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A PANEL DATA ANALYSIS OF EFFICIENCY AND PRODUCTIVITY OF THE U.S. HOSPITAL CARE SYSTEM

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Abstract: *This study utilizes state level hospital cost data from 1999-2009 to evaluate the efficiency and productivity of the U.S. hospital care system. A panel data Stochastic Frontier Analysis shows that hospital care in the U.S. is fairly efficient with an average technical efficiency score of 0.861 ± 0.074. However, we found evidence that the hospital care sector captures economies of scale supporting previous findings in the literature that only had been captured at a disaggregate level. According to our data, a 10% increase in hospital admissions could decrease the short-run average total costs by 8.14% while the same increase in the number of beds could decrease the average total cost by 1.34% in the long run. Additionally, we have found a granger causality relationship between in-hospital mortality rate and hospital technical efficiencies. The latter findings suggest that dynamic fluctuations in technical efficiency may be detrimental to society. In fact, according to our calculations, a one-percentage point decrease in hospital technical efficiency may cost an average increase of approximately 0.6 percentage points in hospital mortality rate. Policy makers should continue to develop further care delivery models that drive efficiency for the entire delivery system.*

JEL: *C12, C13, D24, I10, M11.*

Keywords: *hospital costs, hospital efficiency, hospital productivity, stochastic frontier analysis.*

INTRODUCTION

The proportion of the United States' (U.S.) Gross Domestic Product (GDP) attributed to health care expenditures increased from 8.9% in 1980 to over 17% by 2012 (Bates & Santerre, 2013). The problem of unprecedented growth in health care expenditures is a critical issue in the U.S. (Panopoulos & Pantelidis, 2013) as well as in most developed nations (Hartwig, 2008). Escalating health care expenditures place immense pressure on federal and state budgets, on employers

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experiencing increasing health insurance costs, and on the entire population as individual health related payments increase (Du & Yagihashi, 2015; Vandersteegen, Marneffe, Cleemput, & Vereeck, 2015; Zerihun, Cunado, & Gupta, 2017). Understanding the dynamics of the rising cost of health care is important to policy makers as they actively seek to reduce or control healthcare costs without negatively affecting quality and access to care of those served by the delivery system (Eggleston & Hsieh, 2004; Siciliani, 2006; McKay & Deily, 2008; Panopoulos & Pantelidis, 2013; Ellis, Fiebig, Johar, Jones, & Savage, 2013).

Inefficiently delivered services, high administrative costs, unnecessary services, and fraud are representative of the inefficiencies which exist in the U.S. (or any) health care system. Such inefficiencies are partially responsible for the dramatic rise in health care costs (Young, 2010). Comparisons are often made between health care expenditures in the U.S. and those of other Organization for Economic Co-operation and Development (OECD) countries. These comparisons show that though most developed nations experience escalating health care expenditures, the per capita health care expenditures and percentage of GDP attributed to health care in the U.S. exceeds those of all OECD countries resulting in further speculation regarding the inefficiency of the U.S. health care delivery system (Paul, Babitsky, & Chandra, 2012; Panopoulos & Pantelidis, 2013; Lorenzoni, Belloni, & Sassi, 2014). In addition, while a comparison among the efficiency of healthcare delivery at an aggregate level across several economies of the world has been extensively studied in the literature (c.f. Evans, 2000; Gravelle et al., 2003; Greene, 2004; Hollingsworth & Wildman, 2000), to the best of our knowledge, the literature lacks any similar studies comparing U.S. healthcare delivery at a state level, particularly for the hospital care segment. This is important for two reasons. First, less efficient states may be able to learn and model best practices from more technically efficient states but only if this ranking exists. Second, the data may show differences across regions that may not be captured currently in a one-size-fits-all hospital approach.

Efficiency and productivity of the delivery of health care services is widely studied in Health Economics' literature. For example, Hollingsworth (2003; 2008) reviewed over 300 published studies on the measurement of health care efficiency. Most studies included efficiency in hospitals and in other health care organizations. Two research approaches generally applied to the study of health care efficiency and productivity are the non-parametric method called Data Envelopment Analysis (DEA) (Charnes, Cooper, & Rhodes, 1978) and a parametric approach called Stochastic Frontier Analysis (SFA) (Aigner, Lovell, & Schmidt, 1977). Hollingsworth's (2008) meta-analysis on public and private healthcare provisions concluded that public delivery of health care was more efficient. Efficiency studies included used both DEA and SFA methods.

For over two decades, hospitals have been the focal point of health care efficiency research (Ferrier, Leleu, Moises, & Valdmanis, 2013; Du, Wand, Chen, Chou, & Zhu, 2014). This is not surprising, as hospitals are the largest cost center in terms of health care expenditures with over 30% of all health care cost in the U.S. attributed to hospital care (Ferrier, Leleu, Moises, & Valdmanis, 2013; Lorenzoni, Belloni, & Sassi, 2014). There are approximately 5,600 acute care hospitals in the U.S. (American Hospital Association, 2015) making hospitals a manageable population for research. Information on hospitals is readily available through Centers for Medicare & Medicaid Services (CMS), 990 tax documents, and annual reports. In addition, insurance companies collect vast information regarding hospital costs. The data from 5,600 hospitals are much easier to aggregate than data from over 900,000 physicians that currently practice in the U.S. (Keyser Family Foundation, 2016).

Rosko and Mutter (2011) reviewed the findings of 27 published studies that used SFA to investigate the efficiency of hospitals in the U.S. These studies primarily focused on the correlates of inefficiencies in U.S. hospitals finding some common themes regarding factors related to efficiency but also suggested that much research is still needed in this area. Rosko and Mutter (2011) found that the application of SFA for health policy issues was in its early stages but held promise as a useful tool.

Ferrier, Leleu, Moises, & Valdmanis (2013) examined the efficiency of U.S. hospitals at the metropolitan area level specifically investigating the impact hospital size and service offering had on efficiency. Their findings varied among metropolitan markets. Using a sample of 1,074 U.S. hospitals, Ferrier and Trivitt (2013) applied DEA in analyzing the incorporation of quality information in the study of hospital technical efficiency. Though their study did not provide definitive answers regarding the application of quality data in efficiency studies it did clearly show a close tie between quality and efficiency citing the need for future research in that area. McKay and Deily (2008), using SFA with a sample of U.S. acute care hospital for the time period 1999 – 2001, examined cost inefficiency and hospital health outcomes. Their results showed no systematic configuration of organization between these variables. Overall, studies have used both SFA and DEA finding mixed results regarding efficiency and quality.

The study of efficiency and productivity of hospitals is not limited to the U.S. Mateus, Joaquim, and Nunes (2015) recently compared hospital efficiency across four European countries. Atiglan (2016) used SFA to analyze the technical efficiency of Turkish Public Hospitals and Herr (2008) used SFA to investigate the efficiency of German hospitals specifically analyzing the effect ownership had on efficiency.

Continuing this research stream of efficiency studies for U.S. hospitals, we utilize a panel data of hospital cost at state level to evaluate the efficiency of U.S. hospital care to generate a state level comparison of hospital management efficiency. In addition, we consider state level hospital management efficiency and its effect on state level in-hospital mortality from chronic disease.

Thus, our study contributes to the literature in three ways. First, it is the first study to provide a state level analysis of hospital efficiency. Second, it compares results from two efficiency methodologies, true fixed effect SFA with exogenous influences in the efficiency term and least square dummy variable (LSDV) efficiency analysis similar to Greene (2004) including a ranking comparison of the states using both methods. Finally, it is the first study that uses a dynamic panel model to test for Granger-causality between hospital technical efficiency and hospital fatalities. The remainder of the paper is organized as follows. In the following section, we present the methodology and the data used to conduct our analysis. In the third section, we discuss the results of the analysis, and in the last section, we provide some concluding remarks.

DATA AND METHODS

Data description

To analyze the efficiency and productivity of the U.S. Hospital Care system we use a Stochastic Cost Frontier Analysis (Kumbhakar & Knox Lovell, 2003). We conduct the analysis using annual U.S. state-level data from 1999 to 2009 for Hospital Care Expense. Although aggregate hospital care data were available only for those years, we believe that using this time frame is still valid for our research inquiry for several reasons. First, this period was relatively stable politically for U.S. healthcare as well as a period in which no major advancements were made in cardiovascular care that might impact the results. Second, the period is long enough to capture time invariant technical efficiencies. Third, it is far enough back in time that we can find reasonably complete data for each state but not too far back that the data was no longer available. This state-level data was obtained from the CMS Office of the Actuary National Health Expenditure Hospital. We acquired data for hospital beds per 1,000 residents and number of state, profit and not-for-profit hospitals from the Kaiser Family Foundation (http://kff.org/other/state-indicator/beds-by-ownership — last access 10/17/16). Data on Obesity Rates, Diabetes Rates and Smoking Rates was obtained from the United Health Foundation America's Health Rankings (americashealthrankings.org/explore/2015-annual-report/measure — last access 10/17/16); data on hospital mortality rates of patients with chronic diseases that have been hospitalized in the previous two years were obtained from The Dartmouth Atlas of Healthcare (http://www.dartmouthatlas.org/data/hospital/ — last access 06/18/17)[1]. Finally, we use data on each state's political orientation, GDP, and private consumer expenditure from the Bureau of Economic Analysis, in an attempt to explain possible factors that could influence the technical efficiency of the hospital care system in each state.

We included the political orientation of the state by year so as to control for any potential conservative or progressive state healthcare regulations on the technical inefficiency of the hospital care. For example, while not captured in our data, one of the key provisions of the Affordable Care Act of 2010 was to expand the Medicaid program to low income families by changing their eligibility. In 2017, 19 out of 51 states (including the District of Columbia) opted out from the Medicaid Expansion. These States were: Alabama, Florida, Georgia, Idaho, Kansas, Maine, Mississippi, Missouri, Nebraska, North Carolina, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Wisconsin, and Wyoming. These states have been historically conservative and supported Republican candidates at the presidential elections. Some of these states, though, have swung to Democrats and possible change of political leaning and political orientation of the state is important because it may help to capture any potential state political decisions impacting hospital technical inefficiency.

Based on this data, we constructed panel data that is used to estimate the cost of the hospital care system as a function of the hospital output (admitted patients), hospital size, and an error term, i.e., $AC_{it} = f(q_{it}, S_{it}, e_{it})$ in a similar fashion as in Lave and Lave (1970). The average total cost of hospital care (AC) is derived by taking the ratio of the total expenditure for hospital care in state i in year t to the number of patient days q_{it}[2]. A proxy for public spending and investment was constructed by subtracting private consumer expenditure from the GDP for each state per each year. The average cost and the proxy for public spending and investment have been deflated using the Consumer Price Index (2016 base year) available at the U.S. census. Descriptive statistics of the variable used to construct our model are reported in Table 1.

Table 1
Descriptive Statistics

Year	*AC*[a]		*q*[b]		*S*[c]		*Stateh*[d]	
	mean	*St. dev.*	*Mean*	*St. dev.*	*Mean*	*St. dev.*	*Mean*	*St. dev.*
1999	1,461	1,835	3,908,905	4,200,168	16,873	17,166	23.92	25.04
2000	1,473	1,740	3,830,225	4,103,626	16,405	16,503	23.26	24.79
2001	1,539	1,845	3,863,509	4,137,124	16,393	16,520	23.12	24.65
2002	1,639	1,989	3,912,239	4,204,162	16,332	16,483	22.74	24.54
2003	1,761	2,182	3,907,936	4,212,069	16,198	16,542	22.40	24.45
2004	1,795	2,201	3,922,798	4,180,705	16,047	16,191	22.34	24.26
2005	1,880	2,329	3,911,600	4,157,482	15,892	15,984	22.20	23.97
2006	1,960	2,472	3,904,847	4,181,580	15,973	16,161	22.38	24.00
2007	1,990	2,431	3,873,062	4,091,272	15,953	16,007	22.22	23.69
2008	2,035	2,522	3,900,230	4,141,645	16,090	16,204	22.10	23.54
2009	2,185	2,728	3,830,222	4,062,986	16,021	16,114	21.84	23.40
	profith[e]		*nonprofith*[f]		*PSI*[g]		*Blue*[h,*]	
	Mean	*St. dev.*	*Mean*	*St. dev.*	*Mean*	*St. dev.*	*Mean*	*St. dev.*
1999	14.88	26.30	60.08	51.44	341,125	409,392	32	3.394
2000	14.92	25.72	59.90	50.90	343,954	418,669	32	3.394
2001	15.04	25.94	59.80	50.28	335,706	407,386	21	3.490
2002	15.26	25.80	60.38	49.87	334,491	405,409	21	3.490
2003	15.72	25.88	59.56	48.53	335,051	406,219	21	3.490
2004	16.62	26.25	59.20	48.00	337,671	410,883	21	3.490
2005	17.28	26.23	59.02	48.00	336,568	411,838	22	3.510
2006	17.70	27.01	58.24	47.10	333,906	410,814	22	3.510
2007	17.40	26.31	58.12	46.90	329,000	406,007	22	3.510
2008	19.58	28.26	58.32	46.73	313,901	387,380	22	3.510
2009	19.90	28.98	58.22	46.00	303,488	371,551	29	3.490
	In-Hospital mortality rate[m]		*Cardiac disease mortality rate*[n]		*Obesity rate*[t]		*Smoking rate*[v]	
	mean	*St. dev.*	*Mean*	*St. dev.*	*Mean*	*St. dev.*	*Mean*	*St. dev.*
1999	34.23	3.19	348.40	39.06	18.06	2.51	23.24	2.99
2000	33.11	3.15	345.60	39.26	19.14	2.70	23.09	3.03
2001	32.34	3.50	339.70	39.93	20.03	2.41	22.84	3.03
2002	31.55	3.35	335.90	40.78	21.11	2.44	23.33	2.99
2003	31.24	4.83	330.50	41.26	21.8	2.75	23.37	3.33
2004	29.87	4.89	324.50	40.87	22.47	2.85	22.51	3.33
2005	29.06	4.59	319.10	40.97	23.06	2.83	21.44	3.19
2006	27.98	4.60	312.60	40.37	24.55	3.04	21.01	3.16
2007	27.07	4.21	302.60	39.94	25.12	2.96	20.35	3.14
2008	27.02	4.16	292.50	39.34	26.31	2.87	20.09	3.18
2009	25.62	3.86	282.60	38.68	26.75	3.01	19.00	3.37

Notes: [a]Average Total Cost expressed in 2006 US$ per patient day; [b]patient days; [c]number of beds; [d]number of state public hospitals; [e]number of private hospitals; [f]number of not-for-profit hospitals; [h]states that voted for a democratic candidate at the presidential elections of 1996, 2000, 2004 and 2008; [g]public spenditure and investments (PSI) expressed in millions of 2016 US$; [m]In Hospital mortality rate expressed as percentage of deceased hospitalized patients with chronic disease in the last two years; [n]cardiac disease mortality rate per 1,000 people; [t]Obesity rate as percentage of adult population; [v]Smoking rate as percentage of adult population; *binary variable that is assumed to follow the binomial distribution: mean and standard deviation is computed for the binomial distribution.

Econometric Model

Stochastic Frontier modeling assumes that the error term e_{it} is decomposed in two components: technical inefficiency (u_{it}) and Gaussian noise (v_{it}). As previously mentioned, we also assume that other exogenous factors could influence the technical inefficiency of each state every year. We express the cost function in the Cobb-Douglas self-dual functional form that is flexible and widely used both in Health Economics and Productivity Analysis. Therefore, we can formally rewrite the stochastic cost frontier in logarithmic form as:

$$\ln (AC_{it}) = \alpha_{0i} + \beta_1 \ln (q_{it}) + \beta_2 \ln (S_{it}) + \delta\tau + v_{it} + u_{it} \tag{1}$$

$$u_{it} = \gamma_0 + \gamma_1 \ln (stateh_{it}) + \gamma_2 \ln (profith_{it}) + \gamma_3 \ln (noprofith_{it}) + \gamma_4 \ln (PSI_{it}) + \gamma_5\, Blue_{it} \tag{2}$$

where i=1...50 states and t=1999…2009. q_{it} is the number of patient-days "produced" by the hospital system in state *i* in year *t*; S_{it} are hospital beds available in state *i* in year *t;* τ is a trend variable; $stateh_{it}$ are number of state hospitals, $profith_{it}$ are number of for profit hospitals; $nonprofith_{it}$ is the number of not-for-profit hospitals; PSI_{it} is aggregate public spending and private and public investments; D_{it} is a binary variable set to one if the majority of the voters of the state voted for a Democratic candidate at the presidential elections (between 1999 and 2009) and zero otherwise; v_{it} are the element of a vector of state's unobserved heterogeneities that is distributed as $N(0, \sigma_v^2)$ and u_{it} are the elements of a vector of technical inefficiencies that are assumed to be distributed as $N^{+}(\gamma'\mathbf{Z}_{it}, \sigma_u^2)$.

Schmidt and Sickles (1984) assume that the vector of technical inefficiencies is time invariant (u_i) and they would treat the hospital specific intercept $\alpha_i = (\alpha_{0i}\text{-}u_i)$ as the inefficiency term. Under this assumption, model (1) does not present any estimation difficulty, the inefficiency terms α_i can be recovered after the model is estimated through a least square dummy variable (LSDV) technique; consequently, the vector of technical efficiencies (at state level) could be calculated as (min $\hat{\alpha}_{0i} - \hat{\alpha}_{0i}$). However, Greene (2005) points out that this method of estimating the technical efficiency of firms may be misleading for two main reasons: (i) by identifying the intercepts of (1) as technical inefficiencies one assumes that unobserved time invariant characteristics of producers are not present, and (ii) the inefficiencies are assumed to be time invariant (a strong assumption).

For example, in 2014, the Center for Disease Control and Prevention (CDC) estimated that the smoking rate for residents of Utah is approximately 10% among the adults in 2014 versus almost 27% for residents of West Virginia (CDC, 2016). If one considers smoking rate as a proxy for health risk behavior, it is plausible to assume that Utah residents have a lifestyle that may be healthier compared to other states. Consequently, if hospitalization rates for Utah residents are lower (lower *q*) compared to residents from other states such as West Virginia, then the total cost of the hospital care system in Utah would be lower. The lower hospital care cost would be attributed to the unobserved potential healthier life style of Utah residents rather than to efficient management operations of the hospitals in Utah, which supports Greene's claim (i). Along the same line assuming that inefficiencies are time invariant (Greene's claim (ii)) would be consistent with *a priori* assumption that a healthcare policy aimed to increase the efficiency of the hospital care in a certain year would be ineffective.

To overcome these issues associated with the ordinary least squares estimation of the time invariant inefficiencies, Greene (2005) suggests the use of a true fixed effect estimator of the stochastic cost frontier that can be performed by the method of maximum likelihood estimation. Therefore, following Greene, we rewrite (1) in terms of the composed error term e_{it} as

$$e_{it} = v_{it} + u_{it}\,(stateh_{it}, profith_{it}, nonprofith_{it}, PSI_{it}, Blue_{it}) = \ln(AC_{it}) - \alpha_{0i} - \beta_1 \ln(q_{it}) - \beta_2 \ln(S_{it}) - \delta\tau \tag{3}$$

maintaining the same previous distributional assumptions for the spherical disturbances v_{it} and the inefficiency term u_{it} which include also the exogenous influences on the technical inefficiencies. Assuming that v_{it} and u_{it} are independently distributed, we use a generalization of the truncated-normal model suggested by Kumbhakar and Lovell (2003) to specify the following log-likelihood function for the true fixed-effect stochastic cost frontier model as

$$-\frac{N\cdot T}{2}\ln(2\pi) - \frac{N\cdot T}{2}\ln\left(\sigma_v^2 + \sigma_u^2\right) - \sum_{i=1}^{50}\sum_{t=1}^{11}\ln\,\Phi\left[\frac{\gamma' Z_{it}}{\sigma_u}\right] + \sum_{i=1}^{50}\sum_{t=1}^{11}\ln\,\Phi\left[\frac{(\sigma_v^2\gamma' Z_{it} + \sigma_u^2 e_{it})\sqrt{\sigma_v^2+\sigma_u^2}}{(\sigma_u\sigma_v)(\sigma_v^2+\sigma_u^2)}\right] - \frac{1}{2}\sum_{i=1}^{50}\sum_{t=1}^{11}\frac{(-e_{it}+\gamma' Z_{it})^2}{\sigma_v^2+\sigma_u^2} \tag{4}$$

with Φ and φ representing the cumulative and probability density functions of the standard normal distribution. Equation (4) has to be maximized with respect to the parameters βs, γs, σ_u and σ_v. In order to recover the NxT(=550) vector of technical inefficiencies is necessary to estimate $N+K$(including γs) + 2(=61) parameters. The numerical optimization of (4) and the computation of its Hessian matrix, necessary to derive the Information matrix and the asymptotic variance-covariance matrix of the coefficient, can be performed by using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm as in Affuso *et al.* (2015). The elements of the vector of inefficiencies u_{it} can be recovered, post optimization, by using the formula derived by Jondrow *et al.* (1982):

$$\mathbb{E}(u_{it}\mid e_{it}, Z_{it}) = \frac{\sigma_u\sqrt{\sigma_u^2+\sigma_v^2}}{\sigma_v\left[1+\left(\frac{\sigma_u}{\sigma_v}\right)^2\right]}\left[\frac{\phi\left(\frac{-e_{it}\sigma_u}{\sigma_v\sqrt{\sigma_u^2+\sigma_v^2}}\right)}{\Phi\left(\frac{e_{it}\sigma_u}{\sigma_v\sqrt{\sigma_u^2+\sigma_v^2}}\right)}\right] + \frac{e_{it}\sigma_u}{\sigma_v\sqrt{\sigma_u^2+\sigma_v^2}} \tag{5}$$

where e_{it} are the elements of the estimated error of (4). The vector of technical efficiencies can be easily computed exponentiating the negative of the technical inefficiencies, i.e., $exp(-u_i)$. Efficiently delivered hospital level treatment has consistently been shown to decrease hospital mortality rates for cardiovascular disease (Peterson *et al.,* 2008; Mitsakakis, Wijeysundera, & Krahn, 2013). However, because hospital mortality rates due to cardiovascular disease were not available, we followed the guidance of Deily and McKay (2006) and estimated the potential impact of the efficiency score on in-hospital fatalities of patients with chronic diseases. In addition, we used a more robust approach based on the Generalized Method of Moments (GMM) (Arellano & Bond, 1991) allowing us to test for causality between hospital technical efficiency and in-hospital mortality rate according to the following dynamic panel model:

$$\Delta(inhospitalmortality)_{it} = \zeta_1\Delta(inhospitalmortality)_{it-1} + \zeta_2\Delta exp(-u)_{it-1} + \zeta_3\Delta(obesity)_{it} + \zeta_4\Delta(smoking)_{it} + \zeta_5\Delta\,(diabetes)_{it} + \zeta_6\Delta(cardisease)_{it} + \Delta\varepsilon_{it} \quad (6)$$

where *inhospmortality* is the percentage of patients who have deceased in the hospital due to chronic diseases, *exp(-u)* is the technical efficiency previously estimated by (5), *obesity* is the percentage of residents who identified themselves as obese (obesity rate), *smoking* is the percentage of residents who smoke, *diabetes* is the percentage of people who suffer from diabetes, and *cardiseases* is the mortality rate due to cardiovascular diseases. It should be noted that this model is expressed in first differences (in the time dimension), therefore intercept and unobservable time invariant effects of the regressors are removed. In addition, as is customary for dynamic panel models, we use past lags of the dependent variable and the vector of technical efficiencies (both in first difference form) as instruments to address the endogeneity that arises by the correlation between the cross-sectional units of the lagged dependent variable and those of the error term. Most importantly, and similar to Holtz-Eakin, Newey and Rosen (1988), we tested for a zero coefficient of the lagged technical efficiency (ζ_2) consistent within the null hypothesis that the technical efficiency of the hospital care system in the U.S. does not Granger-cause in-hospital mortality. Since we have no reason to believe that the cardiovascular disease mortality rates, percentage of obese, smokers, and diabetics causes hospital deaths (of any kind) we still include the contemporary effects of these variables to explain their potential association with chronic diseases and in-hospital deaths to mitigate a potential omitted variable bias.

RESULTS AND DISCUSSION

Results of the LSDV model and the true fixed effects stochastic cost frontier model with exogenous influences in the inefficiency term are reported in Table 2 for comparison.

Compared to those of the LSDV model, the parameter estimates of the stochastic frontier model have more statistical power. Both estimates of σ_u and σ_v are statistically significant at 1% alpha level, confirming our hypothesis of the cost frontier being stochastic. In addition, the lower value of the Akaike Information Criterion (AIC) for the stochastic frontier model (2,145) compared to that that of the LSDV model (2,220) further supports our contention that the stochastic frontier model better represents reality with minimum information loss. Consequently, this model should be preferred to the LSDV model. Although the parameter estimates of the cost function are not the main focus of our study, we included a log quadratic term ($\ln^2(q)$) in our statistical model that was not statistically significant. In addition, we tested for joint significance of the log-quadratic term (null hypothesis H_0 that the true model is the log-linear model 1). This test follows the χ^2 distribution with degrees of freedom equal to the number of restrictions (1 degree of freedom in our case). The likelihood ratio statistics for this test was $\Lambda = -3.98$, smaller than the critical value of $\chi^2(1) = 2.71$ with 90% confidence (p-value=1).

Table 2
Results

Variable	*Least Squares Dummy Variable*	*Stochastic Frontier Model*
ln(q)	-0.814***	-0.868***
	(0.057)	(0.053)
ln(S) (# of beds)	-0.134**	-0.184***
	(0.065)	(0.049)
τ (trend)	NA	0.034***
		(0.001)
σ_u	NA	0.026***
		(0.001)
σ_v	NA	0.028***
		(0.002)
constant	NA	0.475***
		(0.182)
ln(stateh)	NA	-0.058***
		(0.011)
ln(profith)	NA	0.011*
		(0.006)
ln(nonprofith)	NA	0.137***
		(0.022)
ln(PSI)	NA	-0.059**
		(0.019)
Blue (0/1)	NA	0.003
		(0.007)
R^2	0.591	NA
F-stat	352.22***	NA
AIC	2,220	2,145
Degrees of Freedom	488	489

Notes: ***99%, **95%, *90% confidence intervals; standard errors in parentheses; dependent variable is ln(AC); *q* is number of patient days; *S* is number of hospital beds; *stateh* is the number of state hospitals; *profith* is the number of for-profit hospitals; *nonprofith* is the number of not-for-profit hospitals; *PSI* is public spending and investment; *Blue* is equal to 1 if the majority of the voters of the state voted for a democratic candidate at the presidential elections. State intercepts (and time dummies for LSDV model) are not reported for the sake of space. These are available from the authors upon request.

Therefore, we failed to reject the restricted model in favor of the estimated stochastic cost frontier model. This finding supports a similar statistical test and the arguments of Walters (1963) and Lave and Lave (1970) who find evidence that short-run empirical cost functions, particularly for hospitals, are L-shaped.

From the parameter estimates it is possible to measure the scale of the hospital care system in the U.S. by partially differentiating the estimated model with respect to ln(q) and ln(S). In the first case, we can calculate the short-run average cost-output elasticity as $\frac{\partial \ln AC}{\partial \ln q} = \widehat{\beta_1} = -0.868.$

This measure implies that, on average, between 1999 and 2009 U.S. hospitals operated on the declining part of the short run average cost curve, i.e., a 10% increase in patient days would lower the short run average total cost by 8.68%. Along the same lines, the estimated coefficient β_2 = -0.184 shows that the long-run average total costs could potentially decline, capturing economies of scale, in the instance that hospitals increased their size[3]. Based on the estimate of the trend parameter, we note that the real average cost of hospital care increased potentially by 3.4% per year. This is not surprising since the annual cost increase of the healthcare appears evident also in the raw data reported in Table 1 (first column). This increase over time may be consistent with a decline in the overall technical efficiency of the hospital care across the modeled years. Another explanation is that Hospitals may not be able to increase their size (especially city hospitals) so they may turn to other more expensive options such as recruiting better, but more expensive, surgeons or other healthcare professionals to use in their existing locations in an attempt to improve their technical efficiency.

In terms of the determinants of technical inefficiency, our analysis shows that an increase in the number of state hospitals is associated with higher technical efficiency. This might be a result of relationships with State or University hospitals that could subsidize better care in a teaching hospital setting but we were unable to confirm with our data. The same relationship (of similar magnitude) exists between public spending and investments and technical efficiency. On the contrary, an increase in the number of profit and not-for-profit hospitals was associated with a decrease in technical efficiency and potential increase in long run costs. This negative relationship may be a result of the simple fact that because these hospitals are not affiliated with the state or university, they are not able to recruit top doctors and surgeons resulting in an efficiency that is less than those that are. This would be especially true in more urban states where the hospitals are needed, but the number of top-rated professionals is limited. The relationship between the presidential political affiliation of a state and the efficiency of the hospital care delivery is statistically equal to zero.

As previously noted, to recover the inefficiency u_{it} of the hospital care system, we can use (5) which provides a point estimate of the inefficiency for each state in each year between 1999 and 2009. However, it is convenient to conduct our analysis in terms of technical efficiencies for each state which can be calculated, as previously mentioned, by exponentiating the negative of u_{it}, i.e., $\exp(-u_{it})$. An average ranking (between 1999 and 2009) of the hospital care system for each state is reported in Table 3. For the sake of comparison, in the same table, we report also a ranking based on the time invariant technical efficiencies as in Schmidt and Sickles (1984) computed from the LSDV model.

Based on our estimation and using the stochastic frontier model, it appears that some of the low populated states (Wyoming and Idaho) are ranked the highest in terms of technical efficiency. Although it is hard to speculate about a relationship between number of residents and technical efficiency of the hospital care, it should be plausible that hospitals with potentially fewer patients could be more dedicated and specialized in the care of their customers. On the other hand, we note that in higher populated and more urban states such as Pennsylvania (second lowest efficiency rank), hospital care costs could be driven by a potential larger volume of customers who demand more tests and options. Thus, doctors may be utilizing more defensive medicine resulting in a lower technical efficiency. In addition, in Figure 1 we present a map of the geographic distribution of the technical efficiency of the hospital care system in the U.S.

Table 3
Technical Efficiency Ranking

LSDV model			*Stochastic Frontier Model*		
Rank	*State*	*Time Invariant Technical Efficiency*[a]	*Rank*	*State*	*Technical Efficiency*[b]
1	California	1	1	Wyoming	0.9910
2	Arizona	0.9787	2	Idaho	0.9746
3	Utah	0.9698	3	Nevada	0.9691
4	Nevada	0.9535	4	Washington	0.9632
5	Georgia	0.9267	5	Louisiana	0.9556
6	Texas	0.9044	6	South Carolina	0.9544
7	Colorado	0.8648	7	Colorado	0.9517
8	Florida	0.8647	8	Alabama	0.9378
9	Virginia	0.8443	9	Mississippi	0.9355
10	Oregon	0.8324	10	Alaska	0.9333
11	Washington	0.8249	11	Georgia	0.9297
12	North Carolina	0.8181	12	Hawaii	0.9204
13	Tennessee	0.8168	13	Delaware	0.9202
14	Alabama	0.8155	14	Iowa	0.9158
15	Idaho	0.7949	15	Oklahoma	0.9132
16	New Jersey	0.7853	16	New Mexico	0.9132
17	Arkansas	0.7663	17	Indiana	0.9047
18	Minnesota	0.7587	18	Texas	0.8992
19	Michigan	0.7454	19	Nebraska	0.8947
20	Oklahoma	0.7443	20	North Carolina	0.8910
21	New Mexico	0.7416	21	Kansas	0.8871
22	South Carolina	0.7389	22	Utah	0.8817
23	Hawaii	0.7377	23	Missouri	0.8798
24	Illinois	0.733	24	Minnesota	0.8768
25	Connecticut	0.7324	25	Oregon	0.8724
26	Kansas	0.727	26	California	0.8651
27	Indiana	0.723	27	Tennessee	0.8617
28	Maryland	0.7186	28	Florida	0.8613
29	Kentucky	0.7162	29	Arizona	0.8442
30	Ohio	0.7118	30	Rhode Island	0.8440
31	Pennsylvania	0.711	31	New York	0.8367
32	Louisiana	0.7051	32	Connecticut	0.8336
33	New York	0.6983	33	West Virginia	0.8283
34	Wisconsin	0.6981	34	Arkansas	0.8255
35	Mississippi	0.6836	35	Illinois	0.8216
36	Iowa	0.6701	36	Ohio	0.8158
37	New Hampshire	0.6626	37	Michigan	0.8111
38	Missouri	0.654	38	Virginia	0.8074
39	Montana	0.649	39	Kentucky	0.7987
40	Nebraska	0.6144	40	Massachusetts	0.7965

contd. table 3

LSDV model			*Stochastic Frontier Model*		
Rank	*State*	*Time Invariant Technical Efficiency*[a]	*Rank*	*State*	*Technical Efficiency*[b]
41	Rhode Island	0.6101	41	Montana	0.7940
42	Delaware	0.6003	42	New Jersey	0.7936
43	South Dakota	0.596	43	Vermont	0.7881
44	Maine	0.5852	44	Maine	0.7763
45	Wyoming	0.5843	45	Maryland	0.7680
46	West Virginia	0.5826	46	South Dakota	0.7657
47	Massachusetts	0.5761	47	New Hampshire	0.7608
48	Vermont	0.5642	48	Wisconsin	0.7136
49	North Dakota	0.5566	49	Pennsylvania	0.6941
50	Alaska	0.472	50	North Dakota	0.6879
	Average	0.7353		Average	0.8612
	St. Dev.	0.1206		St. Dev.	0.0745

Notes: [a] time invariant technical efficiency based on the LSDV model following the method of Schmidt and Sickles (1984); [b] technical efficiencies based on the Stochastic Frontier Model and computed with the formula of Jondrow *et al.* (1982).

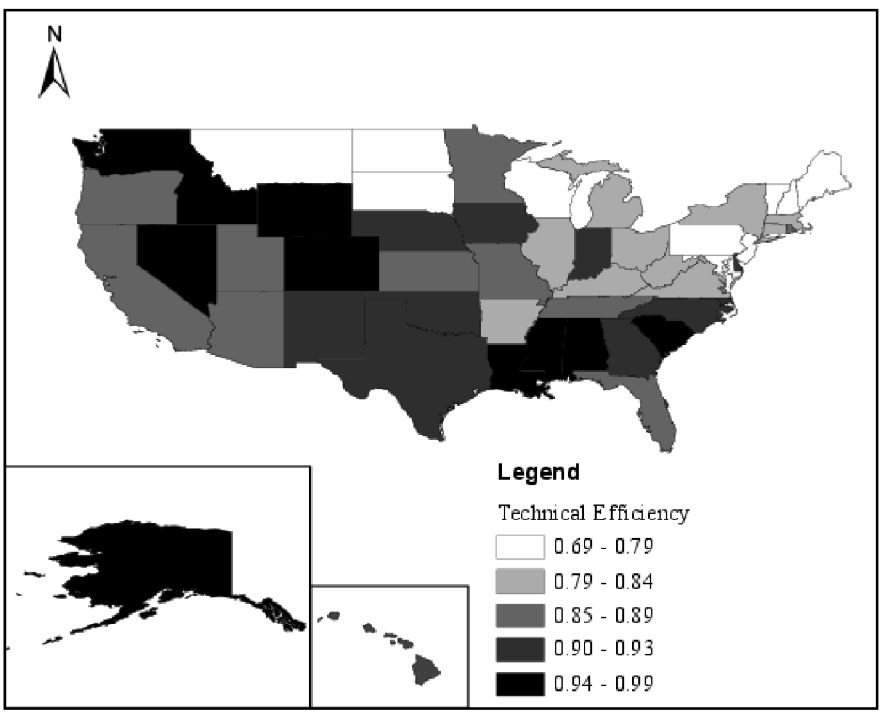

Figure 1: Geographic Distribution of Hospital Care cost efficiency

The map shows a clear pattern of technical efficiency that appears to be geographically correlated. The hospital care delivery of some of the states in the North-Eastern regions (more urban) appear to be less cost efficient when compared to the South/South Western states that have similar efficiency scores. This result could be related to the fact that neighboring states are more likely to share the same pool of hospital managers and workers. However, the relationship between hospital admissions, technical efficiency and potential spatial correlation of the efficiency scores is a topic that should be addressed in future standalone studies. In general, all states have a better and more robust efficiency rating than using the LSDV model and even the lowest ranked state by the SFA model has a better efficiency compared to the states in the LSDV model. This result is consistent with previous findings of Greene (2004).

It is also interesting to note that, based on the time invariant technical efficiency, the Utah hospitals would be ranked third among all states. This confirms our expectation of a potential bias of the time invariant inefficiency method that does not disentangle a potential healthier life style of residents of that state who would make less use of hospital care. Overall, we found that the hospital care in the U.S. is fairly efficient, in fact, according to our computation the average value of the technical efficiency of the U.S. hospital care between 1999 and 2009 was 0.8612 (st. dev 0.0745). Figure 2 illustrates a comparison of the kernel density estimates of the average technical efficiency of the U.S. hospital care system between 1999 and 2009 to the time invariant technical efficiency (column 3 of Table 3) which clearly illustrates the downward bias of the time invariant technical efficiency.

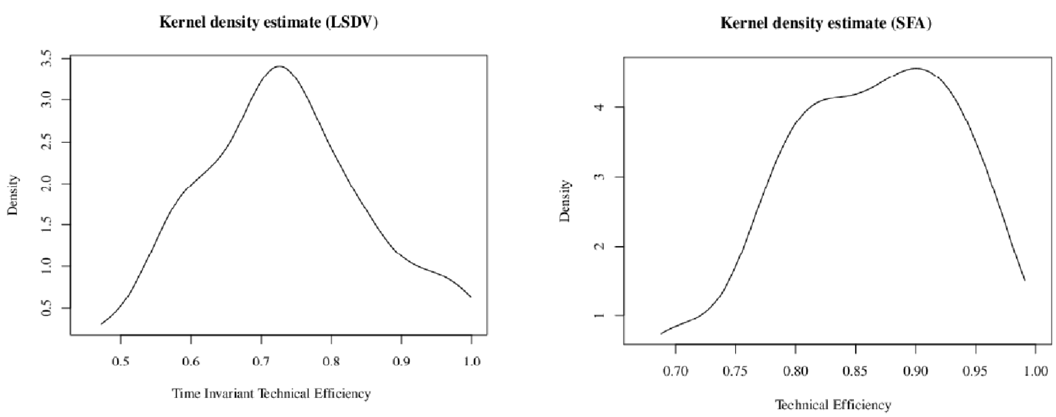

Figure 2: Kernel Density Estimates

Another advantage of estimating the true fixed effect stochastic frontier model is the possibility to analyze the dynamics of the technical efficiency of the U.S. hospital care system across the modeled period between 1999 and 2009. As illustrated in Figure 3, it appears that the efficiency of the hospital care system in the U.S. is cyclical with the minimum reached in 2005. While the cause or causes of this cyclical nature are beyond the scope of our paper, there are some possible contributions to this cycle that we are aware. For instance, the Balance Budget Act (BBA) of 1997 downwardly reduced the annual adjustment to Medicare hospital payments. These payment reductions may have prompted hospitals to find ways to improve operating efficiency. The BBA expired in 2002 removing some of the financial pressure driving efficiency which could had an impact on the declining efficiency after 2002 as illustrated in Figure 3. While the Affordable Care Act (passed in 2009-10) cannot be a direct cause of the declining efficiency after the year 2008, another macroeconomic event, the U.S. recession of 2008 may have impacted the technical efficiency of hospitals for 2009 for at least three reasons. First, hospitals may have attempted to cut costs more resulting in fewer workers covering the same number of patients. Second, patients may have become less concerned about their health needs when the overall economic picture of the nation was looking grim thus reducing utilization of hospital services. Third, according to Hartman et al. (2010), in 2008 the hospital care spending growth in the U.S. slowed down to 4.5% (one of the historical minima), and given the inverse relationship between technical efficiency and potential spending and investments, previously found, it is likely that the reduction in spending and investments in the hospital care could have potentially triggered a decline in technical efficiency. However, as data will be available in the future it will be interesting to study the long-term impact of an economic downturn on the hospital care cost efficiency.

Although the U.S. hospitals appear to be fairly efficient, we now test for causality relationship between technical efficiency and in-hospital mortality rate by estimating the dynamic panel model (6). Results of the GMM estimation in first differences are reported in Table 4.

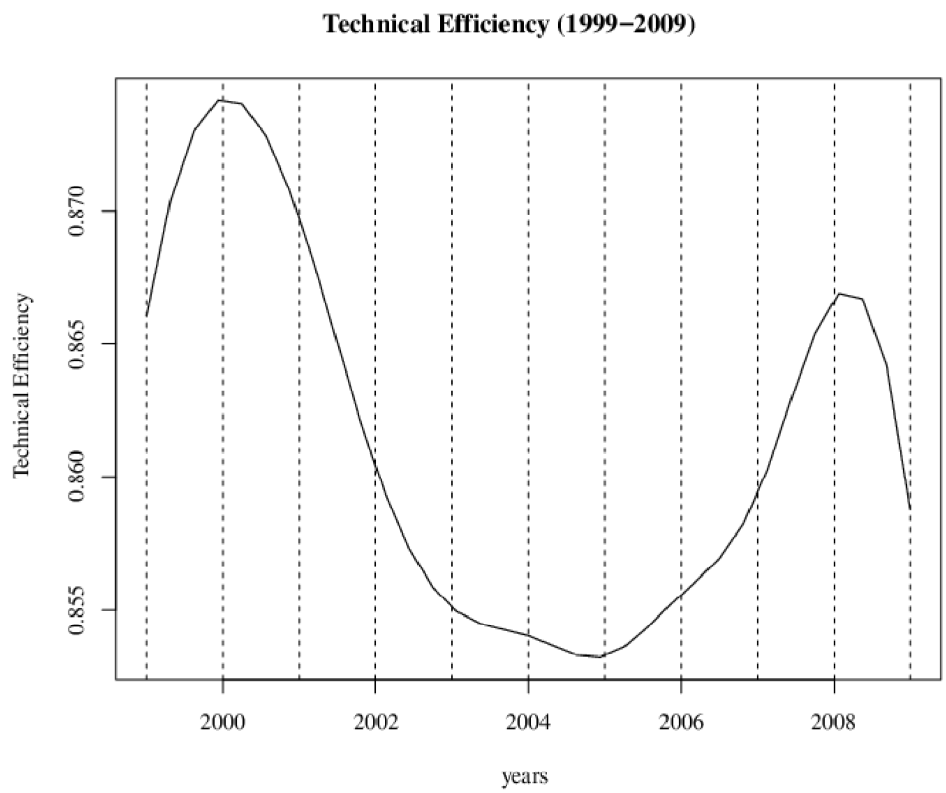

Figure 3: Dynamic Illustration of the Technical Efficiency of U.S. hospitals

Table 4
Technical Efficiency and In-hospital Mortality Rate

Variable	*Estimates*
$\Delta(inhospitalmortality)_{it-1}$	0.050
	(0.122)
$\Delta\exp(-u)_{it-1}$ (Technical Efficiency)	-0.598**
	(0.236)
$\Delta(obesity)_{it}$	-0.034
	(0.083)
$\Delta(smoking)_{it}$	0.014
	(0.102)
$\Delta(diabetes)_{it}$	0.567***
	(0.005)
$\Delta(cardisease)_{it}$	0.404
	(0.305)
Sargan Test[a] $\chi^2(46)$	49.17
	(pval=0.347)
Wald test for coefficients $\chi^2(6)$	15.4**
	(pval=0.017)
Wald test for time dummies $\chi^2(9)$	38.15***
	(pval=0.000)
First order residuals autocorrelation test[b]	-2.69***
	(pval=0.001)
Second order residuals autocorrelation test[c]	-0.934
	(pval=0.350)
# of instruments (including time dummies)	46
# of observations	450

Notes: ***99%, *90% confidence intervals; standard errors in parentheses; dependent variable is ”$(inhospitalmortality)_{it}$; [a]Sargan Test failed to reject H_0: the 88 instruments used are jointly valid; [b]Arellano-Bond test for serial correlation reject H_0: No Autocorrelation; [c]Arellano-Bond test for serial correlation (in differences) failed to reject H_0: No Autocorrelation.

A problem associated with the estimation of dynamic panel GMM model in differences can be the proliferation of too many instrumental variables in the attempt to solve for the endogeneity nature of these models. While too many instruments should correct for endogenous bias, having too many may induce another source of bias associated with overfitting the endogenous variables (Roodman, 2009). Consequently, a sensitivity analysis on the number of instruments used in these models is advisable. We constructed the matrix of instruments starting with only one previous lag of the dependent and technical efficiency variables (t = 2) and increasing the number of periods until the Sargan test failed to reject the null hypothesis of joint validity of the instruments. Therefore, we selected 3 periods: [$\Delta(inhospitalmortality)_{it-2}$, $\Delta(inhospitalmortality)_{it-3}$, $\Delta(inhospitalmortality)_{it-4}$, $\Delta\exp(-u)_{it-2}$, $\Delta\exp(-u)_{it-3}$, $\Delta\exp(-u)_{it-4}$] with the total number of instruments used being equal to 46 (including time dummies). The Sargan test statistics of $49.17 < \chi^2(46)_{10\%} = 58.64$ (p-val=0.347) suggests that the instruments used in the dynamic panel model are jointly valid. In addition, the Arellano-Bond test for serial correlation (-0.93 (pval=0.35)) failed to reject H_0: No Serial Autocorrelation in $\Delta\varepsilon_{it}$ and the F-tests for jointly significance of the estimated parameters and time dummies are statistically significant at 95% and 99%, respectively. Of the three contemporaneous variables, only diabetes rate is statistically significant at 1% alpha-level showing also a positive relationship with in-hospital mortality rate. Our variable of interest, past hospital technical efficiency, i.e., $\Delta\exp(-u)_{it-1}$, is statistically significant at 95% confidence with a negative causality relationship with contemporaneous in-hospital mortality rate. This result suggests that a 1 percentage point increase in hospital technical efficiency could result in a decline of approximately 0.598 percentage points in mortality of hospitalized patients with chronic diseases.

These finding corroborate previous studies showing that efficiency in hospital-based care delivery improves patient outcomes through following proven guidelines and evidenced based medicine protocols (but does not come without a cost). This is particularly true in efficiently delivered hospital-based cardiac care where adherence to American Heart Association and American College of Cardiology recommendations as well as other evidence based care protocols has shown to significantly reduce cardiac related hospital mortality rates (Kaul, *et al.,* 2007; Peterson *et al.,* 2008; Mitsakakis, Wijeysundera, & Krahn, 2013). Thus, as hospital management improves the efficiency of the delivery of evidence based cardiac care, mortality rates from cardiovascular disease decrease. One limitation of our study, which is common to other recent studies such as Lightwood and Glantz (2016), is to use a limited panel dataset that spans from 1999 to 2009. This slightly dated dataset does not cover the most recent changes to U.S. healthcare that have occurred with the passage of the Affordable Care Act. However, to run the statistical analyses and comparisons, we needed to collect data from various sources and these data were only available for the years 1999-2009. Further, by ending our analysis in 2009, we have a natural break point for our analysis being affected by other exogenous variables associated with the passage of the ACA. Thus, we allow for future researchers to compare post ACA versus pre-ACA using either or both analyses.

However, in light of the causality relationship between state level hospital technical efficiency and state level in-hospital mortality, we believe that our findings are still important and pose a valid concern given the intertemporal variability of hospital technical efficiencies (0.69 percentage points) and the cross-sectional variability across the states of the U.S. of approximately 7.45 percentage points. As more data will be available in the future, our study could be replicated and used by public health policy makers to design policies and managerial programs that use federal funds more efficiently to reduce the potential social costs associated with hospital technical inefficiencies.

CONCLUSION

As health care costs continue to escalate, researchers as well as policy makers seek explanations and solutions to curb these ever-increasing costs. Much focus in health care efficiency research is placed on hospital care delivery. This is not surprising as hospital costs make up the single largest category of health care expenditures. Several studies in the healthcare policy literature have aimed to analyze the aggregate healthcare efficiency of different economies and provide a ranking of countries based on the efficiency of healthcare delivery (Gravelle *et al.* 2003; Greene, 2004; Hollingsworth & Wildman, 2003).

We use a similar approach but focused on the cost efficiency and productivity of the hospital care system in the U.S. Our research adds to the hospital efficiency research stream by utilizing panel data for state level hospital cost for the time period 1999- 2009. Using a stochastic frontier analysis with exogenous influences in the efficiency term, this study demonstrates that hospitals on the state level aggregate dimension are operating on average at 86.12% ± 7.45% efficiency score. This indicates that based on the current model of reimbursement and care delivery on aggregate hospitals are fairly efficient. In addition, we found a granger-causality relationship between the hospital technical efficiency and in-hospital mortality rate. Our analysis speculates that changes in the economy, the nature of the hospitals, and potentially federal regulations influence the efficiency of hospital care delivery with possible detrimental effects on lives of hospitalized patients with chronic diseases. However, rather than looking punitively at the hospital care delivery system as a way to curb costs policy makers should continue to seek ways to change the delivery model as they are through Accountable Care Organizations, Bundled Payments, and other Value-based initiatives.

Furthermore, our study found that U.S. hospital managers exploit economies of scale. In fact, as suggested by our analysis, short term costs may be reduced by increasing patient days in the hospital, i.e. increasing the hospital load. However, hospitals may be required to have some slack in their operations to handle emergencies. A long-term solution is also suggested as hospital total costs may be reduced by an increase in total number of beds. Because individual hospitals may not be able to add beds, policy makers may want to investigate whether building bigger hospitals may be a more cost-effective solution, as our analysis suggests.

A limitation of our study, which is common to other recent studies that use the same source of data, is the limited panel dataset that spans from 1999 to 2009. However, it is undeniable that hospital care technical efficiency in the U.S. was not immune to intertemporal and cross-sectional variability across the states. Given the existence of a causality relationship between state level hospital technical efficiency and state level in-hospital mortality, we believe that our findings are still important and as more data become available, the replication of our study could provide a needed comparison with the pre-Affordable Care Act era to current conditions. This could aid healthcare policy makers to design socially efficient policies that aim to smooth the variability and increase the technical efficiency of the healthcare system, reducing both the associated social and managerial costs.

Notes

1. Missing data were imputed with the multivariate chain equation algorithm of Buuren and Groothuis-Oudshoorn (2011) using the remaining full information of our entire panel dataset that was constructed from multiple sources.
2. An anonymous referee rightly observed that q_{it} is exogenously generated by demand for hospital care and there could be a potential short-run disequilibrium between the number of available beds (S_{it}) and the number of patient days.
3. To analyze the sensitivity of this result, we included, alone and jointly, *cardisease* (cardiovascular disease mortality rate) and *inhospmortality* (in hospital death rate) as potential cost exogenous frontier shifters (proxy demand shifters). However, both variables were not statistically significant (both separately and jointly). We have also conducted log likelihood ratio tests which rejected these variables to be included in the stochastic cost frontier.

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