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What Have We Learned From the Application of Stochastic Frontier Analysis to U.S. Hospitals?

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Abstract

This article focuses on the lessons learned from stochastic frontier analysis studies of U.S. hospitals, of which at least 27 have been published. A brief discussion of frontier techniques is provided, but a technical review of the literature is not included because overviews of estimation issues have been published recently. The primary focus is on the correlates of hospital inefficiency. In addition to examining the association of market pressures and hospital inefficiency, the authors also examined the relationship between inefficiency and hospital behavior (e.g., hospital exits) and inefficiency and other measures of hospital performance (e.g., outcome measures of quality). The authors found that consensus is emerging on the relationship of some factors to hospital efficiency; however, further research is needed to better understand others. The application of stochastic frontier analysis to specific policy issues is in its infancy; however, the methodology holds promise for being useful in certain contexts.

Keywords

efficiency, hospitals, stochastic frontier analysis

The trifecta of high costs, low quality, and poor access has been of great concern to health care policy makers and analysts for decades. While it might be relatively easy to deal with any one of the above in isolation, it is very difficult to improve performance in one area without adversely affecting the others. For example, costs could be reduced by taking actions that might adversely affect quality and access (i.e., cutting staff inputs or services). If efficiency were improved, however, it might be possible to

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provide more and better health care services with fewer resources. Thus, it would be possible to reduce costs and improve access simultaneously. Proponents of total quality management and other quality improvement methodologies argue that process improvement could result in increases in quality with reduced costs (Deming, 1982). Thus, if efficiencies are gained through process improvement, the problems of costs, quality, and access could be addressed simultaneously.

The concept of efficiency reflects a relationship between inputs and outputs. The following types of inefficiency have been identified: technical, allocative, scale, and scope. Technical inefficiency arises when the firm does not maximize output given a set of inputs employed. For example, if a hospital that employed a combination of inputs that was capable of producing 1,000 units of output produced only 800 units of output; it would be considered 20% inefficient or 80% efficient. Allocative inefficiency results when firms do not use the least costly combination of inputs in producing output. This occurs when the ratio of the marginal price of capital to the price of capital is not equal to the ratio of the marginal price of labor to the price of labor. Scale inefficiencies occur when the firm fails to produce at the minimum point of its long-run average cost curve. When this occurs, firms are said to be operating at a point on their long-run average cost curve where either increasing returns (i.e., the firm is too small) or decreasing returns (i.e., the firm is too large) exist. Thus, scale inefficiencies are reflective of the size of the firm. Scope inefficiencies are due to the firm'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). They reflect the scope of the firm's operations (e.g., the service lines that a hospital offers).

In the economic market structure termed *perfect competition*, inefficiency is posited not to exist in the long run because firms are expected to follow market signals to become 100% efficient. Firms that cannot become completely efficient do not survive and are forced to exit the market. However, as many analysts have observed, inefficiency does exist in the real world. In particular, Arrow (1963) notes how health care markets depart significantly from the conditions required for perfect competition, and these departures are often given as reasons why so much inefficiency exists in health care firms.

Classical economic theory posits that organizations strive for optimization and that inefficiency cannot exist in the long run. More recent economic theories still hypothesize the existence of optimization but argue that something other than short-run profits are being maximized. These theories have been used to explain rent-seeking behavior, maximization of management compensation, or maximization of social welfare.

However, Herbert Simon won a Nobel Prize in economics for a body of work that challenged the existence of optimizing behavior. He posited that managers tend to be "satisficers;" that is, instead of being optimizers, they are motivated to obtain a "satisfactory" return (Simon, 1965). In a similar vein, Harvey Leibenstein (1976) developed what he termed *X-Efficiency Theory*. This theory assumes that individual behavior contains rational (i.e., maximization of profit or utility) and nonrational

elements (i.e., suboptimal performance that results in inefficiencies). X-Efficiency Theory is most applicable to imperfect markets, a characteristic of the health care industry. Indeed, Rice (1998) suggested that X-Efficiency Theory may be applicable to the analysis of the health care industry. Leibenstein and Maital (1992) argued that the use of a frontier technique such as data envelopment analysis (DEA) or stochastic frontier analysis (SFA) might be the best way to measure and analyze X-Inefficiency. Empirical support for this approach was provided by a DEA-based study of nursing homes (Rosko, Chilingerian, Zinn, & Aaronson, 1995) and SFA-based studies of hospitals (Rosko, 2001a; Rosko & Proenca, 2005).

New Contribution

This article will focus on the lessons learned from SFA studies of U.S. hospitals, of which more than 27 have been published. We will focus on the correlates of hospital inefficiency. For the purpose of this article, we broaden the concept of correlates to include an examination of the relationship between inefficiency and hospital behavior (e.g., hospital exits) and performance (e.g., outcome measures of quality) as well as internal and external environment factors that are likely to create pressures for increased efficiency. Recent reviews of technical issues related to the estimation of hospital inefficiency using SFA have been conducted by Jacobs, Smith, and Street (2006), Rosko and Mutter (2008), and Mutter, Rosko, and Wong (2008). Greene (2008) provides an excellent review of SFA spanning from its early development to current technical issues. Therefore, this article focuses on lessons learned from the application of SFA that can inform policy and practice. It reviews the different factors associated with hospital performance that have been examined with SFA and highlights the areas where consensus is emerging, as well as where conflicting results continue to be reported and further research is needed.

Frontier Analysis

Initially, inefficiency was estimated by ratio analysis or ordinary least squares (OLS) regression. These early techniques have a number of shortcomings: Ratio analysis relies on arbitrary inefficiency criteria, such as a median or percentile cutoff point, and is difficult to use in multi-input/multi-output settings, such as a hospital. (For example, a ratio, such as cost per case-mix-adjusted admission, only reflects a limited component of a hospital's output and the inputs it uses to produce it.) The information loss caused by the averaging out effects of OLS is a drawback to using that approach. Furthermore, in the context of efficiency estimation, OLS may have a biased intercept (Kumbhakar & Lovell, 2000).

To overcome the limitations associated with these methods, frontier techniques have been developed. Frontier methods attempt to determine "best-practice" relationships between inputs and outputs. They measure inefficiency as the distance between actual firm performance and a best-practice frontier. By mid-2006, more than 317 articles

using frontier techniques to study the efficiency of health care organizations in 30 different countries had been published. Fifty-two percent of these analyzed hospitals (Hollingsworth, 2008).

DEA and SFA have been the most popular frontier approaches for measuring efficiency in hospitals. DEA, a nonparametric technique, has been the most frequently used frontier method in studies of health care organizations (Hollingsworth, 2008). It is a mathematical programming technique that affords considerable flexibility in the specification of the input-output relationship in firms' production processes. DEA produces inefficiency estimates based on the performance of firms relative to a frontier of actual firms that are the most efficient producers (Worthington, 2004). Farrell (1957) first operationalized a frontier method to estimate the efficiency of a decision-making unit (DMU) with the distance between the DMU's observed level of outputs and inputs and the best practice production frontier. The term *data envelopment analysis* was first used in the seminal article by Charnes, Cooper, and Rhodes (1978). The first health care application of DEA was published in 1983 (Nunamaker, 1983). Since then, more than 158 DEA studies of health care organizations have been published, including 57 studies of U.S. hospitals (Hollingsworth, 2003, 2008).

SFA is a parametric technique that was developed independently by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). The first SFA study of a health care organization was published by Wagstaff (1989), who examined 49 Spanish hospitals. Zuckerman, Hadley, and Iezzoni (1994) published the first SFA study of U.S. hospitals. Since then at least 26 studies of U.S. hospitals have been published.

DEA and SFA both measure efficiency in terms of the difference between optimal performance (i.e., a best-practice frontier) and actual performance. However, DEA calculates relative efficiency based on observed best practices, while SFA measures efficiency in terms of an estimated or theoretical best practice frontier. As a result, in DEA studies, there are always DMUs that are 100% efficient. In contrast, SFA studies can have no DMUs that are 100% efficient.

SFA was developed in response to concerns that in DEA all departures from the best practice frontier are assumed to represent inefficiency. Thus, random events and measurement errors may be confused with inefficiency. This may result in larger inefficiency estimates compared with those obtained from SFA (Jacobs et al., 2006). In contrast, cost-oriented SFA accounts for statistical noise and random events by decomposing variance into two components: (a) a strictly positive error term that is assumed to be inefficiency and (b) a classical error component. SFA has been criticized about its strong assumptions about the structure of production and the distribution of the error term (Newhouse, 1994). However, both the general literature (Coelli, Rao, O'Donnell, & Battese, 2005; Greene, 2008) and the health care literature (Jacobs et al., 2006; Rosko & Mutter, 2008; Zuckerman et al., 1994) have found that SFA results are robust across assumptions about the distribution of the strictly positive error. Health care researchers have found that inefficiency estimates are not very sensitive to assumptions about the structure of technology (Folland & Hofler, 2001; Rosko & Mutter, 2008; Zuckerman et al., 1994).

A preference for SFA or DEA has not been established in the hospital inefficiency estimation literature, and it is unlikely that such a consensus will occur. Instead, Coelli et al. (2005) suggest that the choice of technique should be context specific (i.e., based on the goals of the analysis and the availability of data). Greene (2008) reports that in the general literature, comparisons of efficiency results generated by SFA and DEA range from highly similar to very divergent. Fried, Lovell, and Schmidt (2008) report that the concordance of results from SFA and DEA increases with the use of higher quality data.

Estimating Hospital Inefficiency Using Stochastic Frontier Analysis

To keep this article to a manageable length, we restrict our review to SFA studies of U.S. hospitals. While valuable lessons could be learned from studies of hospitals in other countries, radical differences in the financing and organization of health care make cross-country comparisons difficult. SFA can measure technical inefficiency with a production function or cost-inefficiency with a cost function. However, the production function approach, when applied to multiproduct industries, requires a summary measure of output in the dependent variable. The use of a summary measure entails substantial information loss. In contrast, when a cost function is estimated, multiple outputs can be entered as separate independent variables. Accordingly, the vast majority of SFA studies have focused on cost-inefficiency, and we restrict our analysis to these. Articles to be included in this review were identified by using two search engines, PubMed and Proquest, and through consultation of recent review articles (Hollingsworth, 2003, 2008; Rosko & Mutter, 2008).

The SFA model assumes a cost function of the following general form:

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

where TC represents total costs, Y is a vector of outputs, W is a vector of input prices, 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, that is, 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).

Recognizing that output heterogeneity may masquerade as inefficiency, every U.S. hospital-based SFA study has included product descriptor variables. These include the following types of variables: (a) case-mix, (b) structural quality, and (c) outcomes (Rosko & Mutter, 2008). Including product descriptor variables can have a substantial effect on mean estimated cost-inefficiency. For example, in a national study, Zuckerman

et al. (1994) compared cost-inefficiency estimated in three models. In a “basic” cost function model in which only input prices and volume of outputs were used as predictor variables, the estimated cost-inefficiency was 18.8%. However, when a second model was formed by adding hospital-level output characteristics variables (i.e., case-mix index, high-technology services index, percentage of admissions in different units, and ratio of births to admissions) to the basic cost function, estimated inefficiency dropped to 13.4%. This suggests that output heterogeneity might have been masquerading as inefficiency in the base model. Similar analyses by Rosko and Mutter (2008) and Mutter et al. (2008) yielded similar results. These findings are consistent with the view of Jacobs et al. (2006) that as SFA models become more specified, estimated average inefficiency is likely to decline as more of the previously “unexplained” composite error is captured by the inclusion of additional explanatory variables.

The largest change in estimated cost-inefficiency because of the inclusion of additional product descriptor variables was found by Rosko and Chilingirian (1999). They used an approach similar to Zuckerman et al. (1994), albeit with a much more modest set of independent variables. In a study restricted to general hospitals located in Pennsylvania, they reported that estimated cost-inefficiency in a basic set (i.e., no product descriptor variables) was 18.0%. When the all-payer Diagnosis-Related Group (DRG) case-mix index was added to the basic model, estimated mean cost-inefficiency fell to 7.5%. However, the addition of an intra-DRG severity of illness index (based on the MedisGroup severity classification system) resulted in a slight increase in estimated inefficiency to 8.2%. Zuckerman et al. (1994) reported a similar result in their most comprehensive model. Thus, while the addition of product descriptor variables may reduce estimated cost-inefficiency, this is not always the case. It appears that there may be something akin to diminishing marginal returns associated with the inclusion of control variables.

While every study in this review has included product descriptors, there has been a substantial variation in the number and type of variables employed. In part, this reflects constraints imposed by research budgets and data availability rather than differences related to theory. Ironically, the seminal study by Zuckerman et al. (1994), which took extensive efforts to control for output heterogeneity, has not been approached in terms of the comprehensiveness of product descriptor variables until recently (Mutter et al., 2008).

Early studies commonly used fairly aggregate variables that were available from the American Hospital Association (AHA) Annual Survey of Hospitals (AHA, 1996, 2007) or the Medicare Cost Reports. The Medicare Case Mix Index (MCMI), which reflects the relative resource intensity of the distribution of DRGs, has been used in most national studies. Some studies that have been restricted to a single state or a few states where more hospital data is available have used all-payer case-mix indexes, including the All-Payer Refined Diagnosis-Related Group (APR-DRG) case-mix index (Carey, Burgess, & Young, 2008). The assumption made in the national studies is that the MCMI (which is readily available) represents the case-mix of all patients in a given facility. Strong correlations have been found between all-payer indexes and the

MCMI (Jensen & Morrissey, 1985; Rosko & Carpenter, 1993). Outpatient case-mix indexes have not been available. Accordingly, researchers have used proportions of outpatients that were treated in the emergency department or had surgery to reflect outpatient case-mix (Carey et al., 2008; Rosko & Mutter, 2008). Other case-mix-related variables include proportion of inpatient days that were for patients treated in intensive care units, births as a proportion of admissions, intra-DRG severity of illness index, and the number of high-technology services offered by the hospital. The latter measure assumes that hospitals with the capability of providing advanced services will attract a more severely ill group of patients.

Teaching status has been the most commonly used structural measure of quality. This has generally been operationalized by the inclusion of binary variables for teaching and nonteaching hospitals. Some studies have split teaching status into major teaching facilities (e.g., academic medical centers or members of the Council of Teaching Hospitals) and institutions with a minor focus on teaching. A few studies have used full-time equivalent (FTE) residents (Rosko, 2004), FTE residents per bed (Deily & McKay, 2006), or binary variables based on the value of the FTE residents to bed ratio (Zuckerman et al., 1994). While research has shown that teaching activities can have a positive impact on patient outcomes (Taylor, Whellan, & Sloan, 1999), teaching variables may also reflect differences in case-mix and mission that may also affect the location of the cost frontier. Other structural measures of hospital quality that have been used in SFA studies include Joint Commission on Accreditation of Healthcare Organizations accreditation (Folland & Hofler, 2001; McKay & Deily, 2008; Zuckerman et al., 1994), number of board-certified medical staff per bed (Deily & McKay, 2006), and existence of a transplant program (Deily & McKay, 2006).

SFA studies have used outcome measures ranging from risk-adjusted all-causes hospital-level mortality rates to variables measuring risk-adjusted mortality rates for specific conditions and risk-adjusted patient safety event rates. Rosko and Mutter (2008) argued that the later approach avoids the information loss associated with the use of a single aggregate measure of hospital outcomes.

More recently, Mutter et al. (2008) tested the impact of including controls for patient burden of illness, in addition to controls for hospital quality, in SFA models. They followed Elixhauser, Steiner, Harris, and Coffey (1998) and contended that patient burden of illness consists of five components: (a) the primary reason for admission to the hospital, (b) the severity of the principal diagnosis, (c) iatrogenic complications, (d) comorbidities that are unrelated to the primary diagnosis and yet have a substantial impact on both the resources used to treat the patient and the outcomes of the care provided, and (e) unimportant comorbidities that have a trivial impact on resources used for treatment and on the patient's outcomes. SFA studies have not directly accounted for the impact of the fourth concept in controlling for patient burden of illness. However, Mutter et al. (2008) were able to do so by including hospital-level sums of 30 comorbidity variables per discharge in the hospital cost function by applying the Comorbidity Software to Healthcare Cost and Utilization Project State Inpatient Databases. They found that mean estimated inefficiency was lower in a model

with the comorbidity variables (14.26%) than in a model with only a control for inpatient risk-adjusted mortality (17.34%). Although they found that some of the comorbidity variables were of an unexpected sign, suggesting that multicollinearity might be a problem, Mutter et al. (2008) recommended including controls for patient burden of illness in the cost function when the purpose of the analysis is estimating mean inefficiency or comparing the efficiency of different groups of hospitals.

Correlates of Hospital Inefficiency

Conceptual Framework

X-Efficiency Theory provides a useful conceptual framework for analyzing hospital cost-inefficiency. In SFA, cost-inefficiency is measured as the percentage difference between the hospital's actual cost and the cost it would incur if it operated on the "best-practice" cost frontier.¹ This is similar to Leibenstein's definition of X-Inefficiency (i.e., the difference between the actual and the optimal performance of a firm). X-Inefficiency may manifest itself in the form of any of the four aforementioned types of cost-inefficiency.

Leibenstein (1987) argues that there exist certain "inert" areas where the firm will behave routinely with respect to input use or output production. Nevertheless, if sufficient pressure is exerted, the firm will be "shocked" into nonroutine behavior aimed at adjusting to the change. The postulate of inert area behavior implies that firms will not actively seek to minimize costs. Rather than continually adjusting to optimize, firms will accept the "normal" effort levels. This behavior is similar to what Simon (1965) termed *satisficing*.

Button and Weyman-Jones (1992) reported that writers on X-Efficiency Theory have identified many possible sources for the failure of environmental pressures to influence maximum managerial effort. These include the degree of competitiveness in a firm's market and the organization's mission and profit orientation. Furthermore, analysis of health care organizations by Weisbrod (1993) and Rosko et al. (1995) suggests that demand patterns may be another determinant of X-Inefficiency. Rosko (2001a) used SFA to analyze X-Inefficiency in hospitals. He identified internal (i.e., ownership and structural characteristics) and external (i.e., competition, public payment policy, private payment policy, demand patterns, and ability to pay) environmental pressures for increased efficiency. The following sections review insights gained from SFA studies in the literature on the impact of internal and external forces, respectively, on hospital inefficiency.

Internal Factors

Ownership status. There were 4,614 registered, short-term, community hospitals in the 2007 AHA Annual Survey of Hospitals; 59.7% of those were not-for-profit (NFP), 23.9% were public, and 16.4% were for-profit (FP) hospitals. In general, while the

absolute number of hospitals in the United States has decreased in recent years, the share of hospitals that are FP has increased. For example, in 1996, the AHA reported 4,852 registered, short-term, community hospitals, of which 59.% were NFP, 27.1% were public, and 13.8% were FP.

There are no laws limiting how much profit or operating surplus NFP hospitals can earn. There are, however, legal restrictions on how those profits can be used. The fundamental difference between the ownership forms is the nondistribution constraint faced by NFP hospitals (Sloan, 2000). This constraint precludes them from distributing profits to individual owners and gives rise to theorized differences in behavior.

Property Rights Theory asserts that profit maximization will be a higher priority for the well-defined residual claimants of a FP hospital than for the decision makers in a NFP hospital. Since profits can be increased by reducing inefficiency, this theory suggests that FP hospitals will engage in more efficient production than NFP hospitals (Folland, Goodman, & Stano, 2007).

Not all theories based on the nondistribution constraint necessarily imply that FP hospitals will be more efficient than NFP hospitals, however. Newhouse (1970) assumes that hospital decision makers (i.e., administrators, trustees, and the medical staff) maximize the quantity and the quality of services a NFP hospital provides, subject to a budget constraint. His model implies that NFP hospitals can behave like FP hospitals and engage in least-cost production. However, he notes that there are several unique features of hospital markets, including philanthropy, preferential tax treatment, and the presence of third-party payers, that bias against this outcome. Therefore, the theoretical predictions of the Newhouse (1970) model of the effects of ownership on efficiency are ambiguous.

Pauly and Redisch (1973) model NFP hospitals as cooperatives over which physicians exercise de facto control.² This control is used by doctors to maximize their net incomes. Physicians could direct NFP hospitals to behave like FPs. They could minimize hospitals' costs so that they can have more resources to allocate to themselves. However, noncooperative behavior among a hospital's doctors could lead to the oversupply of quality as physicians direct the hospital's capital and nonphysician labor without fully taking into account the behavior of other doctors at the hospital. Thus, the efficiency implications of hospital ownership in their model are not straightforward.

The empirical literature that examines the differences in hospital performance by ownership type reflects the ambiguity in the theoretical literature. Studies measuring efficiency using SFA have found that NFP hospitals are more efficient than FP hospitals (Folland & Hofler, 2001; Koop, Osiewalski, & Steel, 1997; McKay, Deily, & Dorner, 2002/2003; Rosko, 1999, 2001a, 2004; Rosko & Mutter, 2008; Rosko, Proenca, Zinn, & Bazzoli, 2007; Zuckerman et al., 1994) and that FP hospitals are more efficient than NFP hospitals (Li & Rosenman, 2001; McKay & Deily, 2005; Mutter & Rosko, 2008; Rosko, 2001b; Sari, 2003).

Mutter and Rosko (2008) used rigorous and preferred strategies identified by Shen, Eggleston, Lau, and Schmid (2007) for assessing differences in hospital performance by ownership type as well as the approach recommended by Rosko and Mutter (2008)

for using SFA to estimate efficiency in the hospital industry. They found that FP hospitals are more cost efficient than NFP hospitals, which, in turn, are more cost efficient than publicly owned hospitals. Their findings were supported by the analysis of ratios commonly used by hospital executives to assess the performance of their institutions. They found that mean case-mix-adjusted length of stay, FTE employees per admission, and expense per admission were significantly lower ($p < .05$) in FP hospitals than in NFP hospitals. These results contribute to the emerging consensus that there are meaningful behavioral differences among ownership forms and that all serve a valuable role and should, therefore, be retained (Horwitz, 2005; Schlesinger & Gray, 2006).

System membership. Another characteristic that might affect cost-inefficiency is membership in a multihospital health care system. Health care systems are defined by the AHA as corporate bodies that may own and/or manage health provider facilities, health-related subsidiaries, and non-health-related facilities. Our analysis of 2007 AHA Annual Survey data found that 53.9% of community general hospitals belonged to a system. System membership varied by location: while 63.3% of urban hospitals were system members, only 41.6% of rural hospitals shared this characteristic.

System membership may convey cost advantages associated with firm-level scale economies that might be because of the opportunities to specialize that occur in larger organizations and the elimination of duplicative administrative functions. Other cost savings attributed to system affiliation include (a) reduced interest rates in capital markets, (b) human resource benefits such as improved recruiting, (c) greater ability to control environmental factors, (d) lower malpractice premiums, and (e) economies in marketing a large organization rather than several smaller firms (Ermann & Gabel, 1985).

Rosko and Proenca (2005) used concepts from resource dependency theory and institutional theory to explain the potential benefits of participation in health care systems or networks. They suggested that hospitals participate in such collaborative ventures to obtain needed resources and knowledge, reap scale and scope economies, share costs, and gain leverage. Resource dependency theory suggests that hospitals should be able to provide services at lower cost and with greater efficiency by collaborating on service delivery with other institutions as part of a network or a system. Prior research has identified the ability to share costs, pool resources and capabilities, improve coordination, and gain greater access to markets as potential benefits of collaboration (Balakrishna & Koza, 1993; Dodgson, 1992; Oliver, 1990).

Centralization of services at the system level should make it easier to achieve the critical mass needed for optimal productivity, reduce administrative overhead, and lower marketing and customer acquisition costs (Dranove & Shanley, 1995). As more services are provided in a joint platform, the combined size of the collaborating entities increases and so too should their leverage in negotiating terms with vendors and buyers of care (Bazzoli, Dynan, & Burns, 1999/2000). Thus, hospitals that provide a greater percentage of their services at the network or system level should be more efficient than hospitals that provide few or no services in this manner.

Despite the many potential cost advantages associated with system membership, cost function studies have found mixed results. Connor, Feldman, and Dowd (1998) explain this by arguing (and providing empirical support) that hospitals join systems more for market power than for cost containment. Rosko et al. (2007) argue that the mixed results are because of the simplistic treatment of system membership in empirical studies. Most studies have entered system membership in the regression model as a binary variable (member = 1, nonmember = 0). This treatment implicitly assumes that all systems convey the same advantages. In contrast, Bazzoli, Shortell, Dubbs, Chan, and Kralovec (1999) argue that it is not system membership per se that conveys performance advantages; rather, it is the characteristics of the system that influences performance. Using cluster analysis, they identified five different types of systems, which they termed *centralized systems*, *centralized physician/insurance systems*, *moderately centralized systems*, *decentralized systems*, and *independent systems*. In a follow-up study, they report that financial performance may be affected by membership in different types of health care systems (Bazzoli, Chan, Shortell, & D'Aunno, 2000), but they did not specifically examine the efficiency implications of different system configurations.

SFA-based analyses of the impact of system membership on hospital performance have used both simplistic and more complex measures of system membership. Rosko (2001a) and Bernet, Rosko, and Valdmanis (2008) used a simple binary variable approach and found that system membership was associated with reduced cost-inefficiency. Rosko and Proenca (2005) found that hospitals providing a moderate to high proportion of services at the network or system level were more efficient than hospitals that did not use networks or systems for service provision. Low users of networks or systems and nonusers had comparable levels of efficiency.

Carey (2003) and Rosko et al. (2007) used the health system typology identified by Bazzoli et al. (1999) to determine if system structure had an impact on the relative cost-efficiency of members. In both studies, binary variables reflecting membership in system type were employed. The studies had different results, which may be because of the use of different estimation methodologies. In each study, selection bias was tested; however, only Rosko et al. (2007) could not reject endogeneity. Also, Carey (2003) used a two-stage SFA approach, which tends to inflate the standard errors of the regression coefficients (Wang & Schmidt, 2002). Carey found that none of the system cluster variables had an estimated coefficient that was significant at $p < .05$.

Rosko et al. (2007) employed a Heckman procedure for the correction of selection bias. This required them to restrict their final analysis to system members and include an Inverse Mill's Ratio as an inefficiency effects variable. They also used a simultaneous estimation procedure and found that three of the four coefficients (the centralized system cluster was the omitted reference category) for variables representing system type were significant ($p < .01$). Moderately centralized systems were the exception. Moreover, they found differences in mean estimated inefficiency by system type. The mean inefficiency was lowest in centralized physician/insurance health systems (4.05%) and decentralized health systems (6.55%). Hospitals in independent hospital systems

tended to be the most inefficient (18.82%). There was little difference in estimated inefficiency between members of centralized (8.8%) or moderately centralized health systems (9.8%). Similar results were found when inefficiency rankings were analyzed.

Specialty hospitals. Specialty hospitals, in the form of psychiatric and children hospitals, existed long before the 1990s; however, during the 1990s, a new type of specialty hospital—small specialty hospitals (SSHs) focusing on cardiac, orthopedic, or surgical services—began to proliferate (Al-Amin, Zinn, Rosko, & Aaronson, in press; Carey et al., 2008; U.S. General Accounting Office, 2003). They more than tripled in number since 1995 and now amount to more than 100 facilities. The growth of these hospitals has sparked an intense debate about the desirability of the growth of SSHs. Proponents of SSHs have cited advantages such as cost efficiency, patient choice, and value (Herzlinger, 2004). On the other hand, opponents have leveled charges about unfair competition, cherry-picking, and limiting the ability of nearby general hospitals to cross-subsidize unprofitable services (Kahn, 2006).

Carey et al. (2008) used SFA to compare the relative cost-inefficiency of SSHs and general hospitals that were located in the same market area during the period 1998–2004. The study was restricted to Arizona, California, and Texas, states that have experienced a high growth of SSHs and where HCUP data are available. (The authors applied the Patient Safety Indicator module of the Agency for Healthcare Research and Quality [AHRQ] Quality Indicator software to these data.) This was the first SFA study to use the APR-DRG case-mix index, a measure that should control patient heterogeneity better than a DRG-based measure. The analytical file included 355 general hospitals and 34 SSHs. Although their file contained 7 years of data, concerns about fixed-effects and random-effects models led them to use a pooled-data approach. The authors found that the mean estimated cost-inefficiency was 27.4% for general hospitals and 42.5% in SSHs ($p < .01$). Breaking down SSHs into two categories, Carey et al. (2008) report the mean cost-inefficiency was 47.1% and 27.7% in orthopedic and surgical SSHs and cardiac SSHs, respectively. The mean for the former group was statistically significantly ($p < .01$) greater than that for general hospitals, but the mean for cardiac SSHs was not. However, the authors estimated separate frontiers for each type of hospital, and this makes comparisons difficult as inefficiency was estimated relative to different references.

External Factors

X-Efficiency Theory suggests that hospitals might respond to external pressures by improving their performance. In this section, we discuss external forces, including public and private payment policy and competition.

Public payment policy. Medicare shifted from retrospective, cost-based reimbursement to a Prospective Payment System (PPS) in 1983 because policy analysts thought that the threat of losses or the attraction of operating surpluses would induce hospitals to reduce costs. Under the PPS, hospital payment rates are determined by the relative costliness of the DRG to which the patient is assigned. If the cost of treating a patient

is less than the DRG payment rate, the hospital earns a surplus; conversely, it could suffer a loss if its resource use is greater than the DRG payment. However, there are concerns that hospitals might have responded to prospective payment by attempting to enhance revenue (e.g., DRG up-coding or charge-shifting) or through the reduction of quality or access. These actions are not consistent with the efficiency enhancing goals of the Medicare PPS.

Medicaid is a joint federal–state program in which payment policy is established at the state level. Many states emulated the Medicare program by implementing their own version of prospective payment. Many states have also implemented managed care systems for some or all of their patients. However, it is commonly believed that Medicaid hospital payments are low in most states and exert cost containment pressures irrespective of the unit of payment (Friedman, Sood, Engstrom, & McKenzie, 2004).

The financial pressures exerted by Medicare and Medicaid have typically been entered in SFA studies by variables measuring the percentage of admissions or discharges represented by Medicare or Medicaid patients. Ideally, a variable related to share of revenue or degree of underpayment would be used. However, such measures are not available in national databases. In many empirical studies, Medicaid or Medicare share of admissions or discharges has been inversely associated with cost-inefficiency (Li & Rosenman, 2001; Rosko, 1999, 2001a; Rosko & Chilingerian, 1999; Rosko et al., 2007; Rosko & Proenca, 2005; Vitaliano & Toren, 1996). However, Rosko (2001b) found a positive association between Medicare share of discharges and cost-inefficiency. He speculated that the unexpected result might be because of unmeasured case-mix variations or the relatively generous payments of Medicare during part of the panel that was used.

Critical access hospital (CAH) status. The enactment of the Balanced Budget Act of 1997 created the CAH program. This program, which has been subsequently modified by additional legislation, such as the Medicare Prescription Drug, Improvement, and Modernization Act of 2003, is intended to enhance the financial viability of small, isolated, rural, and “necessary provider” hospitals by paying them on a cost basis instead of prospectively. By paying on a cost basis, the CAH program keeps small hospitals from being penalized if they lack the economies of scale needed to keep their costs below the prospective payment rates paid by Medicare.

The 2007 AHA Annual Survey reports that there were more than 1,200 CAH hospitals. The program has succeeded in its aim of halting the closure of small rural and necessary provider hospitals by improving their financial condition. However, there is concern that hospitals in the CAH program are not providing care as efficiently as possible. Indeed, the Medicare Payment Advisory Commission (2005) reports, “Although the CAH program has helped to preserve access to emergency and inpatient care in isolated areas, it may not have accomplished this goal in an efficient manner” (p. 167).

Rosko and Mutter (2010) used data from 1997 to 2004 to employ time-varying SFA to estimate the cost-inefficiency of CAH-designated hospitals, as well as a comparison group of prospectively-paid, nonconverting hospitals in rural areas. They

found that CAH facilities are, on average, more cost inefficient than nonconverting hospitals and that they become more cost inefficient the longer they are in the program. They also found that there is a negative correlation coefficient between cost-inefficiency and operating margin for nonconverting hospitals that is much stronger than the relationship between those two variables for facilities with CAH status. The above findings suggest that cost-based reimbursement does not provide a strong incentive for hospitals to increase efficiency, which highlights a policy dilemma. Although the CAH program is succeeding in its aim of keeping hospitals providing care to underserved populations open, the program appears to have an undesirable impact on efficiency.

Unemployment rate. A few studies (Rosko, 1999, 2001a; Rosko & Proenca, 2005) used the county unemployment rate as a proxy for the pressures associated with uncompensated care (Rosko, 1990). They reported the expected inverse relationship between unemployment rate and cost-inefficiency.

Health maintenance organization (HMO) penetration. Gaskin and Hadley (1997) showed that HMOs can slow hospital cost inflation. As a result, hospitals in markets with a large share of managed care patients may be forced to limit their expenses. Therefore, Rosko (2001b) hypothesized that hospitals in markets characterized by a high degree of managed care penetration would be more cost efficient. He included HMO penetration as an inefficiency effects variable and found that it was negative and highly significant ($p < .01$). A Hausman test indicated that HMO penetration was exogenous; however, predicted HMO penetration using instruments suggested by Dranove, Simon, and White (1998) was also negative and significant in a robustness check. Rosko and Proenca (2005) found that HMO penetration was endogenous and predicted HMO penetration was inversely related ($p < 0.01$) to cost-inefficiency. The finding that cost-inefficiency is inversely related to managed care penetration has been corroborated by numerous other studies (Bernet et al., 2008; Rosko, 2001a, 2004; Sari, 2003).

Hospital competition. The impact of increased competition on hospital efficiency depends on the nature of competition. Luft, Robinson, Garnick, Maerki, and McPhee (1986) identified the existence of the so-called medical arms race in the 1970s and 1980s, whereby hospitals practice service-based competition. Firms that engage in service-based competition attempt to differentiate their product on the basis of non-price dimensions, including "hotel" services (e.g., pleasant rooms and good food) and the acquisition and utilization of resource-intensive technologies (i.e., both quality-enhancing and non-quality-enhancing). A result of service-based competition is that institutions in more competitive markets have higher costs. See, for example, Robinson and Luft (1985, 1987). Some of those costs are associated with duplication of services and inefficiency (Noether, 1988). Price-based competition, which emerged in the hospital industry in the late 1980s as a result of selective contracting and managed care, is associated with lower costs in the presence of higher competition (Zwanziger & Melnick, 1988; Zwanziger, Melnick, & Bamezai, 2000). Price-based competition persisted in the 1990s; however, Devers, Brewster, and Casalino (2003) report a return to a new form of medical arms race in the hospital industry beginning around 2000.

Most studies have used a Hirschman–Herfindahl Index (HHI) to measure hospital competition. The HHI measures concentration of output. It equals one in monopolistic markets and approaches zero in highly competitive markets. McKay et al. (2002/2003) used market share, number of area hospitals, and area occupancy rate, and Rosko (2001a) and Rosko and Proenca (2005) used a binary variable for highly competitive markets. Rosko (2004) and Rosko and Proenca (2005) found evidence that hospital competition had no effect on cost-inefficiency.³ Sari (2003) reported more nuanced results: He found that the association between market concentration and hospital inefficiency depends on the amount of competition in the market and was characterized as an inverted “u-shaped” curve. Several studies (McKay et al., 2002/2003; Rosko, 2001a; Rosko et al., 2007) found that more competition is associated with lower hospital cost-inefficiency. However, Rosko et al. (2007) was restricted to system member, urban hospitals. Four studies (Mutter & Rosko, 2008; Rosko, 1999, 2001a; Rosko & Chillingirian, 1999) found evidence to support service-based competition.

Other Results

Change in inefficiency. McKay et al. (2002/2003) are the only researchers to examine the factors associated with a change in inefficiency over time. They used a national sample for the years 1986 and 1991. They found that the biggest efficiency gains occurred among hospitals that had the greatest opportunities for improvement (i.e., those that were most inefficient in 1986). They also found that hospitals with more local competitors had more improvement in efficiency. Furthermore, hospitals with greater market share and those located in markets with greater changes in income and higher area occupancy rates were more likely to improve their efficiency position relative to other hospitals. The later results imply that hospitals with a better cash flow were more able to improve their relative efficiency. This conclusion is corroborated by Bernet et al. (2008), who hypothesized that access to capital may make it easier for hospitals to achieve threshold levels of capital needed for investment in productivity-enhancing projects. They reported that higher bond ratings (which, in part, are influenced by cash flow) were associated with reductions in cost-inefficiency.

Performance measures. Some studies examined the relationship between SFA-derived measures of efficiency and other measures of hospital performance. Consistent with expectations, Zuckerman et al. (1994) and Chirikos and Sear (2000) and found that increased cost-inefficiency was associated with increases in staff ratios (a measure of labor productivity) and decreases in occupancy rate (a measure of capital efficiency). Zuckerman et al. (1994) and Frech and Mobley (2000) found that the more inefficient hospitals also were less profitable.

The National Health Quality Report (Agency for Healthcare Research and Quality, 2008), which is produced by AHRQ, indicated that during the period 2000–2004 hospitals in the lowest quartile of inefficiency outperformed hospitals in the highest quartile of cost-inefficiency in terms of cost per case-mix-adjusted

admission (\$4,224 vs. \$6,345), FTE employees per case-mix-adjusted admission (0.042 vs. 0.057), and operating margin (0.012 vs. -0.095).

Outcome measures of quality. Some studies have used SFA-estimated cost-inefficiency as an independent variable for further analysis. For example, Deily and McKay (2006) found that higher cost-inefficiency in Florida hospitals is associated with a higher mortality rate. In a companion study, McKay and Deily (2005) reported that high-performing hospitals (i.e., those that ranked in the best quartile for both cost-inefficiency and risk-adjusted excess mortality) were more likely to be FP, to have higher occupancy rates, to have proportionately more Medicare and proportionately fewer Medicaid and self-pay patients, to use fewer patient care personnel per admission, and to have higher operating margins than all other hospitals. However, using national data, McKay and Deily (2008) found no association between cost-inefficiency and hospital outcomes (measured by both mortality and complication rates). Comparing their results with their previous study, they suggested that there might be important regional differences in the relationship between hospital quality and cost-inefficiency.

Expansion and closure. Frech and Mobley (2000) reported that hospital growth in California (as measured by increases in net patient revenue or market share of net patient revenue) was negatively related to cost inefficiency. This is consistent with Demestz's (1973) evolutionary view that industry concentration results from the growth of efficient firms at the expense of inefficient firms.

Indeed, in a national study, Deily, McKay, and Dorner (2000) reported that cost-inefficiency is a strong predictor of hospital closure in future years for private FP and NFP hospitals but not for government-owned hospitals. The mean cost-inefficiency for hospitals that subsequently closed was 19.4%, while the mean for those that remained open was 15.3%.

Budgeting. Only two of the published SFA articles can be categorized as having a managerial orientation. Both were analyses of the Veterans Affairs (VA) health system. Yaisawarng and Burgess (2006) demonstrated how SFA could be used to implement a performance-based budgeting system in the VA health system. More specifically, they propose that performance-based funding should allocate resources based on cost-efficiency standards instead of actual costs. This change would place all 21 VA networks on a more level playing field.

The researchers were able to exploit a comprehensive database for 131 hospitals that allowed them to include variables not found in most SFA studies. They included the number of risk-adjusted patients using three types of care, three measures of access (occupancy rate, average wait time for a scheduled appointment, and market penetration), and five patient satisfaction measures. While patient satisfaction is an important dimension of quality, it has not been used in other hospital SFA studies.

The authors conducted a simulation of how resources would be allocated across 141 VA hospitals under the existing budgeting process and the proposed performance-based process that uses SFA. Their results suggest that the VA may have allocated over \$470 million more to inefficient hospitals. The authors wrote,

Perhaps the VERA⁴ system allocated more funds to these less efficient networks because inefficiency-raised operating costs made these less efficient networks appear to receive insufficient funds year-in and year-out. They were able to make compelling cases for requesting additional funds. (Yaisawarng & Burgess, 2006, p. 307)

Gao, Campbell, and Lovell (2006) also used SFA to demonstrate how a performance-based resource allocation system could be implemented in the VA health care system. Their model did not use the rich set of variables employed by Yaisawarng and Burgess (2006). For example, they did not include access and patient satisfaction variables in the regression model. They used SFA, as well as corrected ordinary least squares, and found that the cost-inefficiency estimated by the two methods was almost identical with a correlation coefficient of .999.

They demonstrated benchmarking and budgeting applications of SFA. Regarding the former, they listed efficiency estimates for each of the 138 medical centers and 22 networks in the analytical file. This would allow managers in the VA health care system to compare performance of different medical centers. They calculated an optimal global budget by multiplying the frontier regression coefficient estimates with the value of the independent variable for each medical center. All the independent variables, except number of patients, which used projected patients, took on their actual value.

Lessons Learned

Table 1 provides a summary of key findings from U.S. hospital SFA studies based on estimates that were significant at a significance level of .05 or less. There was strong support that certain internal characteristics were associated with increased hospital cost efficiency. For example, hospitals that were members of multihospital systems, had higher bond ratings, and were organized to provide general medical and surgical services tended to be more efficient. However, more nuanced research found that the efficiency gains associated with system membership may be due more to the structure of the system than to just belonging to any type of system. Furthermore, general hospitals had efficiency advantages over orthopedic hospitals but not over cardiac hospitals. However, similar to results from studies using traditional regression techniques, inconsistent results were found for the association between ownership status and cost-efficiency.

SFA studies corroborated the premise of X-Efficiency Theory that organizations could be shocked into better performance by external environmental pressures. For example, hospitals located in markets characterized by more managed care penetration or higher unemployment rates (a proxy for uncompensated care) tended to be more efficient. Furthermore, consistent evidence (except for one study) found that increased dependence on Medicare prospective payments or Medicaid (a joint federal–state program that features prospective payment in many states and underpayments in virtually all states) was associated with increased cost-efficiency. Hospitals that switched from

Table 1. Summary of Key Findings From SFA Studies of U.S. Hospitals

Key Significant ($p < .05$) Findings	Study
Internal factors	
NFP hospitals are more efficient than FP hospitals.	Folland and Hofer (2001); Koop, Osiewalski, and Steel (1997); McKay, Deily, and Dorner (2002/2003); Rosko (1999, 2001a, 2004); Rosko, Proenca, Zinn, and Bazzoli (2007); Rosko and Mutter (2008); Zuckerman, Hadley, and Iezzoni (1994)
FP hospitals are more efficient than NFP hospitals.	Li and Rosenman (2001); McKay and Deily (2005); Mutter and Rosko (2008); Rosko (2001b); Sari (2003)
System member hospitals are more efficient than independent hospitals.	Bernet, Rosko, and Valdmanis (2008); Rosko (2001b)
Centralization of services in system- or network-member hospitals improves efficiency.	Rosko and Proenca (2005)
Hospitals membership in systems characterized as centralized physician/insurance health systems or decentralized health systems are more efficient than those classified as centralized, moderately centralized, or independent.	Rosko et al. (2007)
General hospitals are more efficient than single-specialty hospitals classified as orthopedic and surgical.	Carey, Burgess, and Young (2008)
Hospitals with higher bond ratings are more efficient than less creditworthy hospitals.	Bernet et al. (2008)
External factors	
Medicare or Medicaid share of inpatients is positively associated with efficiency.	Li and Rosenman (2001); Rosko (1999, 2001a); Rosko et al. (2007); Rosko and Chilingerian (1999); Rosko and Proenca (2005); Vitaliano and Toren (1996)
Medicare share of inpatients is negatively associated with efficiency.	Rosko (2001b)
Participation in Medicare Critical Access Hospital Program, featuring cost-based reimbursement, is negatively associated with efficiency.	Rosko and Mutter (2010)
Unemployment rate, a proxy for uncompensated care, is positively associated with efficiency.	Rosko (1999, 2001a); Rosko and Proenca (2005)
HMO penetration rate is positively associated with efficiency.	Bernet et al. (2008); Rosko (2001a, 2001b, 2004); Rosko and Proenca (2005); Sari (2003)
Hospital competition is positively associated with efficiency.	McKay, Deily, and Dorner (2002/2003); Rosko (2001a); Rosko et al. (2007)

(continued)

Table 1. (continued)

Key Significant ($p < .05$) Findings	Study
Hospital competition is negatively associated with efficiency.	Mutter and Rosko (2008); Rosko (1999, 2001b); Rosko and Chilingirian (1999)
The association between market concentration and hospital inefficiency depends on the amount of competition in the market.	Sari (2003)
Increases in efficiency were positively associated with base year inefficiency and degree of competition.	McKay et al. (2002/2003)
Efficiency was associated with decreases in staff ratios, a measure of labor productivity and increases in occupancy rate, a measure of capital efficiency.	Chirikos and Sear (2000); Agency for Healthcare Research and Quality (2008); Zuckerman et al. (1994)
Increased efficiency was positively associated with profitability.	Frech and Mobley (2000); Agency for Healthcare Research and Quality (2008); Zuckerman et al. (1994)
Increased efficiency was negatively associated with hospital cost per case-mix-adjusted admission.	Agency for Healthcare Research and Quality (2008)
Efficiency is negatively associated with mortality rate.	Deily and McKay (2006)
High-performing hospitals, that is, those that ranked in the best quartile for both inefficiency and risk-adjusted excess mortality were more likely to be FP, to have higher occupancy rates, to have proportionately more Medicare and proportionately fewer Medicaid and self-pay patients, to use fewer patient care personnel per admission, and to have higher operating margins than all other hospitals.	McKay and Deily (2005)
Hospital growth is positively associated with efficiency.	Frech and Mobley (2000)
Hospital closure is negatively associated with efficiency.	Deily, McKay, and Dorner (2000)

Note: SFA = stochastic frontier analysis; NFP = not-for-profit; FP = for-profit; HMO = health maintenance organization.

Medicare PPS to the cost-based CAH payment system tended to become less efficient over time. However, and similar to the general literature, SFA studies did not report a consistent relationship between competition and efficiency.

A number of studies examined the relationship between cost-inefficiency and performance. Increased cost-efficiency was associated with increases in profitability,

labor productivity, and capital efficiency and decreases in mortality rate and cost per case-mix-adjusted admission and closure.

Conclusion

A review of the literature demonstrates that SFA has made important contributions to the understanding of hospital markets and the hospital industry. Consensus has begun to emerge about the efficiency impact of a number of environmental forces, including Medicaid and Medicare share of discharges, HMO penetration, and the unemployment rate. Conflicting findings continue to be reported about the efficiency impact of other factors, such as ownership and hospital competition. Some of these disparate results could be because of the use of different data sources and methodological approaches. Others could be the result of changes in the underlying impacts of the variables studied on cost-efficiency. Further analysis of these variables is certainly warranted. Indeed, recent work has highlighted the important impact of NFP-FP ownership mix in a market on hospitals' performance (Duggan, 2002; Kessler & McClellan, 2002; Santerre & Vernon, 2006; Schlesinger & Gray, 2006; Silverman & Skinner, 2004), as well as the confounding effects of hospital competition on the impact of ownership (Reeves & Ford, 2004; Shen et al., 2007; Sloan, 2000). SFA could be particularly useful in assessing how a market's ownership mix affects hospital efficiency.

There may be opportunities to apply SFA to the evaluation of the efficiency impact of specific policies on U.S. hospitals through pre-post analyses that take advantage of natural experiments. This sort of analysis has generally not appeared in the literature. The investigation by Rosko and Mutter (2010) of the efficiency impact of CAH status is an exception, but it is suggestive of the kind of analysis, particularly in the area of payment policy, where SFA might be able to provide additional insights.

SFA has also only seen limited use in estimating regional variations in hospital efficiency. McKay and Deily (2008), in particular, hint that there could be important regional variations in hospital efficiency that could be investigated with SFA.

Recent work has highlighted the potential applicability of SFA to budgeting in the VA system. The approach shows promise; however, given the unique characteristics of the VA, it is unclear if SFA could offer similar insight to different kinds of systems.

The literature has not focused on the use of SFA to assess individual hospital performance, and there are significant concerns about using SFA for that type of analysis (Newhouse, 1994; Street, 2003). While some of these concerns have been addressed (Rosko & Mutter, 2008), others remain, so SFA has primarily been used to examine the relative efficiency of groups of hospitals (Folland & Hofler, 2001).

Some of the findings in the literature could potentially be used by hospital managers or policy makers to improve individual hospital efficiency (e.g., greater access to capital has been shown to be associated with greater efficiency); however, many of the studies in the literature have focused on variables that are not easy for policy makers

or hospital managers to change (e.g., Medicare share of admissions, ownership status). Nevertheless, since hospital efficiency studies could be used to change policy or practice, researchers should use the best practices identified in the literature for conducting SFA. There are numerous resources available on methodological approaches and study design. See, for example, Jacobs et al. (2006), Hollingsworth (2008), Mutter et al. (2008), and Rosko and Mutter (2008).

While the availability of more data to control variations in quality and patient mix have become available through AHRQ and other sources (Mutter et al., 2008), there is still concern that unmeasured heterogeneity may be affecting SFA estimates of hospital inefficiency. For example, Greene (2008) raises a concern about unobserved heterogeneity in quality and management. New performance measures of interest to policymakers, such as hospital readmission rates and rates of potentially avoidable hospitalizations, which could capture different aspects of hospital performance and the patient mix that hospitals have, including patients' access to ambulatory care, might be appropriate for incorporation into SFA models. As more data on hospital characteristics and performance continues to become available, the insight gained from SFA studies of hospitals should increase.

Authors' Note

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Notes

1. Books by Coelli et al. (2005), Fried et al. (2008), Jacobs et al. (2006), and Kumbhakar and Lovell (2000) provide a detailed treatment of SFA.
2. Sloan (2000) notes that physician influences on the behavior of individual hospitals are mitigated in hospitals that are members of a chain.
3. Bernet et al. (2008) also reported an insignificant coefficient on HHI. However, their focus was on the impact of debt rating on cost-inefficiency, and their result may reflect a lack of association between hospital competition and bond issuance decisions.
4. VERA stands for Veterans Equitable Resource Allocation.

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