AN ANALYSIS OF TRUCKING INDUSTRY PRODUCTIVITY: USING STOCHASTIC FRONTIER FUNCTION

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abstract: The long-run efficiency of the trucking industry in United States of America has been the subject of debates in the past two decades. However, whether one uses a production function or a cost function, the analysis should be consistent with economic theory as well as proper methodology. In this paper, the previous studies of trucking industry productivity are examined for justification of analysis as well as limitations of the functional form analysis. The stochastic frontier or composed error functional form approach allows one to test for each individual firm's efficiency measure in contrast to the average firm used in the traditional approaches. The study focuses on the efficiency changes as regulatory policy was initiated. The result indicates that the technical efficiency increases about 5% in the tested periods. Also, the size related effects concerning efficiency of the trucking industry are indifferent between large and small carriers.

1. INTRODUCTION

The long-run efficiency of the motor carrier industry has been the subject of debates and numerous studies in the past two decades. However, whether one uses a production function or a cost function, the analysis should be consistent with economic theory as well as economic methodology.

The economic definition of production stated that it gives <u>maximum</u> possible output, which can be produced from a given set of inputs. Most of the previous studies have shown the result of tests for the size effect upon efficiency. The size effect has implications for the Interstate Commerce Commission (ICC) regulatory policy of the trucking industry.

But in spite of the popularity of the flexible functional form analysis in studies on the trucking industry's structure, the theoretical meaning of efficiency becomes ambiguous when researchers operationalize the concept of efficiency to test by using a flexible functional form analysis.

In this paper, the previous studies are examined for their justification and the limitations of the cost functional form analysis, and then an alternative methodology is introduced. The stochastic frontier functional form approach allows one to test for each individual firm's efficiency measure, in contrast to the average firm used in the traditional approaches.

Section 2 discusses the limitations of the flexible functional form approach in testing some relationships involving efficiency. In Section 3 presents the alternative stochastic frontier approach and its advantages over the other types of frontier models. Section 4 examines the model specification of this study design and its estimation procedures. Section 5

presents some empirical results and their policy implications, followed by the conclusions.

2. LIMITATIONS OF THE FLEXIBLE FUNCTIONAL APPROACH

Most economic relationships are based on the optimization of an objective as discussed in elsewhere. Optimization involves a search for a maximum or minimum value subject only to the barriers of binding constraints. The locus of constrained maximum or minimum values defines a frontier a set of best obtainable positions. The failure to attain a position on the frontier signifies inefficiency with respect to the stated objective and specified constraints. Inefficient performance may result from a conflict of objectives among firms, a mis-identification of the objectives, or a failure to identify all the relevant binding constraints.

Also, regardless of the sources of inefficiency, all observations will very unlikely lie on the frontier of normative or positive interest. Traditional econometrics techniques may not be suitable to estimate frontier relationships. The flexible functional forms are estimated by least square methods which are essentially a reflection of the average performance of the firms in the industry. Deviation from the estimated function sum to zero since statistically one expects the firm's costs on lie to the estimated cost function.

But the true cost function is the frontier which is the relationship between minimum levels of cost on the one hand and the given sets of input prices and output prices and output levels on the other. Theoretically, the deviation from the frontier function due to inefficiency should be in one direction only - the direction of increased cost (<u>cost frontier</u>) or decreased output (<u>production frontier</u>). Thus, the estimation of a frontier function by the least squares method should produce an average performance frontier function that lies above, in the case of the cost frontier, or below, in the case of the production frontier.

The assumption that all observed deviations from the frontier can only take place in one direction, however, may be too strict. Although deviation due to inefficiency can only take positive values for cost frontier or negative values for production frontier, the concept of a frontier function can encompass stochastic elements. The production processes may have some random components that are unrelated to inefficiency such as weather conditions, vehicle performance, or due to measurement errors in the dependent variables.

While it is plausible to argue that a true frontier exists only under conditions of perfect weather condition and perfect vehicle performance, it is perhaps preferable to allow for a normal symmetric random component for the frontier function. That is, it is not necessary to restrict the frontiers to be solely deterministic. The next section presents the various types of frontier models with criticisms.

3. STOCHASTIC FRONTIER PRODUCTION MODEL

In the traditional approach to the functional forms of either the production or cost function, the concept of maximality or minimality is very important. The word frontier may meaningfully apply to each case because the function sets a limit to the range of possible observation. The amount by which a firm lies below its production frontier and the amount by which it lies above its cost frontier can be regarded as measures of inefficiency.

3.1 Deterministic Non-parametric Frontier

The chief aim of the frontier production function model is to dispense with average measures of efficiency for an industry. The seminal works by Farrell (1957) and later by Farrell and Fieldhouse (1962) provided definitions and a computational framework for both technical and allocate inefficiency.

Technical efficiency relates to the allocation of factors and output among firm's which results in the production of a given output at a minimum expenditure or quantity of productive factors. Consider a firm using two inputs x_1 and x_2, and producing output y, and assume that the firms production frontier function is,

$$y = f(x_1, x_2) \tag{1}$$

If it is assumed that equation (1) exhibits constant returns to scale, then equation (1) can be written as:

$$1 = f(x_1/y, x_2/y) \tag{2}$$
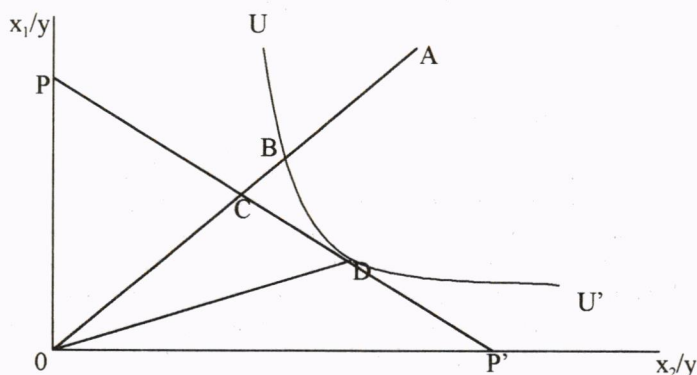
Define a unit iso-quant as UU' in Figure 1.

Figure 1: Measure of Technical Efficiency

Suppose the firm is observed as using (x_1°, x_2°) to produce y°. Let point A in Figure 1 represents $(x_1^\circ/y, x_2^\circ/y)$. Points B and D are technically efficient, but point A is technical inefficient. The ratio 0B/0A can measure technical inefficiency, namely, it is the ratio of inputs needed to produce y° to the input mix used. By the same token, the ratio 0D/0B can measures allocative inefficiency.

Farrell's (1957) original approach is appropriate to estimate technical inefficiency as well as allocative inefficiency. But, as is clearly seen in Figure 1, the unit isoquant function UU' is not observable even though a linear programming approach makes it possible to connect points which are relatively efficient, and to draw the line UU' from the limited number of points.

This approach does not need to impose any functional form on the data. But if the constant return to scales assumption is relaxed, then the estimate procedure is difficult because any extreme observations make the results very biased.

3.2 Deterministic Parameter Frontier

This method was suggested by Farrell (1957) to construct the free disposal convex hull of the observed input-output ratio. As specific functional forms are introduced to construct a convex hull in the input space, the frontier can be expressed in a simple operational form even though some arbitrariness exists in the imposition of functional forms. Aigner and Chu (1968) proposed the following model.

$$y_i = f(x_i;\beta) \qquad (3)$$

where y_i is the maximum obtainable from x_i, a vector of inputs, and β is an unknown parameter vector to be estimated. Aigner and Chu (1968) suggested the estimation of by mathematical programming. First they suggest a linear-programming technique such as:

$$Min \sum_{\beta} |y_i - f(x_i;\beta)| \qquad (4)$$

subject to $y_i < f(x_i; \beta)$. The function $f(x_i; \beta)$ is constrained to be a linear form in β, like a Cobb-Douglas functional form. Second, a quadratic programming problem is written as:

$$Min \sum_{\beta} |y_i - f(x_i;\beta)|^2 \qquad (5)$$

subject to the same constraints as above.

This approach has an advantage over the non-parametric method since this approach can characterize frontier technology in simple mathematical forms, and has the ability to accommodate non-constant returns to scale. But this approach often imposes a limitation on the number of observations that can be technically efficient. Also, this approach shares the same difficulties with the non-parametric case. For example, the estimated frontier is supported by a subject of data and is, therefore, extremely sensitive to outlier. This limitation was strongly objected to by Schmidt (1976) stating that, "this approach really has no statistical properties".

3.3   Deterministic Statistical Frontiers

Equation (3) can be written as:

$$y = f(x)e^{-\mu} \qquad (6)$$

where $\mu > 0$ and, therefore, $0 < e^{-\mu} < 1$. It is assumed that μ is independently and identically distributed, and x is exogenous and independent of μ. The distribution of μ are important because the maximum likelihood estimates depend on it in a fundamental way.

Various estimation method are proposed such as Afraits (1972) maximum likelihood

method which assumes a two-parameter beta distribution of $e^{-\mu}$. Schmidt (1976) shows that if μ is exponential, then Aigner and Chu's (1968) linear programming procedure is maximum likelihood, while their quadratic programming procedure is maximum likelihood if μ is half normal. Also, Greene (1980) suggested if a gamma density function for μ is assumed, then the usual desirable asymptotic properties of the maximum likelihood estimation hold.

But this deterministic statistical frontier method is difficult to justify in empirical analysis since all the deterministic models assume that all the firms in the sample share a common family of production, cost, and profit functions. And, all variations in the firm's performances are attributed to variations in the firm efficiencies relative to the common family of frontiers.

3.4 Stochastic Frontier Model

Because of the unrealistic assumptions involved in the deterministic frontier models, such as a common family of functional forms regardless of the firm efficiencies, Aigner, Lovell and Schmidt (1977) proposed a new approach to estimate the stochastic frontier models. According to the new method, the error term of the production function has two

$$y_i = f(x_i : \beta) + e_i \tag{7}$$

components:

where y_i is output for the ith firm, x_i is a vector of inputs, β is a vector of parameters to be estimated, and e_i is an error term defined below equation (8).

where the error component ν_i represents the symmetric disturbance, and the other

$$e_i = v_i + \mu_i \tag{8}$$

component μ_i is assumed to be distributed independently of ν_i and satisfies $\mu_i < 0$. The distribution of ν_i is defined as a distribution where only the observations lying on one side of the mean are considered. The normally distributed component ν_i reflects the fact that the frontier may vary for each firm because of measurement errors and uncertainty such as favorable or unfavorable external events like luck, climate, topography, and machine performance.

The one-sided error component reflects the differences in managerial abilities. The basic assumption of this model is that a firm operating with the best management should reside on the frontier so any firm not operating on the frontier line in considered to be less efficiently managed. Using a distribution function for the sum of a symmetric normal random variable $v \sim N(0, \sigma^2_v)$ and a truncated random variable $\mu \sim N/(0, \sigma^2_v)/$. Aigner, Lovell and Schmidt (1977) derive a log-likelihood function from which the parameters can be estimated by using maximum likelihood procedures. With n observations, the log-

$$\ln L(y|\beta, \delta, \sigma^2) = n\ln\frac{\sqrt{2}}{\sqrt{\pi}} + n\ln\delta^{-1} + \sum_i \ln\{1 - F^*(e, \delta, \delta^{-1})\} + \frac{1}{2}\delta^2\sum_i e_i^2 \tag{9}$$

likelihood function can be written as:

where $\sigma^2 = \sigma^2_v + \sigma^2_\mu$, $\delta = \sigma_\mu / \sigma_v$ and F^* represents the standard normal distribution function. Using a well known algorithm such as the Davidon-Fletcher-Powell (DFP) method for deriving the first derivatives of equation (9) with respect to β, δ, σ^2, yields their optimizing values.

Despite the theoretical development in this approach, the estimation of the individual technical efficiency from equation (7) has remained an unsolved problem for time. Of

$$E(e^\mu) = 2e^{\sigma^2_\mu}(1 - f^*) \tag{10}$$

course, the average technical inefficiency - the mean of the distribution of μ_i - can be easily calculated. With the truncated normal distribution, Lee and Tyler (1978) showed that the mean technical efficiency measure $E(e+(\mu))$ is:

where F^* is the standard normal distribution function.

Unfortunately, the inability to calculate individual technical efficiency is a major disadvantage of this model compare with the programming models. Jondrow, Lovell, Materor and Schmidt (1982) suggested a decomposition method from the conditional distribution of μ_i given e_i Because of the independent assumption of μ and v, the joint density of μ and v is just the product of their individual densities. Also, if one defines the distributions of $v \sim N(0, \sigma^2_v)$ and $\mu \sim N \,/(0, \sigma^2_v)\,/$, then the distribution of v and μ can be written as:

$$f(v) = \frac{1}{\sqrt{2\pi}} \delta_v e^{(-v^2/2\sigma^2_v)} \tag{11}$$

$$f(\mu) = \frac{1}{\sqrt{2\pi}} \delta_\mu e^{(-\mu^2/2\sigma^2_\mu)} \tag{12}$$

and $f(\mu, v) = f(\mu) f(v)$, therefore,

$$f(\mu, v) = \frac{1}{\pi} \sigma_v \sigma_\mu e^{(-v^2/2\sigma^2_v)} e^{(-\mu/2\sigma^2_\mu)} \tag{13}$$

From the transformation of $e = v + \mu$, the joint density of μ and e becomes,

$$f(\mu, e) = \frac{1}{\pi} \sigma_v \sigma_\mu e^{(-\mu^2/2\sigma^2_v)} - \frac{1}{2}\sigma^2(\mu^2 + e^2 - 2\mu e) \tag{14}$$

And the density of e is given by:

$$f(e) = \frac{2}{\sqrt{2\pi}} \sigma\{1 - f^*(e\delta\sigma^{-1})\} e^{-e^2/2\sigma^2} \tag{15}$$

where $\sigma^2 = \sigma^2_v + \sigma^2_\mu$, $\delta = \sigma_\mu / \sigma_v$ and F^* represents the standard normal distribution function. Given the normal distribution of v and the half-normal distribution of μ, the conditional mean of μ given e is just the ratio of equation (14) to equation (15).

After some simple modification

$$E(\mu|e) = \sigma^* \frac{\{f(e\delta\sigma^{-1})\}}{\{1 - F^*(e\delta\sigma^{-1})\}} - \frac{e\delta}{\sigma} \qquad (16)$$

where f^* and F^* represent the standard normal density and distribution function, respectively, and $\sigma^* = \sigma^2_v \sigma^2_\mu / \sigma^2$, $\sigma^2 = \sigma^2_v + \sigma^2_\mu$, $\delta = \sigma_\mu / \sigma_v$. The estimation of u is, therefore, obtained by replacing e by the observed residual e.

4. MODEL SPECIFICATION AND VARIABLES

4.1 Model

A translog stochastic frontier production function is estimated by using data on the trucking industry in the Middle Atlantic Region for 1976, 1980 and 1982 sample periods. The translog stochastic frontier production model is specified as:

$$\ln y = \alpha_0 + \sum \alpha_i \ln x_i + \frac{1}{2} \sum \sum \beta_{ij} (\ln x_i)^2 + \sum \sum \tau_{ij} (\ln x_i)(\ln x_j) + e_i \qquad (17)$$

where y is output, $x_i's$ are inputs and $e_i's$ are the two component error terms specified above.

4.2 Measurement of Variables

Transportation output is defined of two separate dimensions: total operating revenues and ton-miles of freight transported. Much of the literature in the field of transportation economics is devoted to discussing the critical limitations of either of the two measures for representing the true output generated by a given carrier.

A common reply to the critics, however, is that a more comprehensive measure of transportation output has yet to be developed and even if some modification methods were developed such as the hedonically adjusted one (Chiang, 1979, 1981), or some activities measurement method (Harmatuck, 1981). These methods require extensive data sets not usually available. The most common complaint against the use of either revenues or ton-miles as measures of output, is that the quality dimension of output, is that the quality dimension of output is ignored. The arguments may not be well founded however, once it is recognized that the shippers who utilize motor carriers are, in fact, the final determines of quality.

If a given carriers service is deemed inferior to that of another carriers, while both charge identical prices, then the rational shipper would reduce the purchase of inferior quality service and substitute it with the service of higher quality. Although prices may not reflect service quality differentials due to the regulated environment, output adjustments may. Therefore, the revealed behavior of shippers with respect to the volume of traffic tendered to particular carrier signals to a large extent, the higher quality of services. Furthermore, this choice behavior is reflected in either higher revenues or higher ton-miles of service for the carriers who are producing higher quality transportation services. In this study, both traditional revenues and ton-miles are used as measure of output.

As indicated elsewhere, the capital stock of a firm would be calculated by using a perpetual inventory method whereby each equipment price is a function of its cost, age, and expected lifetime. It is also true that in every industry the depreciation rates used by the carriers in calculating book values may be affected by taxes or regulatory constraints.

Usually the construction of a perpetual inventory model is not possible due to lack of data on the vintage of capital items. The lack of vintage data would not be a serious limitation if the value of a truck were not a function of age. The value of a truck would then be roughly constant until an accident or major breakdown reduces its value to nearly zero. But empirical evidence shows that truck usage, fuel efficiency, and maintenance costs are greatly affected by age.

The book values of capital are reported to the ICC under the title of carrier operating property net. This category includes all capital except for intangibles such as goodwill and ICC operating authorities. For this study, carrier-operating property net is used as the capital input of firms.

A firms fuel usage are difficult to calculate because Trincs Bluebook data set does provide the fuel tax expenditures from which the quantities of fuel can be calculated by dividing fuel and oil tax expenditures by the state tax rates.

Ideally, the labor variable would require the separation of different types of labor used in the trucking industry such as: drivers, helpers, owner-operator drivers, and administrative labor. Again, Trincs data set forces one to use a single measure of labor, namely, the total numbers of employees.

5. EMPIRICAL RESULTS

5.1 Scale Economies

First, a statistical test was carried out in order to test whether the functional form of the production frontier is Cobb-Douglas or translog, as is used in this paper. The production frontier is Cobb-Douglas if the estimated coefficients of all interaction terms, i.e., β_{ii} and β_{ij} in equation (17), are zero.

Tables 1 through 3 show the estimated parameters and statistics when output is measured in revenue for the stochastic translog production frontier model. There are some interesting results. First, the likelihood ratio test is conducted for the null hypothesis where all $\beta_{ii} = 0$, and $\beta_{ij} = 0$. The test statistics are calculated as:

$$-2\,(L^{CD}_{Max} - L^{TS}_{Max}) \approx \chi^2_d \qquad (18)$$

where L^{CD}_{Max} is maximum log likelihood value of the Cobb-Douglas production frontier, L^{TS}_{Max} is a maximum log likelihood value of the translog production frontier model, and χ^2_d is the chi-square statistic with d degrees of freedom.

For all sample periods where output was measured by revenues, the null hypothesis is clearly rejected. For the selected sample periods, the model being analyzed seems to be better represented by the translog rather than the Cobb-Douglas production frontier model.

Table 1   Stochastic translog production frontier model (Year : 1976)

Variables	Coefficient	Estimates	Standard Error
Constant	α_0	7.8829	0.0485[**]
Labor	α_1	0.6961	0.0448[**]
Fuel	α_2	0.2239	0.0363[**]
Capital	α_3	0.0368	0.0251
Labor * Labor	β_{11}	0.2385	0.0599[*]
Fuel * Fuel	β_{22}	0.1210	0.0419[**]
Capital * Capital	β_{33}	0.0151	0.0115
Labor * Fuel	τ_{12}	-0.0276	0.0864[**]
Labor * Capital	τ_{13}	-0.0110	0.0473[*]
Fuel * Capital	τ_{23}	0.0380	0.0282

** Significance at 1% level, * Significance at 5% level, Technical efficiency: 86.52%

As a whole, the translog frontier model, with revenue used to measure output, was statistically better fitted when compared to ton-miles as the measure of output. Also, as far as scale economies are concerned, no significant level of scale economies can be found regardless of the different measures of output. In fact, during the ICCs strict regulatory period, 1976 in the sample, there was a significant decreasing returns to scale and this trend continues in the transition period of 1980.

Table 2   Stochastic translog production frontier model (Year : 1980)

Variables	Coefficient	Estimates	Standard Error
Constant	α_0	8.3969	0.0588[**]
Labor	α_1	0.4907	0.0966[**]
Fuel	α_2	0.2774	0.0769[**]
Capital	α_3	0.1173	0.0623[*]
Labor * Labor	β_{11}	0.2400	0.1148[*]
Fuel * Fuel	β_{22}	0.1867	0.1001[*]
Capital * Capital	β_{33}	0.0574	0.0625
Labor * Fuel	τ_{12}	-0.4623	0.1821[*]
Labor * Capital	τ_{13}	-0.0570	0.1443
Fuel * Capital	τ_{23}	0.0389	0.1124

** Significance at 1% level, * Significance at 5% level, Technical efficiency: 87.12%

And, as the period of more freedom of regulation is entered in the trucking industry in 1982, constant returns to scale are observed, i.e., the value of scale economies is 1.0262 with revenue as the output measure in 1982.

Results in labor being statistically and the dominant factor in the whole sample period using revenue as output measure. But if ton-miles are used as the output, the fuel factor has the same role as the labor factor did with revenue as the output measure.

Table 3   Stochastic translog production frontier model (Year : 1982)

Variables	Coefficient	Estimates	Standard Error
Constant	α_0	8.3217	0.1453**
Labor	α_1	0.7733	0.0845**
Fuel	α_2	0.1786	0.0823
Capital	α_3	0.0744	0.0599
Labor * Labor	β_{11}	0.2500	0.1197*
Fuel * Fuel	β_{22}	0.3416	0.1109*
Capital * Capital	β_{33}	0.0395	0.0419
Labor * Fuel	τ_{12}	-0.4804	0.1483*
Labor * Capital	τ_{13}	-0.0499	0.1842
Fuel * Capital	τ_{23}	-0.0987	0.1419

** Significance at 1% level, * Significance at 5% level, Technical efficiency: 90.44%

5.2 Technical Inefficiency

The subject of scale economies that were discussed above are not a major research objective of this study. The main objective of this paper is to determine whether technical efficiency differs from periods of regulation to periods of deregulation. What are the impacts of the ICC's regulatory policy on this industry's technical efficiency? What are the differences in efficiency among carriers? And if inefficiencies exist, then what are the sources? As far as these questions are concerned, they are never been successfully answered even though the importance of these questions is mentioned frequently in the literature.

Answering these questions item by item: First, what are the technical efficiency differences among different regulatory policies. In 1976, which is the period when the governments strict regulation policy was in force, the symmetric error is a dominant part of the inefficiency measuring such factors as climate, machine failure, and luck where these types of error are assumed to be outside of the firms control. This trend continues into 1980 even though the proportion of these symmetric errors was decreasing dramatically.

But the results are quite the opposite for 1982. The proportion of managerial inefficiencies to the symmetric inefficiencies has changed. Namely, the portion of errors treated as symmetric errors which were outside of the firms control in the regulated period comes under the firms control (i.e., depends on managerial performances) in the deregulated period.

The samples average technical efficiency is 86.52% in 1976 under the ICC's strict regulation policy. This value increases to about 90.44% in 1982. This observation, combined with the above, suggests that during much of the strict regulation period, agencies such as ICC, CAB etc., have reflected a conservative attitude towards innovation in the transportation sectors. Specially, entry, exit, and pricing regulations have usually been structured largely to preserve the competitive status quo. That is, entry and exit have been substantially constrained, and rates have been subject to constraint via regional rate bureaus.

If the frontier is assumed to be a best-practice frontier, as shown in Table 1, the average

sample technical efficiency value was 86.52%, which means that there was about 13.5% technical inefficiency among carriers in 1976.

Also, as shown in Table 3, the sample, average technical efficiency value is 90.44% in 1982, rising by 4% compared to 1976. Also the value of decreased (1.69 to .87) over the period. This decrease denotes the increasing importance of managerial actions in increasing overall technical efficiency. The results confirms that Gellman (1980) hypothesis of the innovation process in the transportation sector under such conditions, which often include the imposition of price identity among competitors in the same market. It is not surprising that the propensities to innovate of the regulated (and their suppliers) have been dramatically different than would have been observed without such regulation.

5.3 The Sources of Technical Inefficiency

The value of the technical efficiency for each observation is calculated from estimates of the one-sided error component μ_i in equation (16). The individual technical efficiencies for all firms in the sample period are not presented here. Rather, the frequency distribution of these efficiencies for large and small firms is shown in Table 4.

Table 4: Frequency Distribution of Efficiency (Year:1976, Year: 1982)

Efficiency Ranges	Year 1976		Year 1982	
	Number of Large Firms	Number of Small Firms	Number of Large Firms	Number of Small Firms
.950 - .975	1	3	1	1
.925 - .950	6	13	1	7
.900 - .925	5	17	8	9
.875 - .900	6	13	6	13
.850 - .875	5	7	1	4
.825 - .850	4	6	1	1
.800 - .825	5	6	2	2
.775 - .800	2	4	2	4
Total	38	88	22	42

As mentioned above, the sample average technical efficiency increased from 86.52% in 1976 to 90.44% in 1982. The managerial role, defined as a one-sided error component σ^2_u, has increased dramatically. This indicates that the technical efficiency under the firm's control increased over time. The results suggested that under the deregulation period, the managerial role was far more important than it was under the regulation periods. Also, size related effects were tested for differences in efficiencies among the carriers. The null hypothesis states that large firms and small firms have the same technical efficiency distribution. According to the two-sample Kolmogorov-Smirnov test of the difference between two cumulative distributions, the test statistic is:

$$D = Max \left| F_m(x) - F_n(x) \right|$$

where $F_m(x)$ is the cumulative frequency distribution of m large firms, and $F_n(x)$ is that of n small firms. $D_{1976}=0.112$ is much smaller than the critical value of 0.264 at the 5%

significance level. D_{1982}=0.116 is also much smaller than the critical value of 0.337 at the same significance level. The estimated results suggest that there is no significant technical efficiency difference between large and small firms statistically.

Also, the difference in capital stock ratio, defined as the total capital stock divided by the operating revenue, in both sample periods was tested. The mean capital ratio is 17.6% in 1976 and 18.9% in 1982, which indicates that there were no significant capital investment differences between the regulated and deregulated and deregulated periods.

Other hypotheses were tested, e.g., can labor usage and fuel consumption influence the differences in technical efficiencies among carriers? The results are opposite for labor and fuel inputs. Regardless of the regulatory policy, the more technical efficient firms have a relatively higher level of fuel consumption and a relatively lower level of labor usage.

6. CONCLUSIONS

In this study, answers to equations relating to efficiency in the trucking industry were sought by using the stochastic translog frontier production method. This method separates the error term in the stochastic frontier model into two components for each observation unit. This new method enables one to estimate the level of technical inefficiency for each observation in the sample, thus largely removing some difficulties that had been viewed as a considerable disadvantage in the other models, such as the deterministic model.

The results of the test on the size-efficiency using the stochastic translog frontier production model shows that there were no statistically significant differences among carriers when revenue was used as a measure of output. This result does not change even if regulatory policies changed. The average sample technical efficiency increased from 86.52% to 90.44% in this period. Also, the production of managerial inefficiencies under the control of firms increased dramatically during the same period. This result indicates that a large portion of inefficiency considered as a symmetric error, which is assumed outside of the firm's control during the regulated period, becomes a portion of managerial efficiency which is regarded under the firm's control during the deregulated period. This is Gellman's hypothesis such that the disincentive to innovate in a regulated environment. During periods of less regulation, managerial ability plays a more important role in the firm's technical efficiency performance.

A firm with relatively higher capital stock ratio is more technically efficient. Also, a firm with a relatively higher level of fuel, and a lower level of labor, tends to be more technically efficient. The frontier technique used in this study has limitations which affect the conclusions. First of all, the technical inefficiency of a particular observation can be estimated using Jondrow et al. (1982) method but not consistently. As indicated by Schmidt and Sickles (1984), "...we can consistently estimate the (whole) error term for a given observation, but it contains statistical noise as well as technical inefficiency. The variance of the distribution of technical inefficiency, conditional on the whole error term, does not vanish when the sample sizes increase"(p.367). Second, the estimation of the model and the specification of technical inefficiency for statistical noise, requires a specific assumption about the distribution of technical inefficiency such as, half-normal, exponential, and gamma. Furthermore, statistical noise such as the normal, which is used in this study, should not be simply assumed a priori.

But it not clear what assumptions about a specific distribution should be made. Schmidt and Sickles (1984) developed a frontier production model using panel data and they claimed that the above mentioned problems can be eliminated or tested at least. Recently bayesian method to analyze stochastic frontier models developed. Bayesian methods had several advantages over classical method which applied in this paper in the treatment of the stochastic model. Also, this study investigated only technical efficiency. But how about allocative efficiency? These questions require further study with the frontier model approaches.

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