Productive Efficiency And Optimal Firm Size: The Case Of US Health Services Industry[1]

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ABSTRACT

This paper examines the link between firm size and productive efficiency. In so doing, it attempts to determine optimal firm sizes in terms of market capitalization and total asset thereby allowing firms to achieve higher level of productive efficiency. The results indicate that the optimal firm size in terms of market capitalization is $13.1 billion. In terms of total asset, the optimal firm size is $10.3 billion. The results also suggest that there is a threshold above which an increase in firm size adversely affects the level of productive efficiency. The results have important implications for managerial policies regarding firm restructuring. To achieve higher productive efficiency, smaller firms have to pursue expansion strategies through mergers and acquisitions. Larger firms, on the other hand, have to pursue divestment strategies to reduce the size of their assets, particularly by refocusing on core competencies.

Keywords: Productive Efficiency; Optimal Firm Size; Health Services Industry; Market Capitalization

1. INTRODUCTION

In the healthcare debate, which began in 2009 when the Obama Administration took over the mantle of power in Washington and continued with intensity through the first quarter of 2010, many reasons were given to explain why US healthcare system needs revamping. The most important argument is the cost of healthcare, which is absurdly high relative to other developed nations. The unfortunate irony is that with such unprecedented astronomical costs, the US still has very many uninsured citizens who desperately need health insurance. Different people have blamed inefficiency in the system as the main cause of the continuously rising healthcare costs. Our objective in this paper is to empirically investigate the level of productive efficiency in the US health services industry. In particular, we focus on the link between firm size and productive efficiency.

Productive efficiency or technical efficiency is a measure widely used to describe the relationship between the level of output and the amount of input used in the production process. The level of firm's productive efficiency is of particular relevance because it provides an insight into resources allocation and has implications for firm financial performance. The extant literature that analyzed the effect of firm size on productive efficiency found mixed results. While one stream of research found a negative correlation between firm size and the level of productive efficiency (e.g., Soderbom and Teal 2004), another stream of research found a positive correlation

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between firm size and productive efficiency (e.g., Lundvall and Battese 2000).[2] Thus the effect of firm size on productive efficiency is an empirical question that remains to be examined. Theoretically large firms can be more efficient because of scale and/or scope economies, or less efficient because of scale and/or scope diseconomies. On the other hand, non-hierarchical structure can allow small firms to reduce transaction costs such as monitoring cost, administrative cost, and information asymmetry cost thereby becoming more efficient. Thus, theory leaves unanswered the question regarding the relation between firm size and productive efficiency.

The US health service industry (SIC 80) is an important segment of the US services industry, consisting of over 700,000 establishments and generating nearly $600 billion in wages. Although the US health services industry has experienced a substantial growth in the last decades, the cost of health care service is still relatively high. According to a study conducted by the Organization for Economic Co-operation and Development (OECD), the cost of health care in the USA is the highest among industrialized nations, accounting for 16% of Gross Domestic Product (GDP). The Center for Medicare and Medical Services further, predicted that by 2013 the cost of health care would exceed 18% of GDP. The question, which arises, is why the cost of health care is high in the USA? A study by New England Health Care Institute (2009) attributes high cost of health care to wastes and inefficiencies. To formally address this issue, we conduct productive efficiency analysis using the stochastic frontier method.

The analysis of productive efficiency in health care has been the focus of a myriad of studies. These studies used either parametric methods (stochastic frontier models), or non-parametric methods (Data Envelopment Analysis). Hollingsworth et al. (1999) surveyed papers that used non-parametric methods to assess efficiency in health care. In a subsequent paper, Hollingsworth (2003) reviewed papers that used both parametric and non-parametric methods to evaluate efficiency in health care. Most of these studies, however, focused either on hospitals, nursing homes, or on health maintenance organizations (HMOs) and little attention has been paid to publicly held firms in the health services industry. This paper contributes to the existing literature in health care in two major ways. First, it focuses on publicly traded companies in health services industry. Second, it emphasizes the link between firm size and productive efficiency. In so doing, this paper attempts to determine an optimal firm size in terms of market capitalization and total asset thereby allowing firms to achieve higher level of productive efficiency.

We find that size has a significant and non-linear effect on firm's productive efficiency in health services industry. Even after controlling for other firm characteristics, firm size continues to have a non-linear effect on productive efficiency. This suggests that firm size contains unique information that explains variation in productive efficiency. This result is robust to a variety of statistical and empirical specifications.

The remainder of this paper is structured as follows. The first section provides productive efficiency analysis. The second section examines the link between firm size and productive efficiency. The last section concludes the paper.

2. PRODUCTIVE EFFICIENCY ANALYSIS

Measurement of technical efficiency can be carried out using either a parametric method: stochastic frontier, or a non-parametric method: Data Envelopment Analysis. To measure the level of productive efficiency for each firm, we use the stochastic frontier methodology (e.g., Coelli et al. 1995). We choose this parametric method because it is, among others, robust to measurement errors in the data and allows for hypothesis testing.

2.1. Stochastic Frontier Model

The stochastic frontier approach assumes that the error term consists of two components. The first component is the inefficiency term, which captures inefficiencies arising from deviations from the efficient frontier. The second component is the random term, which captures random events beyond the control of the manager (e.g., luck, economic and political events). Prior literature assumes various distribution forms for the technical

[2] The importance of small or large firms as evidenced by their contribution to GDP fluctuated over time. In that regard, the Economist (August, 2009, P, 9) stated: "the share of GDP produced by big industrial companies fell by half between 1974 and 1998, from 36% to 17%...today the balance of advantage may be shifting again".

inefficiency term. These forms include: gamma density (Greene 1980); truncated normal distribution (Stevenson 1980); half-normal distribution (Aigner et al. 1977); and exponential distribution (Meeusen and Van den Broeck 1977). Specifically, the stochastic frontier production function can be specified as

$$\ln\left(Y_i\right) = f\left(X_i,\ \beta\right) + \varepsilon_i, \tag{1}$$

such that,

$$\varepsilon_i = v_i - u_i, \tag{2}$$

where Y_i is the amount of output produced by the *i*th firm; X_i is a vector of inputs used by the *i*th firm in the production process; β is a vector of parameters to be estimated; ε_i is the error term; v_i is the random term; and u_i is the inefficiency term.

The output oriented technical efficiency for the *i*th firm (Coelli et al. 2005) can be expressed as

$$Eff_i = \frac{Y_i}{\exp\left[f\left(X_i,\ \beta\right) + v_i\right]} = \frac{\exp\left[f\left(X_i,\ \beta\right) + v_i - u_i\right]}{\exp\left[f\left(X_i,\ \beta\right) + v_i\right]} = \exp(-u_i), \tag{3}$$

where Eff_i is efficiency score for firm *i*. This efficiency score takes on values between 0 and 1. While an efficiency score closer to one implies higher level of productive efficiency, an efficiency score closer to zero implies lower level of productive efficiency.

The estimation of the stochastic frontier model requires specification of a functional form. In this paper, we opt for Translog functional form; which is specified as,[3]

$$\ln S_i = \beta_0 + \beta_l \ln L_i + \beta_k \ln K_i + \beta_{ll}\left[\ln L_i\right]^2 + \beta_{kk}\left[\ln K_i\right]^2 + \beta_{lk} \ln L_i \ln K_i + v_i - u_i \quad , \tag{4}$$

where β's are parameters to be estimated; S_i, L_i, and K_i are: sales, quantity of labor, and quantity of capital for firm *i*, respectively; v_i is the random term; and u_i is the inefficiency term. The stochastic frontier method is based on disentangling the inefficiency term from the random term. To this end, we assume that the inefficiency term follows a half normal distribution (Aigner 1977).

2.2. Data And Sample Selection

Most of the extant literature that analyzed technical efficiency in health care used two inputs: labor proxied by the number of staff and capital proxied by the bed capacity, and one output proxied by discharges or patient days (for a review, see, Worthington 2004). Because this paper focuses on publicly traded companies, we follow prior literature that used accounting data in selecting inputs and output for use in the estimation of the stochastic frontier model (e.g., Athanassopoulos and Bellantince 1995). Thus, we use one output and two inputs. We use sales as a proxy for output. The two inputs used are: labor, proxied by number of employees, and capital proxied by fixed asset. We use cross-sectional data on 91 publicly traded companies in 2006.[4] The firms contained in the sample are

[3] We also tested whether the Cobb-Douglas functional form fits the data. Because Cobb-Douglas is nested in the Translog functional form, this test amounts to testing the joint null hypothesis that $\beta_{ll} = 0$, $\beta_{kk} = 0$ and $\beta_{lk} = 0$. With a χ^2 of 7.640 and a p-value of 0.054 the null hypothesis cannot be rejected at the 5 % level, implying that the Cobb-Douglas functional form is not the appropriate form.

[4] According to Compustat Database, there are130 publicly traded companies in health services industry. Because the disclosure of the number of employees is voluntary, we drop firms from the sample that did not disclose the number of their employees thus reducing the sample size to 91 companies.

relatively homogeneous because they provide similar services; such as medical, surgical, dental and other health services to persons, operate under the same regulatory environment, and employ personnel with similar training. The data used in this paper are taken from Compustat Database and are based on SIC code. The SIC Code is 8000 and the industry title is "Services-Health Services." Again, because of the narrow definition of SIC codes relative to GICS codes, which some studies employ, the firms within the industry code are homogenous. For example, GICS Code 3510 is Health Care Equipment & Services while GICS 3520 is Pharmaceuticals, Biotechnology & Life Sciences. Any data based on these codes would have been heterogeneous and would have produced biased estimates and unreliable results. The homogeneity condition of our data helps to inform and confirm the robustness of the result. For example, recent announced events regarding the improprieties and social losses in the industry go to buttress the findings of this research, specifically that approximately 57 percent of the current expenditure is all that would be needed to meet all the healthcare needs in the United States at this time. The additional percentage goes to waste and mismanagement due in part to inefficiencies; the hallmark of the diseconomies of scale found in the system. Table 1 contains summary statistics for the variables used in the stochastic frontier model.

Table 1: Descriptive Statistics For The Variables

Variable	Mean	CV[1]	Median	Min	Max
Sales ($million)	1059	1.73	236	0.05	8701
Total Asset ($million)	1309	2.21	195	1.19	20132
Number of Employees (1000)	9.50	1.60	2.80	0.01	68.95
Market Capitalization ($million)	1492	2.50	353.30	2.13	26539.71
Fixed Asset ($million)	989.70	2.40	136	0.39	16867

[1]Coefficient of variation (%).

2.3. Empirical Results

Parameter estimates of the Translog production frontier function are reported in Table 2. Of particular importance is the variance parameter γ. Its estimate is 1 and is statistically significant at the 1% level. This result implies that technical inefficiency is a major factor contributing to variability in output in health services industry.

Table 2: Maximum-Likelihood Estimate Of The Stochastic Frontier

Parameter	Estimate	T-ratio
β_0	4.10*	5.15
β_l	0.60***	1.55
β_k	0.30	0.77
β_{ll}	0.02	0.41
β_{kk}	-0.04	-0.79
β_{lk}	0.02	0.41
σ_v	0.49*	5.41
σ_u	0.86	4.88
$\sigma^2 = (\sigma_u^2 + \sigma_v^2)$	1.00*	4.00
λ	1.75*	7.00
Log (L)	-98	

*and *** indicates the level of statistical significance at 1%, and 10%, respectively.

Table 3 provides summary statistics for productive efficiency analysis. The results show that efficiency scores range from 6.9% to 88.2%. The mean efficiency score is 57.3%, suggesting that on average firms in health services industry could use only 57% of the amount of inputs currently used to produce the same level of output. Put differently, firms in health services industry could lower the cost of production or health care expenditure by reducing wastes and improving efficiency.

Table 3: Productive Efficiency Analysis

	Mean	CV[1]	Median	Max	Min
Efficiency score (%)	57.3	26.9	59.1	88.2	6.9

[1]Coefficient of variation (%).

3. THE LINK BETWEEN PRODUCTIVE EFFICIENCY AND FIRM SIZE

3.1. Univariate Analysis

To obtain an insight into the link between firm size and productive efficiency, we use different proxies for firm size. These proxies are: total asset and market capitalization.[5] We then sort firms into three groups (small, medium and large) based on each firm's market capitalization and total asset. We finally compute the average efficiency score for each group. The results are displayed in Table 4 and Figure 1. A glance at the results shows that on average medium sized firms have the highest efficiency score irrespective of the proxy used for firm size. Specifically, the results show that there is a non-linear relation between firm size and the level of productive efficiency. More importantly, the results suggest that there is a threshold above which an increase in firm size adversely affects the level of productive efficiency.

Table 4: Relation Between Productive Efficiency And Firm Size

	Firm Size					
	Small		Medium		Large	
	MC[a]	TA[b]	MC[a]	TA[b]	MC[a]	TA[b]
Efficiency Score (%)	<8.8	<6.7	[8.8,17.7]	[6.7,13.4]	>17.7	>13.4
	56.9	56.8	67.9	71.3	61.3	55.4

[a]MC: market capitalization ($billion)
[b]TA: total asset ($billion)

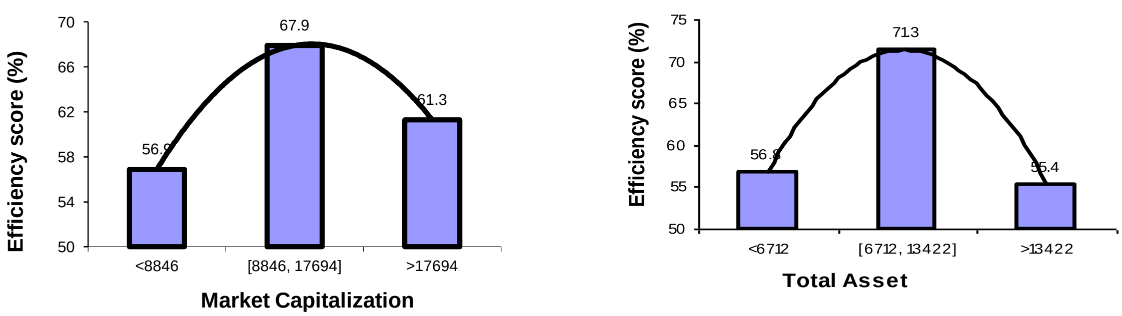

Figure 1: Relation Between Productive Efficiency And Firm Size

To empirically test whether there is a non-linear relation between firm size and the level of production efficiency, we regress efficiency score of each firm on size and size squared. Specifically, we estimate the following regression model

[5] Market capitalization is defined as stock price times the number of shares outstanding at year end.

$$Eff_i = \beta_0 + \beta_1 Size_i + \beta_2 Size_i^2 + \varepsilon_i \,, \qquad (5)$$

where Eff_i is the efficiency score for firm *i*, $Size_i$ is size of the *i*th firm, $Size_i^2$ is size squared, and ε_i is the error term.

For robustness check we estimate the regression model using Ordinary Least Squares (OLS) and Weighted Least Squares (WLS). Because the dependent variable; that is, the efficiency score, is bounded between zero and unity, we estimate the regression model using Tobit specification.[6] In addition, we performed a series of diagnostic tests. First, we tested for heteroskedasticy using Brush-Pagan test. Second, we tested for auto-correlation. The regression model passed these statistical tests.

We estimate equation (5) using market capitalization and total asset as proxies for firm size. The estimates of the parameters in equation (5) are reported in Table 5. The empirical results confirm that firm size has a statistically significant and non-linear effect on productive efficiency. More specifically, the results show that the coefficient on *size* is positive and significant, and the coefficient on $Size^2$ is negative and significant, indicating that firm size in health services industry has a decreasing marginal effect on productive efficiency. The results also suggest that an optimal firm size exists in health services industry.

Accordingly, the regression model in equation (5) can be used to determine an optimal firm size in Health Services industry. To do that, we differentiate equation (5) with respect to *size* and set equal to zero; that is,

$$\frac{dEff}{dSize} = \hat{\beta}_1 + 2\hat{\beta}_2 Size = 0 \,. \qquad (6)$$

Solving for *size* in equation (6) yields,

$$Size^* = \frac{-\hat{\beta}_1}{2\hat{\beta}_2} \,. \qquad (7)$$

Using the estimates for β_1 and β_2 reported in Table 5, the estimates of the optimal firm size in terms of market capitalization and total asset, respectively, are, 13.1 and 10.3 billion dollars, and are statistically significant in both models.[7] These results have important implications for managerial policies regarding firm restructuring. To achieve higher level of productive efficiency, smaller firms have to pursue expansion strategies through mergers and acquisitions.

Larger firms, on the other hand, have to pursue divestment strategies to reduce the size of their assets, particularly by refocusing on core activities. Furthermore, improvements in the level of productive efficiency affect both consumers and firms. On the consumer side, higher level of productive efficiency means lower cost, which in turn translates into lower price of health care services, resulting in affordable health care premium. On the firm side,

[6] As pointed out by Worthington (2004), one of the pitfalls of prior studies that analyzed technical efficiency in health care is the use of OLS in the second stage analysis of factors influencing technical efficiency. The use of OLS, however, can lead to biased and inconsistent estimates because efficiency scores are bounded between zero and unity. To overcome this econometric problem, we estimate the regression model using Tobit specification (Tobit 1958).

[7] Standard errors for the optimal firm size based on market capitalization and total asset are computed using Taylor's non-linear approximation method (Greene 2000). It should also be pointed out that the second order condition for a maximum is satisfied since $\frac{dEff_i^2}{dSize^2} = 2\hat{\beta}_2 \le 0$.

higher level of productive efficiency means higher financial performance (Bowling 1999), which in turn positively affects stock price and the value of the company.

3.2. Multivariate Analysis

In this section, we check whether the results are driven by other firm specific characteristics. Towards this end, we add a set of firm characteristics likely to influence production efficiency and re-estimate equation (5). These firm characteristics include: diversification index, age of the company, and firm profitability.[8] Summary statistics for the variables used in multivariate regression analysis are reported in Table 6.

We include diversification index to account for any cost efficiencies arising from economies of scope (Rumelt 1982). This index corresponds to the number of business segments (i.e., different four-digit SIC) in which the company operates (e.g., Scherer and Ravenscraft 1984). Age of the company is included to account for the experience of the company in the business. Age of the company is obtained by subtracting the year the company started its operation from 2006. We expect the relation between age and the level of productive efficiency to be positive. Firm profitability is included to capture, among others, management efficiency. Firm profitability is proxied by return on asset (ROA), which is defined as net income scaled by total asset. A higher ROA reflects higher management efficiency, which in turn results in higher production efficiency. Hence, we expect a positive association between ROA and production efficiency. Specifically, we estimate the following multivariate regression model

$$Eff_i = \alpha_0 + \alpha_1 Size_i + \alpha_2 Size_i^2 + \alpha_3 Age_i + \alpha_4 Div_i + \alpha_5 ROA_i + w_i , \qquad (8)$$

where Age_i is the age of firm *i*; Div_i is diversification index; ROA_i is return on asset; and w_i is the error term. All the remaining variables are as previously defined.

The estimates of the parameters in equation (8) are reported in Table 7. Of particular interest are the coefficients on *size* and $Size^2$. The coefficient on *size* is positive and significant, and the coefficient on $Size^2$ is negative and significant, confirming that size has a significant and non-linear effect on the level of productive efficiency. The coefficient on diversification index is positive, but is not statistically significant at any conventional level. The coefficient on ROA is positive and statistically significant at the 1% level, implying that more profitable companies have higher level of productive efficiency. This result likely reflects higher management efficiency enjoyed by more profitable companies. Age of the company has a positive and significant effect on the level of productive efficiency, confirming that more years of experience help boost the level of productive efficiency.

The multivariate regression model in equation (8) can be used to check the robustness of the optimal firm size obtained in the previous section. To do that, we differentiate equation (8) with respect to *size* and set equal to zero; that is,

$$\frac{dEff}{dSize} = \hat{\alpha}_1 + 2\hat{\alpha}_2 Size = 0 . \qquad (9)$$

Solving for *size* in equation (9) results in,

$$Size^* = \frac{-\hat{\alpha}_1}{2\hat{\alpha}_2} . \qquad (10)$$

[8] Other firm characteristics such as: research and development intensity and skill intensity are among factors affecting technical efficiency. These variables are not included in the multivariate regression analysis because there no data available on them.

Table 5: Univariate Regression Analysis Of The Link Between Firm Size And Productive Efficiency

		Model 1			Model 2		
Variable	**Parameter**	**OLS**	**WLS**	**Tobit**	**OLS**	**WLS**	**Tobit**
Intercept	β_0	0.55*	0.55*	0.55*	0.55*	0.55*	0.55*
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$Size$	β_1	2.3E-5**	2.3E-5 *	2.3E-5*	2.5E-5*	2.5E-5*	2.5E-5*
		(1.2E-5)	(9.1E-6)	(9.0E-6)	(1.3E-5)	(9.9E-6)	(9.8E-6)
$Size^2$	β_2	-8.71E-10	-8.7E-10*	-8.7E-10*	-1.2E-9	-1.2E-9*	-1.2E-9*
		(5.4E-10)	(3.6E-10)	(3.5E-10)	(8.2E-10)	(5E-10)	(4.9E-10)
	R-square	0.04	0.04	NA	0.04	0.04	NA
	F-statistic	1.89*	6.37*	6.52*	1.93	6.21**	6.35*
	Number of firms	91	91	91	91	91	91
Optimal firm size ($ million)	$\frac{-\beta_1}{2\beta_2}$	13138.43*	13138.43*	13134.47*	10299.01*	10299.01*	10297.06*
		(2989.61)	(474.24)	(470.33)	(3159.03)	(504.38)	(500.37)

Note: In model 1, we use market capitalization as a proxy for firm size. In mode 2, we use total asset as a proxy for firm size. Standard errors are in parentheses. The models are estimated using Ordinary Least Squares (OLS), Weighted Least Squares (WLS) methods, and Tobit specification.
*and ** indicates the level of statistical significance at 1% and 5%, respectively

Table 6: Descriptive Statistics For The Variables

Variable	Mean	CV[1]	Median	Min	Max
Efficiency score (%)	57.27	0.269	59.10	6.94	88.24
Return on Asset (%)	-11.13	-5.66	3.84	-506.36	36.97
Age (year)	18.87	0.69	17	1	107
Diversification	2.20	0.43	2	0	6
Market Capitalization (in $million)	1492	2.50	353.30	26539.71	2.13
Fixed Asset (in $million)	989.70	2.40	136	16867	0.39

[1]Coefficient of variation (%).

Table 7: Multivariate Regression Analysis Of The Link Between Firm Size And Productive Efficiency

		Model 1			Model 2		
Variable	**Parameter**	**OLS**	**WLS**	**Tobit**	**OLS**	**WLS**	**Tobit**
Intercept	α_0	0.52*	0.52*	0.52*	0.52*	0.52*	0.52*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$Size$	α_1	2E-5	2E-5**	2E-5*	2E-5	2E-5*	2E-5
		(1.1E-5)	(8.2E-6)	(8.0E-6)	(1.3E-5)	(8.9E-6)	(8.7E-6)
$Size^2$	α_2	-6.6E-10	-6.6E-10*	-6.4E-10*	-9.1E-10	-9.1E-10*	-8.8E-10
		(5.2E-10)	(3.2E-10)	(3.1E-10)	(7.9E-10)	(4.4E-10)	(4.4E-10)
Age	α_3	0.002***	0.002*	0.002*	0.002***	0.002*	0.0023***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Diversification$	α_4	0.001	0.001	0.002	0.002	0.002	0.003
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ROA	α_5	0.07*	0.07*	0.085*	0.07*	0.071*	0.085*
		(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
	R-square	0.16	0.16	NA	0.16	0.16	NA
	F-statistic	3.19*	3.64*	3.34*	3.79*	3.79*	3.50*
	Number of firms	91	91	91	91	91	91
Optimal firm size ($ million)	$\frac{-\alpha_1}{2\alpha_2}$	13499.2*	13499.2*	13452.6*	10694.6**	10694.6*	10713.2*
		(3934.38)	(875.75)	(3995.96)	(4239.30)	(1003.48)	(1031.53)

Note: In model 1, we use market capitalization as a proxy for firm size. In mode 2, we use total asset as a proxy for firm size. Standard errors are in parentheses. The models are estimated using Ordinary Least Squares (OLS), Weighted Least Squares (WLS) methods, and Tobit specification.
*and ** indicates the level of statistical significance at 1% and 10%, respectively

Using the estimates for α_1 and α_2 reported in Table 7, the estimates of the optimal firm size in terms of market capitalization and total asset, respectively, are, 13.5 and 10.7 billion dollars, and are statistically significant. These results are qualitatively similar to those found using univariate regression analysis. Multivariate regression analysis shows that the results are not driven by other factors affecting productive efficiency thereby providing further robustness check on the link between firm size and the level of productive efficiency.

4. CONCLUSION

This paper seeks to investigate the level of productive efficiency in health services industry with a particular emphasis on the link between firm size and efficiency. Using the stochastic frontier method, the results show that inefficiency largely contributes to variability in the output in the health services industry.

As for the link between firm size and productive efficiency, the results reveal that size has a significant and nonlinear effect on productive efficiency. More importantly, the results indicate that firm size is important in explaining the cross-sectional variation in the level of productive efficiency. Even after controlling for other firm characteristics such as diversification, profitability and age, firm size continues to have a non-linear effect on productive efficiency. This suggests that size contains unique information that explains variation in productive efficiency. Multivariate regression analysis shows that while size has a significant and non-linear effect on the level of efficiency, other firm specific characteristics such as profitability and the experience of the company in the business are important determinants of firm's productive efficiency.

The results found in this paper can be explained by transaction cost effect and cost-efficiency effect arising from firm size. According to transaction cost effect, an increase in firm size can lead to an increase in transaction costs such as monitoring cost, administrative cost, and information asymmetry cost, which in turn affect adversely the level of productive efficiency. According to cost-efficiency effect, however, an increase in firm size can generate cost efficiencies through scale and/or scope economies, which in turn affect positively the level of productive efficiency. Thus, firm size has two countervailing effects on productive efficiency: transaction cost effect and cost efficiency effect. While the former effect has a positive impact on production efficiency, the latter effect has a negative impact on productive efficiency. Accordingly, the effect of firm size on productive efficiency hinges on the magnitude of transaction cost effect compared with that of cost efficiency effect. When the magnitude of transaction cost effect outweighs that of cost efficiency effect, then size has a negative effect on productive efficiency. Conversely, when the magnitude of cost efficiency dominates that of transaction cost effect, size has a positive effect on productive efficiency. It is likely that in health services industry when firm size reaches a certain threshold transaction cost effect becomes larger than cost efficiency effect. This likely explains non-linear size-production efficiency relation in health services industry found in this paper.

The results have important implications for managerial policies regarding firm restructuring. To achieve higher level of productive efficiency, smaller firms have to pursue expansion strategies through mergers and acquisitions. Larger firms, on the other hand, have to pursue divestment strategies to reduce the size of their assets, particularly by refocusing on core competencies.

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