (2007) also suggests that there is clear evidence in favour of the self-selection hypothesis. "*Future export starters tend to be more productive than future non-exporters years before they enter the export market, and often have higher ex-ante growth rates of productivity*" (Wagner, 2007). It is also documented by Wagner (2007) that evidence regarding the learning-by-exporting hypothesis is mixed.

7.2.2 Methods of Study

Before the use of longitudinal firm level data, studies on the impact of export were usually conducted in the form of case study and anecdotal evidence. Case studies about developing countries admit the role of information from foreign customers as an important source of knowledge for domestic enterprises (López, 2005). Keesing (1983) based on interviews and consultant papers points out firms from South East Asia and South America developing countries obtained knowledge by exporting their products. Such information as product design, materials, labelling, packaging and shipping that those firms receive from foreign customers help them to adapt their production and improve their performance. Hobday (1995) surveys firms from Korea, Taiwan, Hongkong, and Singapore which learn to innovate electronic products from foreign customers' ideas and assistance. He argues that with information obtained by entering export markets, firms in East Asian countries evolved from simple to complex activities (see following graph).

Figure 46.Export-led learning from behind the technology frontier

	Simple activities	→	→	→	→	**Complex activities**
Marketing	Simple **OEM**/sub-contracting	⟶	⟶	**ODM**	⟶	**OBM**
Process technology	Simple assembly	Process adaptation	Incremental improvements	Process development	Applied research	Process R&D
Product technology	Assessment selection	Reverse engineering	Prototype development	Design for Mfr.	New design	Product R&D

Notes: OEM: Original Equipment Manufacture; ODM: Own Design and Manufacture; OBM: Own Brand Manufacture

(Source: Hobday, 1995)

Lopez (2003) documents the growth of the wine brewery industry in Chile after a foreign company entered the market and started making wine for export and spurred performance improvement of domestic wine. Pietrobelli (1998) studies 26 Chilean firms exporting non-traditional manufactures and concludes that *"all of these firms had some level of 'export know-how', or at least were trying to acquire it"* (Pietrobelli, 1998, pp.154). These firms got information from their foreign customers about product design, technology design, and adaptation of product to the taste of export markets.

Utilization of longitudinal plant level data firstly proposed by Bernard and Jensen (1995) introduced a new development in exporting and firm performance literature. A usual start for this type of study is to document the differences in labour productivity and/or total factor productivity (TFP) as well as other characteristics of exporters and non-exporters. The difference of productivity in this step is called unconditional differential. In the next step exporter premium is computed by applying regression analysis, in which productivity is regressed against export status and other control variables. The dependent variable in this regression usually takes the form of log labour productivity.

$$\ln LP_{it} = a + \beta Export_{it} + \alpha Control_{it} + \varepsilon_{it}$$

where $_{it}$ is firm i and year t; LP is labour productivity; Export is a dummy variable standing for current export status; Control is a vector of variables, usually including industry, region, firm size and year dummies, and other firm characteristics; and ε is error term. From the regression export premium as difference between exporters and non-exporters can be estimated from the coefficient of Export variable, β.

A further step of analysis is conducted based on before-after occurrence of exporting activity to examine the change in growth rate of labour productivity for export starters, export remainders, and export stoppers. Regression of difference of labour productivity before and after the occurrence of exporting activity against the dummy variables standing for status of export starters, export remainders, and export stoppers and other control variables is taken in this case[36].

This approach has now become a standard method and has been followed by many authors exploiting the richness of longitudinal plant level data (Alvarez and López, 2005, Blalock and Gertler, 2004, De Loecker, 2007, Greenaway and Kneller, 2007, Bernard and Jensen, 1999). However longitudinal plant level data are not often available, especially in developing countries. Moreover, in the regression of productivity difference in a before-after framework applied to the same firm as mentioned above, time dimension

[36] See WAGNER, J. 2007. Exports and Productivity: A Survey of the Evidence from Firm-Level Data. *World Economy,* 30**,** 60-82. for a detailed discussion.

and other variables which change over time is not taken into analysis. For example, business environmental factors that can affect directly the performance of a firm and can change over time are not considered. Also self-selection into exporting is a problem for the method proposed as said by Wagner (2007, pp. 64): *"If better firms self-select into export-starting, and if, therefore, today's export starters are 'better' than today's non-exporters (and have been so in the recent past), we would expect that they should, on average, perform better in the future even if they do not start to export today. However, we cannot observe whether they would really do so because they* do *start to export today; we simply have no data for the counterfactual situation."* This consideration results in the matching approach to the problem at hand.

Matching approach used in searching for the causal effects of exporting activity on the performance of enterprises has been firstly proposed by Wagner (2002), Girma et al. (2003, 2004). With the advantage of being able to use both cross-section and longitudinal data, and the ability to eliminate self-selection bias, matching has been used increasingly in empirical studies on impact of export on firm performance (such as Alvarez and López, 2005, Arnold and Hussinger, 2005, De Loecker, 2007).

The matching method starts with a function on probability to export. This is for the self-selection probability, which researchers will use to eliminate selection bias. Different matching algorithms are utilized to arrive at the impact (or treatment effect in matching jargons) of export activity on firm performance. The most often estimated treatment effect is average treatment effect on the treated suggested by Heckman et al. (1997).

7.2.3 Exporting Impact: Productivity vs. Technical Efficiency

Literature on evaluation of export impact on firm performance focuses on productivity, either labour productivity or total factor productivity (TFP), as the main object. There are only a few studies that did not follow this main stream of research by using technical efficiency instead of productivity as a measure of firm performance and as a subject for evaluation. A dominant number of studies using technical efficiency as an indicator for firm performance use a parametric frontier approach to estimate technical efficiency.

The first study about the relationship between export and technical efficiency may be the paper by Aw and Batra (1998). In this paper, Aw and Batra use a Cobb-Douglas production frontier function to estimate technical efficiencies for Taiwanese firms from 9 different industries. To evaluate the relationship between export and technical efficiency, they divide firms into two groups, high technology firms, and low technology firms. Each group is further divided into exporters and non-exporters. Exporter and non-exporter groups are regressed separately to estimate technical efficiencies. Average technical efficiencies for firms in each group are compared and a mean difference test is conducted to define the impact. They claim the difference in mean efficiency of exporters and non-exporters ranges from 1.4 percent to 6.1 percent. However, their research methodology has several weaknesses. Firstly, since selection bias is not taken into account, they cannot claim efficiency differences are due to export activities or due to self-selection behaviour. Secondly, since they conduct separate estimates of technical efficiencies, exporters and non-exporters do not face the same production frontier even though they are in the same industry. Moreover, without elimination of selection bias as mentioned, the comparison between two groups is biased. In other words, the comparison is invalid since they do not compare comparable firms.

Other studies using a parametric frontier approach in evaluating the impact of export on firm technical efficiency usually include export as an explaining variable of inefficiency. This approach is developed by Battese and Coelli (1995), who estimate simultaneously stochastic frontier and technical inefficiency effects models for panel data. Using this approach, Vu (2003) studies the impact of several factors, including export activity, on technical efficiency of state-owned enterprises in Vietnam. He found that export has a significant impact on the technical efficiency level of enterprises. Hossain and Karunaratne (2004) also apply the Battese and Coelli (1995) approach using a translog production function to analyse the impact of trade liberalisation, proxied as ratio of export over output, on technical efficiency of Bangladeshi manufacturing industries. They found that export has a significant impact on improving technical efficiencies in manufacturing industries. All the above studies face the problem of ignoring selection bias and therefore causal direction of relationship between export and technical efficiency is not established.

An improved approach which takes into account the self-selection problem is used in Hassine-Belghith (2009) in analysing the impact of exporting on the technical efficiency of the agriculture sector in Mediterranean countries. Hassine-Belghith adapts the Bernard and Jensen (1995) approach by replacing labour productivity with technical efficiency. To deal with the self-selection problem, they regress a dynamic technical efficiency determinant function, in which probability to export (export propensity) among other variables is used instead of dummies for export as used in Bernard and Jensen (1995). The export assignment equation is defined by Hassine-Belghith (2009)as follows:

$$EXP_{it} = \begin{cases} 1 \text{ if } \alpha_1 EXP_{it-1} + \alpha_2 TE_{it-1} + \alpha_3 q_{it} + \alpha_4 Spread_{it} + \alpha_5 tariff_{it} + \alpha_6 \tau_{it} + \varepsilon_{it} \geq 0 \\ 0 \quad \text{otherwise} \end{cases}$$

where it is the country and time index of the longitudinal data, respectively; and other variables in turn are: lagged export experience, lagged country technical efficiency, product quality, product diversification, custom duties, and transportation and transaction costs. Hassine-Belghith (2009) conclude that their study supports self the selection hypothesis, while impact on the learning process is less evident.

Besides studies on impact of export on technical efficiency where stochastic frontier analysis is used in estimating technical efficiency, there are studies that use non-parametric frontier analysis. These studies usually include export as a dummy variable in a two-step analysis on the determinant of technical efficiency of enterprises. In this type of research, firstly technical efficiencies of enterprises are estimated by using non-parametric frontier functions. Then due to the nature of range in technical efficiency scores, which lie from 0 to 1 or from 0% to 100%, Tobit regression is used for determining factors influencing firm efficiency

By using DEA analysis in the first step and Tobit regression in the second step, Alvarez and Crespi (2003) found that there is positive links between efficiencies and the experience of workers. It is also happened in the relationship between efficiencies and modernization of physical capital and innovation in product. Meanwhile export, education level of firm owners and public programs participation not affect the efficiencies of the examined firms. Examining sampled enterprises in 7 manufacturing industries of China, Zheng, Liu, and Bigsten (1998) found that ownership has an impact on the efficiency of enterprises. Other characteristics of enterprises also have impacts on efficiencies, including size, and location of enterprises.

Sun Hone and Doucouliagos (1999) also use Tobit regression to determine determinants of efficiencies, focus on the impact of export orientation and foreign investment share. They found that export orientation, foreign direct investment, level of technology applied in production, firm size, and location have positive impacts on technical efficiency.

All studies using the two-step approach above commit serious problems as criticised by Simar and Wilson (1998) and mentioned in the review of the two-step DEA approach in Chapter 3. Moreover, since selection bias is not controlled, the result is export premium, not the impact of export activity on technical efficiency as we would like to find out. In this chapter we will apply the approach developed in Chapter 6 taking into account selection bias. This also has the advantage of reducing the impact of outliers on a non-parametric frontier. The study applies the approach which is developed from conditional frontier approach (Dairao and Simar 2007) and examines the impact of export on Vietnamese textile and garment SMEs.

7.3. Research Methodology and Data

7.3.1 Research Methodology

Propensity matching is a method that is used frequently in studying the effectiveness of medicine on the human body. It is developed to overcome the curse of dimensionality resulting from covariates matching by Rosenbaum and Rubin (1983). Since the work of

Rosenbaum and Rubin (1983), several propensity matching algorithms have been developed by researchers such as nearest neighbour matching, radius matching, kernel matching. Propensity score is also used as a variable in regression to adjust for selection bias. Application of propensity matching spreads quickly to economic studies, and is widely recognised in labour economics. As mentioned in section II, propensity matching is also applied in studies on export and productivity, pioneered by Wagner (2002), Girmar, Greenaway, and Kneller(2003, 2004). The most used algorithm is nearest-neighbour matching while kernel matching is also used. The following table summarizes some studies in export impact on productivity that use propensity matching.

Table 34. Export and Productivity Studies using Matching Techniques

Aston University

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Source: adapted from Juan et al. (2010)

In this research we will use traditional propensity matching as a baseline to compare with our proposed order-m frontier conditioning on propensity score approach. Kernel matching is used since it allows researchers to utilise all observations to establish a counterfactual for a treated observation. It is also consistent with kernel matching that we propose to use in a modified conditional frontier approach. Our kernel propensity matching is applied to technical efficiency, which has subtle difference from productivity as used by previous studies.

Our main subject of consideration in this chapter then is the conditional frontier using propensity scores. Conditional frontier is a nonparametric approach developed by Cazals et al. (2002) and advocated by Daraio and Simar (2005). It is built on the probability approach to technical efficiency. In Chapter 6 we showed that conditional frontier as developed and used by Cazals et al. (2002) and Daraio and Simar (2005) is a kernel matching on a single covariate. Frontier conditioning on propensity score is a natural development and it will enable us to evaluate the impact of a dichotomous exogenous variable on technical efficiency.[37]

7.3.2 Research Data

In this research we utilise the dataset collected by the World Bank's Enterprise Survey. Enterprise surveys are conducted by the World Bank and its partners in every region of the world.[38] The World Bank's enterprise survey initiative aims to achieve 4 objectives: (i) providing significant investment climate indicators; (ii) accessing the constraints to private sector growth and enterprise performance; (iii) building a panel of establishment-level data; and (iv) stimulating policy discussion and shaping policy reform. With these objectives enterprise surveys include questions covering all aspects of business environment and operation of enterprises. For manufacturing sector, beside common qualitative questions sharing with service sector on enterprise manager's opinion on the business environment, there are quantitative questions on the use of production capacity, hours of operation, finance, labour and productivity issues. Therefore the data from the World Bank's enterprise surveys enable us to research on the impact of exporting activities on technical efficiency.[39]

[37] Detailed discussions on methodology can be found in Chapter 6.

[38] The data can be downloaded freely from the World Bank's website dedicated to enterprise surveys: https://www.enterprisesurveys.org/

[39] Detailed description of enterprise surveys can be found at: http://www.enterprisesurveys.org/documents/Implementation_note.pdf

The survey in Vietnam was taken from June 2009 to January 2010 with 1053 enterprises in manufacturing and services sectors. The sample was collected using stratified random sampling. Three levels of stratification were used including: industry, enterprise size, and region.[40] In this chapter we focus on evaluating impact of exporting activities on technical efficiency of textile and garment SMEs. The total of textile and garment SMEs after cleaning obtained from the survey is 95 enterprises, in which 24 enterprises evolved to direct exporting.

Table 35. Summary statistics

Variable	Mean	Std. Dev	Min	Max
Revenues (thousand VND)	10,600,000	20,600,000	600,000	179,000,000
Capital (thousand VND)	2,200,000	2,640,000	17,900	10,000,000
Total wages (thousand VND)	1,750,000	2,170,000	72,000	14,000,000
Raw material (thousand VND)	4,670,000	6,580,000	5,000	38,000,000
Number of employees	72	76	5	300
Number of non-production employees	13	15	0	72
Number of unskilled employees	12	21	0	107
Age of enterprises (years)	8	7	1	41

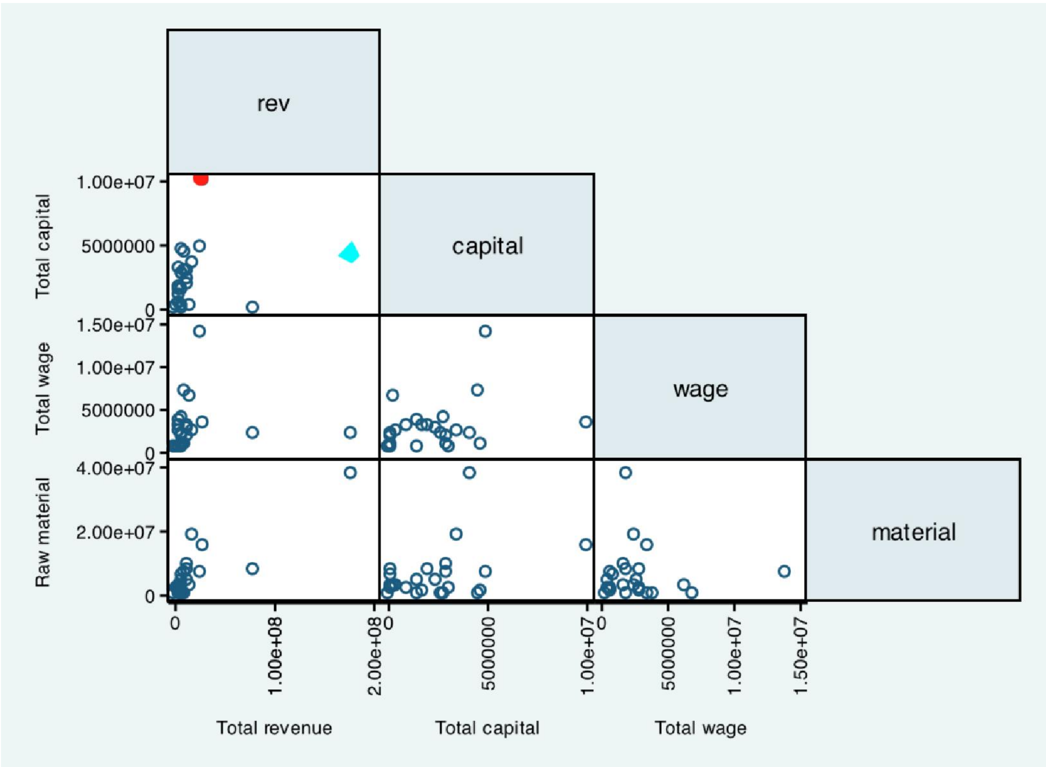
Table 35 shows the summary statistics of textile and garment enterprises. There is a huge gap between the largest and smallest enterprise in the industry. The definition of small and medium-sized enterprises is rather loose which covers enterprises with only a few employees up to 300 employees. In terms of labour the largest enterprise is 60 times larger than the smallest one. While capital value of the largest is 559 times larger than the smallest. Huge variations are also observed in term of input used in the

[40] Detailed description of the World Bank's enterprise survey in Vietnam can be found at: https://www.enterprisesurveys.org/

surveyed year and total wages paid to employees as well as in capital and number of employees.

As presented in Table 35 variables of textile and garment enterprises are highly skewed. Moreover, Figure 47 shows that there are some extreme points clearly being highlighted. For example in the second plot at the far left of the Figure 47 there is an enterprise represented by red dot which is a highly capital-intensive enterprise but produce a high level of revenue. In the same plot, we can see that another enterprise presented by a cyan diamond figure with an average capital level but extremely successful in creating revenue. These characteristics should be taken into account in any analysis.

Figure 47. Scatterplot matrix of inputs and output for all observations



(Unit: Thousand VND)

7.4. Analysis

7.4.1 Definition of Inputs and Outputs

The identification of the inputs and outputs is a necessary and important step in any nonparametric analysis of technical efficiency. The choice of input and output variables for DEA technical efficiency estimation has to satisfy the rule that input variables exclusively and exhaustively influence outputs (Thanassoulis, 2001). Our choice of input and output variables follows this rule and examples from previous studies. Table 35 shows a summary of studies on technical efficiency of SMEs in various countries. Inputs in these studies are chosen based on the basic approach to production function where output is produced through the combination of human labour, capital and materials. There are several output variables chosen, but most often it is revenues or profits.

Table 36. Input and Output Variables in SMEs Efficiency Studies

Studies	Country	Technology	Inputs	Outputs
(Yang, 2006)	Korea	CCR and BCC; both input and output oriented	• Capital • Fixed assets and • Number of staff members • Fund raising and other policy funds as exogenous input variables to determine the effect of funding support	• Profit • Total sales
(Önüt and Soner, 2007)	Turkey	Input CCR approach	• Annual electricity consumption (kW h) • Annual natural gas consumption (m^3) • Annual oil consumption (Ton) • Annual liquefied petroleum gas (LPG) consumption (Ton)	• Annual total sales • Annual total profit
(Reverte and Guzman, 2008)	Spain	Output oriented	• Cost of materials consumed • Personnel expenses • Depreciation expense • Overhead	• Revenues
(Lee, 2009)	Taiwan	Output oriented	• The number of branches • The number of total employees • The number of partners • Total expenditures	• Attestation revenues • Tax business revenues • Management consultancy revenues

Studies	Country	Technology	Inputs	Outputs
				• Corporate registration and other business services
(Halkos and Tzeremes, 2010)	Greek	CRS	• Number of employees • Intangible fixed assets (000s $) and • Tangible fixed assets (000s $).	• Sales

By following the rule that input variables exclusively and exhaustively influence outputs and learning from previous studies, in our studies input variables include total capital of enterprises, employee payment or wage, and materials used in production, while output variable is total revenue. Since the analysed DMUs are profit making enterprises operating in a market mechanism their ultimate objective is to maximize revenue thereby profit, taking revenue as output for analysis is a rational option. There is an advantage of choosing revenue instead of profit as output is that by taking revenue we avoid the problem of negative number as it may be the case if choosing profit. Our study focuses on the impact of dichotomous environmental variable, not on problem of negative number in efficiency analysis, which has been dealt with by several studies.

It is widely accepted in the literature that there are three main inputs for production of an enterprise: labour, capital and raw material. We acknowledge this understanding by choosing total capital, total wage and raw material as inputs of production process. These inputs are measured in currency term. By assuming uniform wages for similar types of labour across regions total wage can be a good proxy for labour input. By using total wage we do not worry about the different quality of employees employed by enterprises since the quality of labour is already captured by its price (i.e. wage). Total capital in our study is the total value of machinery at the end of the accounting year, which is deducted from depreciation. Therefore, the difference in quality of machinery used by textile and garment enterprises across the country is eliminated.

Since our analysis subjects are SMEs, we can assume that they cannot affect the market. In other words, they take the price set by the market and have no control over the market. Also, their business depends on market demand, therefore we can say that their revenue is somehow out of their control. Therefore technical efficiency measurement should follow the input-orientation approach since enterprises have control over their inputs to production. In efficiency analysis jargon, it is input-oriented models that will be used in our analysis.

7.4.2 Are Exporters Superior?

The data on textile and garment SMEs that we have from the World Bank enterprise survey gives us confirmation of the superiority of exporters over non-exporters on efficiency . As in Bernard and Jensen (1995) we find that exporters are substantially larger than non-exporters in number of employees, wage payment, materials used, and total revenue. They are also superior over non-exporters in labour productivity.

There are about 2,000 textile and garment enterprises in Vietnam employing a total more than 2 million workers. The fabrics available in Vietnam are mainly cotton, polyester and silk. While the industry needs about 2,000 tons of cotton for fabricating export products, domestic supply can meet only a meagre 2 percent. Production of polyester can meet 4 percent of domestic demand, and production of silk is not significant (Buisman and Wielenga, 2008). Therefore, most of materials for production in textile and garment are imported. In fact, Vietnamese textile and garment exporters are most often outsourced by foreign companies.

In Table 37 we present summary characteristics of textile and garment exporters and non-exporters. The figure shows that average capital value of an exporter is not very much higher than the one of a non-exporter, while average number of employees of an exporter is more than double that of a non-exporter. Therefore, exporters are more labour-intensive than non-exporters. In other words, textile and garment enterprises in Vietnam are trying to exploit the advantage of abundant and cheap labour for export.

One characteristic of exporters is that they operate in the industry longer than non-exporters. Exporting enterprises' managers also have higher education as well as work longer in the industry than their counterparts in non-exporting enterprises. More importantly, the ratio of managers in exporting enterprises who have enjoyed education abroad is much higher than the one in non-exporting enterprises (see Table 37). These may be important factors that affect the possibility to become exporter of a textile and garment enterprise and will be investigated more in the next section on the propensity to export.

Table 37. Exporter and non-exporter differences

Variable	Exporter	Non-exporter	Difference (%)
Capital (thousand VND)	2,400,535	2,127,451	12.84
Input used (thousand VND)	6,008,165	4,214,914	42.55
Total wages (thousand VND)	2,887,874	1,363,924	111.73
Number of labour	125.75	53.56	134.77
Non-production labour	21.71	10.18	113.18
Revenues (thousand VND)	19,900,000	7,475,551	166.20
Age of enterprises	9	7.85	14.72
Education of owners	0.67	0.55	21.37
Manager study abroad	0.13	0.04	195.83
Manager experience in the industry	19.375	15.21	27.37
Labour productivity (thousand VND)	105,018.3	52,116.32	101.51

The differences between two samples of exporters and non-exporters in several characteristics suggest that an unbiased comparison between exporters and non-exporters should be conducted. Moreover extreme observations in exporters and non-exporters as we can see in the Figure 47 also have to be taken care of. We therefore conduct in the following section the order-m frontier conditioning on propensity score approach which is designed to eliminate selection bias as we present in chapter 6 of the thesis.

7.4.3 The Selection Model

The self-selection hypothesis suggests that there is correlation between firm performance and exports. This is because there exist extra costs when entering foreign markets, including transportation, distribution, marketing and labour training costs. The performance of exporters should be good enough to overcome the barrier of those extra costs. As noted by Bernard and Jensen (2004, pp.563),*"exporting is not a once-and-forever phenomenon."*To study the self-selection hypothesis we investigate how enterprise characteristics affect the probability to export.

An enterprise's decision to export is affected by different factors. Bernard and Jensen (1999) find sunk cost and enterprise characteristics having significant impact on the export decision of enterprises. Alvarez and López (2005) study the impact of enterprises characteristics on probability of beginning to export and find that enterprise size, age of enterprises, ratio of skilled workers in total labour, as well as relationship of enterprises with foreign enterprises (capital invested by or payment to get licenses from foreign companies) have significant impact on the probability of beginning to export. While Bernard and Jensen (2004) find that previous exporting experience, firm size and ratio of nonproduction employee in total labour force have positive association with probability of exporting. However, they cannot find spillover impact on the export decision.

In studying propensity to export of Vietnamese textile and garment SMEs we estimate the logit model:

$$\Pr\left\{D_i = 1 \middle| X_i\right\} = \phi\left(h\left(X_i\right)\right)$$

Where $\Pr\left\{D_i = 1 \middle| X_i\right\}$ is the propensity to export in accordance to X_i characteristics (covariates) of textile and garment SMEs; ϕ denotes the logistic c.d.f and $h\left(X_i\right)$ is starting specification which includes all covariates.

In principle, as pointed out by Caliendo (2006), any discrete choice model which involves choices between two or more discrete alternatives (in our case it is two alternatives) can be used. However the preference is placed on logit and probit models, but the linear probability function since there is possibility that predicted probability can be outside unit interval [0,1]. Caliendo (2006) further points out that in binary discrete choice cases where the dependent variable takes value [0 or 1] the results are very similar. Therefore the choice to make between logit or probit is not important. In our study we will apply logit regression in estimating probability to export.

Following the studies of Bernard and Jensen (2004), Alvarez and López (2005), and others, and given the limitation of our dataset, we investigate the influence of some covariates to propensity to export. The results of the analysis are represented in the following table.

Table 38.The decision to export

Export	Est. Coefficient.
constant	-2.74071 (-4.06) ***
capital	-1.02E-07 (-0.89)
wage	3.49E-07 (2.61)***
Manager study abroad	1.588047 (1.67)*
Manager experience	0.061688 (2.13)**
Age of enterprises	0.002208 (0.05)

*Notes: In parentheses are z-statistics; ***, **, *: significant at 1%, 5%, and 10%, respectively.*

The estimation shows that the export decision by Vietnamese wearing apparel manufacturing SMEs is affected by the manager's working experience and his/her education experience abroad. Capital intensive textile and garment enterprises tend not to join the export sector. Meanwhile enterprises with more labour are more prone to initiate export activities. Our findings are consistent with the conclusion by Alvarez and

López (2005), Máñez-Castillejo et al. (2010) and many others that enterprise size has significant impact on the decision to export. Enterprises which have larger capital capacity and recruit more labour are confident in opting for the exporting sector.

7.4.4 DEA and FDH Efficiency Scores and Propensity Score Matching

In Table 39 we present average efficiency scores of exporters and non-exporters so that the reader can see the difference of performance between exporters and non-exporters. These technical efficiency scores are estimated in input-orientation technology. The inputs we use in the estimations include total capital of enterprises, employee payment or wage, and materials used in production. The output is total revenue[41]. We present both efficiency scores with convex and non-convex technology[42]. We can look at differences in average efficiency scores between exporters and non-exporters. These differences are unconditional efficiency differentials between two groups. Both production technology technical efficiency estimations show an inferior situation of exporters with regards to non-exporters. Average exporters efficiency score is lower than average non-exporters efficiency score by about 4 percentage points[43].

Table 39. Exporter and non-exporter performance differences

Variable	Exporter	Non-exporter	Difference (%)
DEA efficiency score	0.44	0.48	-3.89
FDH efficiency score	0.83	0.88	-4.22

Propensity score matching method can be applied to DEA and FDH efficiency scores to arrive an unbiased evaluation of impact of exporting activities on technical efficiency of textile and garment SMEs. This is similar to the traditional approach to selection bias in exporting and productivity studies as reviewed in the previous section, in which

[41] The argument for choosing these inputs and outputs and optimum orientation is presented in previous section (see section…)

[42] We use DEA for estimating convex technology efficiency scores and FDH for estimating non-convex technology efficiency scores.

[43] For detailed technical efficiency scores, please see the appendix

propensity score matching is applied to performance of enterprises (Alvarez and López, 2005, Arnold and Hussinger, 2005, De Loecker, 2007).

Our study is the first study to our knowledge using propensity score matching to deal with selection bias in evaluation of environmental variables on DEA or FDH technical efficiency. To conduct propensity score matching, there are choices to be made. Firstly, there are several matching algorithms as mentioned in Chapter 3. In this study kernel matching is applied, in which all non-treated (non-exporter in this case) will be taken into account to estimate a counterfactual for a treated enterprise (exporter). This algorithm allows the influence of all non-treated enterprises with different weights applied in accordance to export propensity scores.

Kernel matching uses the following weight:

$$W_{n_0}(i,j) = \frac{K_{ij}}{\sum_{k \in I_0} K_{ik}}$$

Where $K_{ik} = K\left[\left(\Pr_i - \Pr_k\right)/h_{n_0}\right]$ is a kernel, and h_{n_0} is a bandwidth parameter. Kernel can take different forms as described in Table 28 presented in Chapter 6. Bandwidth parameter h_{n_0} can be defined by two data-driven method, least squares cross-validation approach and likelihood cross-validation approach. In this study we use the likelihood cross-validation as the main engine in determining the bandwidth h[44].

Using technical efficiency scores estimated by DEA and FDH techniques as outcomes to do propensity score matching we will apply kernel matching to estimate the average treatment effect of exporting. Differences between exporters and their matched non-exporters can be attribute to the impact of export and are presented in the following table.[45]

[44] More discussion on this issue can be found at section 6.5 of Chapter 6.

[45] In this analysis, the estimation of ATT of export is conducted by applying the add-in function *pscore* for Stata 9 by Becker, S. O. and A. Ichino (2002). "Estimation of average treatment effects based on propensity scores." The Stata Journal 2(4): 358-377.

Table 40. ATT from DEA and FDH efficiency scores

Mean DEA efficiency scores of matched exporters	0.440
Mean DEA efficiency scores of matched non-exporters	0.439
DEA Average treatment effect (ATT)	**0.001**
Mean FDH efficiency scores of matched exporters	0.836
Mean FDH efficiency scores of matched non-exporters	0.851
FDH Average treatment effect (ATT)	**-0.016**

The results show that DEA - the convex production technology approach - produces much lower technical efficiency scores than ones produced by its alternative - the non-convex production technology approach - FDH. The ATT estimations are also different between two approaches. While the convex production technology approach of technical efficiency analysis produces a positive impact of export on efficiency of SMEs, the non-convex production technology approach provides a negative impact. From results of Monte-Carlo simulations presented in Chapter 6, we know that propensity score matching of FDH technical efficiencies provides biased estimation of average treatment effect of dichotomous environmental variables. Therefore, in the following analysis we focus more on the average treatment effect estimated from propensity score matching of DEA efficiencies.

7.4.5 Order-m Frontier Conditioning on Propensity Score

The order-m frontier conditioning on propensity used in this empirical analysis is enabled by the novel approach on conditional order-m frontier initiated by Cazals et al. (2002) and advocated by Daraio and Simar (2005). As discussed on Chapter 6, order-m frontier conditioning propensity scores enables us to examine the impact of dichotomous environment variable, taking into account the selection bias. Originally, conditional order-m frontier is developed on covariate kernel matching (matching of environmental variable).[46] Therefore propensity score matching is a natural

[46] See Chapter 6 for more discussion

development for conditional order-m frontier. It has the advantage of robust nonparametric frontier and enables us to examine the impact of a dichotomous environmental variable. This is the direction developed in Chapter 6 and applied in this chapter to examine the impact of export on technical efficiencies of Vietnamese textile and garment SMEs.

Analysis in the above sections shows that enterprises are opting themselves into the exporting sector. This is the conclusion which prevails in the related literature and is an important factor that needs to be taken into account in any study on performance of exporting enterprises. The order-m frontier conditioning on propensity score takes into account of selection bias by integrating the kernel of propensity score in the estimation of technical efficiency scores. Efficiency scores estimated from order-m frontier conditioning on propensity score, therefore, is the scores that are adjusted by the selection bias. The **input-oriented technical efficiencies** of Vietnamese textile and garment SMEs are estimated from the following order-m frontier conditioning on propensity score function:

$$\hat{\lambda}_m\left(x, y \middle| \mathrm{Pr}_z\right) = \int_0^{\infty} \left(1 - \hat{F}_{X|Y,\mathrm{Pr}_Z,n}\left(ux \middle| y, \mathrm{Pr}_z\right)\right)^m du$$

Where $\hat{F}_{X|Y,Z,n}\left(x \middle| y, z\right) = \dfrac{\sum_{i=1}^{n} I\left(x_i \leq x, y_i \geq y\right) K\left(\mathrm{Pr}_z, \mathrm{Pr}_{z_i}, h\right)}{\sum_{i=1}^{n} I\left(y_i \geq y\right) K\left(\mathrm{Pr}_z, \mathrm{Pr}_{z_i}, h\right)}$

$\hat{\lambda}_m$ is the input-orientation order-m technical efficiency conditioning on propensity score. Pr_z is propensity score, h is bandwidth estimated by likelihood cross-validation method. Other denotations are mentioned in Chapter 6.

The above equation shows that by using smoothing technique with propensity score, the estimated conditional order-m input oriented efficiency scores are adjusted the selection bias. Table 40 shows the summary of technical efficiency scores of exporters and non-exporters estimated by using DEA, FDH, and order-m conditioning on propensity score methods. For technical efficiency scores estimated by order-m conditioning on propensity score method, we applied three difference specifications of m, i.e. m=15, m=20 and m=25, to test the ability to measure impact of exporting activities on technical efficiencies[47].

Table 41. Efficiency scores grouped by treatment

Efficiency Scores	Treatment	Obs.	Mean	Std. Dev.	Min	Max
DEA Efficiency	Tr=0	71	0.48	0.30	0.09	1
	Tr=1	24	0.44	0.31	0.15	1
FDH Efficiency	Tr=0	71	0.88	0.22	0.17	1
	Tr=1	24	0.84	0.22	0.31	1
Order-m efficiency	Tr=0	71	0.89	0.50	0.31	2.79
(m=20)	Tr=1	24	0.96	0.36	0.43	1.74
Propensity conditional order-m efficiency	Tr=0	71	0.707	0.45	0.01	2.17
(m=15)	Tr=1	24	0.711	0.40	0.02	1.57
Propensity conditional order-m efficiency	Tr=0	71	0.778	0.48	0.02	2.33
(m=20)	Tr=1	24	0.782	0.41	0.03	1.66
Propensity conditional order-m efficiency	Tr=0	71	0.835	0.50	0.03	2.56
(m=25)	Tr=1	24	0.837	0.42	0.04	1.71

In the above table, we can see that there are efficiency scores estimated by robust nonparametric frontier methods not being bounded by 1. This is explained by Daraio and Simar (2005) as follows: "*a value of $\theta_m(x,y)$ greater than one indicates that the unit operating at the level (x,y) is more efficient than the average of m peers randomly drawn*". From the above results it is obvious that we are dealing with a sample with some extreme observations.

[47] m=20 is also the default value of order-m frontier package, FEAR, developed by Wilson (WILSON, P. W. 2008. FEAR: A software package for frontier efficiency analysis with R. *Socio-Economic Planning Sciences,* 42**,** 247-254.)

In Daraio and Simar (2005) framework with a continuous environmental variable, impact of environment variable is examined by comparing conditional efficiency scores taking account the existence of environmental variable and unconditional efficiency scores estimated by unconditional order-m frontier method. Conditional efficiency scores is believed to eliminate the impact of environmental variable by being estimated from frontier with m DMUs which are similar in terms of the environmental variable. The similarity among m DMUs used to establish conditional order-m frontier is determined by the kernel function. Difference between the unconditional and conditional efficiency scores are seen as impact of environmental variable. In our approach, conditional efficiency scores are estimated so that selection bias is eliminated. Therefore the direct comparison of efficiency scores between exporters and non-exporters is possible without worrying about the bias due to the fact that SMEs opt themselves into the export sector.

Table 42 shows the export impact coefficients that are ratio of efficiency scores of exporters to non-exporters, in which efficiency scores are estimated. It shows that for normal DEA and FDH estimation entering the export sector actually lowers technical efficiency of textile and garment SMEs. The results after eliminating selection bias as presented by propensity conditional order-m efficiency however show a positive impact of exporting activities on technical efficiency.

Table 42. Export impact coefficients

Method	Value
DEA	0.9188
FDH	0.9519
Propensity conditional order-m efficiency (m=15)	1.0055
Propensity conditional order-m efficiency (m=20)	1.0047
Propensity conditional order-m efficiency (m=25)	1.0035

One of the advantages of the propensity score matching approach is that the impact can be quantified. The interesting result is the average treatment effect on the treated (ATT) which shows the impact level of the export activities on technical efficiency. Taking self selection behaviour into account and applying propensity score matching, the average treatment effect can be estimated by the following equation:

$$\Delta_{ATT} = E(\Delta \mid D=1) = E(Y_1 \mid D=1) - E(Y_0 \mid D=1)$$

Where D=1 is exporting, D=0 is non-exporting, Y_1 is outcome (technical efficiency scores) if exporting, and Y_0 is outcome if not exporting. Table 43 presents the ATT estimated by different methods and specifications.

Table 43. Average treatment effect

Techniques	**Average treatment effect**
Propensity score matching of DEA efficiency scores	**0.001**
Propensity score matching of FDH efficiency scores	**-0.016**
Propensity score conditional order-m (m=15)	0.0039
Propensity score conditional order-m (m=20)	0.0036
Propensity score conditional order-m (m=25)	0.0029

In our analysis ATT estimated by propensity score matching of FDH efficiency scores stands by itself when it projects a negative impact of exporting activities on technical efficiencies of textile and garment SMEs. The level of the negative impact is also very large in comparison with ATT estimated by other methods. However, as shown by Monte Carlo simulations in Chapter 6, propensity score matching of FDH efficiency scores produces large bias for estimation of ATT and there is not a reliable result. Table 44 reproduces the results of simulation which show that ATT estimated by propensity score matching of FDH efficiency scores is not a good estimation of true impact, compared to other methods. Since we are analysing the case where the variable returns to scale assumption is applied, Table 44 presents only results where variable returns to scale dominates. Moreover, we also only reproduce analysis results for a sample of 100 observations which is closest to this chapter empirical analysis for the designed impact of 0%, 5%, 10%, 15% and 25% (i.e. $\alpha = 0;\ 0.05;\ 0.10;\ 0.15;\ 0.25$ respectively). However, detailed results of simulation for constant return to scale production technology and sample larger than 100 observations can always be referred in Chapter 6.

Table 44. Bias from different methods: simulation analysis

	$\alpha = 0$	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.15$	$\alpha = 0.25$
True impact (generated by simulation)	0.00003	0.04223	0.08613	0.13252	0.23060
Bias from conditional order-m ATT to true impact	-14.09	-0.23	-0.27	-0.34	-0.37
Bias from DEA ATT to true impact	-125.78	-0.19	-0.18	-0.22	-0.26
Bias from FDH ATT to true impact	-200.41	-0.62	-0.52	-0.54	-0.52

Notes: all samples have 100 observations

The table shows that all of the estimated ATT are smaller than true impact. The ATT estimation from FDH efficiency scores is furthest from true impact, and about double the bias produced by using DEA efficiency scores. We therefore are sceptical about using FDH ATT as an estimation of exporting impact on technical efficiency.

All other estimates, except FDH ATT, are positive, suggesting that export activities influence positively on performance of wearing apparel manufacturing SMEs of Vietnam. Exporting increases technical efficiency scores of exporters by insignificant level. Our estimation shows that this impact ranges from 0.1% to 0.4%. The most important result from the analysis is that, instead of a negative impact as initially illustrated in Table 39 we find a positive impact from exporting on technical efficiency of textile and garment SMEs. However, the level of impact is negligible.

7.5. Conclusion

In this chapter we have applied the methodology developed in Chapter 6 to the case of Vietnamese textile and garment SMEs. This chapter presents the first application of propensity score matching for technical efficiency scores. We have applied propensity score matching for efficiency scores estimated by DEA and FDH approaches. Also in this chapter order-m frontier conditioning on propensity score has been applied for the first time. The approach allows us to examine the impact of a dichotomous environmental variable on the performance of enterprises taking the advantage of robust nonparametric frontier analysis. The methods used in this chapter help to eliminate selection bias happening when enterprises select themselves into the treatment group (exporter group in this particular study). By this elimination we can estimate the causal impact of the treatment. Therefore we don't need to further nonparametrically regress the efficiency against environmental variable as well as building a direction index and ratio of conditional and unconditional efficiency scores to examine impact of exogenous environmental variable.

Our study confirms the self selection hypothesis that enterprises select themselves into exporting activities. Enterprises characteristics and management experiences as well as study abroad play a significant role in export decision of Vietnamese textile and garment SMEs. The analysis also shows that exporting contributes positively to the better performance of textile and garment SMEs. Exporting activities raise textile and garment SMEs technical efficiency by very small level. This analysis will positively contribute to the design of export supporting policies to aim at higher growth rate of the Vietnamese economy.

Chapter 8. Conclusions and Direction for Future Studies

8.1. Introduction

This thesis has analysed the impact of dichotomous environment variables on technical efficiency. The study originated from the observation that there is no well accepted approach to isolate the impact of a dichotomous environment variable on technical efficiency. There are only two possible approaches in the literature that can deal with dichotomous environment variables. The first approach is the frontier separation approach, which is the oldest one being applied on dichotomous external variables. This approach was proposed by Charnes et al. (1981) and applied firstly to examine the impact of the Follow Through program on schools. The second approach is called two-stage approach, where technical efficiencies of DMUs are estimated in the first stage, usually by non-parametric approach to efficiency analysis, and dichotomous external variable is added as an explanatory variable to the second stage regression to explain the fluctuation of technical efficiency. However, both approaches suffer from defects as discussed in detail in Chapter 3.

Starting with empirical objectives to examine the impact of dichotomous external variables on technical efficiencies of Vietnamese SMEs, the methodological developments of evaluation of external variable impacts on technical efficiency has emerged from the thesis. This chapter will summarise the contributions of the thesis to the understanding of impact of dichotomous external variables on efficiency. Methodological contributions of the thesis will be discussed along with empirical contributions to understanding of the impact of training programmes and exporting on Vietnamese food processing and textile garment SMEs respectively. The chapter also presents the directions for future research. The first part of the chapter will present the contributions of the thesis, and the second part of the chapter will discuss possible directions for future research.

8.2. Contributions to the Literature

8.2.1 Revised Frontier Separation Approach

In this thesis we have made both methodological contributions and empirical applications of the proposed methodology in evaluating impacts of dichotomous external variables on technical efficiency. The methodological contributions were made in developing models capable of evaluating impacts of dichotomous environment variables on technical efficiency, given the presence of selection bias.

By using propensity score matching the thesis is able to revise the traditional separation approach to take into account self-selection behaviour of DMUs and eliminate selection bias to produce more precise average treatment effect of the analysed dichotomous external variable. Among approaches used for evaluating external variable impact on technical efficiency up to the time when this thesis was written, frontier separation approach is the only one that can be used to deal efficiently with dichotomous external variables. The approach, however, is designed not to deal with the self-selection problem. This problem causes bias in estimation of program efficiency since all observations are included into the estimation. This problem will not happen when observations are randomly chosen into 'treated' and 'non-treated' samples. However this assumption is usually violated in real life, where units deliberately select themselves into treatment. They therefore should be compared to the ones with similar characteristics out of all observations.

By applying nearest neighbour matching based on propensity score and then applying frontier separation approach we can arrive at the balanced sample of treated and non-treated observations. The revised frontier separation approach is shown to produce better results than the traditional frontier separation approach. These results are improved by eliminating selection bias and bias due to different sample size between treated and non-treated (Simpson, 2005). The results are confirmed by Monte Carlo type simulation in which, results from the revised approach dominate those from traditional approaches when there is the self-selection problem.

8.2.2 Order-m Frontier Conditioning on Propensity Score

Another methodological contribution of the thesis is the adaptation of the novel conditional frontier approach proposed and developed by Cazals et al. (2002) and Daraio and Simar (2005). Cazals et al. (2002) proposed a new approach to technical efficiency by inventing a probabilistic approach to production frontier estimation. The probabilistic approach opens the door for a new technique to examine external variable impacts on technical efficiency. Daraio and Simar (2005) advanced the Cazals et al. (2002) model by developing the conditional frontier which includes the external variable via a kernel smoothing technique. The conditional frontier approach is in fact a covariate matching which is used by Daraio and Simar (2005) to eliminate the impact of a continuous external variable from technical efficiency. By comparing conditional efficiency scores and their unconditional counterparts Daraio and Simar (2005) could conclude about the impact of the continuous external variable.

Starting with the nature of nonparametric matching of conditional frontier approach in dealing with external variable impact evaluation problem, the thesis proposes the application of kernel matching based on propensity score. This proposal enables the conditional frontier approach to deal with both dichotomous variables and the self-selection problem. By replacing covariate kernel matching used in Daraio and Simar (2005) by an appropriate propensity score matching the thesis is able to evaluate and measure the average treatment effect of the dichotomous external variable on technical efficiency.

Monte Carlo simulations are designed to examine the usability and validity of the approach. The result confirm the accuracy of the proposed approach. It opens a wide opportunity for real life applications in evaluating the impact, among other things, of government policies on technical efficiency of enterprises. In the thesis, the proposed approach is applied to analysing the impact of training on technical efficiency of Vietnamese food processing SMEs.

8.2.3 Impact of Training and Exporting on SME Technical Efficiency

Studies presented in the thesis contribute to the empirical understandings on the impact of training programmes and exporting activities on technical efficiency of food processing and textile and garment SMEs in Vietnam, respectively. There are studies in the literature exploring the relationship between training and performance of enterprises. However, most of the previous studies defined performance in terms of turnover, employee growth, and survival. Our study is the first to explore the impact of training programmes on technical efficiency of SMEs. By applying the revised frontier separation approach, findings of the study show that the eagerly awaited training programmes have no significant impact on technical efficiency of Vietnamese food processing SMEs. This finding confirms the weak link between training and firm performance as reported by Wynarczyk et al. (1993), Westhead and Storey (1997), Marshall et al. (1993).

The study of the impact of exporting on technical efficiency of textile and garment SMEs shows that there is clear evidence about the self-selection hypothesis. Exporters in the textile and garment industry are substantially larger than non-exporters of the same industry in number of employees, wage payment, materials used, and total revenue. They have larger capital investment and are superior over non-exporters in labour productivity. However, normal comparison between averages of exporter and non-exporter DEA and FDH technical efficiency scores, exporters have lower technical efficiency than non-exporters. The difference is about 4 percentage points.

To deal with the self-selection problem in evaluating the impact of exporting on technical efficiency of textile and garment SMEs, we propose to use two approaches: (i) (traditional) propensity score matching; and (ii) order-m frontier conditioning on propensity score. Both approaches are applied for the first time for estimating the impact of external variables on technical efficiency. In the first approach, the thesis applies the propensity score matching method proposed by Rosenbaum and Rubin (1983) and by Wagner(2002) to explore the causal effect of exporting on firm productivity. The approach shows that the average treatment effect estimated through

DEA efficiency scores is 0.01 percentage points, and through FDH efficiency scores is -1.6 percentage points. From the Monte Carlo simulations on Chapter 6 we can reject the result from matching FDH efficiency scores since this production technology produces a biased estimation of the true impact.

In the second approach, which is newly developed from conditional frontier approach, the estimated causal effect of exporting on technical efficiency is: 0.39; 0.36; and 0.29 percentage points, with different order-m value (m=15; m=20; m=25, respectively). The conclusion from the analysis is that exporting contributes positively to the technical efficiency of Vietnamese textile and garment SMEs. However, the impact level is insignificant.

The findings of the study of the impact of training on the technical efficiency of Vietnamese food processing SMEs implies that, Vietnamese policy makers need to reconsider the policy of providing training to SMEs. As discussed in Chapter 2 of the thesis the government of Vietnam has designed a range of training programmes supporting the operation of Vietnamese SMEs. Impact of training programmes on technical efficiency of SMEs as examined in the thesis is not significant. Instead of training programmes provided directly to SMEs, vocational training and the education system should be invested in more and improved. Evidence from the development of enterprises in many countries shows that competition is the source for improvement in performance of enterprises. The scarce resources of the country should be allocated to efficient players in the economy via fair playing-field and competition. Meanwhile supporting policy for exporting SMEs should be designed so that SMEs can access world markets. By expanding their business abroad, SMEs are expected to increase efficiency by the increase of economies of scale. Moreover, learning-by-exporting has proved to have positive impact, even though the level is still small.

8.3. Future Research Directions

Due to the time and space constraint, the thesis has not employed several possibilities to analyse the impact of dichotomous environmental variables on technical efficiency. Further developments of the thesis can be made in various aspects. Concerning the methodological approach, one possibility is to apply order-α quantile-type frontier. It can also be improved by introducing a nonparametric approach to estimate propensity scores, so that the parametric estimation of propensity scores can be avoided and the entire approach becomes nonparametric. Last but not least, large dataset or panel data can be used to improve the quality of analysis. With larger dataset researchers could have more options in dealing with the selection bias. In this case trimming treated observations is possible to form a better matched sample for analysis. Panel data will help to deal with the possible influence of time lag in evaluating policy impact. For example, in Chapter 5 we examined the impact of training on technical efficiency of food processing enterprises. The results of the analysis can be enriched and improved by panel data in which we can take into account the time lag. This is because impact of training on efficiency is not expected to be instantaneous and skills of labours are expected to improve over time.

Instead of using order-m frontier approach, order-α quantile-type frontier can be used to integrate with propensity score matching to form a new methodological approach to analyse the impact of dichotomous external variables. In the order-m frontier used in the thesis, the frontier is defined by m DMUs randomly drawn from the population of firms producing at least a level y of outputs (in the case of input-oriented). In order-α quantile-type frontier, the frontier is defined as *"the input level not exceed by $(1-\alpha)*100$ percent of firms among the population of units producing at least a level y of outputs"* (Daraio and Simar, 2007a, pp.73). A similar approach as order-m frontier conditioning on propensity score can be adopted to formulate the order-α frontier conditioning on propensity score.

In this thesis, we focus on the development of conditional frontier and apply a popular parametric estimation of propensity score. However, with the development of non-parametric econometrics, it is possible to estimate propensity score nonparametrically.[48] By doing this, the approach to evaluate the impact of dichotomous environment variable on technical efficiency will be entirely nonparametric.

Further developments can be made by utilising large dataset or panel data. It is well known in the literature on propensity matching that, the larger the data size the better. It is because with large dataset the chance to find a perfect match for a treated observation is higher. With small sample size propensity score matching might not perform well since the variance dominates the bias (Zhao, 2004). If panel data is available, effects by different factors along time can be netted out from the effect of external variable. Therefore, a more consistent result can be obtained.

[48] Please refer to Li, Q. and J. S. Racine (2007). Nonparametric econometrics: theory and practice, Princeton University Press, Princeton; Oxford.

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Appendices

APPENDIX I. R PSEUDO-CODE FOR SIMULATION OF THE FRONTIER SEPARATION CONDITIONAL ON PROPENSITY SCORE APPROACH

```
# Creating data for the analysis with increasing variable to scale
   X1, X2, Xp <- Observations with N ~ (10,2^2)
   Y <- (X1^0.75)*(X2^0.75)              # true output
   W  <- Observations with Half - N(0,0.36^2) with 20% taking value of 0
inefficiency
   Rn <- Observations with N ~ (0,0.15^2)# random noise

# Generating treatment assignment
   P  <- logit(Xp, X1)                   # true propensity score
   Tr <- Bernouni distribution of P, with 30% taking value of 1

# Generating observed output
   Yu <- Y - W                           # output with inefficiency only
   Yutv <- Y - W + α*(Tr) + Rn           # α = 0.0;0.05;0.1;0.15;0.25 is the
                                         designed policy impact

# Estimating overall and program efficiency scores for full data
   overallEff  <- dea(xobs = (X1,X2), yobs = Yutv, RTS=VRS, ORIENTATION=output)[a]
   withinEffT <- if T==1, dea(xobs = (X1,X2), yobs = Yobs, RTS=VRS,
              ORIENTATION=output)        # within treated group efficiency
              scores
   withinEffC <- if T==0, dea(xobs = (X1,X2), yobs = Yobs, RTS=VRS,
              ORIENTATION=output)        # within control group efficiency
              scores

   withinEff <- cbind(overallEffT , overallEffC)
   progEff_F.data <- (overallEff/withinEff)

# Matching treated with control observation
   m.out <- matchit(Tr ~ X1 + X2 + Xp, method="nearest", distance="logit")[b]
   m.data <- match.data(m.out)
   overallEffmatch<- dea(xobs = (X1,X2), yobs = Yobs, RTS=VRS,
                     ORIENTATION=output, data=”m.data”)
   withinEffTmatch<- if T==1, dea(xobs = (X1,X2), yobs = Yobs, RTS=VRS,
                     ORIENTATION=output, data=”m.data”) # within treated group
                     efficiency scores in matched data
   withinEffCmatch<- if T==0, dea(xobs = (X1,X2), yobs = Yobs, RTS=VRS,
                     ORIENTATION=output, data=”m.data”)# within control group
                     efficiency scores in matched data
   withinEffmatch<- cbind(withinEffTmatch, withinEffCmatch)
   progEff_m.data <- (overallEffmatch/withinEffmatch)

# Treatment effects
   avTrueImpactonTreated <- mean(Yobs/Y if Tr==1) – mean(Yobs/Y if Tr==0)
   ImpactonTreatedF.data <- mean(progEff_F.data if Tr==1) -
                              mean(progEff_F.data if Tr==0)
   ImpactonTreatedM.data <- mean(progEff_m.data if Tr==1) -
                              mean(progEff_m.data if Tr==0)
```

Notes:

[a] R package FEAR by (Wilson, 2008) is used to estimate efficiency scores

[b] R package MatchIt by (Ho et al., 2007, Ho et al., 2009) is used

APPENDIX II. DETAILED STATISTICS OF MONTE CARLO SIMULATIONS

Table 45. Statistics of Monte Carlo simulation with N=100, 100 repetitions, CRS technology

	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	30.35	0.45	30.38	0.48	29.65	0.45	29.99	0.51	30.38	0.55
Average number of control observations	69.65	0.45	69.62	0.48	70.35	0.45	70.01	0.51	69.62	0.55
Average true overall efficiency	0.82	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average overall efficiency by DEA	0.80	0.00	0.79	0.00	0.76	0.00	0.74	0.00	0.69	0.00
Average overall efficiency by FDH	0.88	0.00	0.87	0.00	0.87	0.00	0.86	0.00	0.83	0.00
Average traditional FSAprogram efficiency of the treated	0.98	0.00	0.99	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average traditional FSA program efficiency of the control	0.99	0.00	0.96	0.00	0.93	0.00	0.88	0.00	0.80	0.00
Average revised FSA program efficiency of the treated	0.99	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.98	0.00	0.95	0.00	0.91	0.00	0.87	0.00	0.78	0.00
True impact of external variable	-0.00053	0.00039	0.04250	0.00047	0.08501	0.00052	0.13057	0.00068	0.23038	0.00102
Estimated impact by traditional FSA	-0.01697	0.00192	0.02908	0.00172	0.06797	0.00224	0.11436	0.00167	0.19834	0.00177
Estimated impact by revised FSA	0.00271	0.00221	0.04638	0.00211	0.08946	0.00212	0.13327	0.00187	0.22066	0.00185
MSE of traditional FSA	0.00061	0.00009	0.00045	0.00007	0.00073	0.00012	0.00048	0.00007	0.00130	0.00012
MSE of revised FSA	0.00048	0.00008	0.00045	0.00007	0.00039	0.00005	0.00030	0.00005	0.00036	0.00005
Bias reduction by revised FSA(percentage)	-2741.28	10007.06	41.69	3.43	25.16	1.93	14.54	1.10	9.66	0.68

Table 46. Statistics of Monte Carlo simulation with N=100, 100 repetitions, VRS technology

	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	30.10	0.45	30.16	0.41	29.57	0.43	30.94	0.46	29.11	0.51
Average number of control observations	69.90	0.45	69.84	0.41	70.43	0.43	69.06	0.46	70.89	0.51
Average true overall efficiency	0.81	0.00	0.82	0.00	0.84	0.00	0.86	0.00	0.88	0.00
Average overall efficiency by DEA	0.81	0.00	0.80	0.00	0.79	0.00	0.77	0.00	0.73	0.00
Average overall efficiency by FDH	0.89	0.00	0.89	0.00	0.89	0.00	0.88	0.00	0.85	0.00
Average traditional FSA program efficiency of the treated	0.95	0.00	0.97	0.00	0.98	0.00	0.99	0.00	0.99	0.00
Average traditional FSA program efficiency of the control	0.99	0.00	0.97	0.00	0.94	0.00	0.90	0.00	0.83	0.00
Average revised FSA program efficiency of the treated	0.97	0.00	0.98	0.00	0.99	0.00	0.99	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.97	0.00	0.94	0.00	0.91	0.00	0.87	0.00	0.80	0.00
True impact of external variable	0.00003	0.00044	0.04223	0.00050	0.08613	0.00052	0.13252	0.00060	0.23060	0.00090
Estimated impact by traditional FSA	-0.03978	0.00283	0.00609	0.00269	0.04459	0.00256	0.09005	0.00274	0.15700	0.00292
Estimated impact by revised FSA	-0.00200	0.00312	0.04120	0.00313	0.08025	0.00320	0.12203	0.00328	0.19773	0.00336
MSE of traditional FSA	0.00235	0.00032	0.00193	0.00022	0.00232	0.00022	0.00246	0.00024	0.00614	0.00044
MSE of revised FSA	0.00092	0.00016	0.00089	0.00011	0.00099	0.00014	0.00109	0.00014	0.00209	0.00030
Bias reduction by revised FSA(percentage)	1037.98	644.19	85.01	5.47	41.36	2.88	24.24	1.61	17.67	1.04

Table 47. Statistics of Monte Carlo simulation with N=200, 100 repetitions, CRS technology

	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	60.61	0.61	59.55	0.67	60.42	0.67	60.07	0.57	59.66	0.67
Average number of control observations	139.39	0.61	140.45	0.67	139.58	0.67	139.93	0.57	140.34	0.67
Average true overall efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.86	0.00	0.88	0.00
Average overall efficiency by DEA	0.79	0.00	0.78	0.00	0.75	0.00	0.73	0.00	0.68	0.00
Average overall efficiency by FDH	0.86	0.00	0.86	0.00	0.85	0.00	0.83	0.00	0.80	0.00
Average traditional FSA program efficiency of the treated	0.98	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average traditional FSA program efficiency of the control	1.00	0.00	0.97	0.00	0.92	0.00	0.88	0.00	0.80	0.00
Average revised FSA program efficiency of the treated	0.99	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.99	0.00	0.95	0.00	0.91	0.00	0.86	0.00	0.78	0.00
True impact of external variable	-0.00020	0.00031	0.04137	0.00032	0.08606	0.00038	0.13181	0.00048	0.23201	0.00071
Estimated impact by traditional FSA	-0.01319	0.00140	0.03110	0.00147	0.07664	0.00132	0.12208	0.00131	0.20430	0.00126
Estimated impact by revised FSA	-0.00054	0.00156	0.04587	0.00175	0.09308	0.00150	0.13740	0.00122	0.22100	0.00128
MSE of traditional FSA	0.00034	0.00005	0.00029	0.00004	0.00024	0.00003	0.00024	0.00003	0.00092	0.00007
MSE of revised FSA	0.00021	0.00003	0.00028	0.00005	0.00026	0.00004	0.00016	0.00003	0.00027	0.00003
Bias reduction by revised FSA(percentage)	509.27	353.01	35.60	2.20	19.19	1.14	11.65	0.68	7.20	0.45

Table 48. Statistics of Monte Carlo simulation with N=200, 100 repetitions, VRS technology

	$\alpha=0$		$\alpha=0.05$		$\alpha=0.10$		$\alpha=0.15$		$\alpha=0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	59.87	0.71	59.61	0.67	60.37	0.68	59.77	0.69	60.03	0.69
Average number of control observations	140.13	0.71	140.39	0.67	139.63	0.68	140.23	0.69	139.97	0.69
Average true overall efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average overall efficiency by DEA	0.80	0.00	0.79	0.00	0.77	0.00	0.75	0.00	0.71	0.00
Average overall efficiency by FDH	0.87	0.00	0.87	0.00	0.87	0.00	0.85	0.00	0.82	0.00
Average traditional FSA program efficiency of the treated	0.96	0.00	0.98	0.00	0.99	0.00	0.99	0.00	0.99	0.00
Average traditional FSA program efficiency of the control	0.99	0.00	0.97	0.00	0.93	0.00	0.89	0.00	0.82	0.00
Average revised FSA program efficiency of the treated	0.98	0.00	0.99	0.00	0.99	0.00	1.00	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.98	0.00	0.95	0.00	0.91	0.00	0.87	0.00	0.79	0.00
True impact of external variable	-0.00023	0.00030	0.04130	0.00030	0.08603	0.00037	0.13144	0.00047	0.23000	0.00073
Estimated impact by traditional FSA	-0.02883	0.00219	0.01419	0.00187	0.05877	0.00215	0.09613	0.00208	0.17543	0.00205
Estimated impact by revised FSA	-0.00127	0.00245	0.04142	0.00199	0.08861	0.00209	0.12761	0.00220	0.20937	0.00215
MSE of traditional FSA	0.00129	0.00015	0.00105	0.00011	0.00116	0.00014	0.00163	0.00018	0.00336	0.00022
MSE of revised FSA	0.00059	0.00008	0.00037	0.00005	0.00040	0.00006	0.00045	0.00008	0.00091	0.00010
Bias reduction by revised FSA(percentage)	1172.41	733.33	66.10	3.54	34.74	1.64	24.01	1.18	14.82	0.74

Table 49. Statistics of Monte Carlo simulation with N=300, 100 repetitions, CRS technology

	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	91.23	0.70	90.74	0.84	89.28	0.82	89.82	0.73	89.86	0.84
Average number of control observations	208.77	0.70	209.26	0.84	210.72	0.82	210.18	0.73	210.14	0.84
Average true overall efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average overall efficiency by DEA	0.78	0.00	0.77	0.00	0.75	0.00	0.72	0.00	0.68	0.00
Average overall efficiency by FDH	0.85	0.00	0.85	0.00	0.84	0.00	0.82	0.00	0.78	0.00
Average traditional FSA program efficiency of the treated	0.98	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average traditional FSA program efficiency of the control	1.00	0.00	0.96	0.00	0.92	0.00	0.88	0.00	0.79	0.00
Average revised FSA program efficiency of the treated	0.99	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.99	0.00	0.95	0.00	0.91	0.00	0.86	0.00	0.78	0.00
True impact of external variable	-0.00038	0.00022	0.04136	0.00031	0.08549	0.00031	0.13156	0.00044	0.23027	0.00060
Estimated impact by traditional FSA	-0.01274	0.00117	0.03347	0.00118	0.07775	0.00108	0.12324	0.00119	0.20504	0.00102
Estimated impact by revised FSA	-0.00106	0.00138	0.04627	0.00131	0.09188	0.00124	0.13778	0.00122	0.21971	0.00109
MSE of traditional FSA	0.00028	0.00003	0.00019	0.00002	0.00016	0.00002	0.00020	0.00003	0.00074	0.00006
MSE of revised FSA	0.00018	0.00002	0.00018	0.00003	0.00018	0.00002	0.00017	0.00002	0.00023	0.00003
Bias reduction by revised FSA(percentage)	778.94	356.17	30.62	1.85	16.43	0.87	11.06	0.62	6.37	0.34

Table 50. Statistics of Monte Carlo simulation with N=300, 100 repetitions, VRS technology

	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	91.21	0.83	90.63	0.91	89.66	0.75	90.51	0.85	89.62	0.71
Average number of control observations	208.79	0.83	209.37	0.91	210.34	0.75	209.49	0.85	210.38	0.71
Average true overall efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average overall efficiency by DEA	0.79	0.00	0.78	0.00	0.76	0.00	0.74	0.00	0.70	0.00
Average overall efficiency by FDH	0.87	0.00	0.86	0.00	0.85	0.00	0.84	0.00	0.81	0.00
Average traditional FSA program efficiency of the treated	0.97	0.00	0.98	0.00	0.99	0.00	0.99	0.00	0.99	0.00
Average traditional FSA program efficiency of the control	0.99	0.00	0.96	0.00	0.93	0.00	0.89	0.00	0.81	0.00
Average revised FSA program efficiency of the treated	0.98	0.00	0.99	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.98	0.00	0.95	0.00	0.90	0.00	0.86	0.00	0.79	0.00
True impact of external variable	0.00016	0.00023	0.04181	0.00027	0.08586	0.00032	0.13163	0.00039	0.23145	0.00060
Estimated impact by traditional FSA	-0.02268	0.00141	0.02035	0.00146	0.06433	0.00155	0.10509	0.00169	0.18269	0.00154
Estimated impact by revised FSA	0.00081	0.00150	0.04551	0.00162	0.09130	0.00165	0.13350	0.00177	0.20985	0.00163
MSE of traditional FSA	0.00073	0.00008	0.00066	0.00008	0.00069	0.00007	0.00096	0.00009	0.00260	0.00014
MSE of revised FSA	0.00023	0.00003	0.00026	0.00004	0.00029	0.00004	0.00026	0.00004	0.00072	0.00008
Bias reduction by revised FSA(percentage)	851.16	1124.34	59.94	2.43	31.30	1.35	21.52	0.91	11.73	0.53

Table 51. Statistics of Monte Carlo simulation with N=500, 100 repetitions, CRS technology

	$\alpha=0$		$\alpha=0.05$		$\alpha=0.10$		$\alpha=0.15$		$\alpha=0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	150.24	1.04	152.28	1.10	152.09	1.03	152.30	1.00	150.76	0.93
Average number of control observations	349.76	1.04	347.72	1.10	347.91	1.03	347.70	1.00	349.24	0.93
Average true overall efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average overall efficiency by DEA	0.78	0.00	0.76	0.00	0.74	0.00	0.72	0.00	0.67	0.00
Average overall efficiency by FDH	0.84	0.00	0.84	0.00	0.82	0.00	0.80	0.00	0.76	0.00
Average traditional FSA program efficiency of the treated	0.99	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average traditional FSA program efficiency of the control	1.00	0.00	0.96	0.00	0.92	0.00	0.87	0.00	0.79	0.00
Average revised FSA program efficiency of the treated	0.99	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.99	0.00	0.95	0.00	0.90	0.00	0.86	0.00	0.78	0.00
True impact of external variable	0.00009	0.00018	0.04198	0.00019	0.08584	0.00024	0.13232	0.00032	0.23159	0.00045
Estimated impact by traditional FSA	-0.00988	0.00103	0.03734	0.00096	0.08269	0.00105	0.12695	0.00098	0.20918	0.00091
Estimated impact by revised FSA	0.00019	0.00113	0.04773	0.00095	0.09556	0.00110	0.13861	0.00093	0.21963	0.00091
MSE of traditional FSA	0.00020	0.00002	0.00011	0.00001	0.00011	0.00002	0.00012	0.00002	0.00057	0.00004
MSE of revised FSA	0.00011	0.00001	0.00012	0.00002	0.00021	0.00003	0.00013	0.00002	0.00021	0.00002
Bias reduction by revised FSA(percentage)	-81717.67	80636.44	24.74	1.56	14.97	0.85	8.81	0.52	4.50	0.26

Table 52. Statistics of Monte Carlo simulation with N=500, 100 repetitions, VRS technology

	$\alpha = 0$		$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.15$		$\alpha = 0.25$	
	mean	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**	**mean**	**Std. Dev**
Average number of treated observations	149.82	1.02	150.85	1.07	150.92	0.99	152.63	1.09	150.40	1.01
Average number of control observations	350.18	1.02	349.15	1.07	349.08	0.99	347.37	1.09	349.60	1.01
Average true overall efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.86	0.00	0.88	0.00
Average overall efficiency by DEA	0.78	0.00	0.77	0.00	0.75	0.00	0.73	0.00	0.68	0.00
Average overall efficiency by FDH	0.85	0.00	0.85	0.00	0.84	0.00	0.82	0.00	0.78	0.00
Average traditional FSA program efficiency of the treated	0.97	0.00	0.99	0.00	0.99	0.00	0.99	0.00	1.00	0.00
Average traditional FSA program efficiency of the control	0.99	0.00	0.96	0.00	0.92	0.00	0.88	0.00	0.80	0.00
Average revised FSA program efficiency of the treated	0.98	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
Average revised FSA program efficiency of the control	0.99	0.00	0.95	0.00	0.90	0.00	0.86	0.00	0.78	0.00
True impact of external variable	-0.00024	0.00018	0.04153	0.00021	0.08566	0.00022	0.13158	0.00031	0.23128	0.00048
Estimated impact by traditional FSA	-0.02208	0.00148	0.02672	0.00128	0.06888	0.00121	0.10958	0.00117	0.19528	0.00115
Estimated impact by revised FSA	-0.00238	0.00152	0.04807	0.00133	0.09232	0.00125	0.13211	0.00119	0.21842	0.00109
MSE of traditional FSA	0.00068	0.00008	0.00037	0.00005	0.00042	0.00004	0.00061	0.00006	0.00144	0.00008
MSE of revised FSA	0.00022	0.00003	0.00021	0.00003	0.00019	0.00002	0.00014	0.00002	0.00029	0.00003
Bias reduction by revised FSA(percentage)	-1518.74	1019.30	51.22	2.09	27.34	1.05	17.10	0.61	10.01	0.41

APPENDIX III. ISIC Sector Classifications

ISIC	Description
15	Food production
16	Tobacco
17	Textiles
18	Wearing apparel etc.
19	Tanning and dressing leather
20	Wood and wood products
21	Paper and paper products
22	Publishing, printing etc.
23	Refined petroleum etc.
24	Chemical products etc.
25	Rubber and plastic products
26	Non-metallic mineral products
27	Basic metals
28	Fabricated metal products
29	Machinery and equipment nec.
30	Office machinery etc.
31	Electrical machinery etc.
32	Radio, TV etc.
33	Medical equipment etc.
34	Vehicles etc.
35	Transport equipment
36	Furniture
37	Recycling

APPENDIX IV. DETAILED STATISTICS OF MONTE CARLO SIMULATIONS

Table 53. Statistics of Monte Carlo simulation with N=100, 100 repetitions, CRS technology

	0		5		10		15		25	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of treated observations	30.35	0.45	30.38	0.48	29.65	0.45	29.99	0.51	30.38	0.55
Number of control observations	69.65	0.45	69.62	0.48	70.35	0.45	70.01	0.51	69.62	0.55
Average true efficiency	0.82	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average DEA efficiency	0.80	0.00	0.79	0.00	0.76	0.00	0.74	0.00	0.69	0.00
Average FDH efficiency	0.88	0.00	0.87	0.00	0.87	0.00	0.86	0.00	0.83	0.00
Average order-m efficiency	0.90	0.00	0.90	0.00	0.89	0.00	0.88	0.00	0.86	0.00
Average conditional order-m efficiency	0.90	0.00	0.89	0.00	0.89	0.00	0.88	0.00	0.86	0.00
True impact as mean difference of treated and control	-0.00053	0.00039	0.04250	0.00047	0.08501	0.00052	0.13057	0.00068	0.23038	0.00102
Mean difference of treatment effect by conditional order-m estimator	-0.00403	0.00396	0.03285	0.00370	0.05890	0.00342	0.08292	0.00357	0.13717	0.00355
Average treatment effect, DEA estimator	-0.00339	0.00418	0.04372	0.00398	0.07776	0.00364	0.10724	0.00346	0.17525	0.00359
Average treatment effect, FDH estimator	-0.00730	0.00394	0.02432	0.00348	0.04644	0.00331	0.06672	0.00352	0.12391	0.00375
MSE for full data	0.00061	0.00009	0.00045	0.00007	0.00073	0.00012	0.00048	0.00007	0.00130	0.00012
MSE for order-m estimator conditional on propensity score	0.00161	0.00029	0.00136	0.00020	0.00171	0.00018	0.00329	0.00033	0.00957	0.00056
MSE for kernel matching on DEA estimator	0.00177	0.00029	0.00146	0.00019	0.00119	0.00017	0.00144	0.00019	0.00387	0.00035
MSE for kernel matching on FDH estimator	0.00163	0.00032	0.00144	0.00021	0.00244	0.00024	0.00507	0.00042	0.01237	0.00068

Table 54. Statistics of Monte Carlo simulation with N=100, 100 repetitions, VRS technology

	0		5		10		15		25	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Number of treated observations	30.10	0.45	30.16	0.41	29.57	0.43	30.94	0.46	29.11	0.51
Number of control observations	69.90	0.45	69.84	0.41	70.43	0.43	69.06	0.46	70.89	0.51
Average true efficiency	0.81	0.00	0.82	0.00	0.84	0.00	0.86	0.00	0.88	0.00
Average DEA efficiency	0.81	0.00	0.80	0.00	0.79	0.00	0.77	0.00	0.73	0.00
Average FDH efficiency	0.89	0.00	0.89	0.00	0.89	0.00	0.88	0.00	0.85	0.00
Average order-m efficiency	0.92	0.00	0.92	0.00	0.92	0.00	0.91	0.00	0.89	0.00
Average conditional order-m efficiency	0.92	0.00	0.92	0.00	0.91	0.00	0.91	0.00	0.89	0.00
True impact as mean difference of treated and control	0.00003	0.00044	0.04223	0.00050	0.08613	0.00052	0.13252	0.00060	0.23060	0.00090
Mean difference of treatment effect by conditional order-m estimator	-0.00044	0.00380	0.03249	0.00372	0.06284	0.00389	0.08789	0.00346	0.14424	0.00344
Average treatment effect, DEA estimator	-0.00421	0.00413	0.03419	0.00395	0.07063	0.00390	0.10398	0.00349	0.17144	0.00367
Average treatment effect, FDH estimator	-0.00672	0.00388	0.01622	0.00354	0.04098	0.00377	0.06096	0.00303	0.11135	0.00327
MSE for full data	0.00235	0.00032	0.00193	0.00022	0.00232	0.00022	0.00246	0.00024	0.00614	0.00044
MSE for order-m estimator conditional on propensity score	0.00139	0.00020	0.00136	0.00021	0.00184	0.00029	0.00299	0.00030	0.00839	0.00055
MSE for kernel matching on DEA estimator	0.00166	0.00024	0.00151	0.00023	0.00155	0.00025	0.00180	0.00023	0.00446	0.00041
MSE for kernel matching on FDH estimator	0.00150	0.00021	0.00185	0.00023	0.00328	0.00039	0.00586	0.00042	0.01507	0.00070

Table 55. Statistics of Monte Carlo simulation with N=200, 100 repetitions, CRS technology

	0		5		10		15		25	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of treated observations	60.61	0.61	59.55	0.67	60.42	0.67	60.07	0.57	59.66	0.67
Number of control observations	139.39	0.61	140.45	0.67	139.58	0.67	139.93	0.57	140.34	0.67
Average true efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.86	0.00	0.88	0.00
Average DEA efficiency	0.79	0.00	0.78	0.00	0.75	0.00	0.73	0.00	0.68	0.00
Average FDH efficiency	0.86	0.00	0.86	0.00	0.85	0.00	0.83	0.00	0.80	0.00
Average order-m efficiency	0.89	0.00	0.89	0.00	0.88	0.00	0.87	0.00	0.85	0.00
Average conditional order-m efficiency	0.89	0.00	0.89	0.00	0.88	0.00	0.87	0.00	0.84	0.00
True impact as mean difference of treated and control	-0.00020	0.00031	0.04137	0.00032	0.08606	0.00038	0.13181	0.00048	0.23201	0.00071
Mean difference of estimated treatment effect (full data)	-0.01319	0.00140	0.03110	0.00147	0.07664	0.00132	0.12208	0.00131	0.20430	0.00126
Mean difference of treatment effect by conditional order-m estimator	0.00124	0.00281	0.03557	0.00274	0.06403	0.00210	0.09856	0.00248	0.15928	0.00275
Average treatment effect, DEA estimator	-0.00142	0.00276	0.03879	0.00270	0.07150	0.00209	0.11208	0.00258	0.17625	0.00250
Average treatment effect, FDH estimator	-0.00573	0.00272	0.02283	0.00250	0.04661	0.00208	0.07931	0.00265	0.13524	0.00285
MSE for full data	0.00034	0.00005	0.00029	0.00004	0.00024	0.00003	0.00024	0.00003	0.00092	0.00007
MSE for order-m estimator conditional on propensity score	0.00077	0.00010	0.00070	0.00010	0.00087	0.00011	0.00158	0.00016	0.00582	0.00035
MSE for kernel matching on DEA estimator	0.00075	0.00010	0.00066	0.00010	0.00057	0.00008	0.00091	0.00011	0.00350	0.00025
MSE for kernel matching on FDH estimator	0.00077	0.00010	0.00090	0.00013	0.00194	0.00017	0.00332	0.00024	0.00994	0.00050

Table 56. Statistics of Monte Carlo simulation with N=200, 100 repetitions, VRS technology

	0		5		10		15		25	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Number of treated observations	59.87	0.71	59.61	0.67	60.37	0.68	59.77	0.69	60.03	0.69
Number of control observations	140.13	0.71	140.39	0.67	139.63	0.68	140.23	0.69	139.97	0.69
Average true efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average DEA efficiency	0.80	0.00	0.79	0.00	0.77	0.00	0.75	0.00	0.71	0.00
Average FDH efficiency	0.87	0.00	0.87	0.00	0.87	0.00	0.85	0.00	0.82	0.00
Average order-m efficiency	0.92	0.00	0.92	0.00	0.91	0.00	0.91	0.00	0.88	0.00
Average conditional order-m efficiency	0.91	0.00	0.91	0.00	0.91	0.00	0.90	0.00	0.88	0.00
True impact as mean difference of treated and control	-0.00023	0.00030	0.04130	0.00030	0.08603	0.00037	0.13144	0.00047	0.23000	0.00073
Mean difference of treatment effect by conditional order-m estimator	0.00683	0.00281	0.03921	0.00273	0.07420	0.00253	0.09844	0.00243	0.15862	0.00286
Average treatment effect, DEA estimator	0.00078	0.00289	0.03640	0.00270	0.07578	0.00253	0.10210	0.00243	0.16363	0.00259
Average treatment effect, FDH estimator	-0.00271	0.00275	0.01895	0.00238	0.04624	0.00231	0.06496	0.00232	0.11905	0.00274
MSE for full data	0.00129	0.00015	0.00105	0.00011	0.00116	0.00014	0.00163	0.00018	0.00336	0.00022
MSE for order-m estimator conditional on propensity score	0.00083	0.00012	0.00072	0.00011	0.00069	0.00009	0.00154	0.00016	0.00566	0.00037
MSE for kernel matching on DEA estimator	0.00084	0.00012	0.00071	0.00009	0.00063	0.00008	0.00130	0.00015	0.00482	0.00028
MSE for kernel matching on FDH estimator	0.00077	0.00010	0.00104	0.00013	0.00204	0.00018	0.00484	0.00029	0.01284	0.00053

Table 57. Statistics of Monte Carlo simulation with N=300, 100 repetitions, CRS technology

	0		5		10		15		25	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Number of treated observations	91.23	0.70	90.74	0.84	89.28	0.82	89.82	0.73	89.86	0.84
Number of control observations	208.77	0.70	209.26	0.84	210.72	0.82	210.18	0.73	210.14	0.84
Average true efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average DEA efficiency	0.78	0.00	0.77	0.00	0.75	0.00	0.72	0.00	0.68	0.00
Average FDH efficiency	0.85	0.00	0.85	0.00	0.84	0.00	0.82	0.00	0.78	0.00
Average order-m efficiency	0.89	0.00	0.89	0.00	0.88	0.00	0.87	0.00	0.84	0.00
Average conditional order-m efficiency	0.88	0.00	0.88	0.00	0.88	0.00	0.86	0.00	0.83	0.00
True impact as mean difference of treated and control	-0.00038	0.00022	0.04136	0.00031	0.08549	0.00031	0.13156	0.00044	0.23027	0.00060
Mean difference of treatment effect by conditional order-m estimator	0.00109	0.00224	0.03629	0.00235	0.07316	0.00206	0.10376	0.00204	0.16715	0.00226
Average treatment effect, DEA estimator	-0.00284	0.00206	0.03548	0.00210	0.07456	0.00200	0.10783	0.00206	0.17250	0.00194
Average treatment effect, FDH estimator	-0.00595	0.00216	0.02191	0.00221	0.05183	0.00195	0.08001	0.00197	0.14100	0.00232
MSE for full data	0.00028	0.00003	0.00019	0.00002	0.00016	0.00002	0.00020	0.00003	0.00074	0.00006
MSE for order-m estimator conditional on propensity score	0.00050	0.00006	0.00053	0.00008	0.00051	0.00007	0.00108	0.00010	0.00433	0.00024
MSE for kernel matching on DEA estimator	0.00042	0.00005	0.00044	0.00006	0.00046	0.00006	0.00087	0.00008	0.00357	0.00018
MSE for kernel matching on FDH estimator	0.00049	0.00006	0.00083	0.00010	0.00145	0.00012	0.00294	0.00017	0.00835	0.00036

Table 58. Statistics of Monte Carlo simulation with N=300, 100 repetitions, VRS technology

	0		5		10		15		25	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Number of treated observations	91.21	0.83	90.63	0.91	89.66	0.75	90.51	0.85	89.62	0.71
Number of control observations	208.79	0.83	209.37	0.91	210.34	0.75	209.49	0.85	210.38	0.71
Average true efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average DEA efficiency	0.79	0.00	0.78	0.00	0.76	0.00	0.74	0.00	0.70	0.00
Average FDH efficiency	0.87	0.00	0.86	0.00	0.85	0.00	0.84	0.00	0.81	0.00
Average order-m efficiency	0.92	0.00	0.91	0.00	0.91	0.00	0.90	0.00	0.88	0.00
Average conditional order-m efficiency	0.91	0.00	0.91	0.00	0.91	0.00	0.89	0.00	0.87	0.00
True impact as mean difference of treated and control	0.00016	0.00023	0.04181	0.00027	0.08586	0.00032	0.13163	0.00039	0.23145	0.00060
Mean difference of treatment effect by conditional order-m estimator	0.00932	0.00198	0.04250	0.00208	0.07876	0.00212	0.10895	0.00213	0.17228	0.00237
Average treatment effect, DEA estimator	0.00222	0.00187	0.03616	0.00201	0.07352	0.00208	0.10561	0.00202	0.17272	0.00206
Average treatment effect, FDH estimator	-0.00232	0.00189	0.02068	0.00194	0.04749	0.00197	0.07397	0.00200	0.13150	0.00232
MSE for full data	0.00073	0.00008	0.00066	0.00008	0.00069	0.00007	0.00096	0.00009	0.00260	0.00014
MSE for order-m estimator conditional on propensity score	0.00047	0.00007	0.00040	0.00005	0.00044	0.00006	0.00088	0.00011	0.00388	0.00023
MSE for kernel matching on DEA estimator	0.00035	0.00006	0.00041	0.00006	0.00052	0.00008	0.00099	0.00011	0.00372	0.00020
MSE for kernel matching on FDH estimator	0.00036	0.00005	0.00080	0.00011	0.00180	0.00014	0.00364	0.00021	0.01037	0.00039

Table 59. Statistics of Monte Carlo simulation with N=500, 100 repetitions, CRS technology

	0		5		10		15		25	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Number of treated observations	150.24	1.04	152.28	1.10	152.09	1.03	152.30	1.00	150.76	0.93
Number of control observations	349.76	1.04	347.72	1.10	347.91	1.03	347.70	1.00	349.24	0.93
Average true efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.85	0.00	0.88	0.00
Average DEA efficiency	0.78	0.00	0.76	0.00	0.74	0.00	0.72	0.00	0.67	0.00
Average FDH efficiency	0.84	0.00	0.84	0.00	0.82	0.00	0.80	0.00	0.76	0.00
Average order-m efficiency	0.88	0.00	0.88	0.00	0.88	0.00	0.86	0.00	0.83	0.00
Average conditional order-m efficiency	0.88	0.00	0.88	0.00	0.87	0.00	0.86	0.00	0.82	0.00
True impact as mean difference of treated and control	0.00009	0.00018	0.04198	0.00019	0.08584	0.00024	0.13232	0.00032	0.23159	0.00045
Mean difference of treatment effect by conditional order-m estimator	0.00787	0.00161	0.04466	0.00145	0.07838	0.00173	0.11477	0.00172	0.18083	0.00185
Average treatment effect, DEA estimator	0.00202	0.00158	0.04040	0.00144	0.07548	0.00164	0.11091	0.00160	0.17518	0.00148
Average treatment effect, FDH estimator	-0.00113	0.00157	0.02817	0.00140	0.05592	0.00169	0.08841	0.00173	0.14997	0.00187
MSE for full data	0.00020	0.00002	0.00011	0.00001	0.00011	0.00002	0.00012	0.00002	0.00057	0.00004
MSE for order-m estimator conditional on propensity score	0.00032	0.00004	0.00021	0.00002	0.00031	0.00004	0.00054	0.00006	0.00282	0.00017
MSE for kernel matching on DEA estimator	0.00025	0.00003	0.00020	0.00003	0.00033	0.00004	0.00065	0.00006	0.00332	0.00014
MSE for kernel matching on FDH estimator	0.00025	0.00003	0.00038	0.00005	0.00114	0.00010	0.00216	0.00014	0.00692	0.00027

Table 60. Statistics of Monte Carlo simulation with N=500, 100 repetitions, VRS technology

	0		5		10		15		25	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of treated observations	149.82	1.02	150.85	1.07	150.92	0.99	152.63	1.09	150.40	1.01
Number of control observations	350.18	1.02	349.15	1.07	349.08	0.99	347.37	1.09	349.60	1.01
Average true efficiency	0.81	0.00	0.83	0.00	0.84	0.00	0.86	0.00	0.88	0.00
Average DEA efficiency	0.78	0.00	0.77	0.00	0.75	0.00	0.73	0.00	0.68	0.00
Average FDH efficiency	0.85	0.00	0.85	0.00	0.84	0.00	0.82	0.00	0.78	0.00
Average order-m efficiency	0.91	0.00	0.91	0.00	0.91	0.00	0.90	0.00	0.87	0.00
Average conditional order-m efficiency	0.91	0.00	0.91	0.00	0.90	0.00	0.89	0.00	0.86	0.00
True impact as mean difference of treated and control	-0.00024	0.00018	0.04153	0.00021	0.08566	0.00022	0.13158	0.00031	0.23128	0.00048
Mean difference of treatment effect by conditional order-m estimator	0.00812	0.00177	0.05045	0.00150	0.08216	0.00186	0.11633	0.00173	0.18648	0.00189
Average treatment effect, DEA estimator	0.00015	0.00165	0.04069	0.00133	0.07109	0.00167	0.10454	0.00160	0.17067	0.00174
Average treatment effect, FDH estimator	-0.00348	0.00165	0.02531	0.00128	0.04886	0.00169	0.07694	0.00164	0.14141	0.00191
MSE for full data	0.00068	0.00008	0.00037	0.00005	0.00042	0.00004	0.00061	0.00006	0.00144	0.00008
MSE for order-m estimator conditional on propensity score	0.00038	0.00006	0.00027	0.00004	0.00032	0.00005	0.00047	0.00007	0.00225	0.00014
MSE for kernel matching on DEA estimator	0.00027	0.00004	0.00015	0.00002	0.00046	0.00006	0.00092	0.00008	0.00386	0.00017
MSE for kernel matching on FDH estimator	0.00028	0.00003	0.00040	0.00005	0.00160	0.00012	0.00320	0.00017	0.00832	0.00028

APPENDIX V. SIMULATION CODES IN R FOR CRS TECHNOLOGY

```
## Constant return to scale and Output Orientation[49]

 rm(list=ls())

### Installing necessary packages before running

library(foreign)

library(MatchIt)

library(np)

library(FEAR)

### A function of number of observations (nsize), impact (alpha), and repetition (repet)

###for a Monte Carlo type of simulation

CRSmOut <- function(nsize, alpha, repet, m)

{

### create variables storing values from simulation for later analysis

        AvTrueEff      <- numeric(repet)

        AvOverallFDH_F    <- numeric(repet)

        AvOrderm       <- numeric(repet)

        AvOverallDEA_F <- numeric(repet)# Store average overall efficiency here!

        AvConOrderm    <- numeric(repet)

        AvProgEff_T    <- numeric(repet)# Store average program efficiency of the treated
in full data here!

        AvProgEff_C    <- numeric(repet)# Store average program efficiency of control in
full data here!

        AvProgEff_MT   <- numeric(repet)# Store average program efficiency of the matched
treated here!

        AvProgEff_MC   <- numeric(repet)# Store average program efficiency of matched
control here!

        AvTrueImpact   <-numeric(repet)# Store average true impact on all obs. including
controls (due to noise)

        AvTrueImpactT  <- numeric(repet)# Store average true impact on the treated only
```

[49] In this Appendix we present only the code for creating simulation of CRS technology. The simulation code with VRS technology is not presented here for saving the space and it is only slightly different from the code presented here.

```
        AvTrueImpactC  <- numeric(repet)# Store average true impact on the control only

        MDiffProgFull  <- numeric(repet)      # store mean difference of average program
efficiency in full data

        MDiffProgMatch <- numeric(repet)

        attDEA         <- numeric(repet)      # store of average treatment effect on the
treated with different order-m

        attFDH         <- numeric(repet)

        attmEff        <- numeric(repet)

        attmDEA        <- numeric(repet)

        noT     <- numeric(repet)      # store number of treated and control observations

        noC     <- numeric(repet)

        BiasReFSA      <- numeric(repet)# bias reduction compared between traditional and
revised frontier separation approach

        BiasReORM      <- numeric(repet)# bias reduction compared between traditional
frontier separation and conditional order-m appr

        MDiffTrueImpTC <- numeric(repet)#

        MDiffConM      <- numeric(repet)# store difference between treated and control
observation of conditional orderm

        MDiffDEA       <- numeric(repet)      # store difference between treated and
control observation of overall DEA eff

        MDiffFDH       <- numeric(repet)      # store difference between treated and
control observation of overall FDH eff

        MDiffOrderm    <- numeric(repet)      # store difference between treated and
control observation of overall Orderm eff

        MSEfull        <- numeric(repet)      # store MSE value between true and full data
program efficiency

        MSEmatch       <- numeric(repet)      # store MSE value between true and matched
data program efficiency

        MSEattDEA      <- numeric(repet)      # store MSE value between true and kernel
matching DEA efficiecy

        MSEattFDH      <- numeric(repet)      # store MSE value between true and kernel
matching FDH efficiecy

        MSEattmEff     <- numeric(repet)      # store MSE value between true and kernel
matching nonconvex orderm efficiecy

        MSEattmDEA     <- numeric(repet)      # store MSE value between true and kernel
matching convex orderm efficiecy

        MSEconOrderm   <- numeric(repet)

if (alpha<0 | nsize<=0 | repet<=0) {

print("Parameters must be >=0")

} else {
```

```
for (j in 1:repet) {

### 1. Creating independent variables

ID <- seq(1:nsize)                    # Creating ID & DMUs

Xp <- abs(rnorm(nsize, 10, 2))        # Create variables neccessary for analysis Xp, X1,
X2

X1 <- abs(rnorm(nsize, 10, 2))        # Input 1

X2 <- abs(rnorm(nsize, 10, 2))        # Input 2

### 2. treatment assignment

A <- ((Xp+X1)/2-10)

P <- (exp(A)/(1+exp(A)))

Tr <- ifelse(1.66*(runif(nsize))>=P, 0, 1)# 1.66 parametter for 30% treated obs.

### 3. Output

Y <- (X1^0.5)*(X2^0.5)## 3.1. True output following ### increasing return to scale ###

## 3.1. Inefficiency level

W <- numeric(nsize)

draft1 <- runif(nsize)

draft2 <- abs((rnorm(nsize, 0, 0.36)))

for (i in 1:nsize) {

if (draft1[i]<0.2) { # 20% on the frontier

W[i] <- 0

} else {

W[i] <- draft2[i]

}

}

## 3.2. observed output with inefficiency

Yu <- Y*exp(-W)

## 3.4. observed output with ineff + impact of (alpha)% + noise term

Yutv <- Y*exp(-W)*exp(alpha*Tr)*exp(rnorm(nsize, 0, 0.15^2))

###4. DEA Technical Eff for Full Data

## 4.0 True TE

effTrue <- Yutv/Y

# True impact of discretionary variable

trueImp <- ((Yutv/Y) - (Yu/Y))

### Overall efficiency
```

```
        #### data preparation for full frontier analysis

                XOBS=matrix(nrow=2,ncol=length(X1))

                XOBS[1,]       <- X1

                XOBS[2,]       <- X2

                YOBS=matrix(nrow=1,ncol=length(Yutv))

                YOBS[1,]       <- Yutv

        #### estimate overall DEA efficiency

                DrDEA1         <- dea(XOBS,YOBS, RTS=3, ORIENTATION=2, errchk=TRUE)

                OverallEff_utv <- DrDEA1

        #### estimate FDH efficiency

                efdh    <- fdh(XOBS,YOBS,ORIENTATION=2,XREF=NULL,YREF=NULL,errchk=TRUE)

                efdh1=efdh[1,]

                efffdh=efdh1

        ### estimate Order-M efficiency output oriented (noncnovex)

                ordeff <-
orderm(XOBS,YOBS,ORIENTATION=2,M=25,NREP=200,XREF=NULL,YREF=NULL,errchk=TRUE)

                mEff=ordeff[1,]

        ### global convex order-m efficiency

                mYutv   <- Yutv/mEff

                YOBSM=matrix(nrow=1,ncol=length(Yutv))

                YOBSM[1,] <- mYutv

                mDEAeff <- dea(XOBS,YOBS=YOBSM, RTS=3, ORIENTATION=2, errchk=TRUE)

        ### combine whole data

                data.full <- data.frame(cbind(ID, Xp, X1, X2, A, P, Tr, Y, W, Yu, Yutv,
effTrue, trueImp, OverallEff_utv, efffdh, mEff, mDEAeff))

        ### Sorting data following Tr and ID number

        data.full      <-data.full[order(data.full$Tr, data.full$ID),]

### Within group efficiency - traditional frontier separation approach

        ### data preparation

                data.treated <- data.full[data.full$Tr==1,]### create treated group data

                data.control <- data.full[data.full$Tr==0,]### create control group data

                        XT <- matrix(nrow=2,ncol=length(data.treated$X1))

                        XT[1,] <- data.treated$X1

                        XT[2,] <- data.treated$X2
```

```
                    YT <- matrix(nrow=1,ncol=length(data.treated$Yutv))

                    YT[1,]=data.treated$Yutv

                    XC <- matrix(nrow=2,ncol=length(data.control$X1))

                    XC[1,] <- data.control$X1

                    XC[2,] <- data.control$X2

                    YC <- matrix(nrow=1,ncol=length(data.control$Yutv))

                    YC[1,]=data.control$Yutv

        ### Within group efficiency estimate

                    ### within treated group TE

                    DrT <- dea(XOBS=XT,YOBS=YT, RTS=3, ORIENTATION=2, errchk=TRUE)

                    Within_EffT <- DrT

                    ### within control group TE

                    DrC <- dea(XOBS=XC,YOBS=YC, RTS=3, ORIENTATION=2, errchk=TRUE)

                    Within_EffC <- DrC

        ### combine separated data with program efficiency for later use

                data.treated <- cbind(data.treated, Within_EffT)

                data.treated <- cbind(data.treated, ProgramEff_T
=data.treated$OverallEff_utv/data.treated$Within_EffT)

                data.control <- cbind(data.control, Within_EffC)

                data.control <- cbind(data.control, ProgramEff_C =
data.control$OverallEff_utv/data.control$Within_EffC)

        ### remove unneeded variables

        rm(ID, Xp, X1, X2, A, P, Tr, Y, W, Yu, Yutv, effTrue, trueImp, OverallEff_utv,
efffdh, XOBS, YOBS, DrDEA1, efdh, draft1, draft2, XT, YT, DrT, Within_EffT, XC, YC, DrC,
Within_EffC)



## 5. Matching

write.dta(data.full, "C:/dataCRSm15.dta", version = 9, convert.dates = TRUE,
convert.factors = c("labels", "string", "numeric", "codes"))

m.out <- matchit(Tr ~ Xp + X1 + X2, data=read.dta("C:/dataCRSm15.dta"), method="nearest",
distance="logit")

m.data <- match.data(m.out)

        myscore <- m.out$distance     ### keep the propensity score for later use

## Overall efficiency in matched data

        ### data preparation

                XM      <- matrix(nrow=2,ncol=length(m.data$X1))     ### create matched
group data
```

```
            XM[1,]  <- m.data$X1

            XM[2,]  <- m.data$X2

            YM      <- matrix(nrow=1,ncol=length(m.data$Yutv))

            YM[1,]  <- m.data$Yutv

        ### overall efficiency for matched data

            DrDEA2 <- dea(XOBS=XM,YOBS=YM, RTS=3, ORIENTATION=2, errchk=TRUE)

            OverallEff_utvM <- DrDEA2


        ### incorporate the overall efficiency into matched data

            m.data <- cbind(m.data, OverallEff_utvM)


        ### within group efficiency (matched data) - data preparation

            m.data.treated <- m.data[m.data$Tr==1,]      ### create treated group

            m.data.control <- m.data[m.data$Tr==0,]      ### create control group

            XMT     <- matrix(nrow=2,ncol=length(m.data.treated$X1))     ### create
matched group data

            XMT[1,] <- m.data.treated$X1

            XMT[2,] <- m.data.treated$X2

            YMT     <- matrix(nrow=1,ncol=length(m.data.treated$Yutv))

            YMT[1,] <- m.data.treated$Yutv


            XMC     <- matrix(nrow=2,ncol=length(m.data.control$X1))     ### create
matched group data

            XMC[1,] <- m.data.control$X1

            XMC[2,] <- m.data.control$X2

            YMC     <- matrix(nrow=1,ncol=length(m.data.control$Yutv))

            YMC[1,] <- m.data.control$Yutv

            m.DrT <- dea(XOBS=XMT,YOBS=YMT, RTS=3, ORIENTATION=2, errchk=TRUE)  #
etimating within treated group TE

            m.Within_EffT <- m.DrT                       ### within treated group TE

            m.data.treated <- cbind(m.data.treated, m.Within_EffT)

            m.data.treated <- cbind(m.data.treated, m.ProgEff_T =
m.data.treated$OverallEff_utvM/m.data.treated$m.Within_EffT)

            m.DrC <- dea(XOBS=XMC,YOBS=YMC, RTS=3, ORIENTATION=2, errchk=TRUE)  #
etimating within treated group TE

            m.Within_EffC <- m.DrC                       ### within treated group TE
```

```
        m.data.control <- cbind(m.data.control, m.Within_EffC)

        m.data.control <- cbind(m.data.control, m.ProgEff_C =
m.data.control$OverallEff_utvM/m.data.control$m.Within_EffC)



###Estimate Conditional Order-m Efficiency

    #### estimating order-m efficiency score

        ### create inputs & output matrix

        x=cbind(data.full$X1, data.full$X2)

        y=cbind(data.full$Yutv)

        theta=(data.full$mDEAeff)

    ####bandwidth and kernel density estimation

        data.bw <-data.frame(myscore)

        bw <- npudensbw(dat=data.bw)

        bw.ws <- bw$bw

        kerz <- npudens(bws=bw.ws, ckertype="epanechnikov", tdat=data.bw)

        kerz <-kerz$dens

    f <- function(theta,x,y,i,mm)# define a function, depending on the efficiency
score theta, output oriented

    {

    nsum <- 0; dsum <- 0

    for (j in (1:length(x[,1])))

    {

    n <- (as.numeric(all(x[j,] <=x[i,])) & (y[j,1] >= (y[i,1]*theta )))*kerz[j]

    d <- (as.numeric(all(x[j,] <=x[i,])))*kerz[j]

    nsum <- n+nsum # sum all these integrals

    dsum <- d+dsum

    }

    if(dsum==0)

    {

    dsum=1

    }

    return(1-(1-(nsum/dsum))^mm)

    }

    effm1 <- matrix(nrow=length(x[,1]),ncol=1)# define result matrix
```

```
        for (i in (1:length(x[,1])))

        {

        eff1 <-integrate(f,0,Inf,x=x,y=y,i=i,mm=m,stop.on.error=FALSE)

        effm1[i] <- eff1$value

        }

        effm1


### remove unneeded variables

        rm(bw, data.bw, DrDEA2,XM, XMT, YMT, m.DrT, m.Within_EffT, XMC, YMC, m.DrC, 
m.Within_EffC ,m.data, m.out)

###data        #####

        data.m <- cbind(data.full, myscore, effm <-1/effm1)

        write.dta(data.m, "C:/dataCRSmm15.dta", version = 9, convert.dates = TRUE, 
convert.factors = c("labels", "string", "numeric", "codes"))


### Estimating ATT

        ### estimating for observations in support region only

                maxtreat <- max(data.m$myscore[data.m$Tr==1])

                mintreat <- min(data.m$myscore[data.m$Tr==1])

                data.main <- subset(data.m, (data.m$myscore>=mintreat) 
&(data.m$myscore<=maxtreat))# only data in support region

                data.main <- cbind(data.main, index = c(1:length(data.main$X1)))


        ### Estimating counterfactual for each treated observation

         meandraft2 <- matrix(nrow=length(data.main$X1[data.main$Tr==1]), ncol=1)

         meandraft3 <- matrix(nrow=length(data.main$X1[data.main$Tr==1]), ncol=1)

         meandraft4 <- matrix(nrow=length(data.main$X1[data.main$Tr==1]), ncol=1)

         meandraft5 <- matrix(nrow=length(data.main$X1[data.main$Tr==1]), ncol=1)

        for (o in 1:length(data.main$X1[data.main$Tr==1]))

        {

        draft1 <- matrix(nrow=length(data.main$X1[data.main$Tr==0]), ncol=1) # define a 
matrix to put result

        for (p in 1:max(data.main$index[data.main$Tr==0]))

        {

        dif <- abs(data.main$myscore[p]-data.main$myscore[o])

        if (abs(dif/bw.ws)>1)
```

```
        {
        weight <-0
        } else {
         weight <- (1-(dif/bw.ws)^2)
        }
        draft1[p] <- weight
        }
         meandraft2[o] <- weighted.mean(data.main$OverallEff_utv[data.main$Tr==0], draft1)
         meandraft3[o] <- weighted.mean(data.main$efffdh[data.main$Tr==0], draft1)
         meandraft4[o] <- weighted.mean(data.main$mEff[data.main$Tr==0], draft1)
         meandraft5[o] <- weighted.mean(data.main$mDEAeff[data.main$Tr==0], draft1)
        }

###OverallEff_utv, efffdh, mEff, mDEAeff
        ### Print number of loops on the screen
        print(j)
        ### storing ATT values
        attDEA[j] <- (mean(data.main$OverallEff_utv[data.main$Tr==1])- mean(meandraft2))
        attFDH[j] <- (mean(data.main$efffdh[data.main$Tr==1]) - mean(meandraft3))
        attmEff[j] <- (mean(data.main$mEff[data.main$Tr==1])- mean(meandraft4))
        attmDEA[j] <- (mean(data.main$mDEAeff[data.main$Tr==1]) - mean(meandraft5))

### Results of other variables needed for analysis
        AvTrueEff[j]           <- mean(data.full$effTrue)
        AvOverallFDH_F[j]      <- mean(data.full$efffdh)
        AvOverallDEA_F[j]      <- mean(data.full$OverallEff_utv)
        AvOrderm[j]            <- mean(data.full$mEff)
        AvConOrderm[j]         <- mean(data.m$effm)
        AvProgEff_T[j]         <- mean(data.treated$ProgramEff_T)
        AvProgEff_C[j]         <- mean(data.control$ProgramEff_C)
        AvTrueImpact[j]        <- mean(data.full$trueImp)
        AvTrueImpactT[j]       <- mean(data.treated$trueImp)
        AvTrueImpactC[j]       <- mean(data.control$trueImp)
```

```
        AvProgEff_MT[j]       <-mean(m.data.treated$m.ProgEff_T)

        AvProgEff_MC[j]       <-mean(m.data.control$m.ProgEff_C)

        MDiffProgFull[j]      <-((mean(data.treated$ProgramEff_T))-
(mean(data.control$ProgramEff_C)))

        MDiffProgMatch[j]     <-((mean(m.data.treated$m.ProgEff_T))-
(mean(m.data.control$m.ProgEff_C)))

        noT[j]          <- length(data.full$Tr[data.full$Tr==1])

        noC[j]          <- length(data.full$Tr[data.full$Tr==0])

        BiasReFSA[j]    <- (( MDiffProgMatch[j]- MDiffProgFull[j])/ AvTrueImpactT[j])*100

        MDiffTrueImpTC[j]     <- (AvTrueImpactT[j]-AvTrueImpactC[j])#

        MDiffDEA[j]     <- (mean(data.m$OverallEff_utv[data.m$Tr==1]) -
mean(data.m$OverallEff_utv[data.m$Tr==0]))

        MDiffFDH[j]     <- (mean(data.m$efffdh[data.m$Tr==1]) -
mean(data.m$efffdh[data.m$Tr==0]))

        MDiffOrderm[j] <- (mean(data.m$mEff[data.m$Tr==1]) -
mean(data.m$mEff[data.m$Tr==0]))

        MDiffConM[j]          <- (mean(data.m$effm[data.m$Tr==1]) -
mean(data.m$effm[data.m$Tr==0]))

        MSEfull[j]      <- (MDiffProgFull[j]-MDiffTrueImpTC[j])^2

        MSEmatch[j]     <- (MDiffProgMatch[j]-MDiffTrueImpTC[j])^2

        MSEattDEA[j]    <- (attDEA[j] -MDiffTrueImpTC[j])^2

        MSEattFDH[j]    <- (attFDH[j]-MDiffTrueImpTC[j])^2

        MSEattmEff[j]   <- (attmDEA[j]-MDiffTrueImpTC[j])^2

        MSEattmDEA[j]   <- (attmDEA[j]-MDiffTrueImpTC[j])^2

        MSEconOrderm[j] <- (MDiffConM[j]-MDiffTrueImpTC[j])^2

}

### save simulation results

results <- data.frame(cbind(noT, noC, AvTrueEff, AvOverallFDH_F, AvOverallDEA_F,
AvOrderm,AvConOrderm, AvProgEff_T, AvProgEff_C, AvProgEff_MT, AvProgEff_MC, AvTrueImpact,
AvTrueImpactC,AvTrueImpactT, MDiffTrueImpTC, MDiffProgFull,
MDiffProgMatch,MDiffConM,MDiffDEA,MDiffFDH,MDiffOrderm,attDEA, attFDH, attmEff,
attmDEA,BiasReFSA, MSEfull, MSEmatch, MSEattDEA, MSEattFDH, MSEattmEff, MSEattmDEA,
MSEconOrderm ))

write.dta(results, "C:/CRSoutM1520a.dta", version = 9, convert.dates = TRUE,
convert.factors = c("labels", "string", "numeric", "codes"))

}

 }
```

APPENDIX VI. Technical Efficiency Scores of Treated and Non-Treated Enterprises

SME	Treatment	DEA Efficiency	FDH Efficiency	Order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=15)	Propensity conditional order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=25)	Propensity conditional order-m efficiency (m=30)
1	1	1.00	1.00	0.44	0.26	0.32	0.37	0.41
2	1	0.43	1.00	0.64	0.38	0.51	0.62	0.71
3	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4	1	0.35	0.73	0.88	0.60	0.70	0.77	0.82
5	1	0.32	1.00	0.60	0.39	0.50	0.59	0.67
6	1	0.46	1.00	0.79	0.32	0.34	0.35	0.37
7	1	0.18	0.48	1.41	1.09	1.31	1.48	1.60
8	1	0.21	0.31	1.64	1.00	1.16	1.30	1.43
9	1	0.45	1.00	0.73	0.59	0.69	0.76	0.81
10	1	0.33	1.00	0.83	0.82	0.87	0.89	0.91
11	1	0.27	0.50	1.28	0.90	1.04	1.16	1.25
12	1	0.15	0.60	1.36	0.95	1.01	1.07	1.12
13	1	0.23	0.78	1.08	0.69	0.76	0.82	0.88
14	1	0.58	1.00	0.66	0.31	0.41	0.51	0.61
15	1	1.00	1.00	0.43	0.02	0.03	0.04	0.05
16	1	0.25	0.86	0.98	1.03	1.09	1.12	1.14
17	1	0.18	0.94	1.02	0.99	1.01	1.02	1.02
18	1	0.26	0.55	1.00	0.70	0.80	0.89	0.97
19	1	0.17	0.73	1.32	1.35	1.35	1.36	1.36
20	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00

SME	Treatment	DEA Efficiency	FDH Efficiency	Order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=15)	Propensity conditional order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=25)	Propensity conditional order-m efficiency (m=30)
21	1	1.00	1.00	0.55	0.04	0.05	0.06	0.06
22	1	0.27	1.00	0.62	0.41	0.43	0.45	0.47
23	1	0.29	1.00	0.99	0.65	0.72	0.78	0.82
24	1	0.19	0.57	1.74	1.57	1.66	1.71	1.73
25	0	1.00	1.00	0.61	0.07	0.09	0.12	0.14
26	0	1.00	1.00	0.47	0.30	0.35	0.39	0.43
27	0	1.00	1.00	0.36	0.18	0.23	0.26	0.30
28	0	1.00	1.00	0.42	0.25	0.29	0.32	0.34
29	0	0.72	1.00	0.57	0.44	0.49	0.54	0.58
30	0	1.00	1.00	0.59	0.41	0.47	0.52	0.56
31	0	0.34	1.00	0.60	0.43	0.56	0.66	0.72
32	0	0.69	1.00	0.47	0.30	0.35	0.40	0.44
33	0	0.68	1.00	0.61	0.48	0.55	0.61	0.66
34	0	0.56	1.00	0.63	0.50	0.59	0.65	0.70
35	0	0.54	1.00	0.63	0.42	0.50	0.56	0.62
36	0	0.54	1.00	0.47	0.27	0.30	0.31	0.33
37	0	0.49	1.00	0.53	0.35	0.45	0.54	0.62
38	0	1.00	1.00	0.31	0.09	0.12	0.14	0.17
39	0	0.53	1.00	0.68	0.62	0.68	0.73	0.76
40	0	0.46	1.00	0.67	0.57	0.65	0.71	0.76
41	0	0.41	1.00	0.82	0.71	0.79	0.84	0.87
42	0	0.80	1.00	0.61	0.48	0.53	0.58	0.61

SME	Treatment	DEA Efficiency	FDH Efficiency	Order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=15)	Propensity conditional order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=25)	Propensity conditional order-m efficiency (m=30)
43	0	1.00	1.00	0.42	0.23	0.28	0.32	0.36
44	0	1.00	1.00	0.35	0.11	0.14	0.17	0.20
45	0	1.00	1.00	0.35	0.20	0.22	0.25	0.26
46	0	0.82	1.00	0.52	0.28	0.33	0.38	0.42
47	0	0.93	1.00	0.69	0.46	0.53	0.59	0.64
48	0	0.80	0.86	0.59	0.36	0.43	0.49	0.55
49	0	0.39	0.89	0.86	0.75	0.81	0.85	0.89
50	0	0.86	1.00	0.50	0.36	0.40	0.42	0.45
51	0	0.35	1.00	0.97	0.97	0.99	1.00	1.00
52	0	0.36	0.83	0.83	0.66	0.72	0.77	0.81
53	0	0.51	1.00	0.67	0.57	0.64	0.69	0.74
54	0	0.32	0.95	0.79	0.71	0.79	0.85	0.89
55	0	1.00	1.00	0.52	0.31	0.38	0.43	0.48
56	0	0.30	0.92	0.92	0.86	0.93	0.98	1.01
57	0	0.37	1.00	0.78	0.77	0.82	0.85	0.88
58	0	0.28	0.67	1.03	0.84	0.90	0.93	0.96
59	0	0.50	1.00	0.66	0.57	0.63	0.67	0.70
60	0	0.51	1.00	0.66	0.61	0.67	0.71	0.75
61	0	0.26	0.73	1.38	1.19	1.29	1.34	1.36
62	0	0.25	0.90	1.08	1.10	1.11	1.11	1.11
63	0	0.37	1.00	0.77	0.43	0.46	0.50	0.53
64	0	0.36	1.00	0.79	0.78	0.85	0.90	0.93

SME	Treatment	DEA Efficiency	FDH Efficiency	Order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=15)	Propensity conditional order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=25)	Propensity conditional order-m efficiency (m=30)
65	0	0.22	0.80	1.07	0.99	1.06	1.10	1.14
66	0	0.22	0.76	1.09	1.08	1.12	1.15	1.18
67	0	1.00	1.00	0.37	0.01	0.02	0.03	0.04
68	0	0.37	0.94	0.61	0.31	0.41	0.51	0.60
69	0	0.54	0.94	0.49	0.24	0.30	0.36	0.41
70	0	0.27	0.94	0.91	0.91	0.96	0.99	1.01
71	0	0.38	1.00	0.81	0.83	0.88	0.91	0.94
72	0	0.32	1.00	0.92	0.94	0.97	0.98	0.99
73	0	0.37	1.00	0.81	0.76	0.84	0.88	0.92
74	0	0.16	0.53	1.46	1.45	1.51	1.56	1.60
75	0	0.16	0.89	1.07	0.97	1.00	1.02	1.04
76	0	0.15	0.38	2.59	2.07	2.33	2.48	2.55
77	0	0.21	0.88	1.04	1.02	1.07	1.10	1.12
78	0	0.33	1.00	1.00	1.00	1.00	1.00	1.00
79	0	0.14	0.42	1.73	1.46	1.55	1.62	1.68
80	0	0.52	1.00	0.76	0.20	0.24	0.28	0.32
81	0	0.29	1.00	0.79	0.71	0.79	0.85	0.89
82	0	0.17	0.43	1.13	0.62	0.80	0.95	1.09
83	0	0.21	1.00	0.88	0.88	0.92	0.94	0.96
84	0	0.15	0.40	1.56	1.26	1.43	1.58	1.70
85	0	0.11	0.38	2.18	2.17	2.30	2.39	2.45
86	0	0.28	1.00	0.97	0.86	0.90	0.93	0.95

SME	Treatment	DEA Efficiency	FDH Efficiency	Order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=15)	Propensity conditional order-m efficiency (m=20)	Propensity conditional order-m efficiency (m=25)	Propensity conditional order-m efficiency (m=30)
87	0	0.16	0.68	1.45	1.47	1.48	1.48	1.48
88	0	0.14	0.31	1.33	0.86	1.03	1.19	1.33
89	0	0.22	1.00	1.00	1.00	1.00	1.00	1.00
90	0	0.57	1.00	0.75	0.61	0.70	0.76	0.81
91	0	0.45	1.00	0.96	1.00	1.00	1.00	1.00
92	0	0.16	0.17	2.41	0.41	0.69	1.03	1.41
93	0	0.09	0.17	2.79	1.76	2.17	2.56	2.92
94	0	0.13	0.67	1.27	1.33	1.39	1.43	1.45
95	0	0.19	0.91	1.09	1.07	1.08	1.09	1.09