國立交通大學交通運輸研究所

碩士論文

非意欲產出對市區公車營運效率之影響—隨機邊界分析法

Measuring Bus Transit Efficiency with Consideration of Undesirable Outputs: Stochastic Frontier Analysis Approach

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摘要

過去國內外對於汽車客運業營運績效之研究很多，但大部分僅針對業者的意欲產出（如班次、車公里、座位公里等）分析，鮮少有探討非意欲產出（如噪音、廢氣、事故等）對績效之影響。由於非意欲產出通常會伴隨意欲產出而發生，業者可能無法只生產意欲產出而不帶來一些非意欲產出，故當評估其績效時，理應將非意欲產出亦納入績效評估中，方不致偏頗。

本論文利用隨機邊界分析法，探討公車營運效率是否顯著受到肇事的影響。本研究以台北市聯營公車為研究對象，採用 2001 至 2006 年之營運資料進行分析，構建隨機邊界產出模型，選用之意欲產出項為延車公里，非意欲產出項為肇事率(不區分肇事之嚴重性)及肇事加權(區分肇事之嚴重性，依死亡、重傷、輕傷及僅財務損失賦以適當權重)，投入項則包括營業車輛數、總耗油量及員工數。研究結果發現，台北市聯營公車業之技術無效率具有顯著性。納入肇事考量時（不區分或區分肇事嚴重性），公車業技術效率之排序與未納入肇事考量時之評估結果確有顯著的不同，表示公車業者亦可藉由降低肇事的發生以提升其技術效率。研究結果亦歸納出影響台北市聯營公車營運效率之其他因子，可供業者及政府部門參考。

關鍵字：事故、公車、生產效率、隨機邊界分析法

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Abstract

The issue of efficiency evaluation for bus transit has been extensively studied by transport economists; however, they ignored the effects of undesirable outputs, such as accidents, on the efficiency measurement. While producing the desirable outputs -- transport services, a bus transit in practice also accompanies with some undesirable by-products, such as pollutants and accidents, which would downgrade the environments and even cause the properties or lives loss. As these undesirable by-products are never freely disposable, measuring its productive efficiency without adjustment of their negative effects would be biased. It is therefore important to incorporate both desirable and undesirable outputs into a model to assess the bus transit efficiency in an impartial manner.

This thesis attempts to investigate if the productive efficiency of a bus transit is significantly influenced by accidents involved. Both desirable output and accident rate are incorporated into a stochastic frontier analysis (SFA) model. A panel data of ten Taipei Bus Transit firms over 2001 to 2006 is drawn for the case study, wherein vehicle-kilometer is selected as the desirable output, accident rate (without distinguishing severity) and aggregated accident score (with distinguishing severity by converting fatality, major injury, minor injury, and property loss only into proper weighted score) as the undesirable output, and fleet size, fuel, and labor as the inputs. Our findings indicate that there exists significant inefficiency in the Taipei bus transit industry as a whole. The productive efficiency with adjustment of undesirable accidents (either without or with distinguishing the severity) is significantly different from that measured without adjustment of accident effects. It suggests that ameliorating the operational safety is one of the effective means to promote the efficiency of bus transit.

Keywords: accident, bus transit, productive efficiency, stochastic frontier analysis.

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邱冠熒　　　　　謹誌

中華民國九十六年七月

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Chapter 1 Introduction

1.1 Motivation and background

Bus transit plays an important role on public transportation in urban areas around the world. There has been a significant ratio of people demanding frequent use of buses everyday in each city in Taiwan. However, with the increase of income, the number of private vehicles has increased rapidly, which has led to a vicious circle of diminishing bus passengers. More private vehicle ownership and usage reduced the demand for public transport, to which the operators responded by either raising the fares or curtailing the frequency or both. Thus, the use of private vehicle became more attractive than before and induced more people to purchase them, further accelerating the vicious circle. As a consequence, after several cycles, drivers were facing more congestion, buses were running less frequency because of the roadway congestion, and almost everyone was worse off than originally. One way to break or even reverse such vicious circle of private-public transport system is to provide more efficient and higher quality of bus transit service so as to compete with the private vehicles. Hence, evaluating the efficiency and understanding the causes of inefficiency of bus transit operation are important issues.

The issue of efficiency evaluation for bus transit has been extensively studied by transport economists, for example, Sakano and Obeng (1995), Sakano et al. (1997), Jørgensen et al. (1997), Dalen and Gómez-Lobo (2003); however, they ignored the effects of undesirable outputs on the efficiency measurement. While producing the desirable outputs, namely transport services, a bus transit, in practice, also accompanies with undesirable outputs, such as pollutants and accidents, which would downgrade the environments and even cause the properties or lives loss.

Taking the accident as an example, no matter how carefully a bus driver intends to maneuver the vehicle, accidents are almost inevitable. In case that an accident is involved, the driver must stop the vehicle to check the likely injuries, fatalities or damages, which might cost substantial compensation or revenue loss. At least, the driver must stop operation until the completion of accident documentation by the police. In all cases, the bus operational efficiency would certainly be deteriorated.

In dealing with the undesirable outputs, previous studies generally approached the problem by incorporating an extra undesirable variable into the production model, either as another detrimental input or as a weak disposable bad output, and most of them were applications to the agricultural or environmental fields. For example, Fernández *et al*. (2002) discussed how excess nitrogen production affected the performance of Dutch diary farms. Chung and Färe (1997) measured productivity changes causing from Biological Oxygen Demand and Suspended Solids in the Swedish pulp and paper industry. Coelli *et al.* (2005) measured the effects of nutrient pollution on Belgian pig finishing farms. Studies incorporating undesirable outputs into efficiency measures are rarely found in the transport field, especially in the bus transit system.

1.2 Purposes and topics of the research

Based on the motivation and problem mentioned in previous section, the purposes of current research are as follows. First, to investigate if the technical efficiency of a bus transit is significantly influenced by such undesirable outputs as accidents via a stochastic frontier analysis approach (SFA). The second purpose is to find out determinants of bus efficiency and provide managerial implications for bus firms and the authority.

Topics of the research can be described as follows:

1. With the use of Stochastic Frontier Analysis (SFA), I will construct an efficiency model which can deal with desirable and undesirable outputs to analyze the operational efficiency of urban bus industry.
2. A case study of Taipei bus transit is adopted in this research. Measures of the technical

efficiency under the cases of considering with and without undesirable outputs will be provided separately, and evaluations of the impact on technical efficiency caused by undesirable outputs will also be presented.

3. Testing for technical changes in the sampling period, in order to examine whether the frontier shifts during this period.
4. To have a more complete point of view, a comparison between the efficiency measurements of Taipei bus transit by DEA and SFA models in this thesis is presented, in order to see if the results of the two models are commonly consistent with each other.

1.3 Research object and sampling period

In this study, Taipei bus transit is taken as the case study. Currently there are in total 15 bus operators, all privately-owned. Among them, five firms, all of which are of relatively small scale in terms of market share, have been excluded from the empirical analysis, because of incomplete or unreasonable data. A panel data for the remaining ten firms is drawn over a six-year horizon from 2001 to 2006. The operational data is drawn from *Annually Statistical Reports of Transportation in Taipei City*, while the data of accident is drawn from *Taipei bus transit service appraisal*; both of them are published by the Department of Transportation, Taipei City Government. As these bus firms adopted similar diesel-engine vehicles, the noise and pollutants is assumed indifferent in this study.

1.4 Framework and procedures

The structure of this study will be organized as follows:

A. Introduction

Motivation and purpose of this study will be provided, and objectives of the study will also be defined. Then, the study approach and components of this research will be demonstrated.

B. Literature review

Review of relevant literatures will be separated into two respects: Frontier studies of transit systems, which include papers using either parametric approach (mainly Stochastic Frontier Analysis, SFA) or non-parametric approach (mainly DEA) or both, will be illustrated first. The wide variability in the use of input and output measures in transit will also be presented. The second part of this chapter will be literatures concerning undesirable outputs.

C. Methodology

The origin of efficiency evaluation will be addressed first, and then a brief survey and categories of SFA will also be presented. A stochastic output distance function which is adopted in this study will be specified.

D. Empirical analysis

Data of ten bus firms of Taipei bus transit over the period 2001 to 2006 is adopted. I select vehicle-kilometers as the desirable output and assume that the output is produced by utilizing three inputs: fleet size, measured by the number of vehicles; fuel, measured by the total amount of fuel consumed; and labor, measured by the number of employees. The undesirable output is measured by the yearly aggregate score of various accidents. The operational data and the data of accident are both drawn from publications of the Department of Transportation, Taipei City Government. In the current research the stochastic frontier model will be constructed, in which both desirable and undesirable outputs are accommodated. As for estimation of parameter and firm-specific efficiency, the computer package program named FRONTIER 4.1, developed by Coelli (1996) is adopted. After estimation, the significance of each parameter and monotonicity will be checked, and the hypotheses regarding the existence of productive inefficiency will also be tested.

E. Discussions

After estimation, technical efficiencies both with and without consideration of undesirable outputs will be discussed. In addition, the relationship between two cases will be investigated, so as to find out the effect of traffic accident on performance evaluation. Comparisons of the results between SFA model and Taipei bus transit service appraisal will also be provided. In addition, the differences between the results of SFA and DEA will be investigated.

F. Conclusions and recommendations

The last chapter will illustrate the contribution and policy implications of the study. Topics for further research will also be provided.

Research process is illustrated by Figure 1.1.

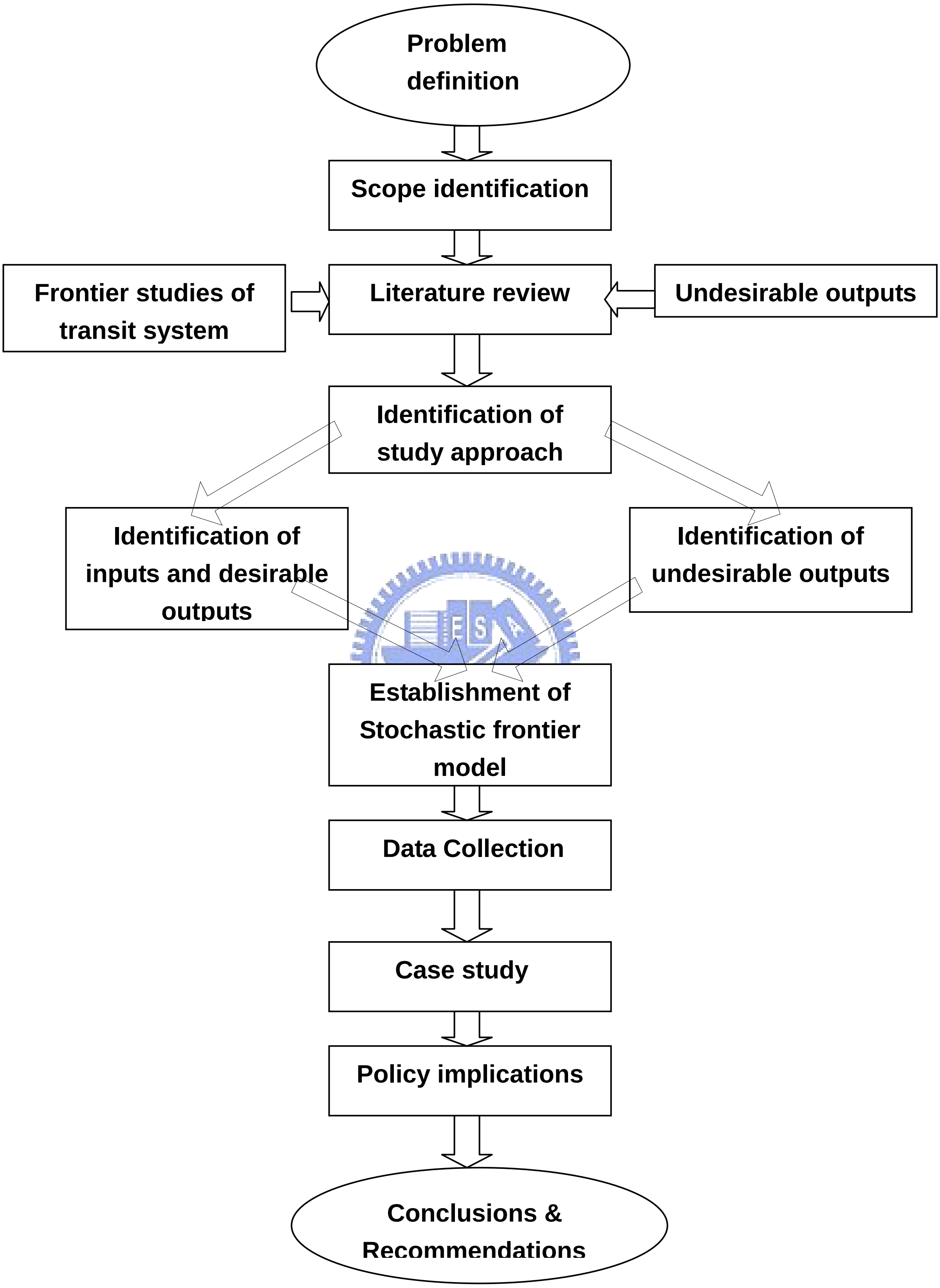

Figure 1.1 Research process flow chart

Chapter 2 Literature Review

Frontier methods have been widely applied to performance evaluation for many fields in the past couple of decades. A number of studies, that adopted the methods for evaluating performance of transport industries, including airlines, railways, bus transit, seaport, airport, motor carrier etc., can be found in the literature. In this chapter, previous studies for measuring efficiency of bus transit are presented in 2.1, while some selected works for measuring efficiency with consideration of undesirable outputs are documented in Section 2.2.

2.1 The applications of SFA to transit systems

The methods of measuring efficiency can be classified into two categories: non-parametric and parametric methods. Non-parametric method need no priori functional forms and number of parameters on the observations, while parametric method requires a specification of functional form for the relationship between inputs and outputs, and a distribution form for technical inefficiency. Since the parametric frontier method, or the Stochastic Frontier Analysis approach (SFA) is adopted in the current research, the review of some selected papers regarding applications of parametric frontier method to measuring efficiency for bus transit systems is presented as follows.

Many economists have employed parametric approaches to analyzing the efficiency of bus transit in the past decade. Studies of parametric approach to transportation efficiency have been employed in the following cases.

Gathon (1989) analyzed the performance, including indicators of partial productivity and technical efficiency, of urban transport companies using a deterministic translog production function. Data of 60 European bus firms in 1984 was adopted. The output variable was seat kilometers, while the inputs were total number of seats and total manpower employed. The results showed that the ranking by degree of technical efficiency was independent of the size of the firm; and technical efficiency was positively affected by operational speed.

Filippini et al. (1992) measured the cost and scale efficiency for 62 Swiss regional bus companies by a deterministic translog cost function. A panel data for four years 1986, 87, 88 and 89 had been used for estimation. Output was measured in seat kilometers, while inputs were labor, energy and capital costs. The results showed that the majority of the Swiss bus companies operate at an inappropriately low scale and density level, and further showed that efficiency was positively and significantly correlated with compensation payments and the share of Cantons in subsidizing the deficit, and was negatively affected by Alpine regions.

Thiry and Tulkens (1992) identified and evaluated efficient versus inefficient observations numerically by the nonparametric FDH method. Next parametric production frontiers were obtained by means of estimating translog production functions through ordinary least square (OLS) applied to the subset of efficient observations only. Technical progress was included at both stages. Monthly data from three urban transit firms in Belgium (from 1977 to 1985, and from 1979 to 1985) were adopted. The output was measured by the number of seats kilometers, while inputs were labor, energy, and vehicles. The results showed widely varying degrees of efficiency over time and across firms. For STIB, the inefficiencies reached the bottom level of 79% in 1982; in the case of STIL, the worst case of inefficiency was 98.4% in 1985; in the case of STIC, the worst inefficiency level was 90.4% in 1983.

Bhattacharyya et al. (1995) estimated the determinants of cost inefficiency of several publicly operated passenger-bus transportation companies in India in terms of their ownership structure as well as other firm-specific characteristics. Inefficiency was specified in such a way that both its mean and variance are firm-and time-specific. A multi-step estimation procedure was adopted for the estimation of production technology and cost inefficiency: In the first step they estimated the translog cost system with heteroskedastic cost function without using any distribution assumptions on the error terms. The second stage used the ML method to estimate the parameters associated with inefficiency, conditional on the parameter estimates obtained from the first stage. Finally, the residual of the cost function was decomposed to obtain firm-and time-specific measures of cost inefficiency, with ownership type and other firm-specific characteristics as explanatory variables. The study used a five-year unbalanced panel data of 32 state-run passenger-bus transportation units, operating in 18 states in India, over the period 1983 to 1987. The output variable was passenger-kilometer, and three input variables had been considered in this study, fuel, and two categories of labor: traffic and maintenance labor, and administrative labor. Apart from these variables inputs they have included two network variables: fleet utilization and load factor. The result showed that the units directly run by the government transportation departments were most efficient, compared to the nationalized units and large transport corporations. The high inefficiency of the large transport corporations relative to the units run by the government departments was of significant interest. On the whole, it seemed to indicate that the large degree of administrative autonomy of the transport corporations allows them to be relatively more irresponsible and inefficient.

Jørgensen et al. (1997) estimated a stochastic cost frontier function based on data from 170 Norwegian subsidized bus companies in 1991 under two alternative presumptions regarding the distribution of the inefficiency among the bus operators. The output was total cost per vehicle-kms, while the inputs were number of vehicle kilometers, bus size and number of passengers. The results showed that when the inefficiency was assumed to be half-normally distributed, the average inefficiency in the industry was nearly halved when the exponential distribution was applied, while the ranking of the companies according to inefficiency was unchanged; it was also seen that inefficiency of the companies which negotiated with the public authorities over the subsidy amounts was slightly higher than the inefficiency of the companies which faced a subsidy policy based in cost norms. However, it was found no significant difference in the efficiency between privately owned bus companies and publicly owned bus operators, and showed only minor economies of scale.

Sakano et al. (1997) studied the US urban transit system which received operating and capital subsidies from various levels of government using a stochastic translog production function. Both technical and allocative inefficiencies were calculated. The allocative inefficiencies were further decomposed among two sources, subsidies and factors internal to the firm. The output variable was vehicle-mile, and input variables included labor, fuel and capital. In addition, there were two exogenous variables, route miles and population density, are added to the production function. The analysis revealed large allocative inefficiencies between labor, fuel, and capital. Furthermore, they found that subsidies lead to excess use of labor relative to capital and excess use of fuel relative to capital and labor. Also, most allocative inefficiencies in firms were due to internal factors and not subsidies, and the sizes of the inefficiencies varied substantially among transit firms.

Dalen and Gomez (2003) addressed a cost frontier model which was estimated for an eleven-year panel of Norwegian bus companies (1136 company-year observations) using the methodology proposed by Battese and Coelli (1995). The main objective of the paper was to investigate to what extent different type of regulatory contracts affect company performance. Unobservable network or other time invariant characteristic of the operating environment could be controlled for by analyzing the dynamics of measured productivity across time for firms regulated under different types of contracts, rather than relying solely on variations across companies during one time period. The main result of the paper was that the adoption of a more high-powered scheme based on a yardstick type of regulation significantly reduced operating costs. The results contained in this paper thus confirmed theoretical predictions regarding the incentive properties of high powered incentive schemes and in particular the dynamic benefits of yardstick competition.

Table 2.1 summarizes the previous studies which apply the parametric frontier method for measuring the efficiency of bus transit system.

Table 2.1 Summarization of transit efficiency researches

Author	Country	Year	Function	Input variables	Output variables
Gathon (1989)	European urban bus	1984	deterministic tranlog production function	number of seats, manpower employed	seat-kms
Filippini et al. (1992)	Swiss regional bus	1986-1989	deterministic translog cost function	labor energy capital	Seat- kms
Thiry and Tulkens (1992)	Belgium urban systems	1977-1985	translog production function	labor energy no. of seats	seat-kms
Bhattach-aryya et al. (1995)	Indian bus firms	1983-1987	stochastic translog cost function	fuel, traffic and maintenance labor, administrative labor.	passenger-kms
Jørgensen et al. (1997)	Norwegian subsidized bus companies	1991	stochastic cost frontier function	average bus size, number of passengers boarding.	vehicle-kms

Author	Country	Year	Function	Input variables	Output variables
Sakano et al. (1997)	US urban transit system	1983-1992	stochastic translog production function	labor, fuel, capital	vehicle-miles
Dalen and Gómez-Lobo (2003)	Norwegian bus companies	1987-1997	stochastic Cobb-Douglas cost frontier	driver, admin. labor, fuel, capital	vehicle-kms (urban), vehicle-kms (inter city services)

DEA and SFA are two common approaches for measuring efficiency of bus transportation companies. There have been large amount of bus efficiency studies using DEA approach in Taiwan, however, there haven't been any applications using SFA methods to measuring efficiency for Taiwan's bus transit industry.

In addition, from Table 2.1 one can see that most researchers choose labor, capital and fuel as input variables in bus efficiency measurement. As for output variables, vehicle-kilometer and passenger-kilometer are two distinct variables commonly used in previous studies. The former indicates essentially the level of capacity produced by bus transit companies and regarded as available output, while the latter indicates the level of output consumed by passengers and oftentimes regarded as revenue output. The current research attempts to measure technical or productive efficiency of Taipei bus transit systems and analyzes the effects of accident on efficiency measurement, thus vehicle-kilometer is selected as desirable output.

2.2 Undesirable Output

In the past two decades, researchers have recognized the effects of undesirable outputs on efficiency measurement and thus proposed to integrate undesirable outputs into the technical and economic efficiency measurement models. Since that, a number of works on efficiency measurement with consideration of undesirable outputs can be found in the literature. Most of which were based on adjustments to standard parametric and non-parametric efficiency analysis techniques. The majority of these studies have approached the problem by incorporating an extra pollution variable into the production model, either as additional inputs or as weak disposable bad outputs (e.g., Färe et al., 1989; Reinhard et al. 2000). Most methods implicitly assume that a reduction in undesirable outputs can only occur via the increases in one or more traditional inputs and/or the reduction in one or more traditional outputs. This assumption discounts the possibility that the firm could alter its input mix to achieve lower pollution, which is a viable option in many industries.

Pittman (1983), in an analysis of Wisconsin paper mills, was perhaps the first researcher to attempt to incorporate environmental pollution into conventional productivity measures. This was done by making adjustments to the Caves et al. (1982) multilateral productivity index. Since the market prices of undesirable outputs are generally unavailable, proxies of prices for the undesirable output (i.e., pollution) were used to adjust productivity indices. These proxies were derived from observed values, such as pollution taxes and marketable permits, or from shadow prices obtained from previous studies.

Färe et al. (1989) incorporated the environmental variables into firm-level efficiency measurement by using DEA methods. Utilizing the data used in Pittman (1983), they indeed included pollution measures into the production model and introduced the concept of weak disposability to account for the fact that the bad outputs (pollution) cannot be freely disposed. It should be noted that strong disposability implies that it is free to dispose the unwanted inputs or outputs. It should also be noted that in contrast with Pittman (1983), who used a superlative index that is exact to a translog transformation function, Färe et al. (1989) constructed a nonparametric piecewise linear technology that satisfied weak disposability of undesirable outputs. In addition, the two approaches also had different data requirements; Pittman (1983) utilized proxies for the undesirable outputs, while Färe et al. (1989) required the data only on the quantities of the undesirable outputs.

A number of subsequent studies have used similar approaches in other industrial applications, such as Färe et al. (1993), Tyteca (1996), Chung et al. (1997), Reinhard et al. (2000) and Fernández et al. (2002). The brief of these studies are described below.

Färe et al. (1993) provided an alternative method of calculating shadow prices of outputs, including undesirable outputs. Moreover, these shadow prices are obtained as part of a procedure that also generates estimates of the structure of production technology as well as producer-specific measures of productive efficiency.

Tyteca (1996) provided a detailed review on the methods that have been used to measure the environmental performance of firms, including parametric and non-parametric approaches. There are two important conclusions in this study. The first one is that a few papers have demonstrated the feasibility of productive efficiency approaches similar to those dealt with in this survey. The second one is that the crucial question of data availability.

Chung et al. (1997) introduced a directional output distance function and used it as a component in a new productivity index that models joint production of goods and bads, and credits firms for reductions in bads and increases in goods. Similar to the productivity index without consideration of undesirable outputs, the productivity index can be decomposed into parts: efficiency change and technology change. The authors also showed how to compute these productivity indexes using simple linear programming techniques and provided an empirical example for the case of Swedish pulp and paper industry over the 1986-1990 period.

Reinhard et al. (2000) estimated comprehensive environmental efficiency measures for Dutch dairy farms. The environmental efficiency scores were based on the nitrogen surplus, phosphate surplus and the total (direct and indirect) energy use of an unbalanced panel of dairy farms. The authors compared two methods: DEA and SFA, for the calculation of efficiency. This paper revealed the strengths and weaknesses for estimating environmental efficiency of the methods applied. The results showed that the mean technical efficiency scores (output-oriented, SFA 89%, DEA 78%) and the mean comprehensive environmental efficiency scores (SFA 80%, DEA 52%) differ between the two methods. SFA allowed hypothesis testing, and the monotonicity hypothesis was rejected for the specification including phosphate surplus. DEA could calculate environmental efficiency scores for all specifications, because regularity was imposed in this method.

Table 2.2 Previous studies with consideration of undesirable output

Authors	Objects	Methods	input	Output
Pittman (1983)	Wisconsin Pulp mills	Translog productivity index, with the utilization of shadow prices	capital, labor, energy.	pulp, BOD, TSS, particulates, sulphur oxides
Färe et al (1989)	Wisconsin Pulp mills	hyperbolic DEA	capital, labor, energy.	Pulp, BOD, TSS, particulates sulphur oxides
Färe et al (1993)	Wisconsin Pulp mills	output distance function	capital, labor, energy	Pulp, BODTSS Particulates, sulphur oxides
Chung et al. (1997)	Swedish paper and pulp industry	directional output distance function	labor, wood fiber, energy, capital.	Pulp, BOD, COD, SS

Authors	Objects	Methods	input	Output
Reinhard *et al.* (2000)	Dutch dairy farms	DEA&SFA	labor, capital, variable-input, energy.	one desirable output (single index of dairy firm output), and two bads: nitrogen surplus and phosphorus surplus.

2.3 Comments on the reviewed studies

The issue of efficiency evaluation for bus transit has been widely studied in the past decade; however, most of the studies ignored the effects of undesirable outputs, which may lead to a biased result, on the efficiency measurement.

In dealing with the undesirable output, previous studies have approached the problem by incorporating an extra undesirable output variable into the production model, either as a detrimental input or as a weak disposable output. Furthermore, most of them were applications to the agricultural fields or environmental issues. Studies incorporate undesirable outputs into efficiency measures for transport field are rarely seen in the literature. In addition, most economists employed DEA method to cope with undesirable outputs, but those who applied SFA to measuring efficiency for transport industry, especially for bus are relatively few.

DEA and SFA employ quite distinct methodologies for frontier estimation and efficiency measurement. DEA assumes all deviations from the frontier are due to inefficiency. If any random error or noise (weather, luck, etc.) is present, the placement of the DEA frontier may be influenced. Since the output of bus firms is influenced by traffic jam (caused by accidents, malfunction of traffic lights, etc.), weather, and other traffic conditions in service area, to account for the random noise, SFA may be more suitable than DEA in bus transit industry.

Chapter 3 Methodology

3.1 Production technology

In the field of economic efficiency, Frontier Analysis is a commonly used approach at present. Non-frontier analysis assumes that all firms are technically efficient, however, it neglects the fact that some firms may be technically inefficient; frontier analysis is in the opinion that only those firms who operate on their frontier are technically efficient.

Let the production technology be represented by the production possibility set containing all feasible input and output vectors: $T = \{(x, y) \mid x \text{ can produce } y\}$. That is, one can define output set $P(x)$ as $P(x) = \{y \mid (x, y) \in T\}$, or, inversely, define input set $L(y)$ as $L(y) = \{x: \mid (x, y) \in T\}$, where $x = (x_1, x_2, ..., x_m) \in R_+^m$, and $y = (y_1, y_2, ..., y_k) \in R_+^k$. It is assumed that that both *P (x)* and *L (y)* satisfy the axioms of convex, closed and bounded, and satisfy strong disposability of outputs and of inputs. The properties of $P(x)$ are:

P.1 $P(0) = \{0\}$,

P.2 $P(x)$ is bounded for $x \in R_+^m$,

P.3 $P(x)$ is a closed set,

P.4 $x' \geq x \Rightarrow P(x') \supseteq P(x)$ and $y \leq y' \in P(x) \Rightarrow y \in P(x)$,

P.5 $P(x)$ is a convex set for $x \in R_+^m$

Property P.1 states that the null input vector yields zero output. P.2 states hat finite input cannot produce infinite output. P.3 states that the output set is closed. P.4 states that an increase in inputs cannot lead to a reduction in output, and a reduction in outputs remains producible with no change in inputs. This property states that inputs and outputs are strongly disposable.P.5 presents a convexity property.

Now a functional characterization of the production frontier can be provided. A production frontier is a function as:

$$f(x) = \max\{y : y \in P(x)\}$$

Since the production frontier is defined in terms of the output sets $P(x)$ and the input sets $L(y)$, both of which satisfy certain properties, so does $f(x)$. These properties are

$f1$ $f(0)=0$,

$f2$ f is upper semicontinuous on R_+^m,

$f3$ $f(x) > 0 \Rightarrow f(\lambda x) \to +\infty \ as \ \lambda \to +\infty$,

$f4$ $x' \geq x \Rightarrow f(x') \geq f(x)$,

$f5$ f is quasiconcave on R_+^m

The production frontier provides the upper boundary of production possibilities, and the input-output combination of each producer is located on or beneath the production frontier. In Figure 3.1, the production frontier $f(x)$ describes the maximum output that can be produced with any given input vector in a single-output circumstance.

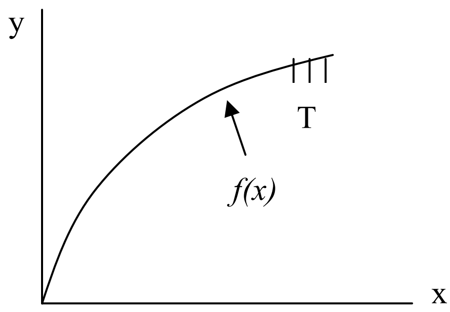

Figure 3.1 Production frontier

A production frontier characterizes the minimum input bundles required to produce various outputs, or the maximum output producible with various input bundles, and a given technology. Producers operating on their production frontier are labeled technically efficient, and producers operating beneath their production frontier are labeled technically inefficient. The gap between the actual production point and the production frontier, which can be treated as the inefficiency index as firms chasing for their optimal object, is thought to be the inefficiency of that production point.

3.2 Output distance function

Distance function is useful in describing the technology in a way that makes it possible to measure efficiency. When multiple inputs are used to produce multiple outputs, distance functions, which are proposed by Shephard (1970), provide a functional characterization of the production technology without the need to specify a behavioral objective, such as cost minimization or profit maximization. In practice, either input or output distance functions may be specified. The input distance function looks for a minimal proportional contraction of the input vector, given an output vector, while the output distance function considers a maximal proportional expansion of the output vector, given an input vector. This research attempts to measure the technical efficiency for Taipei bus transit with consideration of undesirable outputs, thus the output distance function is more suitable than the input distance function.

In words, the output distance function seeks the minimum amount by which an output vector can be deflated and remain producible with given input vector. Figure 3.2 illustrates the concept of an output distance function using an example where two outputs, y_1 and y_2, are produced by one input, x. Here the production possibility set, $P(x)$, is the area bounded by the production possibility frontier and the y_1 and y_2 axes. The output vector y is producible with input x, but so is the radially expanded output vector (y/λ^*).

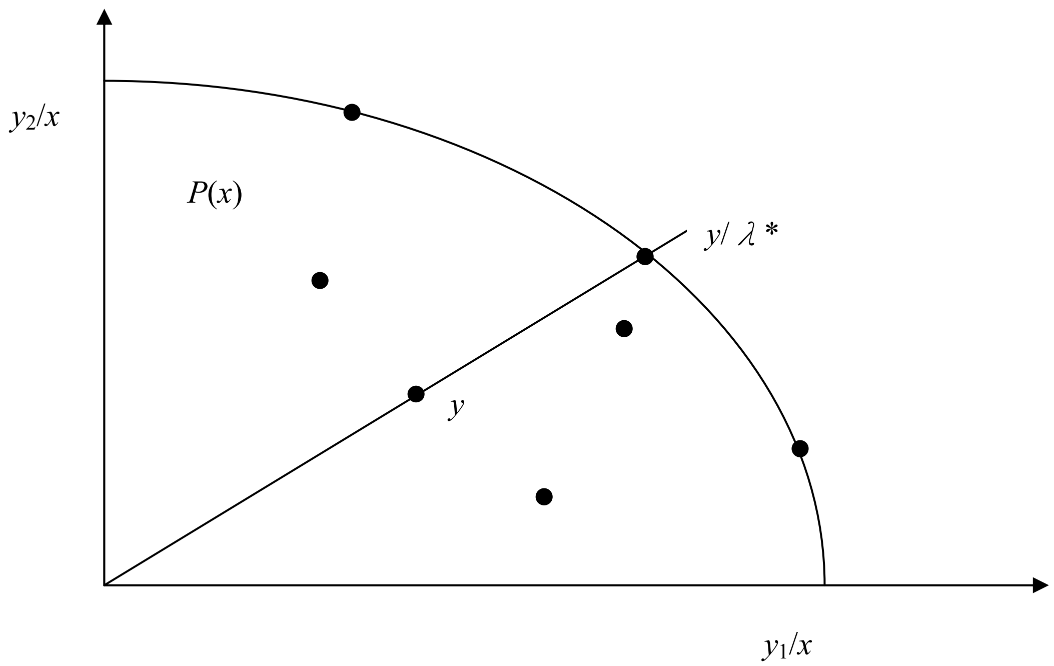

Figure 3.2 Output distance function (two outputs)

Once the output set (or input set) has been defined, the efficiency can be measured by the distance from observed data point to the best practice (frontier). The efficiency of a firm consists of two components: technical and allocative efficiencies. The former reflects the ability that a firm obtains maximal output from a given input set, while the latter reflects the ability that a firm uses the inputs in its optimal proportions, given their relative prices and the production technology. These two measures are combined to provide a measure of total economic efficiency. Technical efficiency is the main focus in this thesis. Thus the measurement method of the distance found observed data point to a production frontier is provided.

Based on literature, there are input-oriented and output-oriented measures of technical efficiency, and the output-oriented measure is specified in the current research. The output-oriented measures, considering the case where production involves two outputs and a single input, also can be illustrated in Figure 3.2. Point y corresponds to an inefficient firm and the distance between y and y/λ^* represents technical inefficiency, which is the amount by which output could be increased without requiring extra input. A measure of output-oriented technical efficiency is the ratio $TE = \frac{Oy}{Oy/\lambda^*} = D_o(x, y)$.

The output distance function can be defined as:

$$D_o(x, y) = \min\{\lambda : y/\lambda \in P(x)\}\text{, where } P(x) = \{y \in R_+^m : x \ can \ produce \ y\}$$

Following Lovell *et al*. (1994), assume that the output distance function, $D_o(x, y)$ satisfies the following conditions:

(1) $D_o(x, y)$ is non-decreasing in y and non-increasing in x;

(2) $D_o(x, y)$ is linearly homogeneous and convex in y;

(3) $D_o(x, y) \le 1, if \ y \in P(x) = \{y : y \in P(x)\}$;

(4) $D_o(x, y) = 1, if \ y \in Isoq \ P(x)$.

From linear homogeneity, we obtain $D_o(x, \omega \cdot y) = \omega \cdot D_o(x, y)$ for any $\omega > 0$. Thus, we can arbitrarily choose one of the outputs (e.g., the *Kth* output) and set $\omega = 1/y_K$, then $D_o(x, y/y_K) = D_o(x, y)/y_K$. When applying an econometric approach to estimate the efficiency, it is necessary to specify a suitable functional form. If we adopt the standard flexible translog output distance function, as did by many previous studies, the estimated results (parameters) would violate the monotonicity assumption (i.e. condition (1)). Thus, we specify a simplified log-linear form and the deterministic output distance function (DODF) can be written as:

$$\ln(D_{oi} \big/ y_K) = \alpha_0 + \sum_{k=1}^{K-1} \alpha_k \ln y_{ki}^* + \sum_{m=1}^{M} \beta_m \ln x_{mi}, \quad i = 1,2,...,N \tag{3.1}$$

where $y_k^* = y_k / y_K$. Let $\ln(D_{oi} / y_{Ki}) = TL(x_i, y_{ki} / y_{Ki}, \alpha, \beta, \rho), i = 1,2,..., N$, Or $\ln(D_{oi}) - \ln(y_{Ki}) = TL(x_i, y_{ki} / y_{Ki}, \alpha, \beta, \rho), i = 1,2,..., N.$, Hence,

$$-\ln(y_{Ki}) = TL(x_i, y_{ki} / y_{Ki}, \alpha, \beta, \rho) - \ln(D_{oi}), i = 1,2,..., N \tag{3.2}$$

3.3 Stochastic Frontier Analysis (SFA)

The efficiency can be measured by the distance from observed data point to the frontier, and it can be solved by using programming technique or econometric method. Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are the two most commonly used methods of non-parametric and parametric frontier analysis. This research attempts to measure the technical efficiency of bus firms via a stochastic frontier analysis approach, thus the paragraph below will briefly introduce SFA method for efficiency measurement.

The development of the current econometric methodology has two distinct stages. In the early applications, a specification of Deterministic frontier is proposed, which attributes all deviations from the observation to best practice to technical inefficiency without consideration of random errors. In order to modify the drawback of deterministic frontier analysis, Aigner et al.(1977) , Meeusen and van den Broeck(1977) introduced Stochastic production frontier models to allow for technical inefficiency and also acknowledge the fact that random shocks outside the control of producers can affect output. This stochastic production model is a more flexible approach to the specification of the frontier model.

A Cobb-Douglas deterministic production function is presented as equation 3.3.

$$y_i = x_i'\beta - u_i \qquad i=1,\ldots,I, \tag{3.3}$$

Where y_i denotes the appropriate function (e.g logrithm) of the production for the ith sample firm ; x_i is a vector of appropriate functions of inputs associated with the ith sample firm ; β is a vector of the coefficients for the associated independent variables in the production function. u_i represents the technical inefficiency. The output y_i is bounded from above by the deterministic quantity $\exp(x_i'\beta)$. Deterministic frontier analysis assumes that each firm faces common frontier, the technical efficiency of specific firm is measured by the deviation from observation to the frontier.

Stochastic frontier analysis put down the error terms as a mix error, which is divided into two parts. One is the random error v_i, which captures the uncontrollable part such as statistical noise, measurement error, influence of weather, strikes, luck, etc. The other part, u_i, captures the technical inefficiency, which represents the gap between frontier and firm's production. Equation 3.4 is a Cobb-Douglas stochastic production frontier, where output is specified as a function of a non-negative random error and a symmetric random error.

$$y_i = x_i'\beta + v_i - u_i \tag{3.4}$$

The noise component v_i is assumed to be iid and symmetric, distributed independently of u_i. The output values are bounded from above by the stochastic variable $\exp(x_i'\beta + v_i)$. Equation (3.4) is a cross-sectional form, which measures only one year of the firm data. Battese & Coelli(1988) proposed a stochastic frontier production function for panel data as equation (3.5), where t presents the year of the data.

$$y_{it} = x_{it}\beta + v_{it} - u_{it} \tag{3.5}$$

The random error v_i can be positive or negative and so the outputs vary about the deterministic part of the model, $\exp(x_i'\beta)$. The features of stochastic frontier model can be illustrated graphically by Figure 3.3, where the inputs and outputs of three firms were plot. Firm A uses the input level x_A to produce the output y_A, while firm B and firm C uses the input level x_B and x_C to produce the output y_B and y_C, respectively.

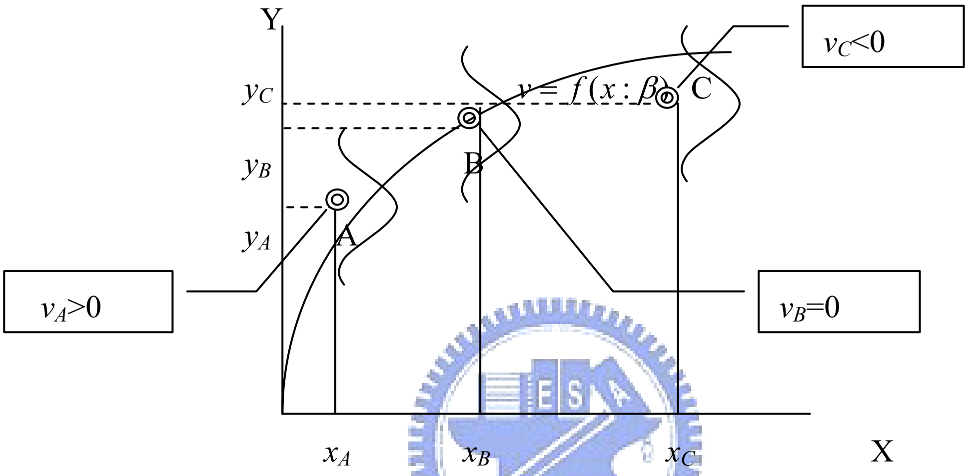

Figure 3.3 Stochastic Frontier Model

Here v_i is the random error term. The frontier moves randomly with v_i. If v_i is greater or smaller than zero, the stochastic frontier will be also greater or smaller than the deterministic frontier $f(x_i;\beta)$. It is clear that the frontier output for firm A lies above the deterministic part of the production frontier because of the positive noise effect (v_A>0), while the frontier output for firm C lies below the deterministic part of the frontier because the noise effect is negative (v_C<0); firm B lies on the deterministic frontier because the value of noise effect is equal to zero (v_B=0) . Because of the random error term, this model is called Stochastic Frontier Analysis.

In the current research, technical efficiency is of much concern. The most common output-oriented measure of technical efficiency is the ratio of observed output to the corresponding stochastic frontier output:

$$TE_i = \frac{y_i}{\exp(x_i\beta + v_i)} = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i) \tag{3.6}$$

This measure of technical efficiency takes a value between zero and one. It measures the output of the *i*th firm relative to the output that could be produced by a fully-efficient firm using the same input vector.

To estimate the stochastic production frontier model, distributional assumptions are required. There is a two-step procedure, in which the first step involves the use of OLS to estimate the slope parameters, and the second step involves the use of ML to estimate the intercept and the variances of the two error components. Distributional assumptions are used in the ML method and in the second step of the procedure. Four types of distributions for the inefficiency u_i are commonly used: half normal distribution, truncated normal distribution, exponential distribution and gamma distribution. Taking half-normal distribution as an example, following Kumbhakar and Lovell (2000), one can assume that

(1) $v_i \sim iid\ N(0, \sigma_v^2)$;

(2) $u_i \sim iid\ N^+(0, \sigma_u^2)$;

Because v_i is independent of u_i, the joint probability density function of v_i and u_i is

$$f(\varepsilon) = \frac{2}{\sigma\sqrt{2\pi}} \exp\left[1 - \Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \times \exp\left(-\frac{\varepsilon^2}{2\sigma^2}\right) = \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right) \tag{3.7}$$

Where $\varepsilon = v - u$, $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, $\lambda = \sigma_u / \sigma_v$, $\varphi(\cdot)$ and $\Phi(\cdot)$ are respectively the standard normal cumulative distribution function and probability density function. The log-likelihood function of $f(\varepsilon)$ for a sample of N producers is as follows.

$$\ln L = consant - N\ln\sigma + \sum_{i=1}^{N}\ln\Phi(-\frac{\varepsilon_i\lambda}{\sigma}) - \frac{1}{2\sigma^2}\sum_{i=1}^{I}\varepsilon_i^2 \tag{3.8}$$

One can estimate (3.8) by using maximum likelihood estimation method. Maximizing a log-likelihood function usually involves taking first-derivatives with respect to the unknown parameters and setting them to zero. Since the first-order conditions of equation (3.8) are nonlinear and cannot be solved analytically for the parameters, an iterative optimization procedure is used. This procedure involves selecting starting values for the unknown parameters and systematically updating them until the values that maximize the log-likelihood function are found.

After the iterative optimization procedure, the log likelihood function in equation (3.8) can be maximized with respect to the parameters to obtain maximum likelihood estimates of all parameters. The conditional distribution $f(u \mid \varepsilon)$ is given by

$$f(u \mid \varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi}\sigma_*}\exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\} \Big/ \left[1-\Phi(-\frac{\mu_*}{\sigma_*})\right] \tag{3.9}$$

Since $f(u \mid \varepsilon)$ is distributed as $N^+(\mu_*, \sigma_*^2)$, either the mean or the mode of this distribution can serve as a point estimator for u_i. They are given by

$$E(u_i \mid \varepsilon_i) = \mu_{*_i} + \sigma_*\left[\frac{\phi(-\mu_{*_i}/\sigma_*)}{1-\Phi(-\mu_{*_i}/\sigma_*)}\right] = \sigma_*\left[\frac{\phi(\varepsilon_i\lambda/\sigma)}{1-\Phi(\varepsilon_i\lambda/\sigma)} - (\frac{\varepsilon_i\lambda}{\sigma})\right] \tag{3.10}$$

Once point estimates of the u_i are obtained, estimates of the technical efficiency of each producer can be obtained from

$$TE_i = \exp\left\{-\hat{u}_i\right\} \tag{3.11}$$

Where $\hat{u}_i$ is $E(u_i \mid \varepsilon_i)$.

3.4 Stochastic Output distance function

This study attempts to investigate the effects of accidents on the technical efficiency of bus transit. Same issue has been addressed by Lin and Lan (2006) using DEA method. In practice, however, if measurement error, missing variables, weather, etc. are likely to play a significant role, then the imposition that all deviations from the frontier are due to inefficiency, may be a brave assumption (Coelli, 1995). Since the output of bus transit is deeply influenced by weather, traffic condition in service area, measurement error, to account the random noise, we thus try another method -- SFA.

Since there are two outputs, desirable and undesirable, in this study, a stochastic output distance function is adopted to accommodate multiple inputs and multiple outputs. The SFA method used in this study with its specified functional form are briefly narrated as follows.

We can specify stochastic output distance function (SODF) by adding symmetric error term v_i to the deterministic model shown in equation (3.1) and (3.2). The model becomes equation (3.12).

$$\ln(D_{oi} / z_i) = \alpha_0 + \alpha_1 \ln y_i^* + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + v_i,\ i = 1,2,\ldots,N \tag{3.12}$$

where z_i represents the undesirable output -- aggregated score for various accidents of the ith-firm, y_i is the desirable output -- vehicle-kilometers, and $y^* = y/z$; x_1 is the fleet size, x_2 is total amount of fuel consumed, x_3 is the number of employees, α_0, α_1, β_1, β_2, β_3 are the parameters to be estimated, N is the number of bus transit companies, and finally, v_i is an error term. Equation (3.12) can be rewritten as

$$\ln(D_{oi}) - \ln(z_i) = \alpha_0 + \alpha_1 \ln y_i^* + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + v_i,\ i = 1,2,\ldots,N \ ,$$

or

$$-\ln(z_i) = \alpha_0 + \alpha_1 \ln y_i^* + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + v_i - \ln(D_{oi}),\ i = 1,2,\ldots,N \quad (3.13)$$

Letting $\ln(D_{oi}) = u_i$, equation (3.13) is then identical to the typical stochastic production frontier model proposed by Aigner et al (1977) and Meeusen and van den Broeck (1977). In order to estimate u_i, one has to further impose a distribution form (e.g. half-normal, truncated-normal, gamma, etc.) onto the model. Half-normal distribution is specified in the current research, following Kumbhakar and Lovell (2000), assume that

(1) $v_i \sim iid\ N(0, \sigma_v^2)$;

(2) $u_i \sim iid\ N^+(0, \sigma_u^2)$;

Assumption (1) says that $v_i s$ are independently and identically distributed normal random variables with zero means and variances σ_v^2; Assumption (2) says that $u_i s$ are independently and identically distributed half-normal random variables which are truncated at zero and with parameter σ_u^2. Because $v_i s$ are independent of $u_i s$, one can estimate the parameters and u_i in equation (3.13) by maximum likelihood (ML) method.

Chapter 4 Case study

4.1 The data

In this thesis, Taipei bus transit is used as the case study. Currently there are in total 15 bus operators, all privately-owned, serving for over six-million people inhabited in Taipei metropolitan area. With 287 routes and 3,877 buses, these 15 transit operators provided 255,802 thousand vehicle-kilometers of transport services, carrying 616,105 thousand passenger-trips in 2006. Meanwhile, there were 669 cases of accident, causing 7 fatalities and 335 injuries in the same year. Notice that prior to December 31, 2003, Taipei Municipal Bus (TMB) was the only government-owned public operator and the other 14 firms were all private. Under Taipei City Government's policy, TMB has been successfully privatized, renamed as Metropolitan Bus Corporation (MBC), since January 1, 2004.

The data set is drawn from Annually Statistical Reports of Transportation in Taipei City published by the Department of Transportation, Taipei City Government. Bus firms with incomplete data and observations with problematic or unreasonable data are deleted. As such, five firms have been excluded from our empirical analysis because of their relatively small scale of market share. The exclusion of bus companies with erroneous seems reasonable since the market shares of remaining ten companies in terms of vehicle-kilometers and revenue are both over 92 percent. To avoid low degree of freedom, a panel data for the remaining ten firms is drawn over a five-year horizon from 2001 to 2006. Totally, there are 60 observations (DMUs) in my sample.

As these ten bus firms adopt similar diesel-engine vehicles, their related noise and pollutants can be assumed indifferent. However, their related accidents and severity are quite different, thus the accident rate and aggregated score for various accidents are both used as the undesirable outputs for the empirical analysis. The accident rate considers accidents on an average manner, however, it cannot account for the severity of various accidents. The aggregated accident score converts fatality, major injure, minor injure, and property loss only into proper weighted score by considering different degrees of accident severity. Following Satty's 1 to 9 scales are used for the scores of various accidents to denote the relative importance of each criterion. The weights of various accidents are assigned using number of 1, 3,7 and 9, and Table 4.1 shows the weights.

Following previous studies, the current research selects vehicle-kilometers as the desirable output, y, and assume that the output is produced by three inputs: (1) fleet size x_1, measured by the number of vehicles; (2) fuel, x_2, measured by the total liter of fuel consumed; and (3) labor, x_3, measured by the number of employees. The undesirable output, z is measured by the number of accidents per million passengers and the yearly aggregated score of various accidents.

Table 4.2 summarizes the descriptive statistics of the 60 observations, from which one can see that the desirable output varies from 8,538 to 48,202 thousand vehicle-kilometers, with average and standard deviation 22,873 and 10,562 thousand vehicle-kilometers, respectively. Firm 1 is the largest company in terms of both fleet size and number of employees in the industry. On the other hand, the accident rate ranges from 0.15 to 7.76 accidents per million passengers, while the aggregated score of accidents ranges from 5 to 301 with mean and standard deviation values of 96.58 and 64.61, respectively. Figure 4.1 and Figure 4.2 show the average accident rate and the average aggregated accident score of each firm. One can easily see that firm 7 and firm 1 produce the largest accident rate and accident score, with values of 3.1 and 172, respectively, while firm 8 produces the least accident rate and score, with an average value of 0.5 and 29.3. It is worthy to note that both of the average accident rate and the average accident score have exhibited increasing trend over the sampling year. That is, the average accident rate increased form 1.6 by year of 2002 to 2.1 by the year of 2006, while the average accident score increased from 66 by the year of 2001 to 139 by the year of 2006, as shown in Figure 4.3 and 4.4.

Table 4.1 Aggregated score of various accidents

Accident severity	Score
Fatalities	9
Serious injuries	7
Minor injuries	3
Property damage only	1

Table 4.2 Descriptive statistics of the samples

Variable	Max.	Min.	Mean	Std. Dev.
Vehicle-km (y) (10^3)	48,202	8,538	22,873	10,562
Vehicle (x1)	1,006	140	364	193.26
Fuel (x2)	66,087,116	4,017,669	11,961,825	9,099,859
Labor (x3)	2,118	159	665.02	402.91
Accident rate (z1)	7.76	0.15	1.94	1.09
Aggregated accident score (z2)	301	5	96.58	64.61

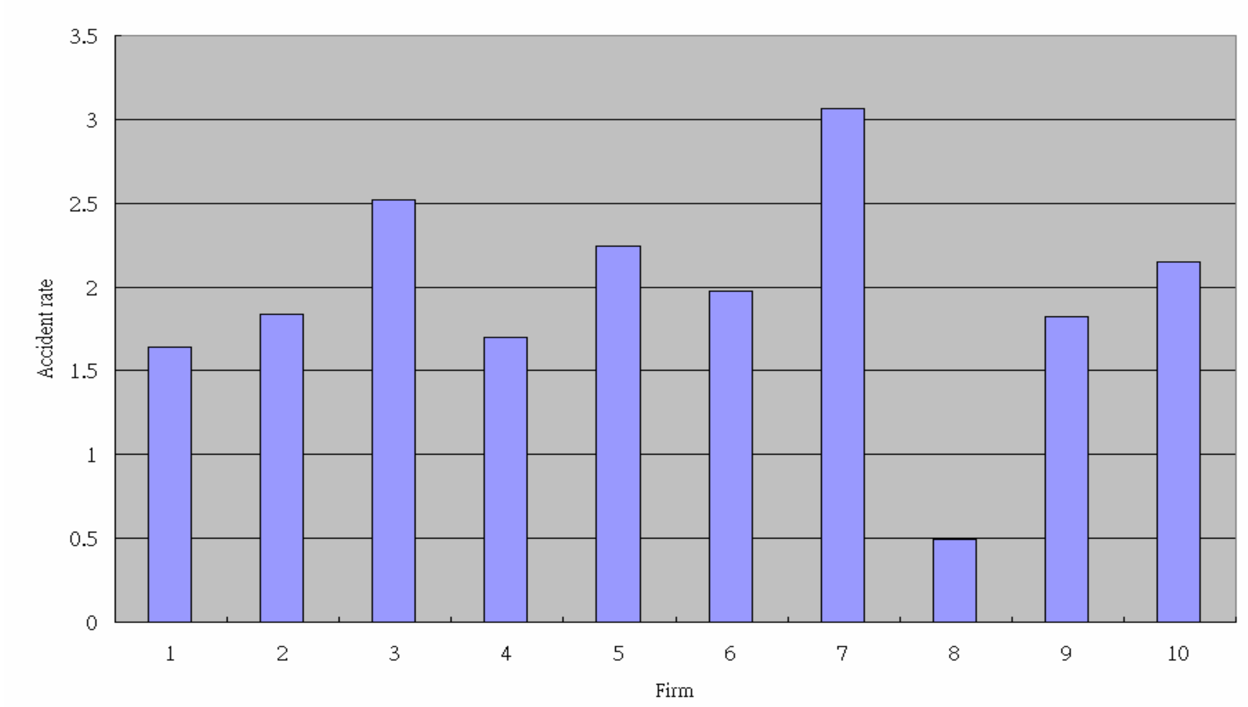

Figure 4.1 The average accident rate by the firm.

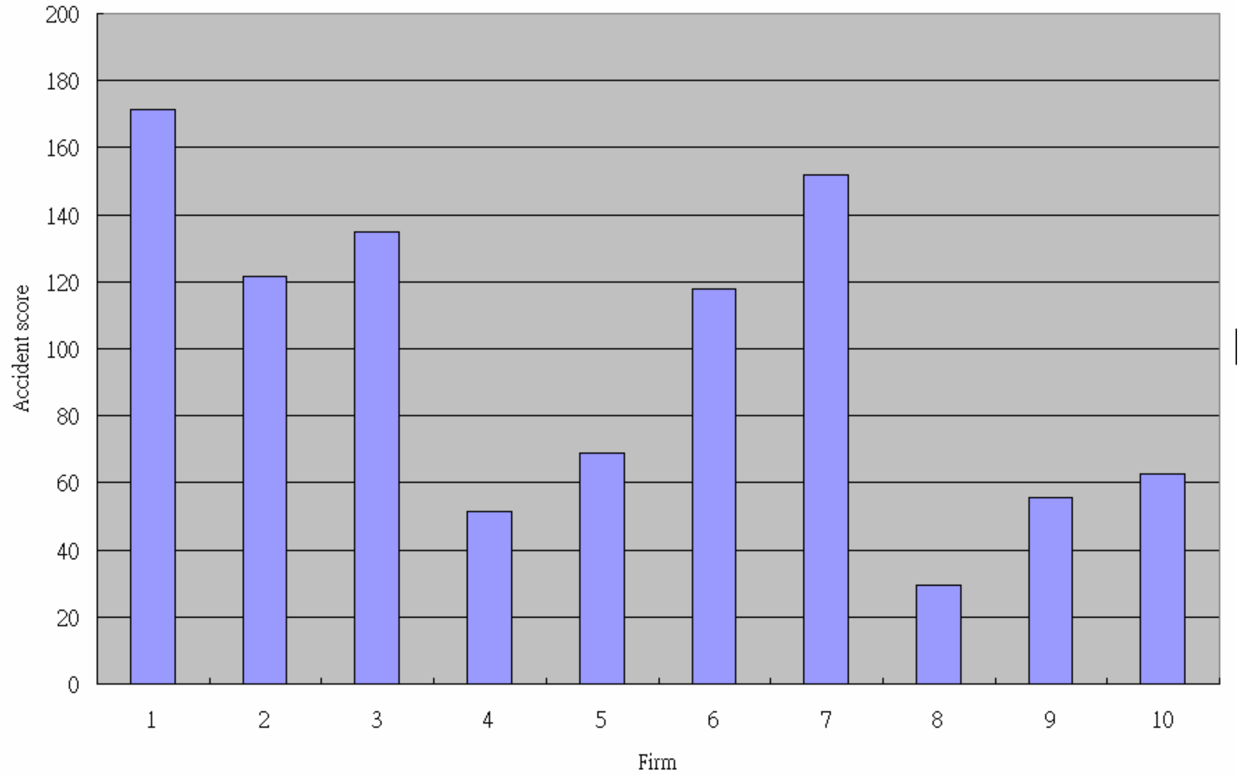

Figure 4.2 The average accident score by the firm.

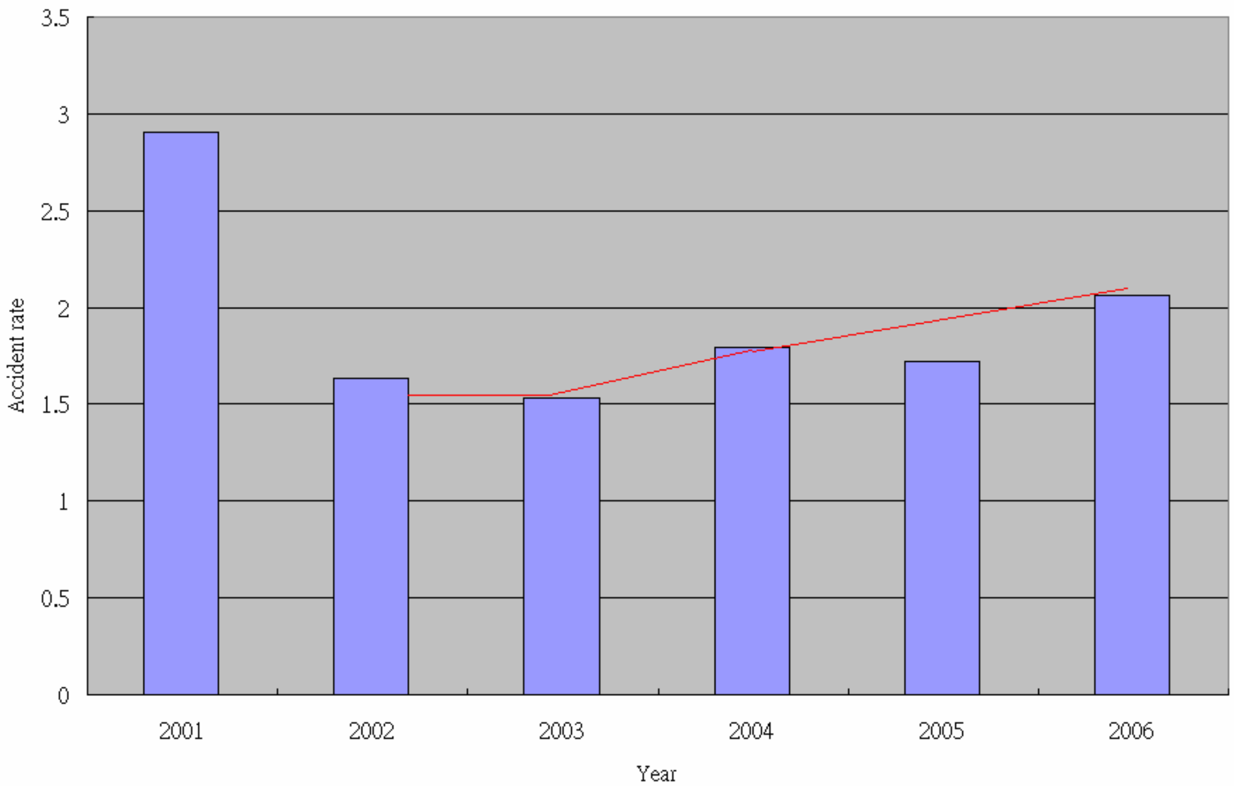

Figure 4.3 The trend of average accident rate by the year

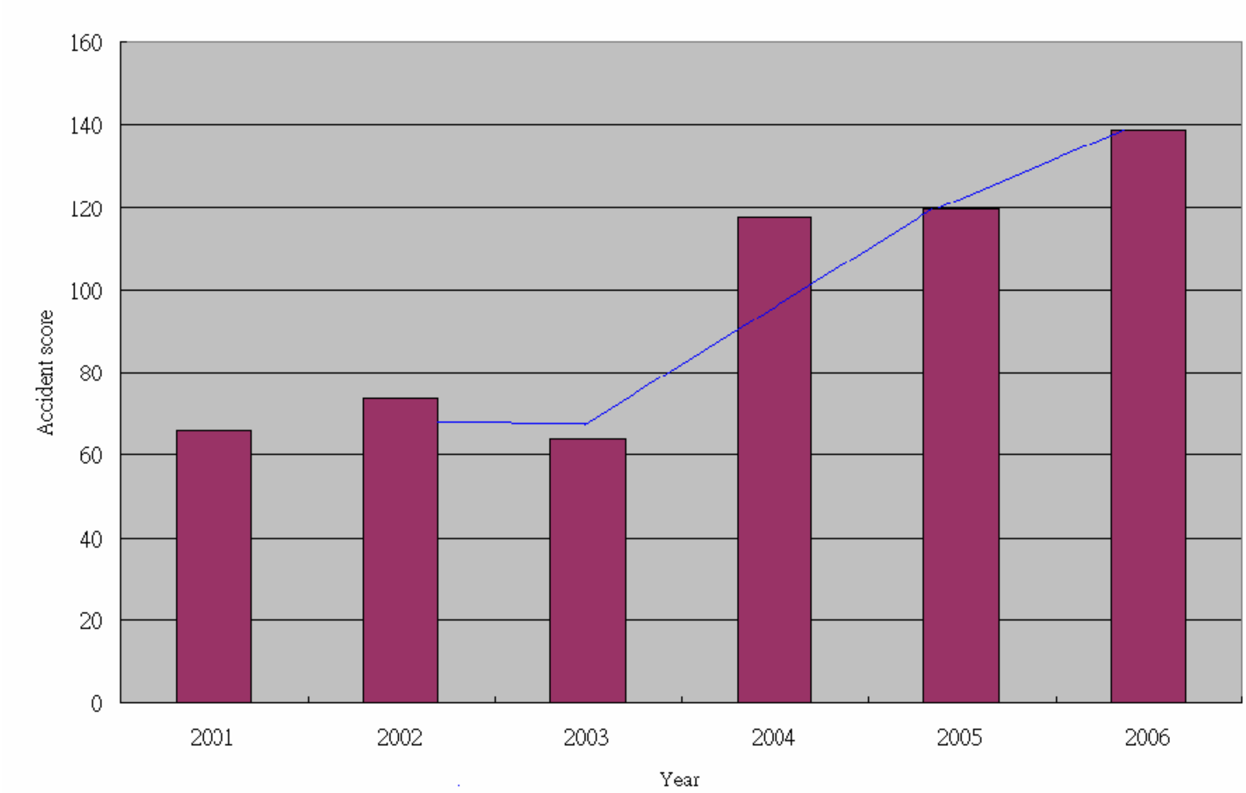

Figure 4.4 The trend of average aggregated accident score by the year

4.2 Empirical results

4.2.1 Without consideration of accidents

We first try to estimate the efficiency scores without consideration of the undesirable output, accidents. A standard stochastic production function without considering accidents is applied first in the empirical study, in order to check for the relationships between x_i and y and the significance of x_i. A Cobb-Douglas stochastic production function is specified as equation (4.1):

$$\ln y = \lambda_0 + \lambda_1 x_1 + \lambda_2 x_2 + \lambda_3 x_3 + v_i - u_i \qquad (4.1)$$

Where y represents the desirable output, vehicle-kilometers, and x_1, x_2 and x_3 are fleet size, fuel consumption and employees, respectively.

Table 4.3 Estimated results of standard stochastic production function

standard stochastic production function (Without consideration of accident)				
Parameter	Variable	Coefficient	Std. Dev.	t-ratio
λ_0	Constant	-5.8857	0.5279	-11.1475*
λ_1	$\ln x_1$	0.1448	0.0698	2.0729*
λ_2	$\ln x_2$	0.7504	0.0716	10.4850*
λ_3	$\ln x_3$	0.0428	0.0216	1.9795*
σ_v^2	Variance	0.0122	0.0023	3.3239*
γ	Variance ratio	0.9809	0.0441	22.2528*

** denotes statistically significant at the two-tailed 10 percent of significance level*

The estimated results are indicated in Table 4.3, from which one can see that all of the parameters (α, β,) are statistically significant at the 10 percent of significance level, except for λ_1. The results reveal that the output is significantly influenced by the amount of fuel consumed, and the number of employees. The variance α_v^2 and variance ratio γ are also significant, supporting that the stochastic production model is appropriate, and there exists significant inefficiency effect.

From Table 4.3, the stochastic production function can be expressed as equation (4.2):

$$\ln y = -5.8857 + 0.1448x_1 + 0.7504x_2 + 0.0428x_3 + v_i - u_i \tag{4.2}$$

According to the economic axiom, the partial derivatives of output y with respect to input variable x must be greater than or equal to zero. It means that additional units of an input do not decrease output. As one can see from equation (4.2), the positive value of x_1, x_2, and x_3, have ensured the monotonicity. It means that the output variable is positively influenced by the three inputs: vehicles, fuel, and labor.

4.2.2 With consideration of accident rate

To investigate if the productive efficiency of a bus transit is significantly influenced by accidents, the accident rate is involved in the efficiency measurement. An evaluation of the efficiency scores without distinguishing the accident severity is provided in this section, where the accident rate, z_1, is used as solely the undesirable output. The accident rate is measured by the number of accidents per million passengers. A translog and a Cobb-Douglas functional form are both specified in order to see which functional form is more appropriate in this empirical study.

---Translog functional form

The translog functional form, used in many previous papers, differs from the Cobb-Douglas by the addition of the squared and cross-product terms. These additional terms allow for a quite general specification of the production surface. Thus we first specify the standard flexible translog functional form in our stochastic output distance model, as shown in equation (4.3).

$$\begin{aligned}
-\ln(z_{1i}) &= \alpha_0 + \alpha_1 \ln y_i^* + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \delta_1 \ln y_i^{*2} + \delta_2 \ln x_{1i}^2 + \delta_3 \ln x_{2i}^2 + \delta_4 \ln x_{3i}^2 \\
&+ \xi_1 \ln y_i^* \ln x_{1i} + \xi_2 \ln y_i^* \ln x_{2i} + \xi_3 \ln y_i^* \ln x_{3i} + \xi_4 \ln x_{1i} \ln x_{2i} + \xi_5 \ln x_{1i} \ln x_{3i} + \xi_6 \ln x_{2i} \ln x_{3i} \\
&+ v_i - \ln(D_{oi}),\ i = 1,2,\dots,N
\end{aligned} \tag{4.3}$$

We regress $-ln(z_1)$on y^*, x_i , and also the squared and cross-product terms by using maximum likelihood estimation method. The computer software package, FRONTIER 4.1, developed by Coelli (1996), is applied to estimate the parameters and technical efficiency. Table 4.4 shows the estimated results of translog production form. The significances of parameters and monotonicity are checked below, in order to see if the model is well-behaved without violating the monotonicity.

Table 4.4 Estimating results of translog form

Parameters	Variables	Coefficient	Std. Dev	t-ratio
α_0	Constant	-12.0811	9.2063	-1.3122
α_1	$\ln y^*$	2.5955	0.7583	3.4228*
β_1	$\ln x_1$	5.6787	1.9945	2.8471*
β_2	$\ln x_2$	-0.5078	1.3887	-0.3657
β_3	$\ln x_3$	-5.0235	2.3625	-2.1264*
δ_1	$\ln y^{*2}$	-0.0034	0.0284	-0.1188
δ_2	$\ln x_1^2$	2.0071	0.5294	3.7908*
δ_3	$\ln x_2^2$	0.3978	0.0855	4.6521*
δ_4	$\ln x_3^2$	-0.8795	0.2642	-3.3291*
ξ_1	$\ln x_1 \ln x_2$	-1.1438	0.2964	-3.8586*
ξ_2	$\ln x_1 \ln x_3$	0.0097	0.2569	0.0379
ξ_3	$\ln x_2 \ln x_3$	0.4916	0.2873	1.7110*
ξ_4	$\ln y^* \ln x_1$	-0.1750	0.1142	-1.5329
ξ_5	$\ln y^* \ln x_2$	-0.2057	0.0904	-2.27438*
ξ_6	$\ln y^* \ln x_3$	0.3573	0.1262	2.8319*
σ_v^2	Variance	0.0043	0.0031	1.3652
γ	Variance ratio	0.7541	0.4981	1.5139

* denotes statistically significant at the two-tailed 10 percent of significance level

From Table 4.4, we find that most of the parameters ($\alpha, \beta, \delta, \xi$) are statistically significant at the 10 percent of significance level, with some exceptions of the parameters for fuel consumption (β_2) and the cross-product terms. The σ_v^2 here is not significant, either, indicating that the stochastic model is not appropriate.

Moreover, the results indicate that some of the estimated results in the translog stochastic output distance model violate the assumption of monotonicity. From Table 4.4, the stochastic output distance frontier can be expressed in equation (4.4) as follows:

$$\begin{aligned}\ln D_o - \ln(z) = &-12.0881 + 2.5955 \ln y - 2.5955 \ln z + 5.6787 \ln x_1 - 0.5078 \ln x_2 - 5.0235 \ln x_3 \\ &- 0.0034 \ln y^2 + 2.0071 \ln x_1^2 + 0.3978 \ln x_2^2 - 0.8795 \ln x_3^2 - 1.1438 \ln y \ln x_1 + 0.0097 \ln y \ln x_2 \\ &+ 0.4916 \ln y \ln x_3 - 0.1750 \ln x_1 \ln x_2 - 0.2057 \ln x_1 \ln x_3 + 0.3573 \ln x_2 \ln x_3 + v_i ,\end{aligned}$$

or,

$$\begin{aligned}\ln D_o - \ln(z) = &-12.0881 + 2.5955 \ln y - 1.5955 \ln z + 5.6787 \ln x_1 - 0.5078 \ln x_2 - 5.0235 \ln x_3 \\ &- 0.0034 \ln y^2 + 2.0071 \ln x_1^2 + 0.3978 \ln x_2^2 - 0.8795 \ln x_3^2 - 1.1438 \ln y \ln x_1 + 0.0097 \ln y \ln x_2 \\ &+ 0.4916 \ln y \ln x_3 - 0.1750 \ln x_1 \ln x_2 - 0.2057 \ln x_1 \ln x_3 + 0.3573 \ln x_2 \ln x_3 + v_i ,\end{aligned} \tag{4.4}$$

The condition that $D_o(x, y)$ is non-decreasing in y means that the partial derivatives of D_o with respect to y must be greater than or equal to zero. Another condition that $D_o(x, y)$ is non-increasing in x means that the partial derivatives of D_o with respect to x must be less than or equal to zero. As one can see from equation (4.4), the positive value of y and negative values of x_2 and x_3 have ensured the monotonicity, but the positive value of x_1 obviously violates the monotonicity assumption. It means that the output distance function, D_o , is positively influenced by the input quantities, x_1 , and this is unreasonable in the production process. Furthermore, α_v^2 is not significant, indicating that the stochastic model is not appropriate. Consequently, a Cobb-Douglas output distance function is specified in our stochastic frontier model.

--Log-linear functional form

A log-linear stochastic output distance function model with consideration of undesirable output as shown in equation (3.7) is specified to measure the technical efficiency of Taipei bus transit. We regress $-ln(z_1)$ on y^* and x_i by using maximum likelihood estimation method, and FRONTIER 4.1 is also applied to estimate the parameters and technical efficiency.

Table 4.5 shows the estimated results of the log-linear distance function with consideration of accidents. Based on the estimated results and extended analysis, some important testings are summarized as follows.

Table 4.5 Estimating results of Log-linear function

Parameter	Variable	Coefficient	Std. Dev.	t-ratio
α_0	Constant	-3.9939	0.8857	4.5092*
α_1	lny*	1.0019	0.0293	34.2128*
β_1	lnx1	-0.3518	0.1260	-2.7920*
β_2	lnx2	-0.3552	0.1260	-2.7920*
β_3	lnx3	-0.1789	0.0991	-1.8053*
σ_v^2	Variance	0.0367	0.0085	4.3249*
γ	Variance ratio	0.9957	0.0022	46.3057*
μ	Mean	0.9707	0.1063	9.1344*

** denotes statistically significant at the two-tailed 10 percent of significance level*

Table 4.5 indicates that all of the parameters (α, β,) are statistically significant at the 10 percent of significance level. The results reveal that the technical efficiency is influenced by the desirable output, the number of vehicles, the amount of fuel consumed, the number of employees, and the accident rate significantly. Furthermore, α_v^2 is significant, supporting that the stochastic model is appropriate, rather than a deterministic one.

From Table 4.5, the stochastic output distance frontier can further be expressed in equation (4.5) as follows:

$$\ln D_0 - \ln z = -3.9939 + 1.0019\ln y - 1.0019\ln z - 0.3518\ln x_1 - 0.3552\ln x_2 - 0.1789\ln x_3 + v_i,$$

or,

$$\ln D_0 - \ln z = -3.9939 + 1.0019\ln y - 0.0019\ln z - 0.3518\ln x_1 - 0.3552\ln x_2 - 0.1789\ln x_3 + v_i, \qquad (4.5)$$

The positive value of y and negative values of x_1, x_2, and x_3 in equation (4.5) , have ensured the global monotonicity. In other words, the output distance function, D_o, is positively influenced by the output level and negatively affected by the input quantities. As for the coefficient of the undesirable output, the negative value shows that the accident rate has negative effect on technical efficiency, although the value is quite small (0.0019), indicating that higher accident rate would lower the technical efficiency, as we expected.

4.2.3 With consideration of aggregated accident score

We already know that accident rate has significantly effects on technical efficiency. However, choosing the accident rate as the undesirable output cannot distinguish the accident severity. The more sever the accident is, the more the efficiency is affected. In order to distinguish from various accidents, an aggregated accident score is adopted. The weights of various accidents are shown in Table 4.1.

As shown in the last section, we know that a translog functional form will violate the monotonicity assumption, thus the log-linear form is adopted to measure the technical efficiency with consideration of aggregated accident score.

Table 4.6 shows the estimated results of the log-linear distance function with consideration of aggregated accident score. Based on the estimated results and extended analysis, some important testing and checking are summarized as follows.

Table 4.6 Estimating results of aggregated accident score

Parameter	Variable	Coefficient	Std. Dev.	t-ratio
α_0	Constant	-10.7719	0.1265	-85.1128*
α_1	ln$y$*	1.0055	0.0122	82.10393*
β_1	lnx_1	-0.1751	0.0319	-5.4926*
β_2	lnx_2	-0.7088	0.0409	-17.2912*
β_3	lnx_3	-0.0555	0.0376	1.7461*
σ_v^2	Variance	0.0131	0.0022	5.9941*
γ	Variance ratio	-0.9925	0.0118	-83.5226*

** denotes statistically significant at the two-tailed 10 percent of significance level*

Checking for significance of parameters

From Table 4.6, it indicates that all of the parameters (α, β) are statistically significant at the 10 percent of significance level. The results reveal that the technical efficiency is influenced by the desirable output, the inputs and the undesirable output, aggregated accident scores, significantly. Furthermore, σ_v^2 is significant, supporting that the stochastic model is appropriate, rather than a deterministic one.

Testing for significance of inefficiency

Since we estimate parameters and efficiency by maximum likelihood estimation method, we thus conduct a generalized likelihood ratio test for the null hypothesis H0: $\sigma_u^2 = 0$. It is found that LR = -2{ln [L (H0)]-ln [L (H1)]}= -2[763.9488-793.4448)]=29.496, which is greater than the 5 percent critical chi-square value of 5.138 (with number of restrictions = 2), hence we reject H_0, that is, $\sigma_u^2 \neq 0$, indicating that there exists significant inefficiency in the Taipei bus transit industry. Same result can be obtained from Table 4.5 since $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2) = 0.9925$, with t-ratio=83.5226, indicating that inefficiency effect (σ_u) is significantly different from zero.

Checking for monotonicity

From Table 4.5, the stochastic output distance frontier can further be expressed in equation (4.6) as follows:

$$\ln D_0 - \ln z_2 = -10.7719 + 1.0055 \ln y - 1.0055 \ln z - 0.1751 \ln x_1 - 0.7088 \ln x_2 - 0.0555 \ln x_3 + v_i,$$

or,

$$\ln D_0 - \ln z_2 = -10.7719 + 1.0055 \ln y - 0.0055 \ln z - 0.1751 \ln x_1 - 0.7088 \ln x_2 - 0.0555 \ln x_3 + v_i, \quad (4.6)$$

As one can see from equation (4.6), the positive value of y and negative values of x_1, x_2, and x_3, have ensured the global monotonicity. It means that the output distance function, D_o , is positively influenced by the output level and negatively affected by the input quantities. The negative coefficient of the undesirable output, z_2, shows that the aggregated score of accidents has negative effect on technical efficiency, indicating that higher accident rate would lower the technical efficiency, as we expected.

Chapter 5 Discussions

Based on the estimated results, some findings are summarized and discussed as follows. Table 5.1 indicates the evaluated technical efficiency for the ten bus firms with and without consideration of accidents over the six years. The distribution of technical efficiency scores estimated by stochastic distance function is reported in Table 5.2. Table 5.3 indicates the ranks of efficiency scores with and without consideration of accident.

5.1 Testing for shift of frontier and improvement of efficiency

Since our data set covers the years from 2001 to 2006, it thus needs to examine whether frontier shifts during this period. The test statistic of Kruskal-Wallis rank test is $H = [12/60(60+1)][412^2/10 + 330^2/10 + 305^2/10 + 291^2/10 + 243^2/10 + 249^2/10] - 3(60+1) = 6.31$, which is smaller than the 5 percent critical chi-square value of 11.070, indicating that the null hypothesis (technical changes do not occur during the observed period) cannot be rejected.

5.2 Testing for improvement of efficiency

To test whether the average efficiency of Taipei transit industry has improved, the Mann-Whitney U test method is applied. The test statistic U can be calculated by $U = N_1N_2 + {N_2(N_2+1)}/{2} - \sum R_2$, where N_1 and N_2 are numbers of samples and ΣR_2 is the larger sum of ranks . Five pairs of calculation (2001 and 2002, 2002 and 2003, 2003 and 2004, 2004 and 2005, 2005 and 2006) during the period from 2001 to 2006 are presented, and the test statistics U are 33, 42, 48, 46, and 48, respectively. Once the test statistic U have been calculated, one can thus test the null hypothesis that every two of these samples are from the same population. The z test statistic, $z = {U - \mu_r}/{\sigma_r}$, where, $\sigma_r = \sqrt{\frac{N_1N_2(N_1+N_2+1)}{12}}$ and $\mu_r = {N_1N_2}/{2}$. In the current case, one can easily get z = -1.28, -0.60, -0.15, -0.30, and -0.15, which are all smaller than the 10 percent critical z value of 1.645, hence we cannot reject H_0, indicating that there is no evidence to show that the average efficiency of Taipei bus transit has shifted during the period.

5.3 Comparing efficiency with and without consideration of accidents

For comparison, we also estimate technical efficiency by specifying a stochastic production function, which does not take undesirable output into account, and the results are also displayed in Table 5.1 and Table 5.2. The correlation coefficient of the technical efficiency scores estimated by two SFA models is 0.815, indicating that the technical efficiency measured by the model with consideration of accident has significantly differed from that measured by the model without taking accident into account.

In the case of without considering the undesirable output, on average, the technical efficiency of Taipei bus transit is 0.914 with standard deviation 0.060. The high average technical efficiency and low standard deviation indicate a high level of competition within the bus industry. The high average efficiency also shows that the observations are close to the best practice frontier (1.000), reflecting the fact that the production technology of Taipei bus transit service has been well developed due to strict periodical assessment (twice a year) by the City Government. Moreover, the average efficiency of Taipei transit industry has shifted from 0.876 in 2001 to 0.932 in 2006.

If we take into account the aggregated score of accidents, the mean efficiency score would be 0.911 with standard deviation 0.063. Similar to the case without consideration of accident rate, the average efficiency score has shifted from 0.875 in 2001 to 0.925 in 2006. Obviously, most observations are performing worse than those without considering the accident effects. For example, the mean efficiency of firm 4 and firm 8 have increased from 0.903 to 0.908 and from 0.914 to 0.918, separately. The main reason is that these two firms have produced much lower aggregated score of accidents (51.5 and 29.3) in comparison with the mean score (96.6) of the whole industry. Firm 1 and firm 3 are two opposite cases, since they produce relatively higher aggregated score of accidents (171.5 and 134.7) than the mean value, its performance with consideration of accident as becomes worse than that without consideration of accidents.

We can also compare the results of the two SFA models by comparing the ranks of efficiency scores. We rank all the efficiency scores of 10 firms in six years and try to find the differences of the two results. It is found that the rank of firm 8 increased from 47 to 43 in 2003. The reason is that firm 8 produced much lower aggregated accident score (22) than average, thus the rank of firm 8 improved when accident is taking into consideration. An opposite case is firm 10, since it produced much higher aggregated accident score (184) than the mean value in 2004, the rank of it worsened with consideration of accident.

Table 5.1 Technical efficiency scores

(a) without consideration of accident

Firm	2001	2002	2003	2004	2005	2006	Average
1	0.762	0.762	0.792	0.859	0.869	0.877	0.820
2	0.876	0.889	0.926	0.973	0.954	0.939	0.926
3	0.993	0.980	0.875	0.822	0.807	0.807	0.880
4	0.824	0.866	0.901	0.924	0.933	0.972	0.903
5	0.907	0.896	0.939	0.933	0.965	0.914	0.926
6	0.964	0.982	0.990	0.988	0.981	0.984	0.982
7	0.876	0.890	0.927	0.950	0.955	0.951	0.925
8	0.845	0.900	0.874	0.926	0.968	0.970	0.914
9	0.858	0.980	0.984	0.968	0.989	0.974	0.959
10	0.853	0.887	0.937	0.883	0.930	0.932	0.904
Average	0.876	0.903	0.914	0.923	0.935	0.932	0.914

(b) with consideration of accident							
Firm	2001	2002	2003	2004	2005	2006	Average
1	0.751	0.747	0.779	0.854	0.864	0.871	0.811
2	0.873	0.887	0.927	0.969	0.947	0.932	0.923
3	0.995	0.977	0.873	0.811	0.795	0.793	0.874
4	0.821	0.866	0.896	0.970	0.927	0.966	0.908
5	0.899	0.887	0.930	0.915	0.947	0.898	0.913
6	0.965	0.983	0.993	0.986	0.977	0.983	0.981
7	0.883	0.897	0.936	0.950	0.958	0.952	0.929
8	0.861	0.906	0.874	0.928	0.970	0.972	0.918
9	0.853	0.985	0.992	0.958	0.988	0.963	0.956
10	0.851	0.879	0.934	0.869	0.918	0.918	0.895
Average	0.875	0.901	0.913	0.921	0.929	0.925	0.911

Table 5.2 Distribution of efficiency scores (No. of DMUs = 60)

Efficiency score	Without consideration of accident rate	With consideration of accident rate
≧ 0.90	37 (62%)	34 (57%)
0.80~0.89	20 (33%)	21 (35%)
< 0.8	3 (5%)	5 (8%)
Min.	0.762	0.747
Max.	0.993	0.995
Mean	0.914	0.911
St. Dev.	0.060	0.063

Table 5.3 Ranks of efficiency scores

(a) ranks of efficiency scores (without consideration of accident)

Firm	2001	2002	2003	2004	2005	2006
1	59	60	58	50	48	43
2	45	40	31	12	20	23
3	1	10	46	55	56	57
4	54	49	36	33	27	13
5	35	38	24	26	17	34
6	18	7	2	4	8	5
7	44	39	30	22	19	21
8	53	37	47	32	16	14
9	51	9	6	15	3	11
10	52	41	25	42	29	28

(b) ranks of efficiency scores (with consideration of accident)

Firm	2001	2002	2003	2004	2005	2006
1	59	60	58	51	49	46
2	44	39	29	14	23	26
3	1	10	45	55	56	57
4	54	48	38	12	30	15
5	35	40	27	33	22	36
6	16	8	2	5	9	7
7	41	37	24	21	18	20
8	50	34	43	28	13	11
9	52	6	3	19	4	17
10	53	42	25	47	32	31

5.4 Checking for scale economy

Once the parameters of output distance function have been estimated, it is of interest to check scale economy for the Taipei bus transit industry. Taking the industry as a whole, the scale economy (ε) can be calculated from the equation of $\varepsilon = -\sum_{m=1}^{3} \partial \ln D_o / \partial \ln x_m$, and it can be obtained from every model in the current research. The scale elasticity (ε) of model 1 (without consideration of accidents) is 0.9380, while that of model 2 (with consideration of accident rate) and model 3 (with consideration of aggregate accident score) are equal to 0.8859 and 0.9394, all of them are less than one. It indicates that, in general, Taipei bus transit exhibits decreasing returns to scale. This finding is consistent with Lin and Lan (2006), who concluded that most (34 of 40, or 85%) of DMUs are scale inefficient and all exhibit decreasing returns to scale.

It is also interesting to investigate the relationship between desirable output and scale as well as technical efficiency and scale. Letting the sum of logarithm of inputs as proxy of scale, the scatter diagrams and the line of trend is plotted as indicated in Figure 5.1 and Figure 5.2. One can see from the two Figures, both slope of production curve (Fig. 5.1) and technical efficiency (Fig. 5.2) drop as scale index increased (larger than 21). These findings are consistent with neoclassical production function indicated in general economic textbooks. Based on the findings, it suggests that Taipei bus transit as a whole may need to downsize its scale so as to be more efficient, especially for those bus companies with scale index larger than 21.

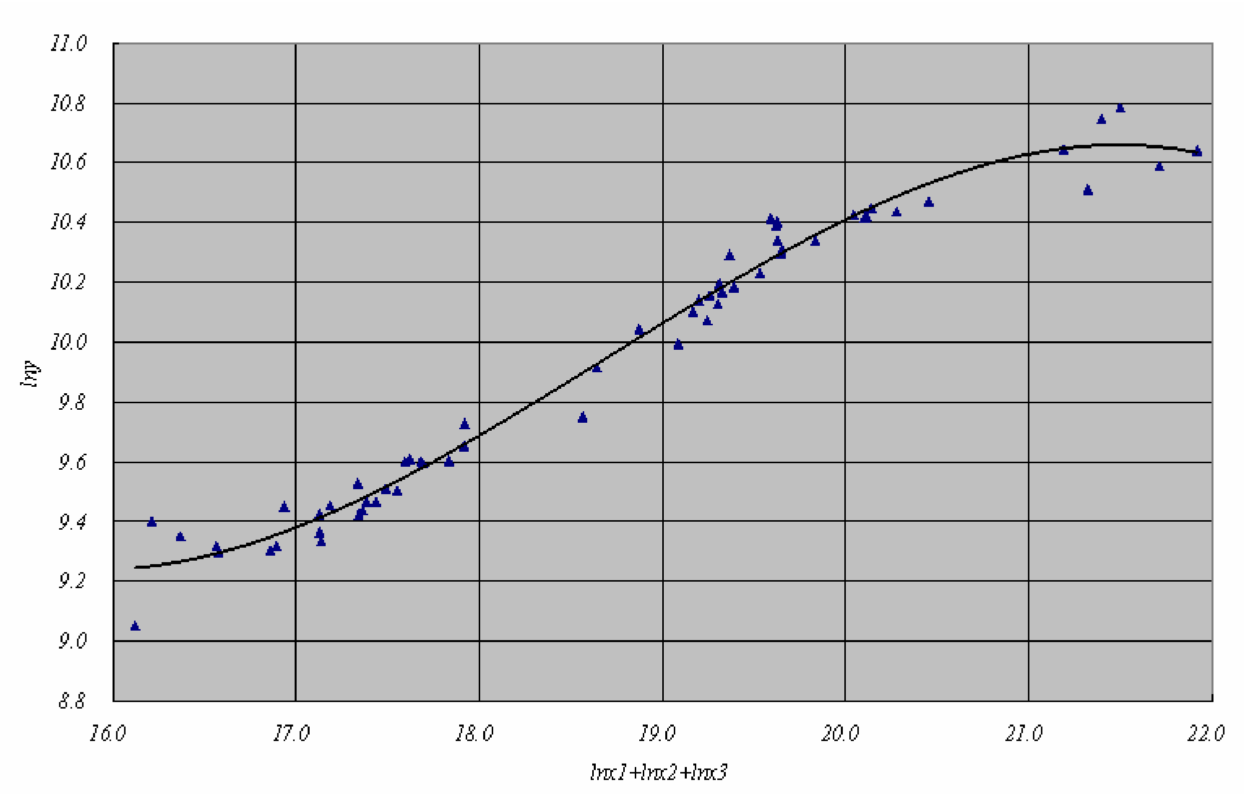

Figure 5.1 The relationship between output and the sum of inputs

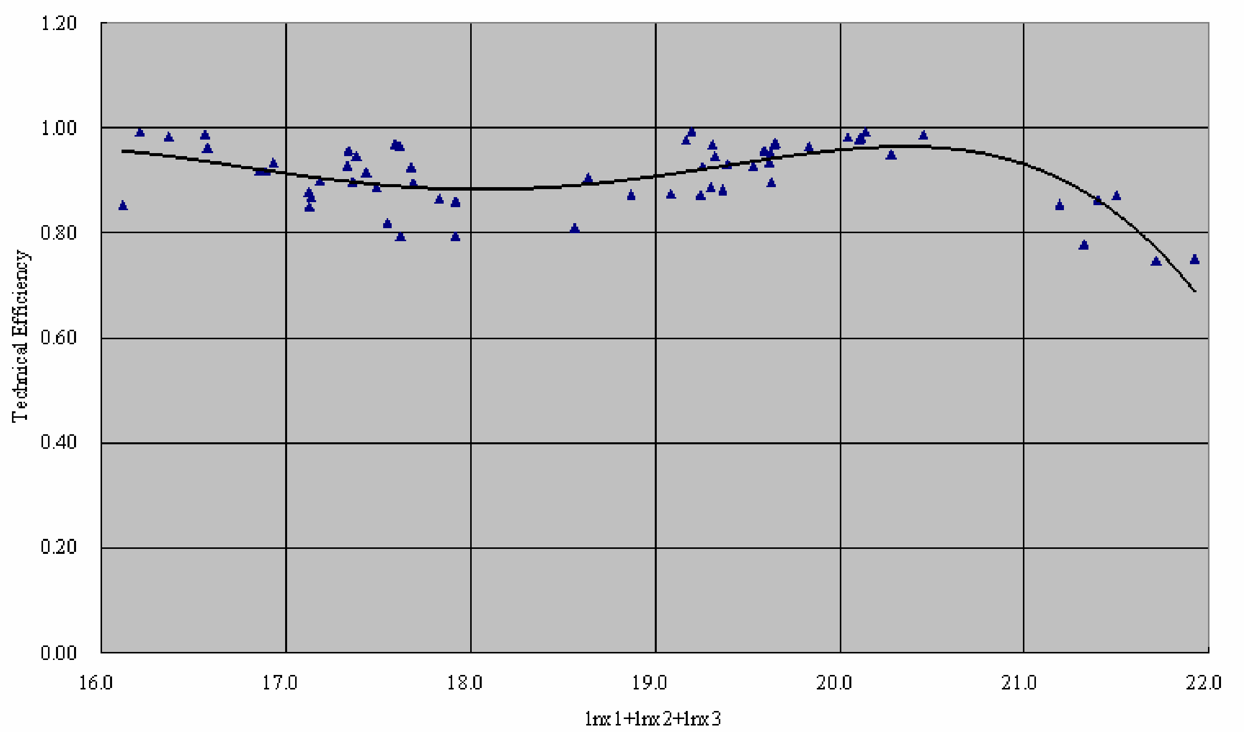

Figure 5.2 The relationship between technical efficiency and the sum of inputs

5.5 Comparing efficiency for firm 1 -- before and after privatization

Note that firm 1 was the only government-owned public operator (TMB), which has undergone a successful privatization as a private operator (MBC) since January 1, 2004. One is curious about whether the private MBC has performed more efficiently than it was before privatization (TMB). Table 5.1 shows that the privatized MBC (2004 to 2006) has higher efficiency than the public operator TMB (2001 to 2003), regardless of with or without consideration of accident.

5.6 Comparing the results with Taipei bus transit appraisal

Taipei bus transit appraisal, a convincing evaluation held by Department of Transportation, Taipei City Government, has been made twice a year since 1992. Four types of indexes are adopted to evaluate the service level of bus firms in this appraisal: (1) index of vehicles and stations, including the ratio of vehicle age, space of station and depot; (2) index of quantitative service level, including the rate of bus departing on schedule, the rate of bus passing the stop without stopping, and indexes of bus information facilities, environmental quality and accidents ; (3) index of qualitative service level, including service attitude of drivers, smoothly drives, comfort and noise, obedience of drivers on routes, bad habits of drivers while driving, and refusal to carry old or disabled passengers; (4) index of important transportation policies, including indexes of driving safety and management, driving service inspection, and serious violation. It is a guiding principle of policy for bus firms to provide better transit services.

This thesis has different point of view with Taipei bus transit service appraisal. This thesis measures the technical efficiency of a bus firm, while the service appraisal mainly assesses the service level from a different perspective. Thus only the index of accidents in the appraisal is compared with this thesis, in order to ensure the result of this thesis is consistent with reality.

Table 5.4 shows the ranks of our stochastic output distance model and the index of accidents in Taipei bus transit service appraisal each year. Firm 6 is the most efficient firm in our stochastic frontier model, and it also performs well in the appraisal. The reason is that firm 6 has produced great amount of vehicle-kilometers and needed less fuel assumption. In addition, it has produced less accidents than average, thus the ranks of firm 6 are relatively higher than others. Firm 3 performs badly in our model and the appraisal, since it produces relatively higher aggregated score of accidents than average. Firm 1 has produced the most vehicle-kilometers, but also needed the most employees, vehicles and fuel consumption; moreover, the aggregated accident score of firm 1 has increased after privatization. As a result, the ranks of firm 1 are relatively lower than before since 2004, both in our model and the appraisal. As for firm 8, it performs best in the appraisal but not in our model. The main reason is that it mainly emphasizes on the service quality, with less care on the vehicle-kilometers produced, and leads to its relatively lower efficiency score. However, with its extremely low score of accidents, the ranks of firm 8 have been getting better by years.

Table 5.4 Comparing results with Taipei bus transit appraisal

(a) Taipei bus transit service appraisal (index of accidents)

	2001 (1)	2001 (2)	2002 (1)	2002 (2)	2003 (1)	2003 (2)	2004 (1)	2004 (2)	2005 (1)	2005 (2)	2006 (1)	2006 (2)
1	3	2	3	6	2	4	9	6	9	6	7	3
2	8	3	8	2	6	2	2	8	6	8	5	8
3	9	7	7	5	10	10	6	3	10	9	10	2
4	10	8	2	3	9	6	8	2	2	2	1	4
5	4	5	6	4	3	7	10	5	8	10	6	9
6	5	6	5	10	5	5	5	4	5	4	3	5
7	7	10	9	8	8	8	4	7	7	3	4	6
8	1	1	1	1	1	1	1	1	1	1	2	1
9	6	4	4	7	7	3	3	9	3	5	9	10
10	2	9	10	9	4	9	7	10	4	7	8	7

(b) stochastic output distance model (with consideration of accident)						
1	1	10	10	9	9	9
2	6	6	6	3	5	6
3	2	3	9	10	10	10
4	10	9	7	2	7	3
5	4	7	5	7	6	8
6	3	2	1	1	2	1
7	5	5	3	5	4	5
8	7	4	8	6	3	2
9	8	1	2	4	1	4
10	9	8	4	8	8	7

5.7 Comparisons between DEA model and SFA methods

Lin and Lan (2007) adopted DEA method to measure technical efficiency with consideration of traffic accidents and also chose Taipei bus transit as their case study. To have a more complete point of view, a comparison of the results between Lin and Lan (2007) and this thesis is presented.

Table 5.6 shows the distribution of efficiency score of three SFA models in current research and DEA model, and Table 5.7 presents the ranks of DEA and SFA model (with consideration of aggregated accident score). One can see from Table 5.6 that the average efficiencies of both models are close to the best practice frontier, reflecting that the productive technology of Taipei bus transit service has been well developed. The high efficiency and low standard deviation also indicate that there exists high competition in Taipei bus transit. In addition, it is found that the DEA model has the highest mean efficiency score, while the SFA model with consideration of accident rate has the lowest mean efficiency. The mean efficiency of SFA model with consideration of aggregated accident score is just a little lower than that of the model without consideration of accident. One can find from equation 4.5 and 4.6 that the elasticity of stochastic output distance function associated with accident rate and aggregated accident score are quite small (-0.0019 and -0.0055), indicating that the effect of accident is slight. Thus, the result supports that taking aggregated accident score into account is more suitable than accident rate. Same result can be found in Figure 5.3.

In order to check if the results of the two models are related, Spearman rank correlation test is conducted. The correlation coefficient can be calculated by following equation.

$$r = 1 - \frac{6\sum D^2}{n(n^2-1)},$$

where,

r = Spearman rank correlation coefficient, it will always has the value between 1 and -1,

n = the number of items or individuals being ranked, in the case study, n= 60,

D = the difference between two items to be compared.

Thus, $r = 1 - \frac{6\sum D^2}{n(n^2-1)} = 1 - \frac{6 \cdot 18760}{60(60 \cdot 60 - 1)} = 1 - 0.521 = 0.479$

Once the Spearman rank correlation coefficient has been calculated, one can thus test the null hypothesis of no rank correlation ($H_0 : \rho_{sp} = 0$), the test statistic, $z = {r - \mu_r}/{\sigma_r}$, where, $\sigma_r = \sqrt{\frac{1}{n-1}}$. In the current case, one can easily get z = 3.679, which is greater than the 10 percent (two-tail) critical z value of 1.645, hence we reject H_0, that is, $\rho_{sp} \neq 0$, indicating that there is a significant rank correlation between the results of SFA and DEA.

From Table 5.7, it is found that firm 6 has well performed during the period, while firm 1 and firm 3 have had relatively bad performance. Also, the privatized MBC (2004 to 2006) has better ranks than the public operator TMB (2001 to 2003). All of these are consistent with the results of the SFA model in this thesis. However, DEA and SFA have different definition of frontier, the efficiency score of the two models are not exactly the same. DEA assumes all deviations from the frontier are due to inefficiency, while SFA considers random error, such as weather and luck. Some firms are measured to be technically efficient in DEA, but not in SFA, thus the ranks of these firms are distinct from each other, such as firm 7 and firm 9.

An observation of the relationship between outputs and inputs is provided to see which model is more suitable for Taipei bus transit industry. It is found that firm 7 has produced higher aggregated score of accidents (152) in comparison with the mean score (96.6) of the whole industry, and it has produced less vehicle-kilometers per unit fuel (1.98 vehicle-kilometers / fuel) than average (2.15 vehicle-kilometers / fuel). Consequently, it is not reasonable to give firm 7 the efficiency score of one. As for firm 9, it produced much less vehicle-kilometers per vehicle (60986 vehicle-kilometers / vehicle) than average (64136 vehicle-kilometers / vehicle) in 2001, and much more of that (77061 vehicle-kilometers / vehicle) than average in 2003. The ranks of firm 9 should be lower in 2001 and higher in 2003, but not all the same. The results indicate that SFA model may be more suitable than DEA model for Taipei bus transit industry.

Table 5.6 Distribution of efficiency score (DEA and SFA)

	SFA model			DEA model
Firm	Without accidents	Accident rate	Aggregated accident score	Aggregated accident score
1	0.820	0.788	0.811	0.942
2	0.926	0.913	0.923	0.945
3	0.880	0.849	0.874	0.930
4	0.903	0.863	0.908	0.926
5	0.926	0.838	0.913	0.955
6	0.982	0.956	0.981	0.992
7	0.925	0.975	0.929	0.998
8	0.914	0.897	0.918	0.935
9	0.959	0.916	0.956	1.000
10	0.904	0.839	0.895	0.912
mean	0.914	0.883	0.911	0.954
st. dev	0.044	0.058	0.046	0.050

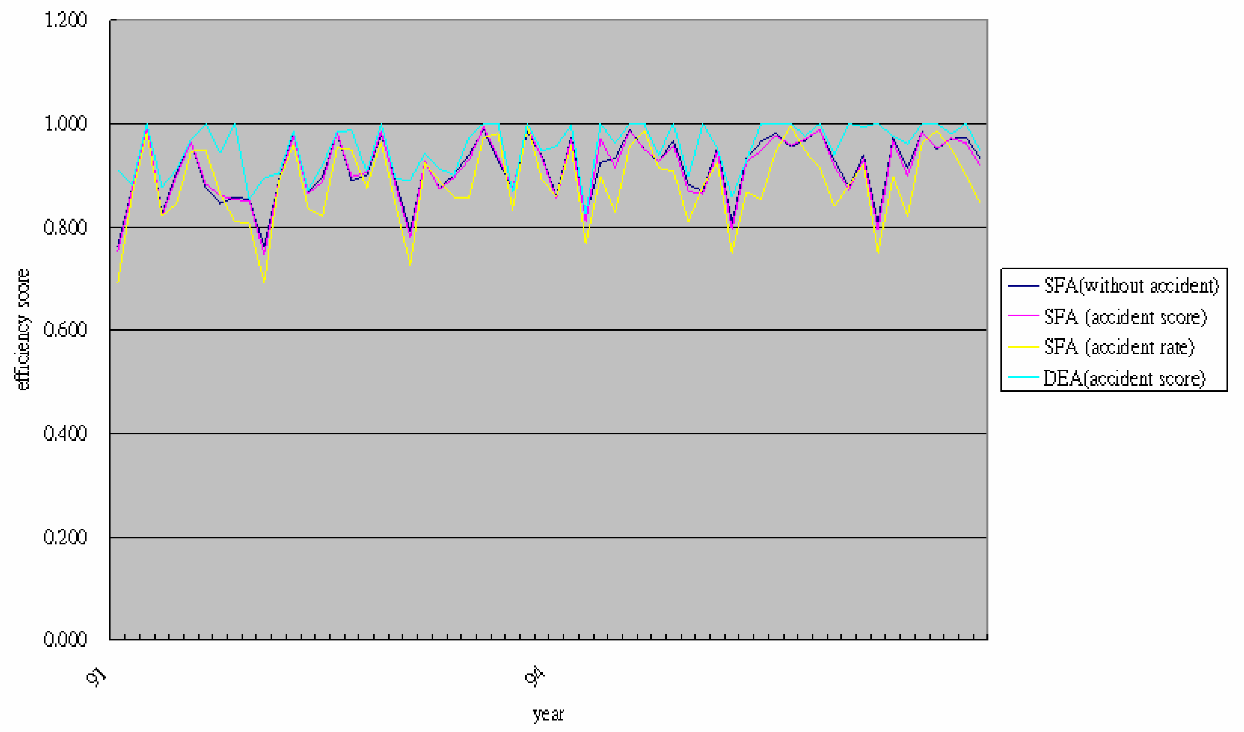

Figure 5.3 Scatter plot of efficiency score (DEA and SFA)

Table 5.7 The ranks of DEA and SFA model

Ranks of efficiency score (DEA)						
firm	2001	2002	2003	2004	2005	2006
1	46	51	53	34	1	1
2	54	48	39	22	35	23
3	1	25	44	60	58	1
4	55	56	49	1	42	29
5	45	43	30	32	1	33
6	31	26	1	1	1	1
7	1	24	1	1	1	1
8	38	47	57	40	28	27
9	1	1	1	1	1	1
10	59	52	37	50	41	36

Ranks of efficiency score (SFA)						
1	59	60	58	51	49	46
2	44	39	29	14	23	26
3	1	10	45	55	56	57
4	54	48	38	12	30	15
5	35	40	27	33	22	36
6	16	8	2	5	9	7
7	41	37	24	21	18	20
8	50	34	43	28	13	11
9	52	6	3	19	4	17
10	53	42	25	47	32	31

5.8 The determinants of efficiency

There are some factors that have affected the technical efficiency of Taipei bus transit. If these factors that have influenced technical efficiency can be found, it will be a lot helpful for the operations of Taipei bus transit. Thus some issues are discussed, including the ratio of aged vehicles of each firm, the length of exclusive lanes and the age of each firm in order to find out the factors and how they affect the technical efficiency. It is found that the effect on technical efficiency caused by the age of each firm is not significant, thus this factor is discarded in this discussion.

The ratio of aged vehicles differs from each firm year by year, and it may has brought some effects to the technical efficiency of bus firms. Here the ratio of aged vehicles is measured by the number of vehicles aged over 8 years, divided by the number of all vehicles of a firm. The correlation coefficient between technical efficiency and the ratio of vehicle age is -0.511. The negative value of the correlation coefficient indicates that the ratio of aged vehicles has negatively influenced the technical efficiency.

Exclusive lanes have been established in Taipei since 1996, and they have raised the travel volume of bus transit. The total lengths of exclusive lanes have been extended gradually, from

21.87 kilometers in 2001 to 28.4 kilometers in 2006. The correlation coefficient of the length of exclusive lanes and the average technical efficiency of bus firms is 0.768, indicating that the length of exclusive lanes has significantly influenced technical efficiency and there exists positive relationship between them.

We thus regress the ratio of aged vehicles and the length of exclusive lanes on efficiency score, and an ordinary least squares estimation is adopted to measure the significances and coefficients of these factors. The results of the regression model are shown in Table 5.8.

Table 5.8 The determinants of efficiency

Variable	Coefficient	Standard error	t-ratio
Constant	0.6910	0.0906	7.6255*
Ratio of aged vehicles	-0.2668	0.0582	-4.5819*
Length of exclusive lanes	0.0098	0.0036	2.6951*

* denotes statistically significant at the two-tailed 10 percent of significance level

The results indicate that both of the parameters are statistically significant at the 10 percent of significance level. It reveals that the technical efficiency is significantly influenced by the ratio of vehicle age and the length of bus lanes. The negative value of ratio of vehicle age indicates that higher ratio of old vehicles would lower the technical efficiency, thus operators should accelerate the elimination of retirements and the substitution of new ones. Vehicles aged over eight years should be eliminated and new vehicles should be substituted for the old ones. The positive value of the length of bus lanes indicates that more bus lanes upgrade the technical efficiency of bus firms. The main reason is that bus lanes upgrade the travel speed, and the vehicle-kilometers are increased as well, thus higher technical efficiency would be obtained. It thus suggests that Taipei government should keep establishing bus lanes so as to promote the technical efficiency of Taipei bus transit industry.

Chapter 6 Conclusions and Recommendations

6.1 Conclusion

In order to investigate the effects of various degrees of accidents on the technical efficiency of a bus transit, the current research incorporates both desirable and undesirable outputs into a stochastic frontier model. An aggregate score of accidents is chosen as the undesirable output and a log-linear stochastic output distance function is specified to estimate the technical efficiency for Taipei bus transit systems. The aggregate score of accident converts fatality, major injury, minor injury, and property loss only into proper weighted score, and thus can distinguish the severity of accidents. For comparison, the research also estimates the technical efficiency without consideration of accidents by specifying a standard production function frontier.

The findings indicate that the inefficiency term in the stochastic output distance function model is significant taking Taipei bus transit industry as a whole, which means that the industry needs to curtail inputs and expand outputs so as to improve their productive efficiency. In addition, the results also reveal that the productive efficiency with adjustment of either accident rate or weighted accident severity is somehow different from that measured without adjustment of accident effects.

Furthermore, the empirical results also show that both desirable output (vehicle-kms) and undesirable output (aggregate accident score) have affected the technical efficiency of Taipei bus transit. The elasticity of vehicle-kms (=1.0055) is greater than that of accident rate (=-0.0055). The managerial implication is that the bus firms can improve technical efficiency by increasing their desirable outputs and/or reducing the inputs and accidents, thus a bus company can promote its efficiency via safer operation. This thesis contributes to identify the effects of undesirable outputs in bus transit efficiency measurement, through which one can propose more practical strategies for improving the bus operating efficiency.

The case study shows that the elasticity of stochastic output distance function associated with fuel consumption (0.7088) is much greater than that associated with the other two inputs (fleet size=0.1751 and number of employees=0.0555), implying that energy consumption can be a dominant factor affecting the efficiency of Taipei bus transit. Thus, one promising strategy for improving the efficiency is to provide more bus exclusive lanes with preemption signals. Another strategy is perhaps to train the drivers to operate the vehicles more smoothly. As such, the energy consumption can be saved. Introduction of innovative fuel economy technologies, such as diesel- or gas-electricity hybrid, is of course also promising for the enhancement of bus transit technical efficiency.

Moreover, the case study of the current research shows that the privatized MBC (2004 to 2006) has higher efficiency than the public operator TMB (2001 to 2003), indicating that privatization has indeed improved the technical efficiency. In addition, the empirical results indicate that the scale economy for Taipei bus transit exhibits decreasing returns to scale, suggesting downsizing its scale should be able to enhance the technical efficiency. It is also found that the ratio of aged vehicles can deteriorate the technical efficiency, while the length of bus exclusive lane has positive contribution on productive efficiency. These findings suggest that new vehicles should be substituted for the old ones and that more bus exclusive lanes should be introduced so as to promote the technical efficiency of bus transit systems.

Comparisons between SFA and other methods are provided. It is found that the results are generally in common with Taipei bus transit appraisal, indicating that the results in this thesis do not violate the real situation. In addition, from the comparison between DEA and SFA methods, one can see that SFA method is better-behaved than DEA in Taipei bus transit industry. This result indicates that random error (such as traffic jam, caused by accidents or malfunction of traffic lights) has significant influence on the efficiency of bus transit, thus SFA may be more suitable than DEA when measuring bus efficiency. Also, the result support that aggregated accident score is more appropriate to be the undesirable output than accident rate, as we expected.

6.2 Recommendations

The remaining issue to be resolved in the future study is of four aspects. First, this thesis uses accident rate and aggregate score of accidents as the undesirable outputs for bus transit. In fact, there are other undesirable outputs, such as complaints from passengers, noise and pollutants, which may also influence the technical efficiency of bus operation. It deserves further exploration in the future study.

Second, the case study shows that translog functional form is not suitable for measuring the efficiency of Taipei bus transit, thus a log-linear stochastic output distance function is specified in the current research. However, a log-linear functional form may not be general enough for the production surface. Other functional form may be needed to further investigate, in order to have a more approximate frontier for bus transit.

Third, this thesis concludes that the ratio of aged vehicles and the length of exclusive lanes are two external factors which influence the efficiency. In fact, this may not be enough to explain the determinants of efficiency. In other words, the technical efficiency may be influenced by some other external factors, thus it deserves to further investigate the efficiency by taking into account more determinants.

Finally, this research measures the efficiency by considering only one kind of vehicle, in fact, apart from the city bus; there are still mini buses in Taipei bus transit systems. Thus, the one of the potential avenue for future study is that it deserves further investigation by dividing the vehicle into two categories: city bus and mini bus when measuring the efficiency of Taipei bus transit industry if the data is available.

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