



Efficiency and profitability in US not-for-profit hospitals

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Abstract

This article examines the relationship between hospital profitability and efficiency. A cross-section of 1317 U.S. metropolitan, acute care, not-for-profit hospitals for the year 2015 was employed. We use a frontier method, stochastic frontier analysis, to estimate hospital efficiency. Total margin and operating margin were used as profit variables in OLS regressions that were corrected for heteroskedacity. In addition to estimated efficiency, control variables for internal and external correlates of profitability were included in the regression models. We found that more efficient hospitals were also more profitable. The results show a positive relationship between profitability and size, concentration of output, occupancy rate and membership in a multi-hospital system. An inverse relationship was found between profits and academic medical centers, average length of stay, location in a Medicaid expansion state, Medicaid and Medicare share of admissions, and unemployment rate. The results of a Hausman test indicates that efficiency is exogenous in the profit equations. The findings suggest that not-for-profit hospitals will be responsive to incentives for increasing efficiency and use market power to increase surplus to pursue their objectives.

Keywords Hospitals · Profits · Stochastic frontier analysis · Payment policy

JEL Classification I1 · I11

Introduction

In this article we examine the relationship between efficiency and hospital profits. Jacobs et al. (2006, p. 1) state that “The pursuit of efficiency has become a central objective of policy makers within most healthcare systems”. Rosko and Mutter (2011) point out that while costs can be reduced by socially undesirable ways such as reducing quality or reducing quantity of services (which reduces access), improvements in efficiency allow

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an increase in quality or quantity of services for the same outlay. However, increasing efficiency allows a reduction of costs without affecting quality or access and the attention to efficiency in the literature has been substantial. For example, Hussey et al. (2009) reported that over 5550 titles related to healthcare efficiency were published between 1990 and 2005. The Institute of Medicine included efficiency as one of six aims for the twenty-first century health system in its report *Crossing the Quality Chasm* (2001). As a result of the provisions of the Affordable Care Act of (2010), Medicare has implemented the Value-Based Purchasing (VBP) Program which rewards hospitals for the provision of efficient and good quality and patient centered care (Turner et al. 2015).

This study focuses on the relationship between efficiency and profit in 1317 not-for-profit (NFP) hospitals in 2015. Profit, the difference between revenue and expenses, is needed to sustain and grow the organization. It is likely that the COVID-19 pandemic has had a substantial negative effect on hospital profitability. Financial difficulties can deter hospital efforts to acquire new technology (Huang 2016), attract well-trained and gifted healthcare professionals, and make structural changes needed to deliver patient care in today's value-based purchasing environment (Bazzoli et al. 2014; Singh and Wheeler 2012). Furthermore, poor financial performance influences outcomes of care and limits access by either reducing services or causing hospital closure (Bazzoli et al. 2014; Bazzoli et al. 2008). Profits allow organizations to have a financial buffer to respond to the ever-changing healthcare environment and to commit resources to performance improvement projects which are highly needed in today's VBP reimbursement schemes. NFP hospitals rely on retained earnings (i.e., operating surplus) as an important source of funding capital projects and, unlike for-profit (FP) hospitals, they cannot sell shares to raise financial resources (Singh and Wheeler 2012). Therefore, profitability is important for both for-profit and not-for-profit hospitals.

There has been much interest in measuring health care efficiency and identifying sources of inefficiency. Hussey et al. (2009) point out that the term efficiency is used by different stakeholders to connote various constructs. While the Institute of Medicine (IOM) (2001) has defined efficiency as "avoiding waste", most definitions consider a relationship between inputs and outputs. Further, the definition of efficiency may have an output (e.g., the maximization of outputs, quality of care, and outcomes given the resources committed (Davis et al. 2014)) or an input orientation (e.g., the minimization of inputs needed to produce a target output). In this study, we use stochastic frontier analysis (SFA) to estimate cost-inefficiency (i.e., the difference between observed costs and the costs that would occur on the Best Practice Cost Frontier, given the hospital's output mix and the input prices it faces) because it reflects most sources of measurable inefficiency. SFA cost-inefficiency is very similar to X-Inefficiency (i.e., the difference between optimal performance and actual performance) (Leibenstein 1987).

Cost-inefficiency may be due to any of the following types of inefficiency: technical, allocative, scale, or scope. Technical inefficiency arises when the hospital does not maximize output given a set of inputs consumed. For example, if a hospital that employed a combination of inputs that was capable of producing 1000 units of output, but only produced 600 units of output, it would be considered 40 percent inefficient or 60 percent efficient. Allocative inefficiencies occur when hospitals do not use the least costly combination of inputs in producing output. Scale inefficiencies occur when the hospital fails to produce at the minimum point of its long-run average cost curve because it is either too small (i.e., experiencing increasing returns to scale) or too large (i.e., experiencing decreasing returns to scale). Scope inefficiencies are due to the hospital's inability to

reap the advantages that sometimes occur in the joint production of outputs that require similar inputs (e.g., providing adult and pediatric care in the same general hospital).

This is the first article that uses a measure of efficiency based on stochastic frontier analysis (SFA) to examine the association between efficiency and hospital profitability with a focus on NFP hospitals. We followed the methods of Greene and Segal (2004), who studied the association between efficiency and profitability in the life insurance industry.¹ Although the conventional wisdom argues that increases in efficiency should increase profitability, Kaplan and Norton (1992) argued that the linkage between operating performance and financial success is actually tenuous and uncertain. This is especially true in NFP organizations. While it is expected that FP hospitals will attempt to increase efficiency in their quest for profits, NFP hospitals have other goals. For example, Newhouse (1970) postulated that administrators at NFP hospitals attempt to maximize their utility from quality and quantity subject to a break-even constraint. Pauly (1987) agreed that NFPs act differently than FPs but mentioned that it is impossible to directly identify which objective NFP hospitals pursue because it is impossible to observe a hospital's utility function. Recognizing the aphorism, no margin/no mission, while NFP hospitals may not aim to maximize profits, we hypothesize that increasing efficiency would help to earn a surplus, which in turn, would help fund future activities that are implemented to achieve their objectives. Furthermore, given that profitability is not the main objective of NFP hospitals, we expect the relationship runs from efficiency to profitability and is not the two-way relationship we might expect in FP hospitals. We checked for this using a Hausman test which could not support the existence of endogeneity.

Conceptual framework

The association between efficiency and firm profitability is well established and an important area of research given the impact profitability has on organizational survival and growth. Organizations need to generate profits to ensure the availability of resources needed for the continuity, adaptability, and growth of the firm. In this section, we focus on the relationship between efficiency and profitability and present other organizational and market determinants of profitability.

Profit is the difference between revenue and expense. Organizations can increase their profitability by either increasing their revenues or by decreasing their expenses or a combination of both. Increased profitability is the result, among other factors, of organizations efficiently transforming their inputs (resources) to increase their output (Baik et al. 2013). Greene and Segal (2004) argue that “inefficiency affects profits and growth through the negative effects of wasted resources on earnings and cash flow” (p. 230). Efficient organizations are capable of transforming input into output through processes that are designed to minimize waste. Findings from different industries support the proposition that organizational efficiency is associated with profitability. For example, Greene and Segal (2004) found a negative association between inefficiency and organizational profitability in the life

¹ A reviewer raised the concern that there might be reverse causality between efficiency and profitability. If this existed, the estimates would be biased. However, in the frontier literature none of the articles (Goddard et al. 2004, Greene and Segal 2004; Papadopoulos 2004) that examined the relationship between efficiency and profitability expressed a concern about reverse causality. Further, as mentioned below, the results of a Hausman test ($p < 0.05$) could not support the existence of endogeneity.

insurance industry. Berger (1995) identified a positive impact of efficiency on the profitability of banks. In a descriptive study, Rosko et al. (2018) found that hospitals in the highest quartile of efficiency were substantially more profitable than hospitals in the lowest quartile of efficiency. However, two frontier studies in the banking industry could not find a relationship between efficiency and profitability (Goddard et al. 2004; Papadopoulos 2004).

NFP hospitals are private charitable institutions that are owned by religious or private secular entities. They operate under a non-distribution constraint, i.e., they are not allowed to directly distribute residual income to managers or board members. Thus, NFP hospitals are likely to be utility maximizers (Newhouse 1970). While many things might yield utility, NFPs are likely to attempt to provide high quality and prestigious services and graduate medical education, as well as community benefits and charity care, as long as this does not threaten their financial solvency. Given the absence of residual claimants who would pressure managers for profits, managers of NFP hospitals may be less likely to aggressively seek to maximize profit. However, Leibenstein's (1987) X-Efficiency theory predicts that external pressures that threaten solvency would cause managers of NFP hospitals to adopt strategies and tactics (including actions to increase efficiency) similar to their FP counterparts to improve their financial position. Indeed, Potter (2001) found that NFP hospitals that faced similar competitive and regulatory (e.g., under-payment by public payers) dynamics as FP hospitals tended to behave like FP hospitals. Therefore, we predict a positive relationship between efficiency and profits in NFP hospitals.

Since profitability is the difference between revenue and expense, a comprehensive model of profit determinants must consider factors that influence revenues and not focus solely on efficiency which primarily affects expenses. It has been argued that firm size is probably one of the most important structural dimensions that influences a firm's performance (Damanpour 1992; Hannan and Freeman 1984; Smith et al. 1986). Previous research found a positive relationship between organizational size and profitability (Hall and Weiss 1967). Lee (2009) studied 70,000 publicly traded firms over a 9-year period and found a significant positive relationship between organizational size and profits. Porter (1998) argues that larger organizations build on brand recognition and economies of scale in their strategies. This is particularly true in the hospital industry where larger hospitals and systems tend to be more visible in their communities and to have more bargaining power with suppliers (Kazley and Ozcan 2007) and insurers. Related to size are also the effects of system membership, which can convey the benefits of market power and firm-level scale effects (Rosko et al. 2007; Melnick and Keeler 2007).

Larger organizations possess an array of attributes that allows them to achieve higher levels of profitability. Larger hospitals tend to have more market power, slack, administrative and marketing resources, research and development capabilities, and other advantages that allow these organizations to innovate (Gaynor and Town 2012; Nord and Tucker 1987). As Damanpour (1992) explains; "larger organizations employ more professional and skilled workers, hence, these organizations have higher technical knowledge and technical potential" (p. 377). Larger hospitals, like larger firms, are expected to have the financial, human and technology resources and capabilities needed to capitalize on opportunities in the environment to generate more profits. We predict that hospital size is positively associated with hospital profitability.

Economic theory emphasizes the role market factors play in shaping firm performance (Hansen and Wernerfelt 1989). Industry attractiveness influences firm profitability (Grant 1996). Industry factors such as market share enable organizations to maximize their profitability by allowing them more freedom in setting service and product prices (Bai and

Anderson 2016). This is particularly true in the hospital industry whereby in addition to size, market share strengthens a hospital's position in negotiation with insurance companies (Gaynor and Town 2012). Therefore, we predict that hospitals with a greater market share are more profitable. Similarly, we expect profitability to be positively associated with market concentration.

Another external factor that can affect hospital profitability is regulatory and public payment policy. Medicare and Medicaid account for over 40% of payments to hospitals, on average. The relative generosity of these payments can have an important impact on hospital profits. In the early years of prospective payment, Medicare was a munificent payer for most urban hospitals. However, in recent years most hospitals have tended to lose money when serving Medicare patients (Medpac 2006; MedPac 2018). Medicaid, a joint federal-state program for the categorically needy, has underpaid most hospitals since its inception (Cunningham, et al. 2016). Therefore, we expect increases in the share of patients covered by Medicare or Medicaid would adversely affect hospital profits. We included another policy variable to reflect hospital location in a Medicaid expansion state. Hospitals in states that expanded Medicaid eligibility, pursuant to the provisions of the Affordable Care Act of 2010, should have less uncompensated care expense (Dranove et al. 2016) and this should lead to increased profitability.

Consistent with other hospital studies (Bai and Anderson 2016; Bazzoli et al. 2014; Blavin 2016; Rosko et al. 2018; Schneider et al. 2007; Turner et al. 2015), we also included variables for academic medical center, average length of stay, and occupancy rate. These will be discussed in the methods section.

Methods and data

Our primary interest is the relationship between cost efficiency and hospital profitability. We first describe how hospital efficiency is estimated and follow that with a discussion of our hospital profitability model.

SFA cost-efficiency model

We use an SFA model developed by Jondrow et al. (1982) to estimate hospital cost- efficiency. Early techniques to measure hospital efficiency included ratio analysis and OLS regression (Rosko 1990b). Ratio analysis does not work well for multi-product firms (too many ratios to consider), relies on arbitrary inefficiency criteria, such as a median or percentile cutoff point, and there is an information loss caused by the averaging out effects of OLS. Moreover, OLS may have a biased intercept (Kumbhakar and Lovell 2000). Frontier techniques such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA) were developed to overcome these problems. A particularly useful feature of SFA is that it allows for the inclusion of many product descriptor variables which helps account for output heterogeneity.

The first health care application of SFA was published by Wagstaff (1989), who examined 49 Spanish hospitals. Zuckerman et al. (1994) published the first SFA-based study of US hospitals. Rosko and Mutter (2011) reviewed the results from 27 U.S. hospital SFA studies. The non-parametric alternative to SFA is DEA. A preference for SFA or DEA has not been established in the hospital efficiency estimation literature, and it is unlikely that such a consensus will occur. Frontier experts suggest that the choice of technique should

be context specific (i.e., based on the goals of the analysis and the availability of data; Coelli et al. 2005). We choose SFA because it estimates cost-efficiency which is a broader measure (i.e., is based on a best practice cost frontier rather than a best practice production frontier) than technical efficiency which is usually estimated by DEA. Therefore, it is likely to reflect more factors that affect profitability than would a DEA-based measure of technical efficiency.

Model specification

SFA decomposes variations from the best practice frontier (BPF) into a random or classical error and a deterministic error, which is assumed to represent cost-inefficiency. Our framework for the estimation of the BPF is the neoclassical cost function which assumes that total expenses depend upon input prices and output volumes. Recognizing that outputs, such as admissions, are heterogeneous, it is important to control variations in input requirements for different types of admissions by including product descriptor variables that reflect differences in services, patient case mix, and hospital quality. Following theory (Kumbhakar and Lovell 2000) and the hospital literature (Grannemann et al. 1986; Rosko et al. 2018), we use the following hybrid cost function:

$$TC_i = f(Y_i, W_i, PD_i) + e_i \quad (1)$$

where TC represents total costs; Y is a vector of outputs; W is a vector of input prices; PD is a vector of product descriptors; i indexes the hospital being observed, and e is the error term, which can be decomposed as follows:

$$e_i = v_i + u_i \quad (2)$$

where v is statistical noise (i.e., assumed to be distributed as $N(0, \sigma^2)$), and u consists of positive departures from the cost-frontier and represents cost-inefficiency (i.e., the percentage by which observed costs exceed minimum costs predicted for the best practice cost frontier) (Lovell 1993).

Although u is frequently assumed to follow a half-normal distribution, there is no theoretical reason for the selection of this or other distributional forms for u . Coelli et al. (2005) indicate that the specification of a more general distribution such as the truncated-normal has partially alleviated concerns about the arbitrary choice of a distribution. However, concerns about this issue may be overstated as reviews of both the general literature (Coelli et al. 2005) and the health services research literature (Rosko and Mutter 2008) have consistently reported that varying assumptions about the distribution of the deterministic error has had little impact on estimated inefficiencies.

We used a hybrid form of the Cobb–Douglas cost function model to estimate the stochastic cost frontier for a sample of U.S. hospitals. It can be expressed as follows:

$$\ln TC_i = \alpha_o + \sum_{j=1}^j \alpha_j \ln Y_{ji} + \sum_{k=1}^k \beta_k \ln W_{ki} + \phi PD_i + v_i + u_i \quad (3)$$

where TC , Y , W , and PD are the same as defined above; and α , β , and ϕ are parameters to be estimated; and v_i and u_i are random variables described above. Due to data constraints, we used only prices for capital and labor inputs. A more complete specification would be desirable, but we follow the practices of most SFA hospital studies.

We imposed the standard assumption of linear homogeneity in input prices by normalizing the equation by the Medicare Wage Index. Thus, the dependent variable is the logarithm of total expenses divided by the wage index. The continuous output and input price variables also were also log-transformed. The price of two inputs, capital and labor, are recognized by the cost-function. The Medicare Wage Index was used for the price of labor. Following past practices (Rosko et al. 2018; Zuckerman et al. 1994), the price of capital was approximated by the area (i.e., core-based statistical area) average depreciation and interest expenses per bed. The input price variables were also normalized by the price of labor. Since the price of labor (i.e., Medicare Wage Index) was divided by itself, it is removed from the equation.

The outputs in the cost function included inpatient admissions, outpatient visits, and post-admission patient days (i.e., total inpatient days minus total admissions). The results of a Hausman specification test ($p < 0.05$) suggest that hospital outputs can be treated as exogenous, an assumption common to hospital cost studies (Grannemann et al. 1986).

A key concern in hospital SFA studies is hospital quality and patient burden of illness might masquerade as inefficiency (Mutter et al. 2008). This could cause a downward bias in the efficiency estimates for hospitals (e.g., academic medical centers) that tend to attract patients that present more severe problems. Therefore, we used a variety of product descriptor variables to control for the heterogeneity of output in hospitals. Following the methods of Rosko et al. (2018) we included: the Medicare Case-Mix Index, the ratio of outpatient surgeries to total outpatient visits, the ratio of emergency department visits to total outpatient visits, and the ratio of beds classified as acute care to total hospital beds and the ratio of births to total admissions. All of these reflect case mix severity and the first four are expected to have positive coefficients. The absence of publicly available case-mix indices for outpatient care necessitated the use of proxies for this measure. While the Medicare Case-Mix Index has been shown to be highly correlated with the overall case-mix index of hospitals, we included the ratio of births to total admissions to reflect a dimension of case-mix among the non-Medicare population. Since some hospitals serve a mixture of acute care and nonacute care patients, we included the proportion of total hospital beds classified as acute care to reflect patients who would not be included in the DRG-based Medicare Case-Mix Index. Following an approach similar to Zuckerman et al. (1994), teaching status was incorporated using three binary variables related to the number of residents and interns trained by the hospital. The three categories of teaching are based on tritiles of the number of residents and interns trained by the hospital and non-teaching hospitals serve as the omitted reference category. The teaching variables reflect monotonically increasing levels of teaching activity. Teaching status reflects not only post-graduate medical education output but also it is a structural measure of quality (Taylor et al. 1999).

We also included a measure of reservation quality in the cost function. The use of reservation quality is consistent with the premise that some empty beds are not waste (Folland and Hofler 2001). Rather, they provide a safety margin for surges in demand. The use of this variable may reduce a potential bias against small hospitals that typically experience more variation in inpatient utilization (Folland and Hofler 2001). We followed Joskow's (1980) method of calculating reservation quality by dividing the difference between total beds and average daily census by the square root of average daily census.

In addition to the above, variations in quality were controlled by the inclusion of variables for the clinical process of care and patient and caregiver centered experience of care.² This data has become available to the public only recently and this is the first time these variables have been used in an SFA study. The Centers for Medicare and Medicaid Services (CMS) Value Based Purchasing (VBP) program rewards or penalizes hospitals based on their performance on key domains of performance which include clinical processes, patient safety, patient outcomes, patient experiences and efficiency (cost per Medicare beneficiary) (Turner et al. 2015). The domains and measures have changed over time; some measures have been dropped and new measures have been added. For example, the patient safety and efficiency domains were added in recent years. This data is reported on CMS Hospital Compare website (www.medicare.gov/HospitalCompare/Data/total-performance-scores.html). Descriptive statistics for the variables in the SFA model are provided in the Appendix in Table 4.

The parameters of the cost frontier and cost-efficiency were estimated by a maximum likelihood method using the FRONTIER 4.1 program (Coelli 1996). The cost efficiency of the i th hospital is defined as the ratio of the stochastic frontier total costs to observed total costs. The stochastic total cost frontier is defined by the value total costs would be if u_i (i.e., the cost-inefficiency effect) were zero (i.e., full efficiency).

Our SFA model assumed a Cobb–Douglas production technology and that the composed error that represents inefficiency followed a truncated-normal distribution. Although the translog cost function is often used in hospital-based SFA studies because of its flexibility (Rosko and Mutter 2011), we estimated a Cobb–Douglas function which restricts the higher-order terms (i.e., squared and cross-products which are very highly correlated) of the output and input price variables to equal 0. Estimating the translog cost function can lead to counter-intuitive parameter estimates. This is a common side-effect of multi-collinearity, which can cause estimates to be less reliable and make sign changes (Greene 2018). The parameter estimates for the SFA model are presented in Table 5 in the Appendix. The cost-inefficiency estimates were slightly larger (i.e., mean of 0.1048 vs. 0.0766) when the Cobb–Douglas form was assumed rather than the translog. The hospital-level inefficiency scores obtained from the two models were very highly correlated—i.e., $r=0.923$. As expected with these high correlations, the parameter estimates in the profit equations were very similar when the efficiency scores based on either of the two models were used.

In specifying the model, we also had to make an assumption about the distribution of the composed error that represents efficiency. Although the half-normal distribution has been used the most, there is no a priori justification for the use of any particular distribution for the cost inefficiency effects, u_i . Stevenson (1980) addressed this issue by specifying a truncated-normal distribution, which is a generalization of the half-normal distribution. Since the half-normal distribution is a special case of the truncated-normal distribution where the mode (designated by μ) equals 0, the appropriateness of using the half-normal distribution was assessed by testing $H_0: \mu=0$. [A more complete discussion is available in Kumbhakar and Lovell (2000)]. Based on the results ($p < 0.01$) of a log-likelihood restriction test we rejected the null hypothesis and chose the truncated-normal distribution. However, the efficiency scores were not sensitive to our choice of error term as the scores obtained when using the two distributions were very highly correlated—i.e., $r=0.959$.

² Information for these variables and the Medicare Case-Mix Index was not collected in Maryland because these hospitals were exempt from Medicare's Value-Based Purchasing Program. Therefore, the use of these variables led to the exclusion of Maryland hospitals ($n=41$) from this study.

The mean estimated cost-inefficiency was 10.48%. In the profit equation we reverse code it (i.e., 1—cost-inefficiency) and call it efficiency for ease of interpretation. This yields a mean efficiency score of 89.52%. Our mean efficiency estimate is within the range (albeit towards the upper limit) of past SFA studies. For example, in Rosko and Mutter's (2008) review of U.S. hospital studies, the mean estimated efficiency score ranged from 62.9 to 92.5%. Hollingsworth (2008) reviewed 59 frontier studies (i.e., SFA and DEA) of US hospitals and found that the mean of all efficiency scores was 82.6%. Looking at other industries, Vitaliano and Toren's (1994) study of US nursing homes estimated that cost efficiency was 71.0% and Greene and Segal's (2004) study of US insurance companies had efficiency estimates that ranged from 62.1 to 65.2%. Greene's (2008) study of the electricity industry had estimates ranging from 92.1 to 93.5%.

Higher efficiency scores tend to be found in studies of industries where the output is more homogenous (e.g., electricity) or when more elaborate controls for product mix variations are used. For example, Zuckerman et al. (1994) reported that the mean efficiency score increased from 81.2% in an equation where just a basic cost function was used to 86.6% when variety of variables representing hospital characteristics and output were used. Rosko and Chilingerian (1999) reported similar results (i.e., means increased from 82.0 to 92.5% when a basic model was replaced by a model with control variables for severity and complexity of illness).

Hospital profitability model

Data

The dependent variables in the profitability analysis are operating margin (i.e., [(net operating revenue – total operating expenses)/net operating revenue]) and total margin (i.e., [(total net revenue – total expenses)/(total net revenue)]). Both are commonly used in hospital profitability studies (Bazzoli et al. 2014; Burkhardt and Wheeler 2013; Blavin 2016). The former more closely reflects the effect of payment pressures on hospital financial performance while the latter more closely reflects the solvency of the hospital.

We started with 1439 metropolitan,³ NFP, general, acute care hospitals. However, we excluded 96 hospitals because they did not report data for at least 360 days ($n=30$) or had missing data ($n=66$). Following past practices (Goddard et al. 2009; Bazzoli et al. 2014), we excluded an additional 26 hospitals that fell outside the 1st through 99th percentiles of operating margin or total margin to avoid outliers and/or implausible values for these margins. This resulted in a final file with 1317 hospitals located in the contiguous United States (except for those located in Maryland which were excluded because they did not report two key quality variables pertaining to process of care and patient experience as well as the Medicare Case-Mix Index that were used in the SFA efficiency estimation) and the District of Columbia. The mean values of the variables in the trimmed and untrimmed files were almost identical. We found the regression results for the data set that was untrimmed were very similar (in terms of sign and level of significance) to those obtained with the smaller data set.

³ Hospitals in rural areas were excluded from the analysis because most were exempt (due to small volume of care or exemption from the Medicare PPS) from reporting the same three variables that resulted in the exclusion of the hospitals located in Maryland.

We used data for 2015 for all variables. Data for operating and total margin were obtained from Medicare Hospital Cost Reports. The American Hospital Association (AHA) Annual Survey was used for hospital characteristics. The Area Health Resources File was used for market-level (i.e., county) data for the unemployment rate. AHA data for hospital admissions was aggregated to the county level to create a market competition variable (i.e., Hirschman–Herfindahl Index (HHI) based on inpatient admissions). Wong et al. (2005) reported that the definition of the market (i.e., county or geographical radius from the hospital) had little impact on association of the impact of competition on hospital expenditures.⁴

Binary variables (0/1) were entered for the following hospital characteristics: academic medical center (i.e., member of the Council of Teaching Hospitals), location in a Medicaid expansion state, and system member (i.e., member of a multi-hospital system). We expect the last two variables to be positively associated with profits as Medicaid expansion should reduce uncompensated care expenses (Dranove et al. 2016) and system membership should confer the advantages of firm-level scale effects to the hospital. However, it is impossible to develop a priori expectations for the variable reflecting academic medical centers. While these hospitals receive extra payments from public and private payers, it is unclear whether these extra payments accurately reflect the extra costs that academic medical centers incur.

We used Medicare and Medicaid share of admissions (i.e., Medicaid or Medicare admissions divided by total admissions) to reflect financial pressures associated with serving patients funded by the two dominant public payers in the United States. Medicare payments were less than expenses in the average hospital in 2015 (MedPac 2017). Medicaid is a joint federal/state program for the categorically needy. Medicaid payments to hospitals tend to be less than the costs incurred in treating Medicaid patients in most states (Cunningham et al. 2016).

We also included variables for average length of stay (i.e., total patient days divided by total admissions) and occupancy rate (total patient days divided by total bed days available). The latter variable should be positively associated with profits (Schneider et al. 2007). The former variable might reflect the effectiveness of care processes or unobserved variations in the patient burden of illness. We expect this variable to be inversely associated with profitability, a proposition supported by Rauscher and Wheeler (2012).

We used the number of beds to reflect size. Larger hospitals might be able to negotiate higher payment rates from private health plans, and this should contribute to enhanced profitability. However, to the extent that diseconomies of scale exist, larger hospitals will have greater increased average costs. We expect that larger hospitals would be more profitable.⁵

We included two market-level variables; market concentration and unemployment rate. We used the county as the market area. We constructed a Herfindahl–Hirschman Index (HHI) based on admissions in the county as a measure of market power.⁶ Hospitals in

⁴ We also estimated an HHI at core-based statistical area (CBSA) level. CBSAs are geographic areas defined by the federal Office of Management and Budget (OMB). The OMB categorizes counties within a CBSA as metropolitan statistical areas and micropolitan areas (i.e., areas containing between 10,000 and 50,000 people). Counties defined as micropolitan are not included in this study. The two HHIs were highly correlated ($r=0.63$) and regression results were very similar when either of the HHIs were used.

⁵ We included beds-squared in preliminary analysis to reflect possible scale effects. However, its coefficient was not significantly different from 0 ($p < 0.05$), so we did not include it in the final model.

⁶ We included the hospital's market share in preliminary analysis. However, because of its strong correlation with HHI we removed it to avoid multi-collinearity problems.

Table 1 Descriptive statistics for variables in the profit models (n = 1317)

Variable	Mean	SD	Min	Max
Operating margin	0.0113	0.1081	-0.4321	0.3379
Total margin	0.0513	0.0905	-0.2918	0.3523
Efficiency score ^a	0.8914	0.0536	0.4388	1.0000
Academic medical center	0.1230	0.3286	0	1
Average length of stay	4.7476	1.2313	1.7026	15.2356
Beds	295.3789	239.0801	20	2654
Herfindahl–Hirschman Index ^{b,c}	0.3454	0.2376	0.0523	1
Medicaid expansion state	0.6674	0.4713	0	1
Medicaid share of admissions	0.1966	0.0924	0.0106	0.7457
Medicare share of admissions	0.4792	0.0959	0.1296	0.7496
Occupancy rate	0.6168	0.1432	0.1532	0.9853
System member	0.8011	0.3994	0	1
Unemployment rate ^c	5.2117	1.3343	2.2000	21.8000

^aTo facilitate interpretation, we reverse coded (1-inefficiency score) cost-inefficiency. To provide a “truer” benchmark for the efficiency estimate, the SFA analysis included all (n = 1823) metropolitan, NFP and FP, general, acute care hospitals for which complete data were available

^bBased on all competing hospitals (includes acute, general, local government hospitals but not federal hospitals) for which admissions data were available

^cCounty-level variable

Table 2 Mean values of operating margin and total margin by binary variables in regression equations

	Operating margin		Total margin	
	Yes	No	Yes	No
Academic medical center	-0.0112	0.0145**	0.0608	0.0499
Medicaid expansion state	-0.0016	0.0371**	0.0427	0.06842**
System member	0.0183	-0.0172**	0.0557	0.0334**

*Mean significantly different at $p < 0.05$

**Mean significantly different at $p < 0.01$

the same system in the same market area were treated as one firm in the calculation of the HHI.⁷ We expect profits to be positively associated with concentration of output. The unemployment rate is used to reflect the level of demand for health services and ability to pay and we expect it to be inversely related with profits. Descriptive statistics for the variables are presented in Table 1.

⁷ In the calculation of the HHI we used all general, acute hospitals (except federal) that reported data for admissions in 2015, even if they were missing other data or were non-federal, public hospitals. Thus, the HHI was based on a sample of 2200 hospitals.

Table 3 Parameter estimates (OLS with robust standard errors), operating margin and total margin, 2015 (n = 1317)

Variable	Operating		Total	
	Margin		Margin	
	Reg. coef.	t value ^a	Reg. coef.	t value ^a
Efficiency score	0.2204**	3.83	0.1555**	3.18
Academic medical center	-0.0212*	-2.14	0.0031	0.41
Average length of stay	-0.0230**	-7.50	-0.0159**	-4.81
Beds	0.0000*	2.46	0.0000**	2.90
Herfindahl index ^b	0.0529**	4.46	0.0377**	3.77
Medicaid expansion state	-0.0180**	-2.78	-0.0127*	-2.27
Medicaid share of admissions	-0.1779**	-4.38	-0.1022**	-3.20
Medicare share of admissions	-0.0843*	-2.34	-0.1117**	-3.46
Occupancy rate	0.0639**	2.66	0.0612**	2.97
System member	0.0215**	3.32	0.0106*	2.01
Unemployment rate ^b	-0.0048*	-2.13	-0.0054**	-2.88
Constant	-0.0465	-0.83	0.0278	0.57
R-squared	0.1549		0.1106	

* $p < 0.05$; ** $p < 0.01$

^aBased on robust-standard errors

^bMarket-level variable

Results

As Table 2 shows the mean value of operating margin was significantly higher ($p < 0.01$) in system member hospitals and significantly lower ($p < 0.01$) in academic medical centers (AMCs) and in hospitals located in states that expanded their Medicaid programs. Similar results were found for the total margin except that the mean difference for AMCs was no longer significant.

Preliminary analysis of the regression equations, using a Breusch-Pagan test for heteroskedasticity, rejected the null hypothesis of constant variance against the number of inpatient beds, a proxy for size. Therefore, we used the robust standard error in Stata, Version 15. We were also concerned that reverse causality (i.e., profits could also affect efficiency e.g., hospitals might invest profits into efficiency improvement initiatives) could bias the results. However, the results of a Hausman test ($p < 0.05$) could not support the existence of endogeneity.

The OLS parameter estimates, corrected for heteroskedacity, when operating margin and total margin were used as dependent variables, are reported in Table 3. We use $p < 0.05$ as our threshold for the significance of the parameter estimates. The estimated coefficient of efficiency was significant in both equations with a slightly larger value in the operating margin equation. Hence, we reject the null hypothesis that efficiency is not associated with profitability. The results suggest that operating margin would increase by 0.02204 if efficiency increased by 10 percent and all other factors remained the same.

Regarding the control variables, consistent with our expectations we found that operating margin was positively associated with number of beds, Hirschman–Herfindahl Index (an inverse measure of competition), occupancy rate, and system membership. It was negatively associated with academic medical center status, average length of stay, location in a Medicaid expansion state, Medicaid share of admissions, Medicare share of admissions, and county unemployment rate. The results for the total margin were similar to those for the operating margin equation with the exception of the estimate for the coefficient of academic medical center which was no longer significant.

Discussion

A major assumption of federal hospital payment policy in the United States is that hospital managers will respond to the incentives to cut expenses. Expenses could be cut by reducing the volume or quality of services or by increasing efficiency. Our results suggest that if hospitals increase efficiency, they will be rewarded with increased profits. Increased surplus can be used to fund future capital projects to expand services to the community. Inefficient hospitals will face either financial losses or be forced to reduce volume or quality of their services. Increased efficiency is important as it is the only way to increase services without increasing costs or compromising quality. From another perspective, increased efficiency allows hospitals to cut expenses without compromising the quality or quantity of services provided.

When we examine the results for the other variables, for simplicity we will use the term profitability since the results are similar in the operating margin and total margin equations for all variables, except academic medical center. As expected, the results suggest that academic medical centers (AMCs) are less profitable than other hospitals due to their teaching and research missions. AMCs tend to be much more expensive than other types of general acute care hospitals because they are tertiary care centers that attract patients who are more expensive to treat. Furthermore, they have additional costs regarding their teaching and research missions, and they require more expensive capital technology. Besides the direct expenses of graduate medical education programs and the more severely ill patients they attract, AMCs are more expensive because medical students, interns and residents tend to have an adverse impact on the productivity of other staff. The lack of significance in the total margin equation reflects the additional sources of non-operating revenue that AMCs are able to attract.

Medicare and other payers have long recognized the value and cost of graduate medical education and have reimbursed these hospitals at a much higher rate than other hospitals. MedPac (2017) reported that “Major teaching hospitals have higher overall Medicare margins than the average IPPS (inpatient prospective payment system) hospital in large part because of the extra payments they receive through the IME (indirect medical education) and DSH (disproportionate share hospital) adjustments and uncompensated care payments.” However, in recent years Medicare has cut back on the generosity of its payments to AMCs. For example, in 2001, the Medicare margin for major teaching hospitals was 4.7% while this margin was 0.9% for other and non-teaching hospitals (MedPac 2006). In 2015, mean Medicare margins were negative for all types of hospitals with values of -5.2% , -5.8% and -9.6% for major-, other- and non-teaching hospitals

respectively (MedPac 2017). While many payers reimburse AMCs at a higher rate than other hospitals, their payment increases do not cover all the extra costs that AMCs incur. Accordingly, the mean profitability (i.e., all-payer total margin) of AMCs has been less than that for other types of hospitals each year from 2006 to 2015 (MedPac 2018).

The coefficient of system-member was positive and significant. This probably reflects firm-level scale economies which should reduce costs and enhance the bargaining power of systems which should increase revenue. Size, represented by beds, had a positive coefficient. This may reflect the ability of larger hospitals to negotiate better rates with suppliers and health plans. The former would reduce expenses and the latter would increase revenue.

Average length of stay, Medicaid share of admissions, Medicare share of admissions and unemployment rate had negative coefficients. In today's healthcare environment, over-utilization of services and unnecessary longer stays in hospitals are discouraged by both private and public payers. Expenses associated with longer hospital stays, under various reimbursement models, are not associated with more revenues. The Medicare and Medicaid variables have negative signs because public payers tend to underpay hospitals. For example, the mean overall Medicare margin ranged from -4.9% in 2010 to -7.1% in 2015 (MedPac 2017). While Medicaid payment policy varies by state, historically Medicaid payments have been even less than Medicare payments (Cunningham et al. 2016). It was not surprising that hospitals located in counties with higher rates of unemployment would be more unprofitable. Unemployment is associated with charity care and bad debt expense (Diehr et al. 1991; Rosko 1990a). While this is less important in the wake of the implementation of the Affordable Care Act, in 2015 there were over 30 million persons without health insurance in the United States (Kaiser Family Foundation (2017) accessed online, December 2018). Much of the gains in reducing the number of uninsured was due to the expansion of Medicaid eligibility in 30 states. Thus, the gains associated with fewer uninsured patients are tempered by the low payments by Medicaid programs.

The Herfindahl–Hirschman Index (HHI) and occupancy rate had positive coefficients. The positive coefficient for the HHI suggests that profits are larger in areas in which output is more concentrated, in other words in areas where there is less competition. There is a substantial body of evidence (Dranove 2012; Gaynor and Town 2012) that market power allows hospitals to increase prices.

The coefficient for location in a Medicaid expansion state was negative in both equations. This is consistent with the comparison of means shown in Table 3. However, in a cross-sectional study, it is impossible to attribute causality. Rosko et al. (2018) reported that mean hospital profit margins in expansion states were lower than those in non-expansion states during the entire period 2000–2015. Therefore, hospitals in expansion states were already at a financial disadvantage which could be attributed to many factors, including uncompensated care.

It is important to indicate some potential weaknesses in our methods. This is the first study to use an SFA-based measure of efficiency to examine the relationship between efficiency and profitability in NFP hospitals. There has been some controversy over the application of SFA in hospital studies. Newhouse (1994) has been one of the most vocal critics and has expressed concerns about the strong assumptions pertaining to the structure of production and the probability distribution of the composed error that is used to reflect inefficiency. However, studies in both the general literature (Greene 2008) and the hospital literature (Rosko and Mutter 2008) have found that cost-inefficiency estimates are robust over

different cost functions and distributions for the error terms. The advantage of SFA lies on its use of a regression technique that allows it to represent the multi-product nature of hospitals with a variety of output variables and product descriptors. SFA estimates efficiency as a departure from the Best Practice Frontier (BPF). However, the BPF is not observable. Rather it is estimated by data from a sample. If all the firms in the sample are very inefficient, then the BPF is a very low bar. Nevertheless, it represents the best of what has been achieved. Another concern is that there might be reverse causality between efficiency and profitability. As mentioned earlier, we followed a standard procedure (i.e., a Hausman test) to try to ascertain if there was a simultaneity issue. However, we must point out that there is no simple test to prove that a right-hand side variable is exogenous. So, our test cannot be considered definitive. We also note that there is no technique available to deal with a potential simultaneity issue within an SFA framework. Finally, this is the first hospital SFA study to use data (i.e., clinical processes and patient experiences) from the CMS Value Based Purchasing Program. While this approach is novel and consistent with CMS measures of quality, it has not been tested in other studies. Further, this data is new and does not allow us to construct a panel study that will cover previous years.

Conclusions

As discussed above, improving efficiency may be the best way to decrease or contain hospital costs. Our study finds a strong link between efficiency and profit in NFP hospitals. Therefore, hospital managers should be motivated to use techniques such as Lean or Six Sigma to improve processes that will lead to efficiency enhancements. X-efficiency theory posits that increased financial pressures will motivate managers to improve organization performance (Leibenstein 1987), including efficiency. Further, efficiency is one of the domains of the Medicare Hospital Value Based Purchasing Program (VBP). Hospitals that increase efficiency (defined as Medicare spending per beneficiary) will receive bonus payments. However, the incentives for reduced spending embedded in the Medicare VBP are small (Werner and Dudley 2012). Stronger incentives would improve the linkage between efficiency and profitability and would create a stronger motivation for hospital managers to increase efficiency.

This study also found a positive association between hospital size, system membership, industry concentration of output and profitability. This raises a concern that hospitals might be using market power to increase their profits rather than emphasizing a strategy in which scale economies were used to drive down costs that would, in turn, allow them to reduce prices to help make hospital care more affordable. Reviews by Dranove (2012) and Gaynor and Town (2012) found that industry concentration is associated with increased prices. Gaynor and Town (2012) wrote, "if there are significant cost reductions associated with mergers, they are not passed on to the purchasers of hospital services in the form of lower prices" (p. 552).

We found that AMC status and dependence on a larger share of Medicare or Medicaid patients was negatively associated with operating margin. Indeed, AMCs in this study had a mean operating margin of -0.0120 in 2015, while the other hospitals in the study had an operating margin of 0.0124 . In the early years of the Medicare PPS major teaching

hospitals received, what was widely considered, generous Medicare payments. In fact, the Medicare indirect medical education (IME) payments overpaid major teaching hospitals by substantial amounts during the first two decades of the Medicare prospective system (MedPac 2017). However, since 2000 the IME payments have been reduced substantially to reflect the “true cost” of medical education and the provision of free care to the indigent patients that these hospitals tend to attract (MedPac 2017). Further, the implementation of the ACA led to reductions of Medicare DSH payments but provided for increases in uncompensated care payments sources of revenue that academic medical centers depend upon more than other-teaching or non-teaching hospitals. However, the sum of these two DSH and uncompensated care payments to all hospitals fell from \$12.2 billion in 2014 to \$10.9 billion in 2015 (MedPac 2018). It is not clear that the reduction in uncompensated care expenses associated with the implementation the Affordable Care Act, offset all of these reductions. AMCs rely on Medicare for a substantial portion of their revenue. While our results for the total margin suggest that AMCs have been able to obtain non-operating revenue to make up for short falls in Medicare and other payments, the anticipated future cutbacks in Medicare payments raise some concerns for the financial stability of AMCS (Chokshi et al. 2016).

Appendix

See Tables 4 and 5.

Table 4 Descriptive statistics for variables in SFA equation

Variable	Mean	SD	Minimum	Maximum
Acute care beds as a proportion of total beds in the hospital	0.9147	0.1047	0.50	1.00
Births as a proportion of total admissions in hospital	0.1139	0.0853	0.00	0.58
Clinical process of care domain score	58.2904	28.8609	0	100
Emergency department visits as a proportion of total outpatient visits in hospital	0.3153	0.1817	0.00	1.00
Log(admissions)	9.1630	0.8476	6.31	11.89
Log(outpatient visits)	11.9448	0.9359	8.26	15.54
Log(post-admission days)	10.4203	1.0037	6.42	13.31
Log(price of capital)	11.0944	0.2955	9.96	11.92
Log(total expenses/wage index)	19.1168	0.8798	16.30	22.37
Medicare case-mix index	1.6321	0.2516	0.86	2.87
Outpatient surgical operations as a proportion of total outpatient visits in hospital	0.6479	0.1211	0.15	1.00
Patient and caregiver centered experience of care domain score	30.4083	16.3709	1	99
Reservation quality	7.8729	3.6755	0.00	29.32
Low teaching intensity (0/1)	0.1487	0.3559	0	1
Medium teaching intensity (0/1)	0.1492	0.3564	0	1
High teaching intensity (0/1)	0.1454	0.3526	0	1

Table 5 Parameter estimates for the SFA cost frontier model (Cobb–Douglas cost function with truncated-normal residual, $n = 1823$, 2015 cross-section)

Variable	Coefficient	t-ratio
Constant	6.1119	23.9683**
Log(admissions)	0.4365	14.6781**
Log(outpatient visits)	0.2202	18.4747**
Log(post-admission days)	0.2438	9.8447**
Log(price of capital)	0.1920	9.6228**
Acute care beds as a percentage of total beds in hospital	0.3631	5.7623**
Births as a percentage of total admissions in hospital	0.0440	0.6250
Emergency department visits as a percentage of total outpatient visits in the hospital	-0.0323	-0.7137
Medicare case-mix index	0.5967	20.8302**
Outpatient surgical operations as a percentage of total outpatient visits in the hospital	0.1943	3.2389**
Reservation quality	0.0067	4.2867**
Low teaching intensity (0/1)	0.0018	0.1058
Medium teaching intensity (0/1)	0.0570	3.3324**
High teaching intensity (0/1)	0.1157	5.8448**
Clinical process of care domain score	-0.0002	-0.9129
Patient and caregiver centered experience of care domain score	0.0036	9.2834**
Log likelihood	28.4198	

* $p < 0.05$; ** $p < 0.01$

References

- Bai, G., & Anderson, G. (2016). A more detailed understanding of factors associated with hospital profitability. *Health Affairs*, 35(5), 889–897.
- Baik, B., Chae, J., Choi, S., & Farber, D. (2013). Changes in operational efficiency and firm performance: A frontier analysis approach. *Contemporary Accounting Research*, 30(3), 996–1026.
- Bazzoli, G., Fareed, N., & Waters, T. (2014). Hospital financial performance in the recent recession and implications for institutions that remain financially weak. *Health Affairs*, 33, 739–745.
- Bazzoli, G. J., Chen, H., Zhao, M., & Lindrooth, R. (2008). Hospital financial condition and the quality of patient care. *Health Economics*, 17, 977–995.
- Berger, A. (1995). The profit-structure relationship in banking. Tests of market-power and efficient-structure hypotheses. *Journal of Money, Credit and Banking*, 27(2), 404–431.
- Blavin, F. (2016). Association between the 2014 Medicaid expansion and US hospital finances. *JAMA*, 316, 1475–1483.
- Burkhardt, J. H., & Wheeler, J. R. (2013). Examining financial performance indicators for acute care hospitals. *Journal of Health Care Finance*, 39, 1–13.
- Chokshi, D., Chang, J., & Wilson, R. (2016). Health reform and the changing safety net in the United States. *New England Journal of Medicine*. <https://doi.org/10.1056/NEJMp1608578>.
- Coelli, T. (1996). *A guide to Frontier (Version 4.1) computer program*. Armidale, NSW: University of New England.
- Coelli, T., Rao, D., O'Donnell, C., & Battese, G. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). New York, NY: Springer.
- Cunningham, P., Rudowitz, R., Young, K., Garfield, R., & Foutz, J. (2016). *Understanding Medicaid hospital payments and the impact of recent policy changes, Issue Brief*. Washington, DC: Kaiser Commission on Medicaid and the Uninsured, June 2016.
- Damanpour, F. (1992). Organizational size and innovation. *Organization Studies*, 13(3), 375–402.

- Davis, K., Stremikis, K., Squires, D., & Schoen, C. (2014). *Mirror, mirror on the wall, 2014 update: How the US health care system compares internationally*. New York, NY: Commonwealth Fund.
- Diehr, P., Madden, W., Cheadle, A., Patrick, D., et al. (1991). Estimating county percentages of people without health insurance. *Inquiry*, 28(Winter), 413–419.
- Dranove, D. (2012). Health care markets, regulators, and certifiers. In T. McGuire, M. Pauly, & P. Barros (Eds.), *Handbook of health economics* (Vol. 2, pp. 639–690). Oxford: Elsevier.
- Dranove, D., Garthwaite, C., & Ody, C. (2016). Uncompensated care decreased at hospitals in Medicaid expansion states but not at hospitals in nonexpansion states. *Health Affairs*, 35(8), 1471–1479.
- Folland, S., & Hoffer, R. (2001). How reliable are hospital efficiency estimates? Exploiting the dual to homothetic production. *Health Economics*, 10, 683–698.
- Gaynor, M., & Town, R. (2012). Competition in health care markets. In T. McGuire, M. Pauly, & P. Barros (Eds.), *Handbook of health economics* (Vol. 2, pp. 499–638). Oxford: Elsevier.
- Goddard, J., Molyneux, P., & Wilson, J. (2004). Dynamics of growth and profitability in banking. *Journal of Money, Credit, and Banking*, 36(6), 1069–1090.
- Goddard, J., Tavakoli, M., & Wilson, J. (2009). Sources of variation in firm profitability and growth. *Journal of Business Research*, 62, 495–508.
- Grannemann, T., Brown, R., & Pauly, M. (1986). Estimating hospital costs: A multiple-output analysis. *Journal of Health Economics*, 5, 107–127.
- Grant, R. (1996). Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. *Organization Science*, 7(4), 375–387.
- Greene, W. (2008). The econometric approach to efficiency analysis. In H. Fried, C. Lovell, & S. Schmidt (Eds.), *The measurement of productive efficiency and productivity growth* (pp. 92–250). Oxford: Oxford University Press.
- Greene, W. (2018). *Econometric analysis* (8th ed.). London: Pearson.
- Greene, W., & Segal, D. (2004). Profitability and efficiency in the US life insurance industry. *Journal of Productivity Analysis*, 21(3), 229–247.
- Hall, M., & Weiss, L. (1967). Firm size and profitability. *Review of Economics and Statistics*, 49, 319–331.
- Hannan, M., & Freeman, J. (1984). Structural inertia and organizational change. *American Sociological Review*, 49(2), 149–164. <https://doi.org/10.2307/2095567>.
- Hansen, G., & Wernerfelt, B. (1989). Determinants of firm performance: The relative importance of economic and organizational factors. *Strategic Management Journal*, 10(5), 399–411.
- Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health Economics*, 17(10), 1107–1128.
- Huang, S. (2016). Financial leverage and hospital technology adoption. *Journal of Health Care Finance*, 42(4), 1–22.
- Hussey, P., de Vries, H., Romley, J., Wang, M., Chen, S., et al. (2009). A systematic review of health care efficiency measures. *Health Services Research*, 44(3), 784–805.
- Institute of Medicine. (2001). *Crossing the quality chasm*. Washington, DC: National Academies Press.
- Jacobs, R., Smith, P., & Street, A. (2006). *Measuring efficiency in health care: Analytical techniques and health policy*. Cambridge: Cambridge University Press.
- Jondrow, J., Lovell, K., Materov, I., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2–3), 233–238.
- Joskow, P. L. (1980). The effects of competition and regulation on hospital bed supply and the reservation quality of the hospital. *Bell Journal of Economics*, 11(2), 421–447. <https://doi.org/10.2307/3003372>.
- Kaiser Family Foundation. (2017). *Key facts about the uninsured population*. Retrieved November 8, 2018, from <https://www.kff.org/uninsured/fact-sheet/key-facts-about-the-uninsured-population/>.
- Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard—measures that drive performance. *Harvard Business Review*, 74(1), 71–79.
- Kazley, A., & Ozcan, Y. (2007). Organizational and environmental determinants of hospital EMR adoption: A national study. *Journal of Medical Systems*, 31(5), 375–384.
- Kumbhakar, S. C., & Lovell, C. K. (2000). *Stochastic frontier analysis*. Cambridge: Cambridge University Press.
- Lee, J. (2009). Does size matter in firm performance? Evidence from US public firms. *International Journal of the Economics of Business*, 16(2), 189–203.
- Leibenstein, H. (1987). *Inside the firm: The inefficiencies of hierarchy*. Cambridge: Harvard University Press.
- Lovell, C. K. (1993). Production frontiers and productive efficiency. In H. Fried, C. K. Lovell, & S. S. Schmidt (Eds.), *The measurement of productive efficiency*. New York: Oxford University Press.
- MedPac. (2006). *Report to the congress: Selected Medicare payment issues*. Washington, DC: MedPAC.

- MedPac. (2017). *Report to the congress: Selected Medicare payment issues*. Washington, DC: MedPAC.
- MedPac. (2018). *Report to the congress: Selected Medicare payment issues*. Washington, DC: MedPAC.
- Melnick, G., & Keeler, E. (2007). The effects of multi-hospital systems on hospital prices. *Journal of Health Economics*, 26(2), 400–413.
- Mutter, R., Rosko, M., & Wong, H. (2008). Measuring hospital inefficiency: The effects of controlling for quality and patient burden of illness. *Health Services Research*, 43(5), 1992–2013.
- Newhouse, J. (1970). Towards a theory of nonprofit institutions: An economic model of a hospital. *American Economic Review*, 60(1), 87–92.
- Newhouse, J. (1994). Frontier estimation: How useful a tool for health economics? *Journal of Health Economics*, 13, 317–322.
- Nord, W., & Tucker, S. (1987). *Implementing routine and radical innovation*. Lexington, MA: Lexington Books.
- Papadopoulos, S. (2004). Market structure, performance and efficiency in European banking. *International Journal of Commerce and Management*, 14(1), 79–97.
- Pauly, M. (1987). Nonprofit firms in medical markets. *American Economic Review*, 80(3), 257–262.
- Porter, M. E. (1998). *Competitive strategy: Techniques for analyzing industries and competitors*. New York: Free Press.
- Potter, S. (2001). A longitudinal analysis of the distinction between for-profit and not-for-profit hospitals in America. *Journal of Health and Social Behavior*, 42(1), 17–44.
- Rauscher, S., & Wheeler, J. (2012). The importance of working capital management for hospital profitability: Evidence from bond-issuing, not-for-profit U.S. hospitals. *Health Care Management Review*, 37(4), 339–346.
- Rosko, M. (1990a). All-payer rate-setting and the provision of hospital care to the uninsured: The New Jersey experience. *Journal of Health Politics, Policy and Law*, 15(Winter), 815–831.
- Rosko, M. (1990b). Measuring technical efficiency in health care organizations. *Journal of Medical Systems*, 14(5), 307–322.
- Rosko, M., & Chilingerian, J. (1999). Estimating hospital inefficiency: Does case mix matter? *Journal of Medical Systems*, 23(1), 51–71.
- Rosko, M., & Mutter, R. (2008). Stochastic frontier analysis of hospital inefficiency: A review of empirical issues and an assessment of robustness. *Medical Care Research and Review*, 65(2), 131–166.
- Rosko, M., & Mutter, R. (2011). What have we learned from the application of stochastic frontier analysis to U.S. hospitals? *Medical Care Research and Review*, 68(1 Suppl.), 75S–100S.
- Rosko, M., Proenca, J., Zinn, J., & Bazzoli, G. (2007). Hospital inefficiency: What is the impact of membership in different types of systems? *Inquiry*, 44(3), 335–349.
- Rosko, M., Wong, H., & Mutter, R. (2018). Characteristics of high- and low-efficiency hospitals. *Medical Care Research and Review*, 75(4), 454–478.
- Schneider, J., Ohsfeldt, M., Morrissey, P., Li, P., Miller, T., et al. (2007). Effects of specialty hospitals on the financial performance of general hospitals, 1997–2004. *Inquiry*, 44, 321–334.
- Singh, S., & Wheeler, J. (2012). Hospital financial management: What is the link between revenue cycle management, profitability, and not-for-profit hospitals' ability to grow equity? *Journal of Healthcare Management*, 7, 325–339.
- Smith, K. G., Guthrie, J. P., & Chen, M. J. (1986). Miles and Snow's typology of strategy, organizational size and organizational performance. *Academy of Management Proceedings*. <https://doi.org/10.5465/ambpp.1986.4978509>.
- Stevenson, R. (1980). Likelihood functions for generalized stochastic frontier estimation. *Journal of Econometrics*, 13(1), 58–66.
- Taylor, D., Whellan, D., & Sloan, F. (1999). Effects of admission to a teaching hospital on the cost and quality of care for Medicare beneficiaries. *New England Journal of Medicine*, 340(4), 293–302.
- Turner, J., Broom, K., Elliott, M., & Lee, J. (2015). A decomposition of hospital profitability: an application of DuPont analysis to the US market. *Health Services Research and Managerial Epidemiology*, 2, 1–10.
- Vitaliano, D., & Toren, M. (1994). Cost and efficiency in nursing homes: A stochastic frontier approach. *Journal of Health Economics*, 13(3), 281–300.
- Wagstaff, A. (1989). Estimating efficiency in the hospital sector: A comparison of three statistical cost frontier models. *Applied Economics*, 21(5), 659–672.
- Werner, R., & Dudley, R. (2012). Medicare's new hospital value-based purchasing program is likely to have only a small impact on hospital payments. *Health Affairs*, 31(9), 1932–1940.
- Wong, H., Zhan, C., & Mutter, R. (2005). Do different measures of hospital competition matter in empirical investigations of hospital behavior. *Review of Industrial Organization*, 26(1), 27–60.

Zuckerman, S., Hadley, J., & Iezzoni, L. (1994). Measuring hospital efficiency with frontier cost functions. *Journal of Health Economics*, *13*, 255–280.

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