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While producing the desirable outputs (transport services), a bus transit occasionally also produces accidents, which may lead to fatalities, serious injuries, slight injuries and/or property losses. As such, without explicitly taking into account the negative effects of accidents on the outputs when measuring efficiency for bus transit, the interpretation of results could be misleading. To be more rational, this article proposes a stochastic production frontier model that incorporates the effects of accidents into the measurement. A case study with 10 Taipei bus transit carriers over 2001–2006 is carried out. The results show that the ranking of technical efficiency with consideration of accidents has significantly differed from that without accounting for accidents. The managerial implications suggest that bus carriers can level up their productive efficiency not only by means of decreasing the inputs and/or increasing the desirable outputs, but also by way of ameliorating their safety records.

Keywords: accidents; bus transit efficiency; stochastic frontier analysis

1. Introduction

While producing the desirable outputs, namely transport services, a bus carrier in practice may also accompany with undesirable outputs – traffic accidents, which could cause a substantial loss of properties or lives. As the accidents are never freely disposable, without explicitly taking into account the negative effects of accidents on the outputs when measuring efficiency for bus transit, the interpretation of results could be misleading. In case that an accident is involved, the driver must stop the bus immediately to look over the likely damages, injuries, or fatalities and to wait for the police to complete the *in situ* accident report. Whether or not the accident eventually causes any significant compensation, the carrier is deemed to lose its production efficiency to some extent.

Previous literature dealing with undesirable outputs can be classified into two categories: parametric and non-parametric approaches. In treating the undesirable outputs, the undesirable output variable is normally incorporated into the production model either as another detrimental input or as a weak disposable bad output. Most relevant works were found in the agricultural and environmental fields. For instance, Pittman (1983) was perhaps the pioneer who treated desirable outputs and undesirable outputs (pollution) in measuring the efficiency of the paper manufacturing industry.

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Henceforward, some researchers have recognised that it is necessary to incorporate bad outputs into the technical and economic efficiency measurements. Färe *et al.* (1989) implemented the non-parametric efficiency analysis using the same dataset studied by Pittman (1983). Reinhard *et al.* (2000) treated undesirable outputs as environmentally detrimental inputs in a parametric stochastic frontier analysis (SFA) model to estimate comprehensive environmental efficiency for the Dutch dairy sector. However, little has been found in the transport field. Until recently, Weber and Weber (2004) started to measure the productivity and efficiency in the US trucking and warehousing industry with consideration of traffic fatalities. Yu and Fan (2006) employed the non-parametric method to measure the performance of Taiwan bus transits with consideration of traffic accidents. The authors explicitly assumed that accidents have negative effects on the bus transit efficiency in such a way that accidents can reduce the passenger-kilometres. One may argue that since accidents have been reflected in the reduction direction of transport services, penalising accidents would probably double-count the effects of such undesirable outputs on the overall efficiency measurement.

To rectify the deficiency of the early works that either ignored or double-counted the effects of accidents, this article proposes a stochastic production frontier model that incorporates the inefficiency effects of accidents into the bus transit efficiency measurement. The case of Taipei transit over 2001–2006 will be examined to gain deeper insight into how technical efficiency is affected by the accidents.

The remainder of this article is organised as follows: Section 2 briefly reviews some important studies on the efficiency measurement for bus transit with a parametric approach. Section 3 describes the proposed stochastic production frontier model that incorporates the accidents into relative efficiency measurement. Section 4 presents the Taipei bus transit case study and discusses the managerial implications. The concluding remarks and possible avenues for future study are addressed in the last section.

2. Literature review

Stochastic frontier analysis method, first proposed by Aigner *et al.* (1977) and by Meeusen and van den Broeck (1977), is perhaps the most commonly-used parametric approach to measuring the relative efficiency of different agencies within an industry. Since the SFA method accounts for noise and can easily conduct conventional tests of hypotheses, many researchers have employed SFA to estimate the technical efficiency or inefficiency of bus transits over the past decade. For instance, Sakano and Obeng (1995) examined the inefficiency of local transit firms by estimating a stochastic production function and two relative cost equations. From their results, technical and allocative inefficiencies are evaluated and related to input levels, outputs, and subsidies. Sakano *et al.* (1997) adopted SFA to investigate the causality between subsidies and inefficiency for US urban transit systems. Choosing vehicle-miles as the output and labour, total gallons of fuel, fleet size as the inputs, they concluded that subsidies have led to excess use of labour relative to capital and excess use of fuel relative to capital and labour. Jørgensen *et al.* (1997) estimated a stochastic cost frontier function for 170 Norwegian subsidised bus companies with two alternative assumptions regarding the distribution of the inefficiency. They found that inefficiency of the companies, which negotiated with the authorities over the subsidy amounts was slightly higher than that of the companies which faced a subsidy policy based on cost norms. de Jong and Cheung (1999) specified a stochastic Cobb–Douglas production frontier to estimate the technical efficiency of 19 urban and regional bus transits over 1994–1995 in the Netherlands. Number of staff, number of total seats and total energy cost were selected as inputs, and passenger-kilometre was chosen as output in their measurement model. Their results indicated that regional firms are in general more efficient than urban firms. Loizides and Giahalis (1995) utilised annual time series data and specified a Cobb–Douglas production and cost functional forms to estimate the technical efficiency for one regional bus company over 1970–1989 in Greece. They selected number of staff, capital, and other services as three input factors, and passenger-kilometres as the output, and found that average total factor productivity declined at 2% over the study period.

More recently, Dalen and Gómez-Lobo (2003) adopted the stochastic cost frontier model to investigate how different types of regulatory contracts affect Norwegian bus companies' performance. They found that the adoption of a more high-powered scheme based on a yardstick type of regulation has significantly reduced the operating costs. Barros (2005) also analysed the technical efficiency of the Portuguese bus transport companies by estimating a Cobb–Douglas cost frontier model. The author concluded that inputs and outputs play a major role on efficiency measurement and found that efficiency scores are time varying. Note that almost all of the relevant works have selected number of employees, number of vehicles, total amount of fuel consumed as inputs and vehicle-kilometres or passenger-kilometres as outputs when measuring the bus transit efficiency, but none have accounted for the effects of accidents on the relative efficiency measurement.

3. Methodologies

3.1. *Production frontier model*

In the production economics context, the production technology can be represented by using either production function or cost function. The major disadvantage for specifying a cost function is that the factor prices must be known for the estimation purposes. However, acquiring the input factor prices data is usually difficult due to confidential in practice, particularly across the companies. Hence, this study represents the technology by production function.

Consider a firm that produces a single output, y, by using N inputs $x = (x_1, x_2, \dots, x_N)$. The production function, $y = f(x)$, satisfies the following properties:

P1. *Non-negativity*: The value of $f(x)$ is a non-negative, real number.

P2. *No free lunch condition*: The positive value of output cannot be produced without utilisation of input.

P3. *Monotonicity*: An additional unit of input will not decrease output; that is, if $x^1 \geqq x^0$, then $f(x^1) \geqq f(x^0)$. Monotonicity implies all marginal products are non-negative if the production function is continuously differentiable.

P4. *Concave in x*: Concavity implies all marginal products are non-increasing if the production function is continuously differentiable.

Traditionally, the economists estimated an average production function by using econometrics techniques such as ordinary least squares (OLS). In the following case study, three input factors are selected ($N = 3$), thus we specify a log-linear Cobb–Douglas production function as (M1).

$$\ln y_i = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \varepsilon_i \tag{M1}$$

where β's are unknown parameters to be estimated and ε_i represents the residual term, which accounts for unexplained terms and all measured errors. The estimation of OLS itself does not provide the measurement of efficiency; however, the residual of OLS can be used to test for the presence of technical inefficiency in the data. Assume that ε_i can be decomposed into two terms: u_i and v_i, i.e. $\varepsilon_i = v_i - u_i$ and that u_i and v_i are distributed independently. If $u_i = 0$, then the error term $\varepsilon_i = v_i$ is symmetric, suggesting that the dataset does not support any technical inefficiency. If $u_i > 0$, then $\varepsilon_i = v_i - u_i$ is negatively skewed; this is the evidence of presence of technical inefficiency in the data.

In his note on Farrell's (1957) work, Winsten (1957) suggested that the efficient production function in effect would be parallel to the average production function; thus, it can be estimated by fitting a line to the averages and then shifting it parallel to itself. This estimation technique is termed as corrected ordinary least squares (COLS). Specifically, the production frontier model could be estimated with two steps. In the first step, one uses OLS to obtain the estimates of the slope and intercept parameters as well as the residuals. In the second step, the intercept is shifted up (i.e. corrected) to ensure that the estimated frontier bounds the data from above. This can be easily done by subtracting the maximum residual from all residuals so that one of the transformed residuals is zero and all others are negative.

Figure 1 demonstrates the concept of COLS with one-input one-output production technology. Assume that there are some observations, each produces output y with input x. By using OLS technique one can estimate an average practice function and all residuals. The average estimates are then shifted parallel to its maximum positive residual (point A)

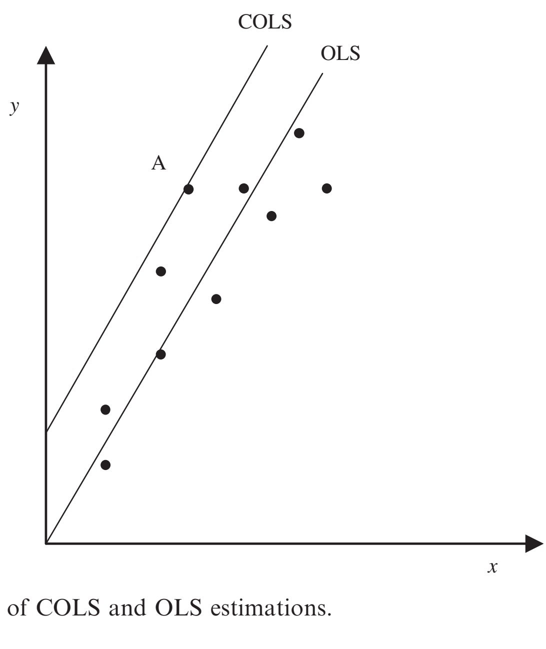

Figure 1. The concept of COLS and OLS estimations.

so that one of the transformed residuals is zero, and all others become negative. The technical inefficiency for each DMU can thus be obtained by taking exponent on its transformed residual.

3.2. *Stochastic production frontier model*

The major weakness of OLS production models is that they do not account for inefficiency. Although one can adopt COLS to estimate technical efficiency as described above, COLS is in effect deterministic, which attributes all deviations from the best practice as inefficiency without considering the statistical noise. To rectify, Aigner *et al.* (1977) proposed a composite error model to account for both technical efficiency, $\mathrm{TE}_i = \exp(-u_i)$, and statistical noise, $\exp(v_i)$. The model can be defined as

$$y_i = f(x_i; \beta) \times \exp(v_i) \times \exp(-u_i) = f(x_i; \beta) \times \exp(v_i) \times \mathrm{TE}_i$$

or in log-form,

$$\ln(y_i) = \ln[f(x_i; \beta)] + v_i - u_i$$

Following (M1), we thus re-specify the stochastic Cobb–Douglas production frontier model as (M2).

$$\ln y_i = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + v_i - u_i \tag{M2}$$

where y_i and x_1, x_2, x_3 have the same meanings as those in (M1), v_i is a symmetric random error term to account for the measurement noise and other factors out of control. Aigner *et al.* (1977) assumed that v_i follows a normal distribution with zero mean and constant variance; u_i is a non-negative independently and identically distributed (i.i.d.) random variable used to account for technical inefficiency. The technical efficiency thus becomes

$$\mathrm{TE}_i = \exp(-u_i) = \frac{y_i}{f(x_i; \beta) \times \exp(v_i)}, \quad i = 1, 2, \ldots, N$$

To estimate u_i, one has to impose a distribution form. Half normal distribution is the most generally used in literature since u_i is a non-negative random variable. Thus, we adopt a half normal distribution for u_i and assume that

(i) $v_i \sim$ i.i.d. $N(0, \sigma_v^2)$
(ii) $u_i \sim$ i.i.d. $N^+(0, \sigma_u^2)$
(iii) both v_i and u_i are independently and identically distributed

Then, p.d.f. of v_i and u_i can be expressed as

$$f(v) = \frac{1}{\sigma_v \sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{v}{\sigma_v}\right)^2\right]$$
$$f(u) = \frac{2}{\sigma_u \sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{u}{\sigma_u}\right)^2\right]$$

Because v_i is independent of u_i, the joint p.d.f. of u_i and v_i can be expressed as

$$f(u, v) = \frac{2}{2\pi\sigma_u\sigma_v}\exp\left[-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right]$$

From $\varepsilon_i = v_i - u_i$, one gets

$$f(u, \varepsilon) = \frac{2}{2\pi\sigma_u\sigma_v}\exp\left[-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon + u)^2}{2\sigma_v^2}\right]$$

Integrating with respect to u, one obtains

$$\begin{aligned} f(\varepsilon) &= \int_0^\infty f(u, \varepsilon)\mathrm{d}u = \frac{2}{\sigma\sqrt{2\pi}}\exp\left[1 - \Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \times \exp\left(-\frac{\varepsilon^2}{2\sigma^2}\right) \\ &= \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right) \end{aligned}$$

where $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, $\Phi(\cdot)$ and $\phi(\cdot)$ are standard normal cumulative distribution and density functions, respectively. Because u_i is a non-negative normal distribution, $f\,(\varepsilon)$ is asymmetrically distributed with its mean and variance. Once the p.d.f. is derived, one can estimate the parameters and technical inefficiency of each firm by using the maximum likelihood method. For more detail, see Kumbhakar and Lovell (2000).

3.3. *Stochastic production frontier with inefficiency effect model*

One still cannot investigate the determinants of inefficiency via the above stochastic production frontier model (M2) because it did not include the factors influencing technical inefficiency. To rectify, Battese and Coelli (1995) proposed the inefficiency effect model, which allows the estimation of the parameters of the factors affecting the technical inefficiency of each firm. More specifically, the model permits a simultaneous estimation of both stochastic production model and inefficiency effect model. We thus formulate a stochastic production frontier with inefficiency effect model (M3), which combines an inefficiency effect model with the stochastic production frontier model (M2) as follows:

$$\left\{\begin{aligned} \ln y_i &= \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + v_i - u_i \\ u_i &= \delta_0 + \delta_1 \cdot z_{1i} + \delta_2 \cdot z_{2i} + \omega_i \end{aligned}\right\} \qquad \text{(M3)}$$

where y_i and x_1, x_2, x_3 have the same meanings as in (M1); u_i is assumed to be a function of z_{1i}, and z_{2i}, which are observable explanatory variables used to explain inefficiency (in this case study, z_1 and z_2 stand for time trend and accident index, respectively); δ is a vector of unknown parameters to be estimated; ω_i is the random variable defined by the truncation of the normal distribution with zero mean and variance (σ^2) such that the point of truncation is $-z_i\delta$. These assumptions are imposed to make sure that u_i is a non-negative truncated normal distribution. As such, the technical efficiency of production can be obtained by the following equation.

$$\mathrm{TE}_i = \exp(-u_i) = \exp(-z_i\delta - \omega_i).$$

Same as (M2), (M3) can also be estimated by the maximum likelihood method.

As we mentioned in Section 1, in case that an accident is involved, the driver must stop the bus immediately. Therefore, one may reasonably hypothesise that accident should function as an input factor that would cause reduction in outputs; as such, the accident variable is supposed to be one of the inputs in the production function specification. We have tried this hypothesis but the estimation results are unreasonable – the positive coefficient (0.015) implies that higher accident index will lead to higher output, violating the monotonicity assumption and indicating the problematic specification of production function. In fact, in the neoclassical production economics, the input factors used to explain the outputs are, in general, 'resources to be consumed' in the production process. It may not be appropriate to interpret the shortage of outputs by choosing accident as an explanatory variable. In this study, we attempt to investigate how the technical efficiency is affected by the bad by-product – accident, we thus specify the model by incorporating accident index into the inefficiency effect, rather than into the production function specification.

4. Case study

4.1. *The data*

Currently, 15 bus transit operators, all privately-owned, serve over six million people in the Taipei metropolitan area. With 287 routes and 3796 buses, these 15 operators provided 256 million vehicle-kilometres, carrying 616 million passenger-trips, but unfortunately, also involving 7 fatalities and 335 injuries in 2006. Following the previous literature, three major input factors are considered: capital, labour and fuel. In this article, capital is measured by the total number of vehicles operated by each firm; labour is measured by total number of employees including drivers, maintenance and administrative personnel; fuel is measured by total amount of fuel consumed. For the desirable outputs, we choose vehicle-kilometre because it is the direct transport service produced and sold to passengers. As for the undesirable outputs, we choose the number of fatalities, number of serious injuries, number of slight injuries, and number of accidents without any fatality or injury (a proxy of property loss) to represent four different types of accidents. These four types of accidents are further converted to an aggregated accident index via a conversion of different weights. Such an aggregated index can account for different degrees of accident severity.

Our panel dataset, drawn from the *Annually Statistical Report of Transportation in Taipei City* published by the Department of Transportation, Taipei City Government, contains 60 DMUs – 10 bus firms over 6 years (2001–2006). As above-mentioned, there are 15 bus firms in Taipei. Unfortunately, due to incomplete and/or incorrect data, we are restricted to using data from only 10 firms to represent the bus transit industry in Taipei. These 10 firms in fact took a large share of the entire transit market – over 94% in terms of vehicle-kilometres or revenues during the study period, which is sufficient large to represent the entire bus transit market. These 10 bus companies have been adopting similar diesel vehicles and operating in the same urbanised area, thus their operating environments can be viewed as homogeneous. Following the previous literature, for simplicity, we assume that the differences of production technologies adopted between these 10 bus firms can be neglected.

Fatal, serious and slight casualties were evaluated by Evans and Morrison (1997) with relative weights of 1, 0.1 and 0.005, respectively. However, the weightings adopted here are different because we intended to convert the weightings to more in line with the Taiwan situations. Based upon the number of claims for different casualties regulated by the Compulsory Automobile Liability Insurance Act in Taiwan and upon the amount of actual claims for different causalities reported by Taiwan Insurance Institute, on average, each fatality claim was 1500 thousand NT dollars, each serious injury claim 750 thousand NT dollars, each slight injury claim 100 thousand NT dollars and each property loss claim 10 thousand NT dollars (1US dollar is approximately equivalent to 30 NT dollars in 2008). Therefore, 1500, 750, 100 and 10 are respectively used to convert these four types of causalities to the aggregated accident index value in our case study.

Table A1 in the Appendix summarises the descriptive statistics of three inputs, one desirable output and accident index. The desirable output ranges from 8538 to 48,201 with mean value 22,873 thousand vehicle-kilometres. The aggregated accident index value ranges from 120 to 11,720 with mean 3367. The number of vehicles ranges from 140 to 1006 vehicles. Table A2 in the Appendix further presents the average inputs, output, and accident index for the studied bus firms for the years 2001–2006.

Figure 2 displays the average accident index value and output for each firm over the observed period. One can see that firm A is the operator with the highest average accident index value (6100), whereas firm H has the least average accident index value (980). As for the average output, firm A is the largest operator with an average value of 42,462 thousand vehicle-kilometres, while firm I and J are the two smallest operators with average output 11,098 and 11,711 thousand vehicle-kilometres, respectively.

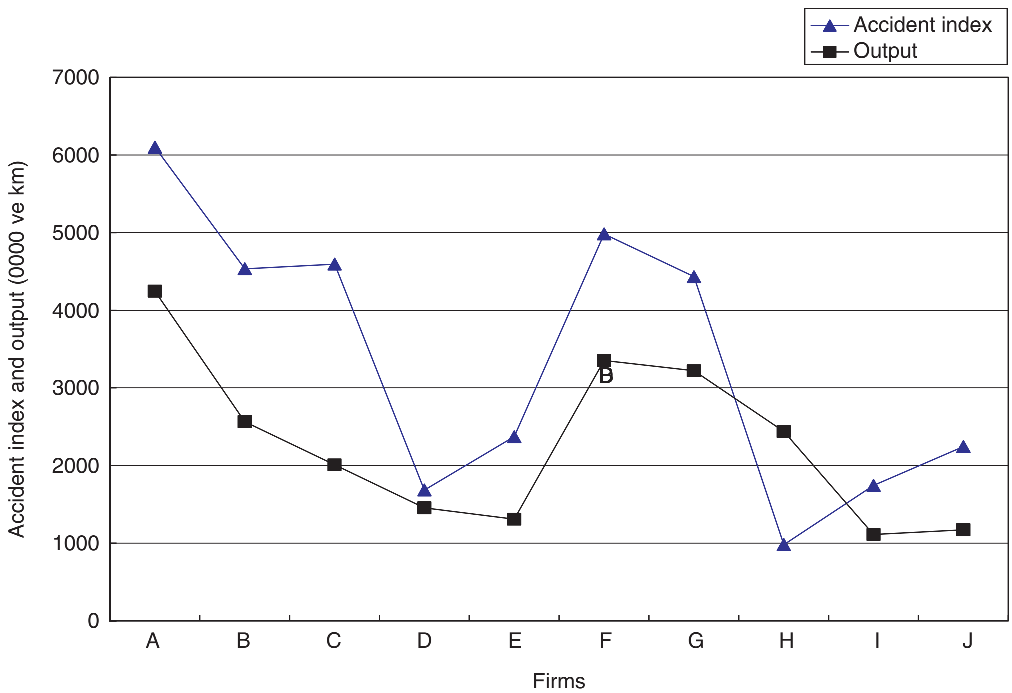

Figure 2. Individual firm's accident index value and output.

As for the trend of average accident index values, Figure 3 shows that Taipei bus transit, overall, had a better safety record in the first three years than that in the remaining three years. The average accident index value was 2471 in 2001, decreased to its lowest of 1760 in 2003, and then sharply increased to 4328 in 2004 and to 5008 in 2006. Figure 3 also shows the trend of the average output. It exhibited a steady state over the studied period, ranging from 21,440 thousand vehicle-kilometres in 2001 and slightly increasing to 23,580 thousand vehicle-kilometres in 2006.

4.2. *The results*

In the following analysis, the econometric computer software SHAZAM, developed by White (1993), is used to estimate the OLS production model (M1) and FRONTIER 4.1, developed by Coelli (1996), is used to estimate SFA production model (M2) and SFA production with inefficient effect model (M3). The technical efficiencies with accounting for the accidents are compared with those without accounting for the accidents. The detailed results of efficiencies and rankings are displayed in Table A3 in the Appendix. Table 1 summarises the estimation results from three models. Table 2 further presents the descriptive statistics of efficiency results. Based on the results and extended analysis, some important findings are discussed below.

4.2.1. *The estimated parameters and efficiencies of (M1)*

We estimate (M1), which does not account for accidents, by OLS technique; the results are indicated in the first two columns of Table 1. As expected, all parameters are significant at 5% significance level with positive sign, consistent with the monotonicity property of production function. The R^2 is 0.9266 and adjusted R^2 is 0.9226, indicating that representing the production technology of Taipei bus transit with Cobb–Douglas

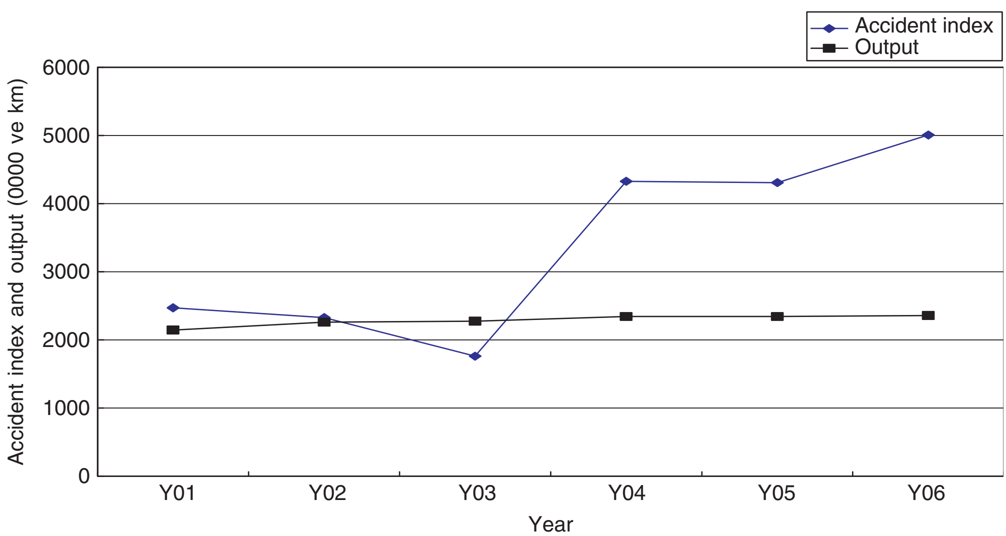

Figure 3. The trend of accident index value and output.

Table 1. Estimation results of three models.

	(M1)		(M2)		(M3)	
Parameters	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio
β_0	10.006	16.550*	11.582	42.721*	9.874	47.735*
β_1	0.359	3.599*	0.336	4.039*	0.246	4.810*
β_2	0.145	2.712*	0.396	11.348*	0.657	17.969*
β_3	0.383	4.457*	0.149	2.348*	0.044	1.883*
δ_0	–	–	–	–	−6.794	−2.198*
δ_1	–	–	–	–	−0.265	−1.172
δ_2	–	–	–	–	0.672	2.365*
σ^2	0.017		0.049	6.102*	0.432	2.108*
γ			0.771	108.990*	0.865	2200.793*

Note: *Indicates significant at 5% significance level.

Table 2. Statistics of technical efficiencies measured by three models.

Statistics	(M1)	(M2)	(M3)
Max	1.000	0.994	0.996
Min	0.530	0.694	0.734
Mean	0.743	0.869	0.914
SD	0.087	0.080	0.065

Note: SD = Standard deviation.

production function is satisfactory. One may argue that specification of other functional forms, such as translog or quadratic, would be more flexible; however, the principle of parsimony says that one should choose as simple functional form as possible when specifying. In practice, one can determine whether the model specification is satisfactory or not by evaluating the residual analysis, hypothesis tests, goodness-of-fit, or predictive power. Since our OLS estimation results have rather low standard deviation of residuals (0.1313) with rather high goodness-of-fit ($R^2 = 0.9266$), indicating that the Cobb–Douglas specification is already satisfactory in this case study.

Once the parameters and residuals in (M1) are estimated by OLS, one can further calculate the transformed residuals by COLS, as depicted in Figure 1. The efficiency score for each DMU is then determined by taking exponent on each transformed residual. At the aggregate level, Table 2 shows that the average efficiency for 10 bus firms over 6 years is 0.743 with standard deviation 0.087. At the disaggregate level, Table A3 in the Appendix further shows that I03 (firm I in 2003) is the most efficient DMU, followed by G01 and G05, while A01 and A02 are the least efficient ones. On average, firm G is the most efficient firm in our observations. As for the temporal trend, Figure 4 presents the average efficiency on each year estimated from three models. Note that the average efficiencies of Taipei bus transit have been improved from 0.719 in 2001 to 0.774 in 2003, dropped to 0.712 in 2004, and then increased to 0.752 and 0.760 in 2005 and 2006, respectively, based on (M1).

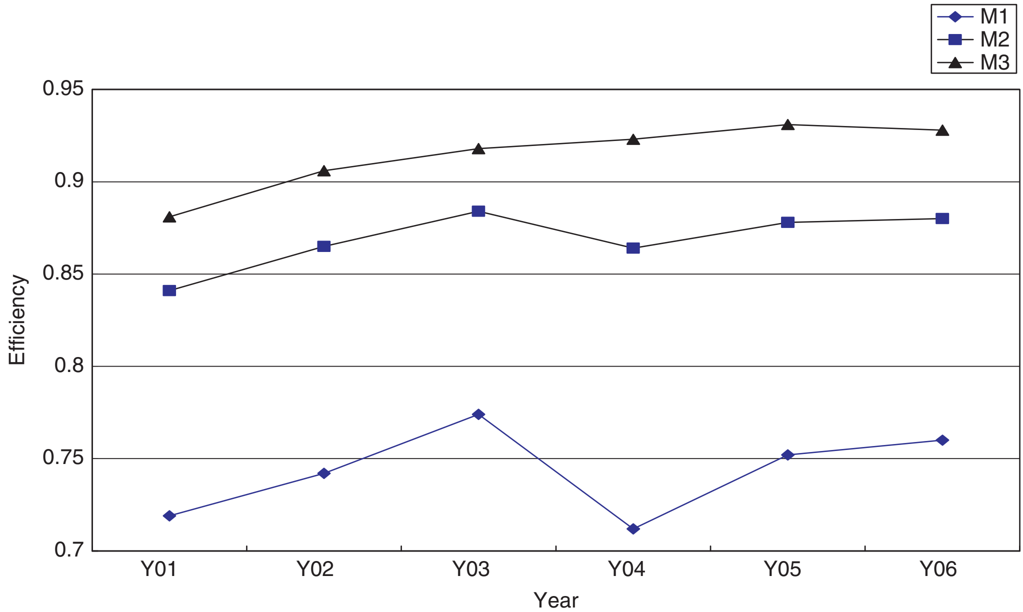

Figure 4. The trend of average efficiencies measured by three models.

4.2.2. *The estimated parameters and efficiencies of (M2)*

Once (M1) is estimated, the skewness of the residuals can be obtained from the third sample moment of the OLS residuals. We obtain a negative skewness of the residuals (−0.553), which provides strong evidence of technical inefficiency in the data, further justifying the usage of SFA approach. The SFA production frontier model without considering the inefficient effect of accidents (i.e. (M2)) is estimated by the maximum likelihood method. The estimated parameters, β's, are indicated in Table 1. It indicates that all parameters are significant at 5% significance level. As we expected, all parameters of inputs are positive, which indicates that an additional unit of input would not decrease the output.

The technical efficiency for each firm measured from (M2) are detailed in Table A3 in the Appendix and summarised in Table 2. Once again, firm G is the most efficient company with average efficiency value 0.988, followed by firm *F* (0.966), while firm A is the least efficient one with average efficiency 0.798 (see the Appendix). As for the trend of the average efficiency measured from (M2) over the 6 years, it is similar to the trend based on (M1) (Figure 4). Note that the average efficiencies of Taipei bus transit have been improved from 0.841 in 2001 to 0.884 in 2003, dropped to 0.864 in 2004, and then increased to 0.880 in 2006, based on (M2).

4.2.3. *The estimated parameters and efficiencies of (M3)*

We jointly estimate the parameters of production function and its associated inefficiency effect model (M3) by the maximum likelihood method and the results are presented as follows (also see Table 1):

$$\ln y = 9.874 + 0.246 \cdot \ln\left(\frac{\text{veh}}{10}\right) + 0.657 \cdot \ln\left(\frac{\text{fuel}}{1000}\right) + 0.044 \cdot \ln\left(\frac{\text{labour}}{10}\right) + v - u$$

$$u = -6.794 - 0.265 \cdot \text{year} + 0.672 \cdot \ln\left(\frac{\text{accident index}}{10}\right) + \omega$$

As shown in Table 1, the signs of the coefficients of the specified production function and its associated inefficiency effect model are as what we expected. In production function model, parameters of vehicle, fuel, and staff are all positive and significant at 5% significance level, implying that an additional unit of input will not decrease the output. In inefficiency effect model, δ_1 (year) is negative but not significant; δ_2 is positive and significant, implying that the DMU with higher accident index will lead to higher technical inefficiency, consistent with the underlying hypothesis.

To account for the effects of accidents on efficiency measurement, we estimate the technical efficiency for each DMU from (M3). The results are detailed in Table A3 in the Appendix and summarised in Table 2, with the trend displayed in Figure 4. Note that the average efficiencies of Taipei bus transit have been improved from 0.881 in 2001 to 0.928 in 2006, based on (M3). Since the average accident index values have increased from 2471 in 2001 to 5008 in 2006, the improvement of overall efficiency must be mainly ascribed to the reduction of employees and vehicles for the entire bus transit. As for the individual firm's efficiency, F is the most efficient firm with the efficiency value 0.980, followed by firm I (0.962), while firm A is still the least efficient one with the efficiency value 0.808, based on (M3).

4.3. *Comparison and discussions*

To examine whether the efficiencies measured by different models are significantly different, the Mann–Whitney (M–W) test is conducted for each pair of models and the results are reported in Table 3. Since all the calculated Z-values are greater than the critical value (1.96) at the significance level of 0.05, we reject the null hypothesis that the efficiencies measured by three models are invariant. Thus, estimating efficiency with

Table 3. Mann–Whitney test between paired models.

	Paired-models 1 and 2		Paired-models 2 and 3		Paired-models 1 and 3	
Comparison	(M1)	(M2)	(M2)	(M3)	(M1)	(M3)
Mean rank	39.1	81.9	50.2	70.8	34.5	86.5
U_A	3082		3359		2418	
$Z_{\text{calculated}}$	6.73		3.24		8.18	
Z_{critical}	1.96		1.96		1.96	
Mean efficiency	0.743	0.896	0.896	0.914	0.743	0.914

Note: U_A is given by $U_A = n_A n_B + n_A(n_A+1)/2 - T_A$, where n_A and n_B are number of samples in group A and B, respectively, and T_A stands for sum of ranks for sample A.

consideration of accident is justified. Since the efficiencies are ranked in an ascent order (from lowest to highest) in the M–W test, a larger mean rank in Table 3 represents a higher efficiency. Accordingly, we conclude that the average efficiencies measured by (M3) are higher than those by (M2), which are higher than those by (M1).

Figure 4 displays the trend of average efficiencies measured by different models. It shows that the efficiencies measured by (M1) are lower than those measured by (M2) and (M3) mainly because that (M1) did not account for the random error thus attributed all the deviations from the frontier (best practice producer) to inefficiency. Similarly, the average efficiencies measured by (M3) are higher than those measured by (M2) simply because that (M2) did not take the effects of accidents into account. As for the individual firm's average efficiency, Figure 5 also displays that the efficiencies measured by (M1) are lower than those measured by (M2), which are lower than those measured by (M3), with an exception of firm G. The reason is probably because the gap of accident index value and output for firm G is relatively smaller than that for firm F (Figure 2), hence the efficiency rankings by (M2) and (M3) swapped.

The main objective of this study is to investigate how the efficiency measure is affected by accident, it is thus of interest to compare the results estimated from (M2) and (M3). However, because (M2) and (M3) are different models with different production frontiers constructed, it makes little sense to compare the efficiency measures directly. Nonetheless, one can still compare their rankings based on the efficiency measures, as presented in Table A3 in the Appendix. The results show that the ranking of technical efficiency with consideration of accidents has significantly differed from that without accounting for accidents. In general, the rankings of those firms with higher accident index have deteriorated when accounting for accidents. Taking firm A as an example, its rankings worsen from 29, 25 and 24 (based on (M2)), to 52, 50 and 45 (based on (M3)), in the years

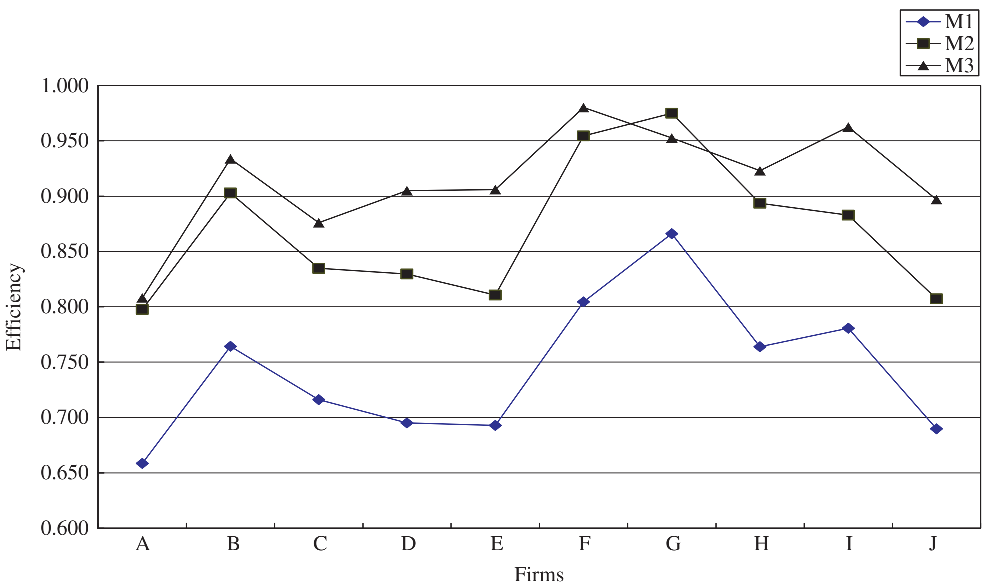

Figure 5. The individual firm's average efficiencies measured by three models.

of 2004–2006, respectively. The reason can be partly ascribed to firm A's producing transport services associated with a relatively high accident index of 6060, 11,720 and 11,350, respectively, which are much higher than the average of the whole industry (3367). In contrast, the rankings of those firms with lower accident index have ameliorated when taking accident into account. Firm I is a good example to support this finding. Its rankings have raised from 54, 18, 1, 36, 28 and 33 (based on (M2)) to 51, 4, 1, 14, 6 and 18 (based on (M3)) in the years of 2001–2006, since its accident indexes are 910, 790, 1870, 1890, 2360 and 2650, respectively, which are relatively lower than the average value. Accordingly, one potential strategy for improving the technical efficiency of Taipei bus transit is to reduce the accidents through drivers training and education, especially for those firms with higher accident index than average.

Our empirical results indicate that, based on (M3), the output elasticity of stochastic production function associated with fuel consumption (0.657) is much greater than that associated with the other two inputs (fleet size = 0.246; number of employees = 0.044), suggesting that energy consumption is the most sensitive factor affecting the transport efficiency for Taipei bus transit. Accordingly, one strategy for improving the bus transit efficiency is to provide more bus exclusive lanes with preemption signals so as to cut down the bus delays at signalised intersections. Another managerial strategy is to train the aberrant drivers to operate the buses in a smooth and correct manner (e.g. right gear positions for various speeds) to save fuel. Of course, introducing fuel-economy vehicles is also imperative in the era of high oil prices.

5. Conclusions

The issue of efficiency measurement for transport industries has been extensively studied by transport economists; however, previous studies ignored the effects of accidents on the efficiency measurement. Consequently, the results could be misleading or at least unfair. To correct this problem, the present article has incorporated both desirable outputs (transport services) and undesirable outputs (accidents) into the SFA modelling to evaluate the relative efficiency of bus transit.

Our empirical results from 10 Taipei bus transit firms over 2001–2006 have revealed strong evidence of the presence of technical inefficiency in the dataset, based on the OLS residuals. Moreover, our results have also shown that the technical efficiencies and their rankings with adjustment of accidents can significantly differ from those without adjustment of accidents. The policy implication behind this is that bus carriers can ameliorate their productive efficiency not only via the conventional measures (e.g. decreasing the inputs or increasing the outputs), but also via improving the safety records. The increasing trend of aggregated accident index during the latest three years (2004–2006) suggests that the City Government should place heavier weights on the number of accidents and on the degree of causalities while performing the periodical service quality assessment. As such, the bus carriers will be willing to pay more attention to discipline the drivers' behaviour.

In this article, the aggregated accident index is converted by different weights, according to the claims of fatalities, heavy injuries, light injuries and accidents without any injury (a proxy of property losses). The appropriate weights to more accurately reflect the degree of causalities deserves further exploration. In addition to accidents, the current bus transit production technology using diesel-powered vehicles will inevitably generate other types of undesirable outputs – noise and air pollution, the so-called 'externality' in economics, which do not affect the firms' decision but do affect our environment. It is a challenging issue to incorporate these externalities into the efficiency measurement modelling to credit the less polluted bus operators who intend to introduce quieter and cleaner vehicles, powered by natural gas, electricity, or hydrogen fuel cell. Furthermore, customers' complaints can also be associated with the bus transit services. A promising avenue for future research is to factor the passengers' complaints or other unsatisfactory qualitative indexes into the efficiency measurement models.

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Appendix

Table A1. Descriptive statistics of inputs, output and accident index for Taipei bus transit.

Year	Variable	Maximum	Minimum	Mean	SD
2001 ($J=10$)	y(vehicle-km)	41,840,199	8,538,143	21,400,655	10,616,588
	x_1(vehicle)	1006	140	352	251
	x_2(fuel)	23,630,293	4,017,669	10,739,484	5,961,803
	x_3(employee)	2118	230	685	545
	z(accidents)	4630	120	2471	1678
2002 ($J=10$)	y(vehicle-km)	39,673,301	11,514,950	22,604,536	9,802,657
	x_1(vehicle)	982	157	371	238
	x_2(fuel)	22,356,598	4,895,003	11,048,371	5,569,822
	x_3(employee)	1766	206	685	444
	z(accidents)	4840	340	2326	1616
2003 ($J=10$)	y(vehicle-km)	36,694,493	12,098,675	22,762,890	9,414,669
	x_1(vehicle)	834	157	363	196
	x_2(fuel)	19,908,938	5,258,931	10,972,340	5,087,169
	x_3(employee)	1514	159	643	397
	z(accidents)	5150	500	1760	1278
2004 ($J=10$)	y(vehicle-km)	41,955,377	11,325,974	23,429,896	11,141,731
	x_1(vehicle)	680	171	355	156
	x_2(fuel)	22,336,369	5,129,174	11,037,572	5,840,182
	x_3(employee)	1331	357	748	383
	z(accidents)	9090	1620	4328	2497
2005 ($J=10$)	y(vehicle-km)	46,407,281	10,991,303	23,419,375	12,122,706
	x_1(vehicle)	734	176	369	170
	x_2(fuel)	24,768,264	4,401,698	10,963,173	6,526,267
	x_3(employee)	1355	264	623	349
	z(accidents)	11,720	870	4309	3433
2006 ($J=10$)	y(vehicle-km)	48,201,504	10,911,104	23,580,423	12,618,748
	x_1(vehicle)	784	177	374	182
	x_2(fuel)	25,378,696	4,453,523	11,062,169	6,689,590
	x_3(employee)	1368	250	608	360
	z(accidents)	11350	850	5008	3397

(*continued*)

Table A1. Continued.

Year	Variable	Maximum	Minimum	Mean	SD
2001–2006 ($J=60$)	y(vehicle-km)	48,201,504	8,538,143	22,872,962	10,562,476
	x_1(vehicle)	1006	140	364	193
	x_2(fuel)	66,087,116	4,017,669	11,961,825	9,099,859
	x_3(employee)	2118	159	665	403
	z(accidents)	11,720	120	3367	2668

Note: SD=standarad deviation.

Table A2. The average inputs, output and accident index of 10 Taipei bus firms (2001–2006).

Firm	x_1(vehicle)	x_2(fuel)	x_3(employee)	y(vehicle-km)	z(accidents)
A	837	23,063,193	1575	4246	6100
B	374	12,134,665	738	2563	4533
C	335	9,576,002	565	2007	4595
D	227	6,721,472	430	1456	1685
E	248	5,624,031	324	1307	2372
F	509	14,780,725	856	3353	4983
G	389	16,236,276	784	3221	4433
H	357	11,618,544	684	2438	980
I	163	4,700,894	227	1110	1745
J	201	5,249,382	295	1171	2243

Table A3. The technical efficiency and ranking measured by three models.

	(M1)		(M2)		(M3)	
DMU	Efficiency	Ranking	Efficiency	Ranking	Efficiency	Ranking
A01	0.5300	60	0.694	60	0.736	59
B01	0.7151	35	0.853	35	0.885	43
C01	0.7720	23	0.953	10	0.994	2
D01	0.6724	50	0.790	51	0.840	54
E01	0.6979	41	0.815	43	0.899	39
F01	0.8064	13	0.942	17	0.965	20
G01	0.9030	2	0.959	8	0.906	36
H01	0.7596	26	0.858	34	0.873	47
I01	0.6637	52	0.771	54	0.862	51
J01	0.6687	51	0.777	52	0.851	53
A02	0.5479	59	0.696	59	0.734	60
B02	0.7487	28	0.880	27	0.901	38
C02	0.7582	27	0.934	19	0.986	7
D02	0.6809	48	0.810	45	0.873	48
E02	0.6935	43	0.801	48	0.880	44
F02	0.8042	14	0.952	11	0.980	9

(*continued*)

Table A3. Continued.

DMU	(M1)		(M2)		(M3)	
	Efficiency	Ranking	Efficiency	Ranking	Efficiency	Ranking
G02	0.8730	5	0.958	9	0.919	30
H02	0.7313	34	0.866	32	0.910	34
I02	0.8709	6	0.940	18	0.987	4
J02	0.7074	37	0.814	44	0.886	42
A03	0.5796	58	0.729	58	0.768	58
B03	0.7843	17	0.917	20	0.939	24
C03	0.7898	16	0.886	26	0.890	41
D03	0.6983	40	0.831	40	0.904	37
E03	0.7385	32	0.839	39	0.921	29
F03	0.8247	9	0.973	5	0.989	3
G03	0.8631	7	0.982	4	0.959	21
H03	0.6884	45	0.825	41	0.873	49
I03	1.0000	1	0.994	1	0.996	1
J03	0.7692	24	0.867	31	0.937	25
A04	0.7368	33	0.869	29	0.861	52
B04	0.7983	15	0.945	15	0.979	11
C04	0.6222	57	0.749	55	0.812	55
D04	0.7050	38	0.839	38	0.916	32
E04	0.6538	55	0.794	50	0.908	35
F04	0.7477	29	0.943	16	0.987	5
G04	0.7840	18	0.969	6	0.979	10
H04	0.7838	19	0.913	21	0.934	27
I04	0.6593	53	0.851	36	0.976	14
J04	0.6319	56	0.771	53	0.875	46
A05	0.7758	22	0.897	25	0.873	50
B05	0.7629	25	0.911	23	0.955	22
C05	0.6569	54	0.740	57	0.790	56
D05	0.6986	39	0.841	37	0.929	28
E05	0.6890	44	0.821	42	0.937	26
F05	0.8094	11	0.949	13	0.976	13
G05	0.8938	3	0.993	2	0.979	12
H05	0.8080	12	0.948	14	0.973	17
I05	0.7465	30	0.879	28	0.986	6
J05	0.6825	47	0.806	47	0.915	33
A06	0.7813	20	0.901	24	0.877	45
B06	0.7769	21	0.912	22	0.943	23
C06	0.6972	42	0.747	56	0.785	57
D06	0.7150	36	0.867	30	0.967	19
E06	0.6842	46	0.794	49	0.891	40
F06	0.8344	8	0.966	7	0.982	8
G06	0.8794	4	0.988	3	0.973	16
H06	0.8125	10	0.952	12	0.975	15
I06	0.7441	31	0.863	33	0.967	18
J06	0.6791	49	0.808	46	0.918	31
Mean	0.743	–	0.869	–	0.914	–

Note: The first letter of the DMU represents the firm; the following two digits represent the year, for example, C03 denotes firm C in 2003.