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ORIGINAL ARTICLE

Does efficiency and quality of care affect hospital closures?

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ABSTRACT
In recent decades, a large number of hospitals in Pennsylvania and across the United States have been forced to close entirely, or to transform their beds for alternative uses including outpatient care. Hospital closures have severe repercussions for the stakeholders. A better understanding of hospital closures could help take corrective measures to alleviate the adverse impact closures have on communities. Using Pennsylvania Department of Health data compiled from various sources, we address the following questions: Are less efficient hospitals less likely to survive in the long run? What are the effects of quality of care on hospital closures? Does teaching status and location (urban or rural) have any impact on the probability of hospital closure? The result demonstrates several factors of varying significance affect hospital closures/survivals. Hospitals with higher ratio of registered nurses per bed, higher operating margin, lower percentage of revenues from Medicare and Medicaid, and lower competition were less likely to close. Efficiency measures such as DEA efficiency, cost per patient day, and cost per discharge were not found to have a significant impact on hospital closures. The results suggest that hospital administrators may focus more on quality of care and less on cost reduction and efficiency.

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1. Introduction

Hospital closure, a phenomenon that has accelerated in recent years, remains a major concern within the health care industry. More than 100 US hospitals have closed since 2010, at an equal rate in rural and urban areas, with more closures in 2013 and 2014 than in the previous 10 years combined. Recent reports suggest that better technology and drugs have allowed patients to shift to ambulatory care centres and home-based medical care, which has led to a decline in hospital admissions and to a concomitant decline in occupancy rates (Evans, 2015). In addition, high deductibles, more case management, and shrinking reimbursements associated with the Patient Protection and Affordable Care Act (ACA) and other legislations have fuelled hospital financial distress, in some cases leading to hospital closures (Evans, 2014).

Hospital closures have severe repercussions including: the availability of health care in many communities (Samuels, Cunningham, & Choi, 1991), the travel time to distant alternative facilities (Capps, Dranove, & Lindrooth, 2010), increased unemployment for health care workers (Holmes, Slifkin, Randolph, & Poley, 2006), and stagnation in local economies (Probst, Samuels, Hussey, Berry, & Ricketts, 1999). A better understanding of hospital closures, therefore, could help inform hospital managers and guide corrective actions to avoid closures.

Previous research has investigated the factors that trigger hospital closures (see Bazzoli & Cleverley, 1994; Kim, 2010; Lynch & Ozcan, 1994; Mullner, McNeil, & Andes, 1986). This paper theoretically argues that survival is the result of managerial decision-making that revolves around both cost-efficiency strategies (efficiency) and differentiation strategies (quality). Thus, as top hospital management allocates resources towards the replication of activities that induce either greater efficiency or higher quality, the marginal probability of survival increases. In addition, the competitive environment is a central focus of this paper. The competitive context in which hospitals operate may affect their odds of survival because competitive forces can drive essential resources into, or extract resources from, hospitals, depending on the market segment in which they operate.

These arguments are underpinned by employing the Resource-Based View (RBV) of the firm and capabilities theory to explain the underlying mechanisms for hospital survival. Theoretically, capabilities theory (as part of the RBV) predicts that organisational survival is partially conditioned on the exploitation of resources to outcompete rival entities (Barney, 1991; Wernerfelt, 1984). In application, hospitals that routinise their

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activities should have a higher propensity to survive. Empirically, the relationships between both hospital efficiency and hospital quality on survival were tested in a sample of hospitals in Pennsylvania from 1999 to 2013. Recent RBV research has employed survival, as opposed to financial returns, as a prevalent dependent variable because survival is the keystone of any organisation, both for-profit and non-profit. The results reported here indicate that efficiency indicators play little role in hospital survival, while among the three quality-of-care indicators, only one was a critical determinant of hospital survival.

This study both adds to the extant theory on firm-level capabilities and extends the literature on hospital closures, resulting in several contributions. First, this work adds to the few empirical studies of closure and efficiency in hospital settings. Second, while previous empirical studies on closure have used either ratio efficiency or frontier efficiency measures such as data envelopment analysis (DEA), the present work uses both of these measures to gather deeper insights into the relationship between closure and efficiency. Third, this study explores the relationship between quality of care and hospital closure, which has rarely been examined in previous empirical works. Fourth, given that the closure of a hospital is the outcome of a long, dynamic process involving a number of complex, interrelated factors, our panel data (1999–2013) accounts for factors in the internal system of the hospitals and in its external operating environment.

The remainder of the paper is organised as follows. Section 2 presents the theoretical framework. Section 3 discusses data and variables. Section 4 describes the methods and results of the empirical findings, and section 5 discusses the practical and theoretical results of this work.

2. Theoretical background

2.1. RBV, capabilities, and survival in the hospital space

The RBV of the firm posits that firm-level success is a function of managerial capabilities that allow the firm to survive through the replication of organisational routines (Nelson & Winter, 1982). While foundational works in the RBV stressed corporate resources (Barney, 1991), recent theory has proposed that it is the manipulation of strategic resources that actually lead to the ability to outcompete rivals (Brown, 2016). This manipulation occurs as superior managerial decision-making enables value creation through resource selection and resource deployment. In other words, while resources are heterogeneously distributed among firms, resources themselves are not able to lead directly to superior firm performance without the internal ability to exploit these for idiosyncratic advantage.

The ability to establish routines within firms allows for temporary relative advantages because the replication that goes along with routinisation allows firms to "make a living" (Helfat & Peteraf, 2003) in the face of dynamic competitive pressures. Capability attainment, therefore, encompasses organisational and managerial processes, which then lead to competitive advantage relative to rivals (Barney, 1991; Khatri, 2006). These processes include both supply-side and demand-side routines as firms must often simultaneously be cost-efficient as well as responsive to customer needs (Barney, 1991). Supply-side capabilities are evident in firms that focus on efficiency through cost minimisation, which subsequently minimises risk. Demand-side capabilities focus more on customer needs in order to separate the organisation from the herd of rivals in its competitive environment. Both strategies result in an explicit resource allocation choice that results in highly replicable activities and is, thus, a managerial decision (i.e., managerial capabilities). As a result, managerial capabilities should materialise as replicable processes that induce both efficiencies and quality (Cho & Pucik, 2005). The end result of such capability build-up and attainment has increased firm survival through intertemporal advantages relative to horizontal rivals (Raposo, Alves, & Duarte, 2009). While other outcome measures have been studied in RBV-based papers (most notably, profitability metrics), survival represents the most observable empirical outcome for the researcher (Kim & Lee, 2016).

In the hospital industry, this theoretical framework can be applied in the study of antecedent conditions to hospital survival. As top management develops the capabilities to compete with respect to efficiency and quality, superior hospitals are predicted to outperform their peers through an increased probability of survival (Leung, 2012). Efficiency in hospitals has become an increasingly important topic of research as hospital profitability in the US has been squeezed through both an increase in inputs and a decrease in payments. Therefore, managerial action that increases efficiency and quality has become a paramount goal in an ever-competitive industry (Ford, Lowe, Silvera, Babik, & Huerta, 2016).

2.2. Efficiency

Much research by both academics and practitioners has been devoted to measuring hospital efficiency. Hundreds of hospital efficiency studies have found evidence that there is a significant operational (technical) inefficiency in the US and other health systems (Chilingerian & Sherman, 2011; Hollingsworth, 2008; Hussain & Malik, 2016). Setting aside factors like fraud, human error, inflated prices, or prevention failure, this waste can be attributed to money spent on inefficient care delivery, and slack in system elements such as unnecessary services or administrative staff (Lowrey, 2012). Hence, there is a consensus on the need for improvement in hospital efficiency. There is no agreement, however, on a universal definition of hospital efficiency or on its measurement. While there are many competing definitions of efficiency, most of them have incorporated the relationship between inputs and outputs. Inputs have typically included items such as registered nurses, beds, labour, suppliers, and capital, while outputs have typically included outpatient visits, admissions, discharges, surgeries, and others.

As theory suggests, in an increasingly competitive market environment, the firms that survive in the for-profit industry would be those able to minimise cost and behave efficiently (Felício & Freire, 2016). However, the hospital industry includes the three types: for-profit, private not-for-profit, and/or government-owned hospitals, each type having its own specific, thus differing, missions. Thus, closure processes may not operate in the same manner in these different market types. For example, the purpose of establishing not-for-profit or government-owned hospitals is to provide health services to the community – particularly the needy – at little or no cost. In addition, government subsidises the services of these hospitals often. Hence, not-for-profit or government-owned hospitals may sustain their operations longer despite low returns and high costs, compared to for-profit hospitals.

Unfortunately, only a handful of studies have examined the relationship between efficiency and hospital closure, and all of them used different measures of efficiency (Wainwright, Boichat, & McCracken, 2014). For example, Lynch and Ozcan (1994) used a DEA efficiency score, Deily, McKay, and Dorner (2000) used a cost function approach, and Ciliberto and Lindrooth (2007) used operating costs per admission. Besides the different ways of operationalising efficiency, these studies also have mixed results. In addition to the measures used in these studies, healthcare researchers have also used a couple other efficiency measures: cost per patient day and cost per patient admission (Hussey et al., 2009; McGlynn, 2008); and costs per discharge (Cleverley, 2002; Zwanziger, Melnick, & Bamezai, 2000). However, this study includes three measures of efficiency that include cost per patient day, cost per adjusted discharge, and DEA efficiency, a frontier efficiency measure. Therefore, the following hypothesis is put forth:

Hypothesis 1: The probability of hospital survival is positively related to hospital efficiency.

The next central hypothesis of this study relates to hospital quality of care.

2.3. Quality of care

Quality of care in US hospitals has been a growing concern ever since the Institute of Medicine's (IOM) landmark reports, "To Err Is Human" and "Crossing the Quality Chasm," revealed widespread incidence of medical errors and substandard care. As a result of preventable medical errors, hospitals incur an estimated total cost of between \$17 billion and \$29 billion per year (Kohn, Corrigan, & Donaldson, 1999). Despite the growing concerns about quality of care, previous literature does not specifically examine its impact on hospital closure (Makarem & Al-Amin, 2014). This gap in the literature could stem from the fact that quality is difficult to define and quantify. Furthermore, characteristics such as the intangibility, simultaneity, and heterogeneity of hospital services outputs made defining and measuring quality challenging.

The problem is further exacerbated by necessary reliance on subjective patient perceptions (Akingbola & van den Berg, 2015). Deily et al. (2000), in their inefficiency residual, include several variables to control for quality-related cost differences: hospital accreditation, medical residents per bed, per cent of intensive care beds, and an index of hi-tech services. Ciliberto and Lindrooth (2007) use revenue premium, the revenue each hospital gets relative to its competitors within the market, as a proxy for quality and case-mix. While the issue of how to measure "quality of care" is a matter of ongoing debate, past literature frequently cited several indicators pertaining to quality including risk-adjusted mortality, risk-adjusted readmission, average length of stay, registered nurse per bed, and risk-adjusted morbidity (Hvenegaard, Arendt, Street, & Gyrd-Hansen, 2011; Needleman, Buerhaus, Stewart, Zelevinsky, & Mattke, 2006; Yang & Zeng, 2014). Finally, Hau, Anh, and Thuy (2017) studied health care experience quality and found a relationship between that factor and loyalty behaviours, which may aid in organisational survival. In this paper, three indicators of quality of care are used: readmission index, mortality index, and registered nurse per bed. The following is posited:

Hypothesis 2: The probability of hospital survival is positively related to hospital quality of care.

3. Data and variables

3.1. Sample selection

Data for the study was retrieved from several different sources, including (1) the Pennsylvania Health Care Cost Containment Council (PHC4) Hospital Performance Reports (HPR), which provide data pertaining to financial analysis, health performance, utilisation, among others; (2) the Centres for Medicare and Medicaid Services (CMS) cost reports, which provide data pertaining to case mix index and average hourly wages; (3) County Health Profiles, from which the demographic was extracted. Closed hospitals were identified using a list of closures compiled by PHC4. Excluded are hospitals that merged during the study period. Table 1 shows the hospital characteristics and Table 2 presents year-wise the number of hospitals and hospital closures.

Table 1. Hospital characteristics.

Hospital characteristics		Number of hospitals 1999	2013
Ownership	For-profit	22	21
	Not-for-profit	148	121
Teaching status	Teaching	41	29
	Non-teaching	129	113
Location	Urban	106	85
	Rural	64	57

Table 2. Hospital count and closures.

Year	Number of hospitals	Closed
1999	170	–
2000	166	4
2001	164	2
2002	161	4
2003	157	4
2004	155	1
2005	154	2
2006	151	3
2007	149	2
2008	149	1
2009	147	2
2010	146	1
2011	146	0
2012	143	3
2013	142	1

The period for the study was 1999–2013. Only those closed hospitals that had at least one year of data prior to the year of closure were included in the final sample. The final sample included 30 hospitals, which closed during 1999–2013. Regression imputation of mortality index (5.83%) and readmission index (6.59%) were used to account for missing data. Analysis on a reduced sample of hospitals with complete data found no significant difference in the results. After imputation, there were a total of 2,300 hospital-year observations, which includes 188 hospital-years for hospitals that have closed. A hospital appearing in our data-set for one year is called a hospital-year. For instance, the Albert Einstein Medical Centre in Philadelphia appears in our data-set for 15 years, which is considered as fifteen hospital-years.

3.2. Variables

3.2.1. Efficiency variables

To examine the impact of hospital efficiency on closure, three measures of efficiency were considered: (1) Cost Per Patient Day, (2) Cost Per Adjusted Discharge, and (3) DEA efficiency, a Frontier Measure. Regardless of the reimbursement methodology, lower costs – cost per patient day and cost per adjusted discharge – lead to higher profitability, *ceteris paribus*. As stated in the discussion of theoretical background, hospitals that *ex ante* choose to allocate their activities towards supply side efficiencies should have a higher probability of survival due to their capability to mitigate risk.

The efficiency measure Cost Per Patient Day is computed by dividing the total operating expenses by patient days, whereas the measure Cost Per Adjusted Discharge is computed by dividing the total operating expenses by total discharges adjusted for case-mix index. The third indicator is computed using DEA, a nonparametric technique that estimates a best practice efficiency frontier by applying linear programming to the observed data. The best practice frontier identifies the most efficient combinations of inputs and outputs and provides relative efficiency scores for each hospital or decision-making units (DMUs). First proposed by Charnes, Cooper, and Rhodes (1978), DEA has been greatly developed and extended since its conception. For an introduction to the basic DEA models and theoretical extensions, we refer the reader to Cooper, Seiford, and Tone (2000). This study adopts an input-oriented, constant returns to scale model to compute the relative efficiency scores for each of the hospitals.

Three categories of inputs – labour, capital, and supplies – were included in the model. Within these three categories, the specific inputs analysed were full-time equivalent registered nurses, full-time equivalent non-health professionals, number of operating rooms, number of CT scan and MRI machines, number of beds set-up and staffed, and operating expenses excluding salaries and wages of registered nurses and non-health professionals. The outputs to the model include adjusted discharges, adjusted patient days, adjusted surgeries, emergency visits, and total operating revenues. The choice of input and output variables is consistent with previous research (Hollingsworth, 2003, 2008). The relative efficiency score obtained from the model ranges from 0 to 1. Also included in the regression equation was a dummy variable to represent DEA efficiency. Following Lynch and Ozcan (1994), DEA efficiency =1 for hospitals that were found technically efficient, =0 otherwise. Two hundred and seventy-two hospital-years, i.e., of the 2300 observations, 272 observations, were found to be on the efficient frontier. For instance, the Albert Einstein Medical Centre in Philadelphia, which appeared in our data-set from 1999 to 2013, was on the frontier in 8 out of the 15 years.

3.2.2. Quality of care variables

To examine the effect of quality of care on hospital closure, three indicators were considered: *readmission index* (Readmission), *mortality index* (Mortality), and *full-time equivalent* registered nurse per bed. The first two indicators measure outcome quality by taking a weighted average of risk-adjusted readmissions rate and risk-adjusted mortality rate, respectively, for 11 common medical procedures and treatments identified by ICD-9-CM (International Classification of Diseases, Ninth Revision, Clinical Modification) codes for hospitals in Pennsylvania. The following procedures and treatments were used: abnormal heartbeat, chest pain, chronic obstructive pulmonary disease, congestive heart failure, diabetes, gallbladder removal, heart attack, hypotension, kidney failure, pneumonia, and stroke. The weighted outcome quality index was computed as follows:

$$\text{Mortality Index}_{ht} = \frac{\sum c_{pht}\text{RAM}_{pht}}{C_{ht}} \quad \forall h;$$

$$\text{Readmission Index}_{ht} = \frac{\sum c_{pht}\text{RAR}_{pht}}{C_{ht}} \quad \forall h$$

RAM_{pht} captures the risk-adjusted mortality rate from the p^{th} procedure for the h^{th} hospital in year t. Similarly, RAR_{pht} captures the risk-adjusted readmission rate from the p^{th} procedure for the h^{th} hospital in year t. c_{pht} captures number of cases in p^{th} procedure for the h^{th} hospital in year t. C_{ht} captures the total number of cases across all of the 11 procedures.

The landmark report of the Institute of Medicine's (IOM) Committee on the Adequacy of Nurse Staffing in Hospitals and Nursing Homes note: "Nursing is a critical factor in determining the quality of care in hospitals and the nature of patient outcomes" (Wunderlich, Sloan, & Davis, 1996). A growing body of evidence demonstrates that higher registered nurse (RN) staffing was associated with reduced adverse events, improved patient safety, shorter lengths of stay, reduced costs, and decreased risk of hospital-related death (Everhart, Neff, Al-Amin, Nogle, & Weech-Moldonado, 2013; Kane, Shamliyan, Mueller, Duval, & Wilt, 2007; Stone et al., 2007). Therefore, registered nurse per bed was included as the third indicator of quality of care. As opposed to the theoretical argument of risk minimisation in the efficiency measures, competing along quality of care variables entails a different logic. This choice is not cost minimising, yet may allow the hospital to increase survival odds through demand-side separation.

3.3.3. Other variables

Based on an extensive literature search, key control variables that may impact hospital closure were identified and also incorporated. The choice of the variables included in the study is consistent with existing literature in the health care and operations management areas (Ciliberto & Lindrooth, 2007; Deily et al., 2000; Kim, 2010): *beds set-up and staffed*, a better indicator of hospital capacity compared with licensed beds; *average length of stay* (ALOS), an important indicator of hospital performance often used in the assessment of quality of care, costs and efficiency; *occupancy rate*, a measure of hospital utilisation, which past literature suggests may have frequently been the cause of financial distress in many hospitals and their eventual closure; *case-mix index* (CMI), used to capture the complexity of operation of a hospital; *ownership*, by which hospitals are categorised as either for-profit and not-for-profit; *teaching status*, as teaching hospitals are generally resource-intensive and may incur higher operating expenses because they are affiliated with medical schools, located in urban areas, treat the most complex patients' cases and the urban underserved population, train physicians and other health professionals, and advance research (Shahian et al., 2012). Recent literature indicates several critical differences in quality of care metrics, costs and operations, and patient population that merit investigation. First, health outcomes for several conditions and procedures, including many cancers and surgeries, are better in the short term in teaching hospitals than in non-teaching hospitals as measured by readmissions, mortality, and complication rates (David et al., 2017; Kowalik et al., 2016). Second, on average, US teaching hospitals have a different patient pool than non-academic institutions. Teaching hospitals tend to see fewer patients on Medicare, treat a more ethnically and racially diverse patient pool, and have a higher proportion of affluent patients in the highest income brackets. Teaching hospitals also see a higher proportion of patients transferred from other hospitals for more advanced care, and appear to use guideline-recommended therapies more consistently across conditions than non-teaching institutions (O'Brien et al., 2014). Finally, cost of care across all service lines has historically been higher at teaching hospitals; many recent studies suggest these costs have been trending upward since 2009 (Burke, Frakt, Khullar, Orav, & Jha, 2017); *location*, which the empirical evidence shows impacts hospital performance (McKay, Lemak, & Lovett, 2008; Younis, 2003). There are several key differences in patient population finances, and operations between rural and urban hospitals that justify separate consideration. First, rural hospitals are typically smaller than urban hospitals – a fact that has implications for economies of scale. Financial performance of rural hospitals in particular has been of concern to regulators, banks, and government agencies because rural hospitals are especially susceptible to various financial pressures that typically larger urban hospitals can easily weather McCue (2007). Rural hospitals of varying sizes have been shown to have lower operating margins than urban hospitals (Kaufman et al., 2016). Finally, American rural populations whose residents are most likely to rely on rural hospitals for care, skew older and poorer than their urban counterparts. Rural populations have lower rates of enrolment in the marketplaces of the Affordable Care Act than their urban counterparts. Rural populations are also more likely to rely on public insurance programmes, and have been found to be in worse health on average than their urban counterparts in prior work (Kaufman et al., 2016); and *year*, which accounts for possible trend effects.

Payer mix, which in this work is the percentage of revenue coming from Medicare and Medicaid was controlled for in this study. Payer mix is important because Medicare and Medicaid typically pay hospitals less than what it costs them to treat. *Percentage of bad debt* and *charity care* were also controlled for as both are known to inflate hospital operating expenses and to be highly correlated with not-for-profit status (Ding, 2014). In the PHC4 data-set, both bad debt and charity care were combined; hence, *bad debt and charity care* were treated as a single variable.

In addition, two demographic variables were included that provide information about the county in which the hospital is located: *percentage population below poverty line* (BPL) and *percentage of residents who are age 65 or older*. Also included were the variables *operating margins* and *number of general acute care hospitals* in the county. Operating margin is one of the most popular metrics for determining hospital profitability. It is surmised that hospitals with deteriorating operating margins are more likely to close than hospitals with healthy operating margins. Similarly, competition may play an important role in determining survival of a hospital. For instance, more hospitals in a region may lead to competition, which may impact survival. Therefore, the number of hospitals in a county was included to control for competition.

3.3.4. Interaction variables

Previous research on the relationship between efficiency measures and quality metrics pertaining to hospitals is rather mixed. Jha, Orav, Dobson, Book, and Epstein (2009) examined the relationship between hospitals' risk-adjusted costs (often described as efficiency) and quality of care. The authors found no evidence that low-cost providers provide better care. In the same vein, Chen et al. (2010) found inconsistent associations between hospitals' cost of care and quality of care and between hospitals' cost of care and mortality rates. Street, Gutacker, Bojke, Devlin, and Daidone (2014) study the interrelationship between costs and health outcomes among National Health Service providers (hospitals) for common surgical procedures. The authors find no general evidence that hospitals with lower resources use have worse health outcomes. Therefore, to test the association between efficiency and quality of care variables, (*efficiency measures* × *quality measures*) interaction variables were included in the models.

Table 3 lists the variables, descriptive statistics, and their expected effect on the dependent variable. The "Effect" column in Table 3 shows the direction of the respective explanatory variables *vis-à-vis* the dependent variable, that is, the " + " sign on an explanatory variable would signify positive association with the dependent variable, whereas, the "–" sign on explanatory would signify negative association with the dependent variable.

Table 3. Variable description, descriptive statistics, and expected effect.

Description	Mean	SD	Effect
DEA efficiency	0.12	0.32	+
Cost per adjusted discharge ($'000)	10.61	4.08	–
Cost per adjusted patient day ($'000)	2.34	1.14	–
Registered nurse per bed	1.53	0.52	+
Readmission index	11.09	8.39	–
Mortality index	2.30	1.77	–
Operating margin (%)	0.77	8.34	+
Beds set-up and staffed	211.41	186.72	+
Average length of stay (Days)	4.76	0.96	–
Occupancy rate (%)	60.99	15.30	+
Case mix index	1.33	0.27	+
Percentage bad debt & charity care (%)	3.28	1.98	–
Percentage Medicare (%)	8.72	7.18	–
Percentage Medicaid (%)	44.57	9.08	–
Ownership (For-profit = 1, Not-for-profit = 0)	0.14	0.35	+
Teaching Status (Yes = 1, No = 0)	0.22	0.41	–
Location (Urban = 1, Rural = 0)	0.60	0.49	–
Percentage population over age 65 years (%)	16.00	2.15	–
Percentage population BPL (%)	11.52	4.56	–
Number of hospitals in the county	6.45	6.62	–

4. Models

This section presents the regression model, which, among other factors, examines the impact of quality of care and hospital efficiency on hospital survival. We model hospital closure using the term survivor, the dependent variable. Here, a survivor hospital is defined as one whose last appearance in the data-set was in 2013. Thus, if a hospital entered into the data-set in 1999, it counts as a survivor as long as it appears in the 2013 data-set. If, however, it was in the hospital industry at any time in our data-set but does not appear in the last year [2013], it is not a survivor. The survivor hospital is represented with a zero/one dummy variable, where SURVIVOR = 1 if the hospital appears in 2013, = 0 if not. Thus, the dependent variable in this study is binary and it is, therefore, appropriate to use a discrete choice probit or a logit model. Previous literature on hospital closure has used logit models (Balasubramanian, 2016; Ciliberto & Lindrooth, 2007; Hung, Kozhimannil, Casey, & Moscovice, 2016; Kim, 2010; Lynch & Ozcan, 1994; Wertheim & Lynn, 1993).

The main difference between logit model and probit model is that the logit assumes the standard logistic distribution, while the probit assumes the standard normal distribution (Maddala, 2001). Maddala (1983) argues that the unequal frequency of the failed and non-failed samples suggests the use of logit model rather than probit estimation, since the logit model is not as sensitive to the uneven sampling frequency problem as probit model. However, caution must be exercised in fitting logit regression models having a smaller number of outcomes (closures). Aldrich and Nelson (1984) suggest logit models should have at least 50 observations per parameter in order to produce an unbiased result. Logit regression uses the maximum likelihood estimation (MLE) technique to estimate model parameters. A drawback, however, with MLE techniques is the effect of small sample sizes on the performance of significance tests for the estimated coefficients. Given the distributional assumptions, the current sample size of 2,300 hospital-years, and the fact that the sample data-set only contains 8.2% of hospitals that closed (unequal frequency), logit analysis is used in the current study. We also computed the results using probit analysis. We then compared the results with the results from our logit analysis. We found both the results to be similar. We report here only the results obtained using logit analysis.

As with linear regression, multicollinearity is a common problem when estimating logistic regression models. High correlations were observed among the independent variables, especially among the quality and efficiency variables, which may lead to unreliable and unstable estimates of regression coefficients. Table 4 presents the correlation among the independent variables. It is evident from Table 4 that there exists a high correlation among the variables. Variance inflation factor (VIF), one of the most widely used diagnostics for multicollinearity, was computed for each independent variable. VIFs were high, ranging from 1.02 to 20.61, especially when readmission index and all the three efficiency variables were included in the models. One of the main objectives of the paper is to determine whether efficiency and quality affect hospital survival. Given the adverse VIFs and in order to discriminate the impact of efficiency variables as well as quality variables, we develop two models: model 1 and model 2. Model 1 determines whether "DEA efficiency" and quality measure "registered nurse per bed" along with other variables affect hospital survival. Model 2 determines whether efficiency measures – "cost per patient day" and "cost per adjusted discharge," and quality measure "registered nurse per bed" and "mortality index" along with other variables affect hospital survival. For base models 1 and 2, VIFs were again computed. The VIF for the independent variables in both models were below 3, indicating absence of any serious multicollinearity effects. Therefore, in the base model 1, only one efficiency and quality variable is included to avoid multicollinearity. The base models are:

$$\begin{aligned}\log\left(\frac{\text{Survivor}}{1-\text{Survivor}}\right) &= \beta_0 + \beta_1(\text{DEA Efficiency})_{it} + \beta_2(\text{Registered Nurse per Bed})_{it}\\ &+ \beta_3(\text{DEA Efficiency x RN per Bed})_{it} + \beta_4(\text{Operating Margin})_{it}\\ &+ \beta_5(\text{Bad Debt and Charity Care})_{it} + \beta_6(\text{Medicare})_{it}\\ &+ \beta_7(\text{Medicaid})_{it} + \beta_8(\text{Occupancy Rate})_{it} + \beta_9(\text{Average Length of Stay})_{it}\\ &+ \beta_{10}(\text{Beds Set up and Staffed})_{it} + \beta_{11}(\text{Case Mix Index})_{it} + \beta_{12}(\text{Ownership})_{it}\\ &+ \beta_{13}(\text{Location})_i + \beta_{14}(\text{Teaching Status})_{it} + \beta_{15}(\text{Percentage of Population over 65 years})_{it}\\ &+ \beta_{16}(\text{Percentage of Population BPL})_{it} + \beta_{17}(\text{Number of Hospitals in the County})_{it}\end{aligned} \tag{1}$$

$$\begin{aligned}\log\left(\frac{\text{Survivor}}{1-\text{Survivor}}\right) &= \beta_0 + \beta_1(\text{Cost per Patient Day})_{it}\\ &+ \beta_2(\text{Cost per Adjusted Discharge})_{it}\\ &+ \beta_3(\text{Registered Nurse per Bed})_{it} + \beta_4(\text{Mortality Index})_{it}\\ &+ \beta_5(\text{Cost per Patient Day x RN per Bed})_{it} + \beta_6(\text{Cost per Patient Day x Mortality Index})_{it}\\ &+ \beta_7(\text{Cost per Adjusted Discharge x RN per Bed})_{it}\\ &+ \beta_8(\text{Cost per Adjusted Discharge x Mortality Index})_{it}\\ &+ \beta_9(\text{Operating Margin})_{it} + \beta_{10}(\text{Bad Debt and Charity Care})_{it}\\ &+ \beta_{11}(\text{Medicare})_{it} + \beta_{12}(\text{Medicaid})_{it} + \beta_{13}(\text{Occupancy Rate})_{it}\\ &+ \beta_{14}(\text{Average Length of Stay})_{it} + \beta_{15}(\text{Beds Set Up and Staffed})_{it}\\ &+ \beta_{16}(\text{Case Mix Index})_{it} + \beta_{17}(\text{Ownership})_{it} + \beta_{18}(\text{Location})_i\\ &+ \beta_{19}(\text{Teaching Status})_{it} + \beta_{20}(\text{Percentage of Population over 65 years})_{it}\\ &+ \beta_{21}(\text{Percentage of Population BPL})_{it} + \beta_{22}(\text{Number of Hospitals in the County})_{it}\end{aligned} \tag{2}$$

where, the subscript $i = 1, \ldots, N$ represents each hospital and $t = 1, 2, \ldots, T$ represents each year from 2000 to 2013.

Each of the above models was tested separately by including readmission index and mortality index, respectively. Furthermore, models were also run by including efficiency measure "cost per patient day." Results are discussed in the relevant sections.

5. Results

The results of random effect logit regression are presented in Tables 5 and 6. Table 5 presents results of model 1, which includes the base model (with and without the year dummies), and the models based on location and teaching status subsamples. Similarly, Table 6 presents results of model 2, which again includes the base model (with and without the year dummies), and the models based on location and teaching status subsamples.

5.1. All hospitals (base models)

Overall, the results indicate that none of the efficiency indicators were significant determinants of hospital survival in the base models. Thus, there was no support for Hypothesis 1 in the sample that included all hospitals. Hypothesis 2 posited that the quality of care attributed to a hospital is positively related to survival. In base model 1, registered nurse per bed was highly significant ($p < 0.01$) and positively associated with survival. In the base model 2, mortality index was highly significant ($p < 0.01$); however, contrary to expectation, it was positively associated with survival. Only one of the interaction variables – cost per adjusted day x mortality index – was significant ($p < 0.01$). The control variables included in models 1 and 2 – average length of stay, bad debt and charity care, Medicare, Medicaid, teaching status, urban hospitals, the population over age 65, and local competition – were all significant and negatively related to survival, which is in line with our expectation. Conversely, the variables operating margins, beds set-up and staffed, occupancy rate, case mix index, for-profit status, and percentage population BPL were all significant and positively related to hospital survival. All control variables had significant estimators and all were in the anticipated direction with respect to hospital survival, with the exception of the percentage of the population below the poverty line. This variable, while marginally significant, was predicted to be negative, but was reported as positive in models 1 and 2.

Regression models were run by replacing quality measures registered nurse per bed and mortality index with "readmission index" in the base models. Concomitant interaction variables were also included.

Table 4. Correlation matrix.

	DEA Efficiency	Cost per Patient Day	Cost per Adjusted Discharge	Operating Margin	Registered Nurse per Bed	Readmission Index	Mortality Index	Bad Debt & Charity Care	Medicare	Medicaid	Beds	Case Mix Index	Population over 65 years	Population BPL
Cost per Patient Day	0.031													
	(0.139)													
Cost per Adjusted Discharge	0.000	0.740**												
	(0.997)	(0.000)												
Operating Margin	0.094**	−0.071**	−0.067**											
	(0.000)	(0.001)	(0.001)											
Registered Nurse per Bed	0.147**	0.327**	0.182**	0.249**										
	(0.000)	(0.000)	(0.000)	(0.000)										
Readmission Index	0.131**	−0.254**	−0.163**	0.233**	0.354**									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
Mortality Index	0.086**	−0.286**	−0.220**	0.197**	0.301**	0.756**								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)								
Bad Debt & Charity Care	0.085**	−0.043*	−0.026	−0.162**	−0.246**	−0.140**	−0.069**							
	(0.000)	(0.038)	(0.206)	(0.000)	(0.000)	(0.000)	(0.001)							
Medicare	−0.096**	−0.257**	−0.295**	−0.242**	−0.233**	−0.054**	−0.060**	0.023 (0.269)						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.004)							
Medicaid	0.113**	−0.005	0.150**	−0.131**	−0.130**	0.078**	−0.067**	0.313**	−0.151**					
	(0.000)	(0.818)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)					
Beds	0.099**	−0.256**	−0.076**	0.213**	0.295**	0.810**	0.731**	−0.123**	−0.239**	0.107**				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Case Mix Index	0.181**	−0.184**	−0.065**	0.264**	0.414**	0.547**	0.490**	−0.243**	−0.291**	0.033 (0.112)	0.710**			
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)			
Population over 65 years	−0.130**	0.044*	0.022	−0.135**	−0.129**	−0.192**	−0.104**	−0.066**	0.434**	−0.094**	−0.192**	−0.193**		
	(0.000)	(0.033)	(0.301)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)		
Population BPL	0.083**	0.030	0.134**	−0.108**	−0.053*	0.090**	−0.047*	0.161**	0.102**	0.467**	0.135**	0.114**	−0.010 (0.619)	
	(0.000)	(0.144)	(0.000)	(0.000)	(0.012)	(0.000)	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Number of hospitals in the county	0.080**	−0.277**	−0.155**	−0.030	0.005	0.416**	0.246**	0.117**	0.157**	0.246**	0.366**	0.274**	−0.186**	0.440**
	(0.000)	(0.000)	(0.000)	(0.154)	(0.826)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

*$p < 0.10$ (Two-tailed tests).; **$p < 0.05$.; ***$p < 0.01$.

Table 5. Results of logistic regression (Model 1).

Independent variables	Base models				Urban		Rural		Teaching		Non-teaching	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
DEA efficiency (DEA)	−0.148	0.876	−0.169	0.904	0.665	1.154	0.656	1.428	1.195	1.655	−0.163	1.177
Registered Nurse (RN) per bed	0.787**	0.400	1.094***	0.382	0.131	0.509	4.234***	1.118	0.164	0.876	2.810***	0.586
Interaction: DEA × RN per Bed	−0.358	0.707	−0.157	0.745	−0.458	0.960	−1.727	1.397	−0.104	1.424	0.019	0.945
Operating Margin	0.106***	0.015	0.105***	0.014	0.140***	0.020	0.063*	0.034	0.181***	0.038	0.061***	0.018
Percentage of bad debt & charity care	−0.103*	0.055	−0.081*	0.047	−0.048	0.055	−0.105	0.124	−0.103	0.097	−0.168**	0.072
Percentage of Medicare	−0.048***	0.016	−0.049***	0.015	−0.038*	0.020	−0.109***	0.034	−0.077*	0.039	−0.041**	0.020
Percentage of Medicaid	−0.048***	0.016	−0.050***	0.015	−0.072***	0.019	−0.108***	0.039	−0.146***	0.044	−0.058***	0.021
Occupancy rate	0.059***	0.012	0.048***	0.011	0.080***	0.015	−0.036	0.027	0.001	0.028	0.031**	0.015
Average length of stay	−0.262**	0.106	−0.181*	0.104	−0.440**	0.205	0.344	0.213	−0.253	0.372	−0.068	0.115
Beds set-up and staffed	0.012***	0.002	0.013***	0.002	0.015***	0.003	0.015**	0.006	0.012***	0.003	0.031***	0.005
Case mix index	4.024***	0.989	2.913***	0.727	3.157***	0.896	0.596	2.079	2.349**	1.147	3.575***	1.073
Ownership (Profit = 1, Nonprofit = 0)	0.895***	0.343	0.927***	0.333	0.844**	0.399	na		na		−0.141	0.434
Location (Urban = 1, Rural = 0)	−2.639***	0.362	−2.458***	0.351	na		na		na		−3.472***	0.434
Teaching status (Yes = 1, No = 0)	−2.589***	0.335	−2.572***	0.322	−2.988***	0.372	na		na		na	
Percentage of population > 65 years	−0.296***	0.065	−0.278***	0.063	−0.451***	0.080	0.701***	0.182	0.228	0.144	−0.492***	0.091
Percentage of population BPL	0.065*	0.038	0.090**	0.036	0.101**	0.043	−0.025	0.106	0.228***	0.075	0.205***	0.057
Number of hospitals in the county	−0.087***	0.026	−0.090***	0.025	−0.129***	0.030	−2.224***	0.456	−0.166***	0.046	−0.068*	0.037
Years	Included											
Constant	4.238	1.544	3.748	1.495	4.165	1.770	−1.600	3.282	−2.345	2.912	2.642	2.047
N	2300		2300		1390		910		507		1793	

Note: SE = Standard Error.
*$p < 0.10$ (Two-tailed tests).; **$p < 0.05$.; ***$p < 0.01$.

Readmission index and the associated interaction variables were not significant in both models 1 and 2.

5.2. Urban vs. rural hospitals

Next, the sample was decomposed into urban and rural subsamples on which logit estimations were run separately to gain better insight into differences engendered by the differing patient demographics and expectations of urban versus rural hospitals. Tables 5 and 6 report the coefficients of the variables for urban hospitals and rural hospitals for models 1 and 2. As with the base models that included all hospitals, barring "cost per adjusted discharge," none of the efficiency measures were significant in determining hospital survival. The efficiency measure cost per adjusted discharge was weakly significant ($p < 0.1$) and positively associated with rural hospitals. The finding with respect to the relationship between "cost per adjusted discharge" and survival is consistent with Hypothesis 1. With regard to the quality of care variables, registered nurse per bed was highly significant for rural hospitals ($p < 0.01$), however, the mortality index was insignificant. These new findings add support to the mixed support found in base models 1 and 2 for Hypothesis 2.

Another interesting finding from the subsamples is the change in significance of some of the control variables. Specifically, five variables – bad debt and charity care, occupancy rate, ALOS, CMI, and population below poverty line – shifted from significant in base models to insignificant in rural hospitals in models 1 and 2. For the rural subsample, the variable "percentage of population over age 65" moved from negative and significant in the base models to positive and significant. Also noteworthy is that the controls in the urban subsample were identical in sign and significance to the base models.

5.3. Teaching vs. non-teaching hospitals

Next, the sample was split between teaching hospitals and non-teaching hospitals. For the teaching subsample, quality measure "mortality index" was significant and, as

Table 6. Results of logistic regression (Model 2).

Independent variables	Base models				Urban		Rural		Teaching		Non-teaching	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	B	SE
Cost per patient day (CPD)	−0.402	0.636	−0.003	0.410	−2.021	1.429	−0.349	1.840	1.147	3.687	0.826**	0.347
Cost per adjusted discharge (CAD)	0.015	0.150	0.011	0.110	0.048	0.350	0.865*	0.488	−1.375*	0.783	0.177*	0.098
Registered Nurse (RN) per bed	0.869	0.962	1.244	0.873	−0.607	1.023	4.387	3.650	2.312	2.705	4.934***	1.062
Mortality index (MI)	1.016***	0.378	0.835**	0.353	0.416	0.409	1.761	1.715	−2.888***	0.901	0.874	0.648
Interaction: CPD × RN per bed	−0.100	0.450	−0.252	0.272	−0.163	0.925	2.761*	1.507	0.347	2.290	−0.387	0.315
Interaction: CPD × MI	0.365	0.284	0.329	0.263	0.912**	0.369	−0.693	1.420	0.812	0.827	−0.047	0.406
Interaction: CAD × RN per bed	0.064	0.132	0.072	0.095	0.196	0.243	−0.708*	0.429	−0.132	0.522	−0.094	0.097
Interaction: CAD × MI	−0.169***	0.065	−0.152**	0.065	−0.215**	0.091	−0.099	0.328	0.179	0.203	−0.091	0.110
Operating margin	0.096***	0.015	0.097***	0.014	0.140***	0.022	0.074*	0.043	0.163***	0.044	0.057***	0.019
Percentage bad debt & charity care	−0.095*	0.057	−0.083*	0.049	−0.068	0.061	−0.001	0.137	−0.253**	0.119	−0.137*	0.077
Percentage Medicare	−0.057***	0.017	−0.053***	0.016	−0.070***	0.022	−0.101**	0.041	−0.164***	0.051	−0.040*	0.022
Percentage Medicaid	−0.052***	0.017	−0.052***	0.016	−0.096***	0.022	−0.159***	0.056	−0.209***	0.056	−0.057**	0.022
Occupancy rate	0.037***	0.014	0.035**	0.014	0.046**	0.018	0.033	0.043	−0.046	0.036	0.034*	0.018
Average length of stay	−0.245*	0.133	−0.149	0.122	−0.613*	0.357	0.048	0.390	1.283	0.950	−0.026	0.146
Beds Staffed and Supported	0.012***	0.003	0.014***	0.002	0.015***	0.003	0.020*	0.012	0.014***	0.004	0.035***	0.006
Case mix index	3.667***	1.015	2.802***	0.749	3.785***	1.002	0.476	2.509	2.217	1.426	3.025***	1.095
Ownership (Profit = 1, Nonprofit = 0)	0.916**	0.363	0.830**	0.345	1.094**	0.456	na		na		−0.459	0.467
Location (Urban = 1, Rural = 0)	−2.822***	0.389	−2.417***	0.356	na		na		na		−3.363***	0.441
Teaching Status (Yes = 1, No = 0)	−2.653***	0.345	−2.656***	0.331	−3.509***	0.428	na		na		na	
Percentage population > 65 years	−0.324***	0.068	−0.306***	0.065	−0.512***	0.089	0.826***	0.243	0.082	0.159	−0.505***	0.093
Percentage population BPL	0.072*	0.039	0.099***	0.037	0.150***	0.048	0.160	0.147	0.320***	0.092	0.203***	0.061
Number of hospitals in the county	−0.084***	0.028	−0.095***	0.026	−0.125***	0.031	−2.730***	0.654	−0.179***	0.052	−0.084**	0.038
Years	Included											
Constant	6.331	2.284	4.398	2.034	11.152	2.711	−13.099	5.539	7.438	6.472	−1.127	2.645
N	2300		2300		1390		910		507		1793	

Note: SE = Standard Error.
*$p < 0.10$ (Two-tailed tests).; **$p < 0.05$.; ***$p < 0.01$.

per our expectation, negatively associated with survival. For the non-teaching subsample, efficiency measures cost per patient day ($p < 0.05$) and cost per adjusted discharge ($p < 0.1$) were significant; both variables were positively associated with survival. Quality measure "registered nurse per bed" was a significant variable for the non-teaching hospitals.

With regard to the control variables, a number of formerly significant variables in base models turned insignificant in the teaching subsample including occupancy rate, average length of stay, case mix index, the percentage of bad debt and charity care, and the percentage population over 65 years of age. For the non-teaching subsample, average length of stay and ownership ceased to be significant compared with the base models.

6. Discussion

This paper empirically examined the impact of efficiency and quality indicators on hospital survival using panel data on Pennsylvania acute care hospitals for the years 1999–2013. The study was underpinned by a capabilities theory framework, which derives from the RBV of the firm. The RBV is an appropriate framework considering the study's goal of modelling the probability of survival conditional on a number of control and explanatory variables.

The empirical analyses reveal several important insights that could be useful to hospital administrators and policy-makers. First, contrary to expectations, efficiency indicators had little influence on hospital survival, which is consistent with mixed results in the literature. For example, Ozcan and Lynch (1992) and Lynch and Ozcan (1994) conclude that inefficient hospitals were not shown to be at increased risk for closure and Deily et al. (2000) found that relative inefficiency did not significantly affect government hospital closure. Furthermore, Ciliberto and Lindrooth (2007) found that efficiency was not a significant determinant of hospital closures. We come to a conjecture that hospital administrators emphasise investments that reduce errors, improve patient flows, speed up patient information access, and optimise supplies, among others. Hence, the focus is on access and quality and not necessarily on cost reduction.

Two of three quality indicators were associated with survival: registered nurse per bed in model 1 and mortality index in model 2. Interestingly, readmission index, also considered as a marker of quality in this study, was not found to have the same effect, whereas average length of stay, a possible proxy for "quality," was associated with hospital survival. This disparity may stem from the fact that longer stays directly impact profitability when they result in less patient turnover and therefore volume in profitable service lines, and can reflect a resource-intensive, severe case mix. By contrast, the connection between readmissions and profits and case mix is less clear, because readmissions are frequently driven by patient lifestyle and social factors rather than strict medical need, while studies on the profitability of readmissions have yielded mixed results (Clement et al., 2016). More nurses per bed may be associated with a hospital possessing a case mix favouring riskier or complex procedures, which are, in turn, associated with profitability. These results should be considered in the context of recent ACA legislation that emphasises patient quality by penalising hospitals with low Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) scores, and realigns reimbursements and financial incentives with patient outcomes rather than procedures. Ironically, a large-scale movement to re-centre reimbursement on such metrics may force more hospitals into closure than procedure-driven reimbursement models, depending on whether these financial incentives truly account for the cost of improved outcomes.

Upon closer examination of rural and urban hospitals, it appears that hospital mission, policy considerations, and subsidies could go a long way in explaining observed differences in closure rates. In the face of discrepancies in the influence of factors such as operating margins on closure, this metric may not tell the whole story in the case of rural hospital because of the availability of Medicare subsidies, donations, and other government incentives that are not accounted for in the calculation of operating margins but that disproportionately impact rural hospitals. Higher adjusted costs per day or the effect of quality-linked, cost-driving metrics such as length-of-stay may not affect rural hospitals as they do urban hospitals because such rural hospitals may be kept open out of necessity, regardless of typical financial performance or efficiency indicators, unlike urban hospitals that face copious competitor institutions and whose patient populations could be accommodated by nearby institutions in the event of closure.

Operating margins were found to be associated with hospital survival, whereas debt and charity care were associated with hospital failure. Along these lines, busier hospitals with higher rates of occupancy and more complex procedures are more likely to survive, for the simple fact they seem to bring the hospital more revenue. Unsurprisingly, then, for-profit hospitals were found more likely to survive than their not-for-profit counterparts. Similarly, teaching hospitals tasked with serving the community and academic research were less likely to survive than non-teaching institutions. Urban hospitals are less likely to survive than rural hospitals in Pennsylvania. There are several possible explanations for this observation: there tend to be fewer teaching hospitals in rural areas, and therefore disproportionately more non-teaching hospitals that are more likely to shutter. Rural hospitals, which are typically not subject to competitive pressures, may be kept open despite unprofitability by governmental mandate or through governmental support when such hospitals are the only centres accessible to a region's patient population. Such hospitals, in addition to incentives stated previously, shoulder less of the burden of "uncompensated care" that is increasingly borne by urban hospitals plagued by larger numbers of uninsured patients using emergency department services in lieu of conventional care.

The fact that hospitals in areas with greater proportions of patients below the poverty level may be more likely to survive for similar reasons: hospitals serving indigent populations may be kept open in the face of dire financial straits as "safety nets" for populations who would be underserved or unserved otherwise. At the same time, hospitals serving larger populations of over-65 patients may fare better than other hospitals because these patients are covered by Medicaid or Veteran's insurance for having served in the armed forces.

7. Limitations

This study has several limitations. First, the study considers data only from the state of Pennsylvania, and does not include data from other states, which may reduce the generalisability of our findings. Second, the sample contains a relatively small number of closed hospitals compared to open hospitals within the state. Third, our independent variables mostly pertain to inpatient care. It would be interesting to explore other services such as outpatient care, emergency care. Fourth, though our data-set spanning 14 years is long enough, adding more hospital-years of data could have provided us with greater insights into why hospitals close. Finally, the study does not consider the number of services and facilities offered by hospitals, which may affect closure. However, the granularity of the data-set, the long time horizon for which data were gathered, and the fact that Pennsylvania is among the largest states of the union, all mitigate the effects of these limitations on the robustness of models and analysis presented in this paper.

8. Practical implications

The practical implications that flow from the current paper are threefold. First, management at hospitals, in general, may consider the value added in having a significant staffing of nurses (i.e., nurses per bed). The findings in this study indicate that quality of care, as measured by the relative staffing of nurses, affects subsequent survival in the industry. As such, it may be practical for hospital management to track this metric to ensure that there are not excessive cuts to nurses.

The second implication that is important is in the urban versus rural subsample. An interesting finding that can be translated into a practical guideline is that the cost per patient day did not lead to increased survival in urban hospitals, contrary to both theory and intuition. Investigating the trade-offs between inefficiency and quality is therefore important for managers of urban hospitals. Urban hospitals in the US tend to offer a range of services that most rural hospitals, and particularly rural hospitals in smaller communities, cannot afford. Patients living in rural areas routinely travel to urban hospitals for treatment of complex or specialty cases that their local hospitals cannot accommodate (Kaufman et al., 2016; Wishner, Solleveld, Rudowitz, Paradise, & Antonisse, 2016). In addition, given that urban hospitals are located in densely populated areas, the facilities are simply statistically more likely to see rarer cases requiring specialised care than rural hospitals in small communities. It is possible that the relatively diverse, clinically complex urban hospital caseload, the treatment of which demands comparatively wide-range resources, is not conducive to hyper efficiencies. In other words, these excessive efficiencies may then become part of the quality issue at hospitals with a more diverse case mix (i.e., urban hospitals), but do not have the same effect on rural hospitals, which have long been known to have a far less intense, less diverse case mix, and have disproportionately more routine cases, than their urban counterparts (Basu & Mobley, 2010; Buczko, 1992).

The third practical implication arising from this study is the need for teaching hospitals to explore optimal nurse staffing levels. As discussed in the results section, registered nurses per bed was a significant predictor of survival; however, this was not the case in the teaching sub-sample, when compared to the non-teaching hospital sub-sample. It is possible that teaching hospitals, which are staffed with multiple medical students and tend to have more young residents, are more apt to survive with a lower nurse per bed metric because these staff members serve as a substitutes for nurses. While not conclusive from the empirical results in this paper, this is an issue that teaching hospitals could study more closely in order to ensure that they are not overspending on redundant labour.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Akingbola, K., & van den Berg, H. (2015). Does CEO compensation impact patient satisfaction? *Journal of Health Organization and Management, 29*(1), 111–127.

Aldrich, J., & Nelson, F. (1984). *Linear probability, logit, and probit models*. Newbury Park, CA: Sage Publications.

Balasubramanian, S. S. (2016). *Evaluating increasing hospital closure rates in U.S.: A model framework and a lean six sigma approach for quality improvement initiatives to prevent further closures in rural and disadvantaged locations* (Doctoral Thesis). Industrial and Manufacturing Systems Engineering, The University of Texas at Arlington.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Basu, J., & Mobley, L. R. (2010). Impact of local resources on hospitalization patterns of medicare beneficiaries and propensity to travel outside local markets. *The Journal of Rural Health, 26*(1), 20–29.

Bazzoli, G. J., & Cleverley, W. (1994). Hospital bankruptcies: An exploration of potential causes and consequences. *Health Care Management Review, 19*(3), 41–51.

Brown, R. (2016). Firm-level political capabilities and subsequent financial performance. *Journal of Public Affairs, 16*(3), 303–313.

Buczko, W. (1992). What affects rural beneficiaries' use of urban and rural hospitals? *Health care financing review, 14*(2), 107–114.

Burke, L. G., Frakt, A. B., Khullar, D., Orav, E. J., & Jha, A. K. (2017). Association between teaching status and mortality in us hospitals. *Journal of the American Medical Association, 317*(20), 2105–2113.

Capps, C., Dranove, D., & Lindrooth, R. (2010). Hospital closure and economic efficiency. *Journal of Health Economics, 29*(1), 87–109.

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Chen, L. M., Jha, A. K., Guterman, S., Ridgway, A. B., Orav, E. J., & Epstein, A. M. (2010). Hospital cost of care, quality of care, and readmission rates *Archives of Internal Medicine, 170*(4), 340–346.

Chilingerian, J. A., & Sherman, H. (2011). Health-care applications: From hospitals to physicians, from productive efficiency to quality frontiers. In W. W. Cooper, L. M. Seiford, & J. Zhu (Eds.), *Handbook on data envelopment analysis springer handbook on data envelopment analysis* (pp. 445–493). New York, NY: Springer.

Cho, H., & Pucik, V. (2005). Relationship between innovativeness, quality, growth, profitability and market value. *Strategic Management Journal, 26*(6), 555–575.

Ciliberto, F., & Lindrooth, R. (2007). Exit from the hospital industry. *Economic Inquiry, 45*(1), 71–81.

Clement, R. C., Gray, C. M., Kheir, M. M., Derman, P. B., Speck, R. M., Levin, L. S., & Fleischer, L. A. (2016). Will Medicare readmission penalties motivate hospitals to reduce arthroplasty admissions? *Journal of arthroplasty, 32*(3), 709–713.

Cleverley, W. O. (2002). The hospital cost index: A new way to assess relative cost-efficiency. *Healthcare Financial Management, 56*(7), 36–42.

Cooper, W., Seiford, L., & Tone, K. (2000). *Data envelopment analysis*. Dordrecht: Kluwer.

David, J. M., Ho, A. S., Luu, M., Yoshida, E. J., Kim, S., Mita, A. C., & Zumsteg, Z. S. (2017). Treatment at high-volume facilities and academic centers is independently associated with improved survival in patients with locally advanced head and neck cancer. *Cancer, 123*(20), 3933–3942.

Deily, M., McKay, N., & Dorner, F. (2000). Exit and inefficiency: The effects of ownership type. *The Journal of Human Resources, 35*(4), 734–747.

Ding, D. (2014). The effect of experience, ownership and focus on productive efficiency: A longitudinal study of U.S. hospitals. *Journal of Operations Management, 32*(1–2), 1–14.

Evans, M. (2014). *Hospitals plan for lasting declines in admissions*. Retrieved June 10, 2015, from http://www.modernhealthcare.com/article/20140222/MAGAZINE/302229969

Evans, M. (2015). *Hospitals face closures as 'a new day in healthcare' dawns*. Retrieved July 3, 2017, from http://www.modernhealthcare.com/article/20150221/MAGAZINE/302219988

Everhart, D., Neff, D., Al-Amin, M., Nogle, J., & Weech-Moldonado, R. (2013). The effects of nurse staffing on hospital financial performance: Competitive versus less competitive markets. *Health Care Management Review, 38*(2), 146–155.

Felício, J. A., & Freire, C. R. (2016). From customer motivation to corporate performance. The role of strategic factors and distribution channels of financial service firms. *Service Business, 10*(1), 135–157.

Ford, E., Lowe, K., Silvera, G., Babik, D., & Huerta, T. (2016). Insider versus outsider executive succession: The relationship to hospital efficiency. *Health Care Management Review*. doi:10.1097/HMR.0000000000000112

Hau, L., Anh, P., & Thuy, P. (2017). The effects of interaction behaviors of service frontliners on customer participation in the value co-creation: A study of health care service. *Service Business, 11*(2), 253–277.

Helfat, C., & Peteraf, M. (2003). The dynamic resource-based view: Capability lifecycles. *Strategic Management Journal, 24*, 997–1010.

Hollingsworth, B. (2003). Non-parametric and parametric applications measuring efficiency in health care. *Health Care Management Science, 6*(4), 203–218.

Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health Economics, 17*(10), 1107–1128.

Holmes, G. M., Slifkin, R., Randolph, R., & Poley, S. (2006). The effect of rural hospital closures on community economic health. *Health Services Research, 41*(2), 467–485.

Hung, P., Kozhimannil, K. B., Casey, M. M., & Moscovice, I. S. (2016). Why are obstetric units in rural hospitals closing their doors? *Health Services Research, 51*(4), 1546–1560.

Hussain, M., & Malik, M. (2016). Prioritizing lean management practices in public and private hospitals. *Journal of Health Organization and Management, 30*(3), 457–474.

Hussey, P., de Vries, H., Romley, J., Wang, M., Chen, S., Shekelle, P., & McGlynn, E. (2009). A systematic review of health care efficiency measures. *Health Services Research, 44*(3), 784–805.

Hvenegaard, A., Arendt, J., Street, A., & Gyrd-Hansen, D. (2011). Exploring the relationship between costs and quality: Does the joint evaluation of costs and quality alter the ranking of Danish hospital departments? *The European Journal of Health Economics, 12*(6), 541–551.

Jha, A. K., Orav, E. J., Dobson, A., Book, R. A., & Epstein, A. M. (2009). Measuring efficiency: the association of hospital costs and quality of care. *Health Affairs, 28*(3), 897–906.

Kane, R. L., Shamliyan, T., Mueller, C., Duval, S., & Wilt, T. (2007). *Nurse staffing and quality of patient care*. Evidence Report/Technology Assessment #151, Minnesota Evidence-based Practice Center, Minneapolis, MN.

Kaufman, B. G., Thomas, S. R., Randolph, R. K., Perry, J. R., Thompson, K. W., Holmes, G. M., & Pink, G. H. (2016). The rising rate of rural hospital closures. *The Journal of Rural Health, 32*(1), 35–43.

Khatri, N. (2006). Building HR capability in health care organizations. *Health Care Management Review, 31*(1), 45–54.

Kim, J., & Lee, C. (2016). Technological regimes and firm survival. *Research Policy, 45*(1), 232–243.

Kim, T. H. (2010). Factors associated with financial distress of nonprofit hospitals. *The Health Care Manager, 29*(1), 52–62.

Kohn, L., Corrigan, J., & Donaldson, M. (1999). *To err is human: Building a safer health system*. Report of the Committee on Quality of Health Care in America, Institute of Medicine. National Academy Press: Washington, DC.

Kowalik, T. D., DeHart, M., Gehling, H., Gehling, P., Schabel, K., Duwelius, P., & Mirza, A. (2016). The epidemiology of primary and revision total hip arthroplasty in teaching and nonteaching hospitals in the United States. *Journal of the American Academy of Orthopaedic Surgeons, 24*(6), 393–398.

Leung, R. (2012). Health information technology and dynamic capabilities. *Health Care Management Review, 37*(1), 43–53.

Lowrey, A. (2012). Retrieved August 31, 2017, from http://www.nytimes.com/2012/09/12/health/policy/waste-and-promise-seen-in-us-health-care-system.html

Lynch, J. R., & Ozcan, Y. (1994). Hospital closure: An efficiency analysis. *Hospital and Health Services Administration, 39*(2), 205–220.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics*. New York, NY: Cambridge University Press.

Maddala, M. (2001). *Introduction to econometrics* (3rd ed.). New York, NY: John Wiley.

Makarem, S., & Al-Amin, M. (2014). Beyond the service process: The effects of organizational and market factors on customer perceptions of health care services. *Journal of Service Research, 17*(4), 399–414.

McCue, M. J. (2007). A market, operation, and mission assessment of large rural for-profit hospitals with positive cash flow. *The Journal of Rural Health, 23*(1), 10–16.

McGlynn, E. R. (2008). *Identifying, categorizing, and evaluating health care efficiency Measures*. Final Report (prepared by the Southern California Evidence-based Practice Center – RAND Corporation, under Contract No. 282-00-0005-21). AHRQ Publication No. 08-0030.

McKay, N. L., Lemak, C., & Lovett, A. (2008). Variations in hospital administrative Costs. *Journal of Healthcare Management, 53*(3), 153–166.

Mullner, R. M., McNeil, D., & Andes, S. (1986). Hospital closure: Who will be at risk in the upcoming decade? *Healthcare Financial Management, 40*(1), 42–48.

Needleman, J., Buerhaus, P., Stewart, M., Zelevinsky, K., & Mattke, S. (2006). Nurse staffing in hospitals: Is there a business case for quality? *Health Affairs, 25*(1), 204–211.

Nelson, R., & Winter, S. (1982). *An evolutionary theory of economic change*. Cambridge, MA: Belknap Press.

O'Brien, E., Subherwal, S., Roe, M. T., Holmes, D. N., Thomas, L., Alexander, K. P., & Peterson, E. D. (2014). Do patients treated at academic hospitals have better longitudinal outcomes after admission for non–ST-elevation myocardial infarction? *American Heart Journal, 167*(5), 762–769.

Ozcan, Y. A., & Lynch, J. (1992). Rural hospital closures: An inquiry into efficiency. *Advances in Health Economics and Health Services Research, 13*(1), 205–224.

Probst, J. C., Samuels, M. E., Hussey, J. R., Berry, D. E., & Ricketts, T. C. (1999). Economic impact of hospital closure on small rural counties, 1984 to 1988: Demonstration of a comparative approach. *The Journal of Rural Health, 15*(4), 375–390.

Raposo, M. L., Alves, H. M., & Duarte, P. A. (2009). Dimensions of service quality and satisfaction in healthcare: A patient's satisfaction index. *Service Business, 3*(1), 85–100.

Samuels, S., Cunningham, J. P., & Choi, C. (1991). The impact of hospital closures on travel time to hospitals. *Inquiry, 28*(2), 194–199.

Shahian, D. M., Nordberg, P., Meyer, G., Blanchfield, B., Mort, E., Torchiana, D., & Normand, S. (2012). Contemporary performance of U.S. teaching and nonteaching hospitals. *Academic Medicine, 87*(6), 701–708.

Stone, P. W., Mooney-Kane, C., Larson, T., Horan, L., Glance, J., Zwanziger, J., & Dick, A. (2007). Nurse working conditions and patient safety outcomes. *Medical Care, 45*(6), 571–578.

Street, A., Gutacker, N., Bojke, C., Devlin, N., & Daidone, S. (2014). Variations in outcome and costs among NHS providers for common surgical procedures: Econometric analyses of routinely collected data. *Health Services and Delivery Research, 2*(1), 71–75.

Wainwright, D., Boichat, C., & McCracken, L. (2014). Competing patient and professional agendas in service development. *Journal of Health Organization and Management, 28*(6), 777–794.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180.

Wertheim, P., & Lynn, M. L. (1993). Development of a prediction model for hospital closure using financial accounting data. *Decision Sciences, 24*(3), 529–546.

Wishner, J., Solleveld, P., Rudowitz, R., Paradise, J.., & Antonisse, L. (2016). *A Look at Rural Hospital Closures and Implication for Access to Care: Three Case Studies*. Henry J. Kaiser Family Foundation Commission on Medicaid and the Uninsured. Retrieved May 30, 2017, from http://www.kff.org/medicaid/issue-brief/a-look-at-rural-hospital-closures-and-implications-for-access-to-care/

Wunderlich, G. S., Sloan, F., & Davis, C. (1996). *Nursing staff in hospitals and nursing homes: Is it adequate*. Washington, DC: National Academy Press.

Yang, J., & Zeng, W. (2014). The trade-offs between efficiency and quality in the hospital production: Some evidence from Shenzhen, China. *China Economic Review, 31*(1), 166–184.

Younis, M. Z. (2003). A comparison study of urban and small rural hospitals financial and economic performance. *Online Journal of Rural Nursing and Health Care, 3*(1), 38–48.

Zwanziger, J., Melnick, G., & Bamezai, A. (2000). Can cost shifting continue in a price competitive environment? *Health Economics, 9*(3), 211–226.