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The Effect of Hospital-Physician Integration On Hospital Costs

by

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Abstract

This thesis evaluates whether hospitals that are integrated with physician practices have lower or higher costs than hospitals that are not integrated, using a large sample of U.S. hospitals from 2000-2013. Some economic theories predict that vertical integration lowers costs and other theories predict higher costs. I therefore conduct an analysis to test these predictions in the context of hospital-physician integration. I use a variety of econometric methods, including regression analysis of cost functions using both Cobb-Douglas and translog specifications. I estimate fixed effects regressions to control for unobserved time-constant factors specific to individual hospitals. I also conduct matching analyses to account for potential endogeneity. The results demonstrate that hospital-physician integration is not associated with lower hospital costs. Instead, depending on the specification, the results show that integrated hospitals have costs that are higher than or equivalent to the costs of non-integrated hospitals. Analyses that include other types of vertical relationships also do not show any consistent effect of these organizational forms on hospital costs. In addition, I find no consistent effects of vertical integration or other organizational forms on the quality of hospital care. These findings suggest that any increases in costs that may stem from hospital-physician integration are not due to higher quality care. The findings also have potential implications for public policy. Although vertical integration is sometimes viewed as a way to stem rising healthcare costs, the evidence suggests that this may not be the case.

1. Introduction

Healthcare spending accounted for 18 percent of U.S. GDP in 2016 (U.S. Centers for Medicare and Medicaid, 2018). In addition to comprising a large share of GDP, healthcare spending is continuing to rise (U.S. Centers for Medicare and Medicaid, 2018). Factors that affect healthcare spending thus merit detailed investigation. In 2016, hospital care accounted for 32 percent of U.S. healthcare spending, and physician and clinical services accounted for 20 percent of healthcare spending (U.S. Centers for Medicare and Medicaid, 2018). Although hospitals and physician practices have generally been separate entities in the past, today many hospitals directly employ their physicians. This could affect spending on healthcare if it leads to changes in hospital costs or revenues. In this thesis, I examine whether hospital-physician integration affects hospital costs. The results may have implications for public policy related to healthcare.

The integration of hospitals with physician practices has increased substantially in the past 15 to 20 years. Between 2010 and 2016, the percentage of primary care physicians working in an organization owned by a hospital or hospital system rose by 57 percent (Fulton, 2017). From 1999-2003, the number of physicians and dentists employed by community hospitals was roughly stable, but this began to trend upward in 2004, increasing by 56 percent from 2003 to 2014 (American Hospital Association, 2016). As of 2015, an analysis by Avalere found that 38 percent of physicians were employed by hospitals (Physicians Advocacy Institute, 2016). This trend appears to be a response in part to pressure on hospitals and other healthcare providers to contain rising healthcare costs. For example, Medicare is encouraging coordinated and high quality care by giving financial incentives called "shared savings" to Accountable Care Organizations—voluntary groups of hospitals, physicians, and other healthcare providers—if they lower their costs of care (U.S. Centers for Medicare and Medicaid, 2017). Some research has argued that quality of care may be easier to control and less costly to coordinate when hospitals and physicians are integrated. However, other theories predict that integrated organizations could have higher costs. There is relatively little evidence about vertical relations in healthcare markets in general, and few studies have examined the impact of hospital-physician integration on hospital costs (Gaynor, Ho, and Town, 2015). My thesis evaluates whether hospitals that are integrated with physician practices have lower or higher costs than hospitals that are not integrated, using a large sample of U.S. hospitals from 2000-2013.

Only one paper has directly examined the efficiency consequences of hospital-physician integration using panel data, which makes it possible to control for hospital-specific fixed effects. Cuellar and Gertler (2006) used annual data for 1994-1998 from Arizona, Florida, and Wisconsin to analyze whether hospitals that employed physicians had lower costs than non-integrated hospitals. They also included other types of vertical relationships that involved contracts and partnerships between hospitals and physicians. Cuellar and Gertler (2006) found no effect on hospital costs of full integration or other vertical relationships. They also investigated whether integrated hospitals had higher quality of care, because the costs of providing higher quality of care could have offset the potential cost savings from integration. The results provided some evidence that integrated hospitals had better mortality outcomes for managed care patients. Since this study was published, empirical analyses of hospital-physician integration have largely focused on prices, spending on healthcare, and quality of care (e.g., Baker, Bundorf, and Kessler, 2014; Capps, Dranove, and Ody, 2016; Koch, Wendling, and Wilson, 2017), and little research has studied the impact of integration on hospital costs.

For my analysis, I use Cuellar and Gertler's (2006) paper as a starting point. I estimate the relationship between hospital-physician integration and hospital costs using similar methods as in their paper, but I improve on their analysis in several ways. First, I use much more comprehensive and recent data on hospital costs. My data covers the entire U.S., and therefore is subject to fewer concerns about regional or local conditions in the three states in Cuellar and Gertler's (2006) sample, which could have had an outsized effect on their estimates. Furthermore, I am using 14 years of cost data, ending in 2013, which is a longer time period that is also more up-to-date. This data provides new information to help answer the question of whether integrated hospitals have lower costs. Second, I control for additional factors beyond those included by Cuellar and Gertler (2006) that might affect hospital costs. Third, I include an additional measure of hospital costs in the analysis. Fourth, like Cuellar and Gertler (2006), I investigate the impact of integration on the quality of care, but I use newer measures that have recently become available. Finally, I use matching methods in an effort to control for endogeneity of the integration decision, in addition to estimating regressions with hospital fixed effects as Cuellar and Gertler (2006) did.

The data for this thesis comes from four sources: the Healthcare Cost Report Information System (HCRIS) of the Centers for Medicare & Medicaid Services (CMS), the American Hospital Association (AHA) Annual Survey of Hospitals, the CMS Hospital Inpatient Quality Reporting (IQR) program, and the Bureau of Labor Statistics (BLS). To estimate the effect of full vertical integration and of other vertical relationships on the total operating expenses of hospitals, I follow Cuellar and Gertler in estimating a Cobb-Douglas cost function and a translog cost function (Christensen and Greene, 1976). I also analyze the impact of vertical integration and other vertical relationships on a measure of costs per patient, and on four different measures of the quality of hospital care.

The empirical results show that hospital-physician integration is not associated with lower hospital costs. Instead, depending on the specification, the results show that integrated hospitals have costs that are higher than or equivalent to the costs of non-integrated hospitals, excluding physician salaries. Analyses that include other types of vertical relationships also do not show any consistent effect of these arrangements on hospital costs. In addition, I find no consistent effects of vertical integration or other vertical relationships on the quality of care. These findings suggest that any increases in costs that may stem from hospital-physician integration are not due to higher quality care.

I begin my analysis by reviewing economic theories that make predictions about the impact of vertical integration on costs, and discuss what these theories imply for hospital-physician integration. Then I review the empirical literature that is related to the efficiency consequences of hospital-physician integration. This is followed by a discussion the data and methods that I use. I then present the results of my analyses, and conclude by discussing the implications of these results for hospitals and for public policy makers.

2. Review of the Theoretical Literature

Several prominent theories argue that vertical integration lowers costs, and these theories apply to integration between a hospital and physician practices. However, other theories argue that vertical integration may raise costs instead. I review these theories below. Additional theories suggest that firms may vertically integrate for many other reasons. For example, theories of vertical foreclosure argue that a firm may be able to gain market power in a downstream market by integrating upstream, and vice versa (Hart and Tirole, 1990). Thus, hospitals might be able to gain market power by integrating with physicians. Vertical integration might also facilitate horizontal collusion between hospitals due to improved coordination (Baker, 1999; Cuellar and Gertler, 2006). In addition, in the context of healthcare, integration could improve the ability of hospitals to raise prices by increasing their bargaining power with insurers (Gal-Or, 1999). Integrated hospitals would control access to more physicians that insurers may want to include in their provider networks, potentially improving the bargaining power of hospitals. Vertical integration may also enable hospitals and physicians to raise entry barriers and increase their market power in this way (Bresnahan and Levin, 2012; Cuellar and Gertler, 2006). Furthermore, if hospitals can offer a differentiated product through integration with physicians, they may be able to increase their profits (Cuellar and Gertler, 2006). And if upstream and downstream firms have market power, integration may enable the firms to solve the double marginalization problem by coordinating pricing decisions, leading to higher profits (Bresnahan and Levin, 2012). This may apply to vertical integration between hospitals and physicians. .

The main theory that I discuss below revolves around transaction costs. I also discuss implications for vertical integration of theoretical research on economies of scope and agency costs. These theories provide rationales for vertical integration, but they also indicate potential drawbacks to integration. Taken together, these theories show that it is possible that vertical integration can lead to lower costs under certain circumstances and higher costs under other circumstances.

Transaction cost theory (Williamson, 1975, 1985) assumes that contracts are inherently incomplete, in that a contract cannot account for all possible events (Bresnahan and Levin, 2012). This is especially true when a contract between two firms involves uncertainty, specificity, and complexity. If the two firms were separate and used contracts to coordinate their interactions, any difficulties caused by unplanned contingencies would have to be settled through negotiation, arbitration, or lawsuits, which is time-consuming and costly. By vertically integrating, unplanned events that were difficult to write a contract for could be handled by a senior manager in the integrated firm, which could be more efficient. This allows firms to leave open some details of future issues because it is assumed that the integrated firm's internal management can adequately address these future difficulties (Robinson, 1997). In addition, for goods that are very complex, such as the delivery of healthcare that is coordinated between hospitals and physicians, contracts are unlikely to be able to adequately address all aspects of the process. By integrating, this complexity is allayed through central management that can facilitate better and more efficient coordination. Additionally, integrated hospitals could restructure the financial incentives of physicians so they align more closely with the hospitals' goals, reducing the transaction costs of cooperating (Cuellar and Gertler, 2006).

Another problem with incomplete contracts involves the potential for future holdups. Due to the likelihood that contracts would not provide adequate protection of specific assets, firms are unlikely to make specific investments (Bresnahan and Levin, 2012). Once the costs of these investments are sunk, each firm could have bargaining power to hold up the other by nature of the assets involved. For example, a hospital might build a surgical center that relies on referrals from a physician practice. After the hospital has built the surgical center, the physician practice might demand additional financial benefits from the hospital. By integrating, a firm can ensure that it can make specific investments without the risk of holdup, thereby resolving an incomplete contract (Bresnahan and Levin, 2012).

These arguments of transaction cost theory imply benefits to integration for a hospital: it does not have to bear the transaction costs of contracts, and by resolving contractual inefficiencies through integration, a hospital can coordinate care more efficiently between the different parts of the organization. By integrating, the hospital spends less time and money on the costly process of negotiation with physicians. Disputes would be resolved internally, and more efficiently, thus reducing costs. In addition, given the difficulty of writing complex contracts, integration would increase coordination between the hospital and physicians. The increased coordination would likely improve healthcare outcomes and efficiency (Cuellar and Gertler, 2006). And because the hospital and the physician are inputs to the "good" of patient care being produced together, an integrated hospital would benefit from economies of scope (Cuellar and Gertler, 2006) due to reduced transaction costs and reduced costs associated with communication between physicians and hospitals. Transaction cost theory further argues that integrated firms can better align incentives. For example, integration makes it possible to more closely align the financial incentives of a hospital with those of physicians to reduce costs and improve quality, such as by paying bonuses to physicians (Cuellar and Gertler, 2006). Hospitals may also be able to better monitor the provision of healthcare by physicians that they employ (Robinson, 1997).

Along with these benefits, transaction cost theory, agency theory, and decision rights models argue that vertical integration can also increase costs by reducing productivity. One cause of reduced productivity stems from changes to incentives when firms integrate. High-powered incentives (performance-based compensation) that existed prior to integration are transformed into low-powered incentives (fixed compensation that is not tied to particular performance outcomes) (Bresnahan and Levin, 2012). For example, a physician that previously had his or her own practice, and kept any profits from his or her services, becomes a salaried employee (an agent) of the hospital. With low-powered incentives, the integrated hospital is worse equipped in situations that require individual action (Cuellar and Gertler, 2006). This arises because individuals such as physicians would have reduced financial incentives to exert extra effort, take risks, and innovate (Robinson, 1997). Low-powered incentives could also generate rewards and provide advancement to people who are skilled at internal politics instead of advancement based on merit (Robinson, 1997). This can generate a culture of bureaucracy instead of a culture of cooperation, which would impede coordination (Robinson, 1997). Additionally, in the model of Hart and Holmstrom (2010), when an integrated firm makes decisions, a manager may, by assumption, not respect the preferences of divisional employees. These employees would then be less productive when assigned to tasks that they are less interested in performing, or are otherwise less productive than if the manager respected employee preferences (Bresnahan and Levin, 2012). Integrated hospitals are multiproduct organizations that offer physician services in addition to inpatient acute care (Robinson, 1997), and might suffer from lower productivity due to the problems that Hart and Holmstrom (2010) identify.

A second cause of reduced productivity from vertical integration arises from increased administrative costs. Any potential efficiency gains could be wiped out if the administrative costs of coordination are greater than the savings from integration (Cuellar and Gertler, 2006). The administrative costs of coordination in an integrated hospital are likely to depend on the policies that a hospital puts in place. In addition, whether an integrated hospital achieves cost savings is likely to depend on the incentives that the hospital gives its physicians. Goldsmith, Burns, Sen, and Goldsmith (2015) argue that there is little evidence that integrated hospitals have effective processes for coordination.

It is worth noting that the discussion of incentives in the literature relating to hospital-physician integration generally focuses on incentives that hospitals have to reduce costs. However, even if hospital-physician integration leads to lower hospital costs per unit of care, this may not necessarily reduce total costs. For example, integrated hospitals might provide incentives to their physicians to order more tests at the hospital in order to increase revenues. This would increase both the quantity of hospital care and total costs.

Overall, the net effect of vertical integration depends on the relative importance of the different factors that may increase or decrease cost efficiency. This depends on the particular setting, including the extent of uncertainty, complexity, and asset specificity, the degree to which incentives and authority relations affect behavior, and the administrative costs of coordination in integrated organizations. In the past 20 years, hospitals have faced uncertainty about the U.S. healthcare system as the federal government has put new policies in place—such as the Affordable Care Act—and as policy makers have called for reductions in healthcare costs. Under these conditions, transaction cost theory suggests that hospitals may see integration as a viable response. However, whether hospitals achieve cost efficiencies may depend on how effectively hospitals manage vertical integration.

The theories that imply efficiency gains from vertical integration are aligned with arguments by hospitals and policy makers that hospital-physician integration will lower costs. In contrast, other theories of vertical integration predict a reduction in efficiency. For individual hospitals, one effect may dominate the other, or their effects may offset one another and there may be little effect on costs. In addition, hospitals may be heterogeneous, and some hospitals may obtain lower costs from integration while other hospitals may not. My thesis investigates whether the different possible influences on hospital costs have a positive or negative net effect, or no net effect.

3. Review of the Empirical Literature

Little empirical research has examined the impact on hospital costs of hospital-physician vertical integration. Instead, the literature has focused on the impact of vertical integration on hospital prices and competition. Only one empirical study by Cuellar and Gertler (2006) has used panel data to analyze whether hospital-physician integration lowers hospital costs. However, a few other studies have analyzed related issues of whether vertical integration reduces hospital utilization, which could lower costs, and whether vertical integration raises the quality of care. I first review articles on the impact of vertical integration on costs, and I then discuss related research.

An article by Burns and Pauly (2002) described the rationales put forward by hospitals from the late 1980s through the late 1990s for what are called "integrated delivery networks," and reviews evidence on the performance of these networks. The article discusses "vertical combinations" that involve different types of hospital-physician relationships, and "horizontal combinations" of different hospitals working closely together or merging with one another. The vertical combinations discussed in the article include: hospitals acquisitions of primary care physicians; alliances between physicians—usually primary care physicians—and hospitals, such as through physician-hospital organizations (PHOs) and management service organizations (MSOs); and health maintenance organizations (HMOs). Physician-hospital organizations include "open" physician hospital organizations (OPHOs) that use contracts to link together physicians in separate practices and "closed" physician hospital organizations (CPHOs), which are PHOs that have exclusive relationships with selected physicians based on their quality of care and costs. MSOs buy the physical assets in the physicians' practices and provide administrative services, such as billing. Table 1 in Cuellar and Gertler (2006), which is reproduced as Table 1 in this thesis, shows the differences between different types of vertical combinations involving hospitals and physicians.

Burns and Pauly (2002) noted that providers rarely mentioned lower costs of contracting with physicians or improved monitoring of physicians as rationales for vertical combinations. However, economic theory suggests that these would be among the primary motivations for integration. In addition, the article stated that hospitals that acquired primary care physician (PCP) practices lost money. The authors argued that this occurred because hospitals paid high prices to acquire the practices, suffered from adverse selection in their choice of PCPs to acquire, did not gain large enough cash flows from the practices that they acquired, and did not have productivity-based compensation incentives for physicians. Hospital-physician alliances also were not successful in general. The authors state that the alliances did not improve physician-hospital collaboration or lower hospital costs (per day or per discharge). Some hospitals also vertically integrated into the insurance market by establishing their own HMOs, but most hospitals lost money in these ventures.

Although the early evidence on hospital-physician vertical integration did not suggest that it lowered costs, Cuellar and Gertler (2006) observed that previous studies had used cross-sectional data. As a result, the studies could not incorporate variation over time, and could not control for hospital-specific effects on costs. This could lead to biased and inconsistent estimates of the effect of integration on costs if hospitals integrated because they were anticipating rising costs, or if hospital-specific factors that were time-constant were also correlated with integration.

To address the problems posed by cross-sectional data, Cuellar and Gertler (2006) conducted an analysis of the impact of hospital-physician integration on costs and quality of care using panel data from three states (Arizona, Florida, and Wisconsin) for the years 1994-1998. Their study examined the effect on hospital operating expenses of several different organizational forms: fully integrated hospitals that employ physicians and pay their salaries, independent practice organizations (loose affiliations of hospitals and physicians that may hold managed care contracts but do not have other linkages), OPHOs, and CPHOs (defined to include MSOs in this study). Cuellar and Gertler (2006) estimated both a Cobb-Douglas cost function and a translog cost function. They included variables that controlled for hospital size (number of inpatient admissions), severity of patient illness, average length of patient stay, hospital capacity (total number of beds), outpatient visits, and wages of hospital employees. They also included year by state fixed effects as well as hospital fixed effects.

In Cuellar and Gertler's (2006) study, the coefficient estimates on all of the organizational form variables were statistically insignificant at the 10 percent level. Thus, Cuellar and Gertler (2006) found no effect on hospital costs of hospital-physician integration or of any type of vertical contractual relationship. The authors further investigated whether this result held for hospitals that had not yet integrated prior to the start of the sample period, but found that the integration variables remained insignificant. The exclusion of hospitals that disintegrated during the sample period also did not change the results.

Cuellar and Gertler (2006) also investigated whether higher quality of care from vertical integration, due to improved coordination, might account for their results. That is, offering higher quality care might raise costs, and offset any cost reductions from vertical integration. The study used three different indicators of quality: rate of mortality for a set of health conditions and hospital procedures; rates of procedures that are often overused; and patient safety indicators for 20 types of complications and adverse events. For patients that had managed care insurance, fully integrated hospitals had lower mortality, but the coefficient was not significant for patients with indemnity insurance. This provided weak evidence that higher quality of care might account for the lack of reduction in hospital costs for fully vertically integrated hospitals. The analysis also found some evidence that OPHOs and CPHOs reduced overused procedures.

Even with improved data and econometric methods, Cuellar and Gertler (2006) did not find that vertical integration of hospitals and physicians is associated with changes in hospital costs, and found only weak evidence of an increase in the quality of care. Ciliberto and Dranove (2006) provided indirect evidence that is consistent with the results of Cuellar and Gertler (2006) regarding hospital costs. Ciliberto and Dranove (2006) examined the effect of vertical integration on prices charged by hospitals in California from 1994-2001 for patients with private insurance, and argued that improved cost efficiency due to vertical integration could lead to lower prices. The study calculated prices as the list price multiplied by the average yearly discount that each hospital applies to privately insured patients. Ciliberto and Dranove (2006) included dummy variables for three organizational forms: OPHO, CPHO, and ISM (integrated salary model, indicating full vertical integration of hospitals and physicians). In separate analyses, the study also included dummy variables for hospitals that adopt and hospitals that leave (or drop) each type of organization form.

Ciliberto and Dranove's (2006) study found that the coefficient on full integration was negative but was not statistically significantly associated with a price reduction when hospital fixed effects were included and correlated errors within hospitals over time were accounted for. A separate regression that included adopting and dropping the three organizational forms as separate variables showed small and insignificant effects of becoming fully vertically integrated, and larger but still insignificant effects of dropping full integration. However, only 22 hospitals became fully vertically integrated during the sample period and only 18 hospitals changed from full integration to another organizational form, so the estimates are imprecise. The authors concluded that there is no evidence of higher prices, and that while integration may be associated with lower prices, the price reductions are not statistically significant. This result suggests that either vertical integration did not lead to a reduction in costs that could translate into lower prices, or that any reduction in costs was offset by other factors.

A more recent article by practicing physicians has offered an explanation for the findings that vertical integration is not associated with lower hospital costs. Kocher and Sahni (2011) contended that hospitals lose $150,000 to $250,00 per year over the first three years of employing a physician, in part due to a slow ramp up period for new physicians to establish themselves and the need for acquired physician practices to transition to hospital ownership and adapt to management changes. These claims are consistent with the earlier argument by Burns and Pauly (2002) that the high costs of acquiring physician practices led hospitals to lose money. Goldsmith, Burns, Sen, and Goldsmith (2015) further argued that vertical integration without effective management of care and internal governance processes may not lower costs or improve care. If correct, initial inefficiencies due to integration could explain the results that hospitals that become integrated do not have lower costs over the relatively short time period of five years investigated by Cuellar and Gertler (2006) and seven years investigated by Ciliberto and Dranove (2006).

Although the evidence does not support the hypothesis that hospital-physician integration leads to lower hospital costs, other research has investigated whether vertical integration leads to lower hospital utilization. It is possible that better coordination of care through vertical integration would enable less utilization of hospitals by shifting care to lower cost physician offices. However, empirical research does not support this argument. Baker, Bundorf, and Kessler (2014) analyzed hospital claims data from Truven Health MarketScan for privately insured non-elderly patients from 2001-2007. This study analyzed the impact of vertical integration on hospital admissions, controlling for county and year fixed effects as well as hospital market and county characteristics. The results showed a small—less than one percent—but insignificant decrease in hospital admissions for fully integrated hospitals, CPHOs, and IPAs. OPHOs had a small—less than one percent—but statistically significant decline in hospital admissions. Again, using data from Truven Health MarketScan for nonelderly patients in 2008 and 2012, Nepresh, Chernew, and Hicks (2015) analyzed annual inpatient utilization. The study found a minimal and insignificant effect of physician-hospital integration at the MSA level on hospital utilization per enrollee. In addition, Koch, Wendling, and Wilson (2017) analyzed acquisitions of physician practices by 27 hospitals between 2005-2010, and found that vertical integration led acquired physicians to shift care out of physician offices and into more costly hospital settings. This result is not consistent with decreased utilization of hospitals. Another small-scale study (Madison, 2004) restricted to Medicare patients with acute myocardial infarction in 1994 and 1998 found similar results that vertical integration is not associated with a decrease in hospital utilization.

One explanation for the findings that vertical integration is not associated with lower costs or less hospital utilization is that vertical integration instead enables higher quality care. This may increase costs per patient, and offset any cost efficiencies from vertical integration. As noted earlier, Cuellar and Gertler (2006) found weak evidence that vertical integration is associated with higher quality care. However, the study by Madison (2004) of acute myocardial infarctions did not find that vertical integration was statistically significantly associated with lower 90-day mortality or 90-day readmission rates. In a recent literature review, Post, Buchmueller, and Ryan (2017) discussed findings on the effects of vertical integration on quality of care and argued that there are uncertain effects on quality.

Finally, Ciliberto (2006) attempted to assess the implications of transaction cost and property rights theories that hospitals will integrate with physicians when they have a higher threat of holdup. The study argued that hospitals in locations where a large percentage of patients were in managed care organizations (MCOs), which could withdraw large numbers of patients at once from a hospital, would be more likely to underinvest due to asset specificity with respect to MCOs. The study found that vertically integrated hospitals, which have less threat of holdup by MCOs, were more likely than independent hospitals to add services when faced with high MCO concentration. Ciliberto (2006) argued that the results suggest that vertical integration enhances efficiency because otherwise the hospitals would underinvest.

Overall, empirical research has not found evidence that hospital-physician integration leads to cost efficiency, or decreased hospital utilization that might indicate cost efficiency. The evidence that vertical integration leads to higher quality of care is mixed at best. The only article that found evidence consistent with efficiency benefits of vertical integration examined hospital investments rather than costs. However, these studies use data that is at least a decade old, and many of the studies have small samples or cover a limited number of years. Thus, the question of whether vertical integration of hospitals and physicians improves cost efficiency is not yet settled.

4. Data

The data for this thesis comes from four sources: the Healthcare Cost Report Information System (HCRIS) of the Centers for Medicare & Medicaid Services (CMS), the American Hospital Association (AHA) Annual Survey of Hospitals, the CMS Hospital Inpatient Quality Reporting (IQR) program, and the Bureau of Labor Statistics (BLS). Most of the variables are constructed using the HCRIS and AHA data. In addition, indicators of healthcare quality come from IQR, and hourly nurse wage data comes from BLS. Table 2 lists all of the variables used in the regressions, and the sources of data from which the variables were constructed. Many of the variables are used in logarithmic form due to skewed distributions of the variables.

As explained in more detail in the section below that describes the empirical methods, I analyze the impact of hospital-physician vertical integration on hospital costs (which exclude physician costs), volume of patients, and quality of care. The data includes annual observations for acute care non-governmental hospitals in all states in the U.S. The data covers the years 2000-2013, except for the IQR quality measures, which are available only for the years 2009-2013. The data for the years 2000-2013 contains a total of 43,372 observations covering 4,554 hospitals, many of which did not report data in every year. In addition, although BLS has nurse wage data at the state level for all years during 2000-2013, nurse wage data at the zip code level is missing for some zip codes in every year.

The AHA data include indicators for different types of organizational forms, where a value of 1 indicates that a hospital has a particular type of vertical relationship involving physicians and a value of 0 indicates that it does not. I am interested in whether or not fully integrated hospitals, which employ physicians, have lower or higher costs than hospitals that do not. The AHA indicator for a vertically integrated hospital is the Integrated Salary Model (ISM). The AHA also has several other organizational form indicators, which reflect differing amounts of coordination between hospitals and physicians. Hospitals may utilize one or more of these other organizational forms, with or without the

Integrated Salary Model. That is, utilizing one organizational form with one set of physicians does not preclude a hospital from utilizing another form with a different set of physicians.

Following Cuellar and Gertler (2006), I analyze the impact on costs of the following organizational forms: Independent Physician Association (IPA), Open Physician Hospital Organization (OPHO), Closed Physician Hospital Organization (CPHO), and Integrated Salary Model (ISM). These organizational forms range from least to most integrated, as shown in Table 1, which is a reprint of Table 1 in Cuellar and Gertler (2006). An IPA, which is the least integrated form, is a contractual network that hospitals use to hold managed care contracts and help doctors obtain these contracts. An OPHO is a joint venture between a hospital and physicians that uses centralized administration for managed care contracting with health plans and provides administrative services for physicians. However, hospitals and physicians do not coordinate their business and healthcare operations. A CPHO has the same features as an OPHO, but a CPHO also contracts to coordinate care on an exclusive basis with a selected set of physicians based on quality and costs. The close relationship between a hospital and physicians in a CPHO makes it a more highly integrated organizational form than an OPHO. The AHA also includes an indicator for a Management Service Organization (MSO), which is similar to a CPHO except that an MSO usually purchases the physical assets of the physicians and provides administrative services. Cuellar and Gertler (2006) include MSO's in the CPHO category due to the similarity of these organizational forms. I use the same approach here. Finally, the Integrated Salary Model (ISM) refers to full integration.

Many hospitals that reported whether they used the Integrated Salary Model did not report any information about the other organizational forms, resulting in large numbers of observations with missing data. Therefore, I constructed two different samples to use in my analysis. The first larger sample includes only the ISM variable in which I am primarily interested. I use this as my main sample. The second somewhat smaller sample includes the other organizational form variables in addition to ISM. I conduct the same analyses using both samples.

For the main sample, I include only hospitals that have continuous annual observations for ISM. The data contains a substantial number of hospitals for which the time series of ISM per hospital includes missing observations interspersed with non-missing observations. This makes it difficult to tell whether and when the hospitals might have changed their organizational form. To construct the first sample, I first dropped observations for which there were continuous missing data for ISM per hospital at the start or end of the entire time period during which the hospital appears in the data. Using this reduced sample, I then dropped all observations for hospitals that had any missing data for ISM. Finally, I checked this sample for values of ISM within hospitals that changed from 0 to 1 for only a single year before reverting to 0, or from 1 to 0 for only a single year and back to 1 again. It seems unlikely that a hospital would fully integrate (or disintegrate) for only one year and then immediately revert back to its previous organizational form. Instead, I believe that these are reporting errors. I therefore converted a value of 1 for ISM to a 0 when the values for ISM for the year before and after the 1 were both 0. I also converted a value of 0 for ISM to a 1 when the values of ISM for the year before and after the 0 were a 1. This process resulted in the alteration of 197 observations of ISM.

The main sample contains a total of 32,742 observations covering 3,575 hospitals (after dropping observations with missing data for other variables used in the regressions, as explained below). The sample includes 757 observations of a hospital changing its organizational form to ISM (full integration) from not being fully integrated, and 316 observations of a hospital changing from ISM to not being fully integrated, including a complete lack of integration. Some hospitals had more than one change in ISM. Table 3 reports the percentage of hospitals each year from 2000 to 2013 that were integrated. The table shows a steady rise in the percentage of integrated hospitals from 18 percent in 2000 to 43 percent in 2013.

For the second sample, I include only hospitals that have continuous annual observations of ISM and all of the other organizational form variables (IPA, OPHO, and CPHO). To construct this sample, I used the main sample as the starting point and employed a similar procedure. I dropped observations with continuous missing data for any of the other organizational form variables per hospital at the start or end of the time period during which the hospital appeared in the data. Using this reduced sample, I then dropped all observations for hospitals that have any missing data for the other organizational form variables. I did not alter any values of these organizational form variables—even if they changed between 0 and 1 or vice versa after only one year—because these are contractual organizational forms and they may be easier to more quickly enter or exit than full integration.

The second sample contains a total of 30,239 observations covering 2,977 hospitals. The number of observations of a hospital adopting a particular organizational form after not having had that organizational form in the previous year is as follows: CPHO, 418; OPHO, 369; IPA, 375. The number of observations of a hospital that no longer has a particular organizational form after having had that form in the previous year is as follows: CPHO, 513; OPHO, 465; IPA, 466. For all three of these organizational forms, a few hospitals adopted or abandoned an organizational form more than once.

Most of the other variables that I use in the hospital cost analysis have some missing data. However there are three variables that are complete for all years and all hospitals: 1) the number of physicians employed by the hospital, 2) the number of outpatient visits, and 3) state level nurse wage data. For the remaining variables, in order to retain as many observations as possible, I imputed a small number of missing values. For the dummy variables indicating a teaching hospital, transplant hospital, or participation in a multi-hospital system, there were some missing values of these variables for hospitals that reported data in the preceding and following years. Hospitals infrequently change their teaching and transplant status, and infrequently move into and out of multi-hospital systems within one year. Therefore, for each variable, if the values for that variable were the same in the years immediately before and after the year in which there was missing data, I replaced the missing value with the value in the immediately preceding and subsequent year.

I also imputed the values of the missing data items for some of the continuous variables by averaging the values in the preceding and following year. I only did this if the difference between the imputed value and the value in the preceding (or following) year was no greater than the largest year-to-year difference for other values of that variable for a given hospital. In most cases, the imputed value of a variable was within 85% of the value of the largest of the two values in the immediately preceding and following years. I was able to do this for the following variables: hospital operating expenses, total number of beds, number of inpatient admissions, average length of patient stay, number of specialty beds, and case mix index. Because I use hospital operating expenses and the number of inpatient admissions to construct my dependent variables, and because these might be affected by a change in ISM status, I made sure that there was no change in ISM status during any years containing imputed values for these variables.

Unfortunately, this procedure did not enable me to fill in many missing values per variable, ranging from two missing values for the length of inpatient stay to 65 missing values for total operating expenses. Some of the variables had missing values for entire hospitals in all years in which they appeared in the main sample. Most notably, the dummy variable indicating whether or not a hospital was in an urban rather than a rural geographic location was missing for a number of hospitals. I attempted to impute values for the missing urban-rural dummy variable based on the values of this variable that other hospitals in the same zip codes had, but this did not work. It turned out that if one hospital in a particular zip code had missing data for the urban-rural dummy variable, all hospitals in that zip code were missing the dummy variable. The main sample drops observations with missing values for the urban-rural dummy variable. There were 354 missing values, which is a small number relative to the total number of observations. Other variables used in the analysis—hospital operating expenses, total number of beds, number of inpatient admissions, average length of patient stay, number of specialty beds, teaching hospital dummy variable, and transplant hospital dummy variable—each had between 36 and 105 missing values. Those observations were dropped when I constructed the main sample.

There are two other variables that have large amounts of missing data: 1) case mix index (CMI), which indicates the severity of illnesses treated by a hospital, 2) a dummy variable indicating whether or not a hospital is part of a multi-hospital system (Sys1Yes). Membership in a hospital system is a form of horizontal rather than vertical integration, and could affect costs (Burns and Pauly, 2002). The case mix index would be expected to affect costs, since less healthy patients should be more costly to treat. Cuellar and Gertler (2006) found that a higher case mix index was associated with higher hospital costs. In the main sample, the case mix index variable has 4,752 missing observations, and the hospital system indicator has 3,982 missing observations. Because dropping the large number of observations with missing values of these variables could alter the results of my analyses, I will investigate the sensitivity of my results to whether these variables are included or excluded. The main sample does not drop these missing observations.

There are also missing values of nurse wages at the zip code level (but not at the state level). I attempted to impute values of missing nurse wage data at the zip code level based on state level data for firms that had zip code level data in some years but not others. I calculated the average ratio of zip code level to state level nurse wage data for each hospital using non-missing observations of zip code level data, and then multiplied this ratio by the state level nurse wage data for the years in which the zip code level wages were missing. However, I found that most of the hospitals that were missing zip code level nurse wage data for a particular year also were missing zip code level data in all years in which they were in the sample. Even after using this procedure, there were 2,856 missing nurse wage observations at the zip code level, which is a large portion of the main sample. Therefore, I will investigate the sensitivity of my results to whether this variable is included or excluded.

One of the variables, average inpatient stay, presented the problem that a few observations had values of less than 1—even though an inpatient stay requires at least one night in the hospital—or values of more than 365—even though it is not possible for the annual inpatient stay of any patient to exceed 365 days. Because there were relatively few observations with these outliers, I dropped them from the main sample and the second sample. This resulted in dropping 61 observations from both samples (8 observations with values less than one and 53 observations with values greater than 365). Dropping these observations had little effect on the results for ISM or the other organizational forms that are reported below.

Finally, the data include six measures of inpatient quality of care from IQR based on Medicare claims information: acute myocardial infarction (AMI) 30-day mortality rate (mortality within 30 days of discharge), AMI 30-day readmission rate (readmission within 30 days of discharge), heart failure 30-day mortality rate, heart failure readmission rate, pneumonia 30-day mortality rate, and pneumonia 30-day readmission rate. Each measure is calculated as the number of deaths or readmissions within 30 days of discharge divided by the number of original admissions of each type. However, the AMI measures have large amounts of missing data. There are approximately 500 fewer observations per year for these measures than for the other quality measures, which amounts to 1/3 to ¼ fewer observations than for the other measures. I do not include the quality measures for AMI due to the large amount of missing data, and instead use only the other four measures. There are 9,852 observations covering 2,339 hospitals in the main sample that have data on the four quality measures with no missing values, and 9,460 observations covering 2,246 hospitals in the second sample.

5. Methods

I analyze the efficiency consequences of hospital-physician vertical integration by following the approach of Cuellar and Gertler (2006), which is the only previous study to have conducted an empirical analysis of this specific type of integration using panel data. I augment their approach by using an additional measure of vertical integration, additional control variables, and additional dependent variables. I also conduct matching analyses in an effort to more fully control for potential endogeneity. Below I discuss the variables used in the estimation, the functional forms of the regression models, fixed versus random effects estimation, and the matching method that I use. I then outline the analyses that I conducted.

5.1. Dependent Variables

For the dependent variables, I first analyze the impact of hospital-physician integration on the primary dependent variable in Cuellar and Gertler's (2006) analysis of hospital efficiency, which is the log of total hospital operating expenses. I then use an alternate dependent variable that measures cost per patient, which Cuellar and Gertler (2006) did not examine. It is possible that hospitals that are integrated also have more patients, and therefore have higher costs. However, this should not affect costs per patient. I assess whether this is the case as an alternative to including the number of patients as a control variable in the regression for the log of total operating expenses. The dependent variable that I use to measure cost per patient is ln(total operating expenses divided by adjusted patient discharges). Adjusted patient discharges is a measure of the number of total patients that is used in healthcare research to account for the fact that many hospitals have both inpatients and outpatients, but inpatient admissions and outpatient visits are qualitatively different (e.g., different lengths of stay and costs) (Unruh, Fottler, and Talbott, 2003). By definition, the number of inpatient discharges is the same as the number of patients admitted to the hospital. Adjusted patient discharges are calculated as follows: number of inpatient discharges + (number of inpatient discharges x outpatient revenues/inpatient revenues). This variable is not perfect. If a hospital has a small number of inpatient discharges and a large amount of outpatient revenues, as is the case for a few hospitals in my data, the adjusted patient discharges variable will be very large.

I also analyze the impact of vertical integration on other types of dependent variables. Cuellar and Gertler (2006) noted that if vertical integration leads to improved coordination, it might also increase the quality of care. However, an increase in the quality of care could lead to an increase in costs if achieving higher quality necessitates additional medical care. As a result, an improvement in quality of care could offset some or all of any efficiency gains from integration. Cuellar and Gertler (2006) therefore analyzed the impact of integration on three measures of quality: inpatient mortality, overused procedures, and patient satisfaction. I use the four measures of hospital quality described above as separate dependent variables. I do not try to combine these variables with one another into a single measure because each quality measure has a different denominator.

In addition to these dependent variables, I analyze the impact of vertical integration on the number of patients, using the log of adjusted patient discharges as the dependent variable. If vertical integration is associated with an increase in costs, it is possible that this increase could be due to a hospital having more patients. If I find that integration is associated with a hospital having more patients, it would be possible that any increase in costs could be due to the larger number of patients.

5.2. Control Variables

Cuellar and Gertler (2006) estimated cost functions with a vector of outputs and a single input price (a hospital wage index), as described below. Their output vector included the number of inpatient hospital admissions, average length of inpatient stay, a case mix index of illness severity, and the total number of outpatient visits. Cuellar and Gertler (2006) also included a hospital wage index as a measure of input prices. I use the hourly average wages of registered nurses instead. The hospital wage index available from HCRIS includes payments to employed physicians under Medicare Part A, which are not included in the hospital operating cost data that I use. In addition, Cuellar and Gertler (2006) included several control variables that I have in my data: the total number of hospital beds, which controls for capacity; an interaction between the total number of hospital beds and teaching status to control for the technology and sophistication of a hospital; state and year effects as well the interactions between them to control for factors at the state level that vary by year. In addition to these controls, I have additional data that allow me to control for several other factors that could affect costs: the number of specialty beds; whether a hospital is a transplant hospital, plus the interaction of transplant hospital status with the total number of beds; whether a hospital is a nonprofit or a proprietary hospital; whether the hospital is part of a hospital system; and whether the hospital is in an urban or rural area.

5.3. Functional Forms of the Models

Cuellar and Gertler (2006) estimated both a Cobb-Douglas cost function and a translog cost function (Christensen and Greene, 1976) with ln(operating expenses) as the dependent variable. In a Cobb-Douglas cost function, the impact of quantity of output on costs is the same for all levels of output, but a translog cost function allows this to vary by level of output. The translog cost function also allows for the impact of quantity of output on costs to depend on the level of input prices. In a Cobb-Douglas cost function, if firms produce multiple outputs, the impact of these outputs on costs are independent. A translog cost function allows for an interactive effect of multiple outputs on costs as well as an interactive effect of input prices and outputs.

I use the Cobb-Douglas cost function as my primary specification, and estimate the translog cost function as a robustness test. I also estimate the cost per patient models using the same right-hand side variables as in the Cobb-Douglas specification for operating costs described below, except that I exclude variables that measure the number of inpatient admissions and outpatient visits because these variables are reflected in the denominator of the cost per patient variable.

The translog cost function that Cuellar and Gertler (2006) estimated is similar to the specification originally given by Christensen and Greene (1976).

The article by Christensen and Greene (1976) provides the formula for a general translog cost function, which can be altered depending on the number of outputs and the number of inputs and their prices. This cost function adds several terms to the Cobb-Douglas specification, including squared terms for each of the variables in the output vector, interactions of the different outputs, and interactions between the outputs and the input prices. In their empirical estimation, Christensen and Greene (1976) had only one output and multiple input prices. In contrast, Cuellar and Gertler's (2006) cost function had multiple outputs and only one input price (a hospital wage index). Cuellar and Gertler (2006) therefore estimated a translog cost function appropriate for multiple outputs and a single input price, which I also do. Including the squared output variables in the model allows the impact on costs of each element in the output vector to vary with the amount of output. Including the interactions among the elements in the output vector allows the impact on costs of each element in the output vector to vary with the amount of output of another element in the output vector. Finally, including the interactions between the elements in the output vector and the input price (nurse wages) allows the impact on costs of each element in the output vector to vary when the input price changes.

5.4. Fixed Versus Random Effects

I estimate an initial set of models based on the main sample using pooled OLS, OLS with hospital random effects, and OLS with hospital fixed effects—all with robust standard errors. I include state by year fixed effects in all of the models that I estimate, but do not cluster standard errors by state or year. I use the *robust* command in Stata to estimate standard errors. In the estimation of random effects and fixed effects models in Stata, the *robust* command produces cluster-robust standard errors with clustering on hospitals, but not clustering on state or year. I use a Hausman test to compare the fixed effects and random effects estimates. Hausman tests reject the hypothesis that the estimates from the fixed and random effects models are equivalent for all of the models that I estimate. Therefore, I do not use random effects specifications except for an initial set of regressions, and instead report the results of pooled OLS and fixed effects models. Although Cuellar and Gertler (2006) reported only fixed effects estimates, these estimates rely on hospitals that changed their organization form during the sample period. However, 76% of the hospitals in my main sample did not change their organizational form during the 2000-2013 time period. Fixed effects estimates would not capture the relationship between the organizational form of these hospitals and their costs. I therefore report pooled OLS estimates in addition to fixed effects estimates.

5.5. Endogeneity

The analyses described above may be subject to endogeneity. The reasons why hospitals choose to integrate could affect their costs. For example, if hospitals integrated in response to the Affordable Care Act (ACA), it is possible that policies put in place by the ACA rather than integration had an effect on costs. Reverse causality may also be a problem. For example, hospitals that are expecting higher costs due to financial difficulties might choose to integrate if they expect that integration will help to lower costs. In this case, costs might have been even higher had the hospitals not integrated, so the actual impact of integration would be to lower costs. Omitted hospital-specific factors that are time-constant and are correlated with integration could cause problems as well. For example, if integrated hospitals are able to attract better managers who are good at controlling costs, it could be the managers rather than hospital-physician integration that accounts for lower costs. In this example, the results would be biased toward the finding that integration lowers costs, because the estimated effect of integration would reflect the unobserved ability of managers. Cuellar and Gertler (2006) did not account for endogeneity other than using fixed effects to control for omitted hospital-specific factors.

Instrumental variables estimation is often used when there is potential endogeneity, but this requires instruments that predict whether or not a hospital is integrated while being uncorrelated with costs. However, most variables that would predict hospital-physician integration are probably correlated with costs. I investigated using an exogenous shock such as state adoption of Medicaid expansion as an instrument, but states could not do this until 2014, which is after my sample ends.

Instead, I use a matching method to help control for endogeneity. I use covariate matching, which matches each hospital that changed its ISM status (the "treatment") with a control hospital based on the distance between pairs of observations with respect to a set of covariate variables (Abadie and Imbens, 2006; Imbens, 2004). A change in ISM status is not exogenous and therefore is not a true treatment effect. But, by matching hospitals that changed their ISM status with hospitals that had similar characteristics but did not change their ISM status, the procedure controls for factors that might have affected the decisions of hospitals to change their ISM status. In matching models in general, this procedure controls for selection bias that arises from the decisions of individuals or other entities to receive a treatment (Caliendo and Kopeinig, 2008).

There are two types of "treatments"—changes in ISM status—in my data. The first type of change involves the adoption of full integration after not being fully integrated. The second type of change in ISM status involves a change from full integration to not being fully integrated. I conduct separate analyses for each type of change. It is difficult to include both directions of change in the same analysis because the treatment effect, which includes the direction of the change, must be the same for all hospitals in the analysis.

For the first analysis, I match hospitals that adopted the ISM organizational form with hospitals that did not do so, and then estimate the difference in costs between the two types of hospitals. I then conduct a second analysis that matches hospitals that abandoned the ISM organizational form with hospitals that retained the ISM organizational form, and then estimate the difference in costs between the two types of hospitals. In each analysis, the treatment hospitals that changed their ISM status are matched to control hospitals based on observable factors (the covariates in the matching analysis). I use the same outcome measures in these analyses that I use in my cost regressions: log of total operating expenses and log of per capita total operating expenses. To control for unobserved differences between the treated and control hospitals, I also use the one-year change in each of these cost variables as two additional dependent variables (Baum, 2013).

To conduct the matching analyses, I use the nearest neighbor nonparametric matching procedure in Stata estimated with the *teffects nnmatch* command, and the Mahalanobis measure of distance, to estimate the average treatment effect on the treated hospitals. This procedure makes it possible to use exact matches for some variables, which is necessary for my analysis, as explained below. Exact matching is not possible using the propensity score matching routine in Stata. I adjust the continuous covariates for large-sample bias using the *biasadj* command in Stata. The estimates use robust standard errors that were proposed by Abadie and Imbens (2006, 2011).

The covariates used to match the treatment hospitals with control hospitals need to have an effect on both a hospital's decision to change its ISM status and the cost outcome of integration. Matching methods rely on the assumption of conditional independence, which states that choosing the treatment depends on observable characteristics of the organizations and that all variables that affect both the treatment and outcomes are observed (Caliendo and Kopeinig, 2008). This implies that the covariates should not be affected by the treatment variable or the outcome variable. Therefore, covariates need to either have fixed values or be measured prior to the treatment.

Since the right-hand side variables in the cost regression analyses could affect ISM as well as costs, I include most of these as covariates. I do not include the teaching and transplant variables and their interaction terms because including too many variables as covariates can make it difficult to find matches (Caliendo and Kopeinig, 2008). I measure most of the covariates in the year prior to the year of the treatment. I use an exact match on the Urban-Rural dummy variable, because it has a fixed value. I also use an exact match on the year when the change in organizational form occurred in order to control for macroeconomic factors. (Given the structure of the analysis, matching on the current year produces the same results as matching on the lagged value of year. I verified that this is the case.) In addition, I include an exact match on the lagged value of ISM, which is not in the regression analyses. This insures that a control hospital has the same ISM status as the treated hospital prior to the treated hospital changing its ISM status.

5.6. Outline of the Analyses

In conducting the analyses described above, I estimated the models in stages to insure comparability across the analyses as much as possible. First, because the organizational form variables other than ISM had large numbers of missing observations, I estimated the regression models using both the main sample with ISM only and the second sample that includes the other organizational form variables. Second, three potential control variables—nurse wages at the zip code level, CMI, and membership in a hospital system—each had very large numbers of missing values. Therefore, I investigated the effect that reducing the sample size—in order to include these variables in the analyses—would have on the estimates. These analyses enabled me to determine the sample and control variables that made the most sense to use in the regression models.

After figuring out the appropriate sample to use, I estimated a base regression for log of operating expenses, my primary dependent variable, to find out whether random or fixed effects was more appropriate. As noted above, a Hausman test strongly rejected the hypothesis that the estimates from the two models were equivalent. I therefore estimated all of the remaining regressions using both pooled OLS and fixed effects models. (Hausman tests on the specifications reported below continued to strongly reject the use of random effects).

For the dependent variables in the regression analyses, I began with the dependent variables for costs, starting with the log of operating expenses using a Cobb-Douglas cost function. I then estimated models with log of per capita total operating expenses as the dependent variable. I also conducted robustness analyses using a translog cost function specification for both of these variables. After this, I estimated regressions using the dependent variables for the log of number of adjusted patients and the quality measures. Finally, I conducted matching analyses for the cost variables.

6. Results

In the cost analyses, I followed Cuellar and Gertler (2006) by using the log of total operating expenses as my initial dependent variable. Like Cuellar and Gertler (2006), I used as control variables the log of inpatient admissions, the log of average inpatient stay, the log of outpatient visits, the log of the total number of beds, a dummy variable indicating whether a hospital is a teaching hospital, as well as an interaction between teaching hospital status and the log of total beds. I added controls for the log of the number of specialty beds, whether a hospital was in an urban or rural location, whether a hospital was a for-profit or not-for-profit organization, a dummy variable indicating whether a hospital performs transplants, and an interaction of transplant hospital status with the log of total beds. My base regression included all of these variables, the dummy variable indicating whether or not a hospital was fully vertically integrated (ISM), and state by year fixed effects. I used this regression for my main sample to investigate whether to include the log of average nurse wages at the zip code level, the case mix index variable, and the dummy variable indicating whether a hospital was part of a system. In doing these initial investigations, I ran regressions using OLS, fixed effects, and then random effects.

Tables 4 and 5 report the results of the analysis that investigated whether to include the log of nurse wages variable in the regressions. For the main sample, Table 4 reports the base regression excluding the log of nurse wages, using OLS, random effects, and fixed effects. To assess whether dropping observations that had missing values of nurse wages would affect the estimate on ISM, I reran the base regression using OLS, random effects, and fixed effects on a sample that excluded all observations with missing values of nurse wages, but did not include nurse wages in the regression. These results are reported in Table 5. A comparison of models 1, 2, and 3 in Table 4 with models 1, 2, and 3 in

Table 5 shows that the change in the composition of the sample had relatively small effects on the estimated coefficients on ISM, which remained statistically significant. Models 4, 5, and 6 in Table 5 report the results for the same sample with the log of nurse wages included in the regression. The coefficient estimates for ISM are almost the same when the log of nurse wages variable is included or excluded.

Given that the reduction in the sample size due to dropping observations with missing values of the nurse wage variable has only a small effect on the estimated coefficients on ISM, and given that the nurse wage variable is needed for the translog specifications, I use this smaller sample as my main sample from here on. This sample has 29,886 observations covering 3,031 hospitals. I also constructed a new second sample that drops observations with missing values of the nurse wage variable, and includes the other organizational form variables. This sample has 28,507 observations covering 2,780 hospitals. In addition, a Hausman test that compared models 5 and 6 in Table 5 rejected the hypothesis that the estimates obtained using random and fixed effects were equivalent at the 0.000 level of significance. In the remainder of the regressions reported below, Hausman tests continued to reject the random effects specification. I therefore report fixed effects rather than random effects for the subsequent regressions that I ran.

As noted earlier, the variables for the log of CMI (case mix index) and the hospital system dummy variable (Sys1Yes) were missing a large number of observations, but Cuellar and Gertler (2006) had used the log of CMI as a control and the prior literature suggests that hospitals that operate as part of a system might be able to reduce their costs. To assess whether dropping observations from the sample that had missing values of CMI would affect the estimated coefficient on ISM, I next ran the base regression using the new main sample with OLS and fixed effects, but I excluded all observations with missing values of CMI and did not include CMI in the regression. The results are reported in Table 6. A comparison of model 4 in Table 5 with model 1 in Table 6 shows that the coefficient on ISM in the OLS specification increased by 6% when the missing observations with missing values of CMI were dropped. However, a comparison of model 5 in Table 5 with model 2 in Table 6 shows that the coefficient on ISM dropped by 46% when using fixed effects, and the coefficient is insignificant when it previously was significant at the 5% level. I then reran the regressions using this smaller sample, but now with the log of CMI included as a control variable, as reported in models 3 and 4 in Table 6. I found that this caused the coefficient on ISM to increase by 6% for OLS, and to increase by 2% for fixed effects. I concluded that dropping the observations that had missing values of the log of CMI had a much larger effect on the fixed effects estimates in particular than did omitting the log of CMI from the regressions. For this reason, I did not include the case mix index variable in future regressions.

I followed the same procedure just described to determine whether to include the dummy variable indicating that a hospital was part of a system (Sys1Yes) in future regressions. Table 7 reports these results. The coefficient on ISM in the new, smaller sample, dropped by 5% for OLS and increased by 3% for fixed effects compared to the base regressions in models 4 and 5 in Table 5. When Sys1Yes is included in the regressions that use the smaller sample, the ISM coefficients are very similar to those in the regressions that do not contain Sys1Yes. It is clear that dropping roughly 3,500 observations that are missing values of Sys1Yes has a small effect on the estimates of ISM. However, including Sys1Yes in the regressions has almost no additional effect on the estimates of ISM. Therefore, I omit the Sys1Yes variable from future regressions.

Tables 8 and 9 report descriptive statistics for all variables in the main sample that were used in regressions, which did not include any organizational form variables other than ISM. For the variables that are used in their natural log form in the analyses, the tables also include descriptive statistics for the underlying variables before conversion to logs. Table 8 reports the descriptive statistics for the main sample without the quality of care variables, and Table 9 reports descriptive statistics for the sub-sample from 2009-2013 that has data for the quality of care measures. Tables 10 and 11 report descriptive statistics for the second sample with and without the quality measures, and contain the same variables as Tables 8 and 9 as well as the organizational form variables of IPA, OPHO, and CPHO.

6.1. Regression Results

The regressions reported below contain the results of my analysis of the effect of integration on hospital costs, output, and quality. These regressions were performed using OLS and fixed effects estimated with robust standard errors. I report all of the results for the main sample first, and then report the results for the second sample that contains the other organizational variables.

6.1.1. Results for the Main Sample with ISM Only

The first set of regressions uses the log of total operating expenses as the dependent variable with the Cobb-Douglas specification. The results of these regressions can be found in models 4 and 5 in Table 5. ISM is highly significant with a coefficient of 0.0575 in the OLS regression. It drops substantially in the fixed effects regression to 0.0134, but remains statistically significant. Depending on the specification, these results imply that being fully vertically integrated leads to between a 1.3% and a 5.8% increase in total operating expenses relative to not being fully integrated.

In the regressions, many of the coefficients on the control variables are statistically significant and have the expected sign. The control variables for total inpatient admissions, average inpatient stay, the number of outpatient visits, the total number of beds, and the number of specialty beds all have a positive and significant effect on total operating expenses, both in the OLS and fixed effects models. The coefficient on the urban-rural dummy variable is positive and significant in the OLS model, indicating that hospitals in urban areas have higher costs. The fixed effects model drops this variable because it is time-constant. The coefficient on the dummy variable indicating a for-profit hospital is negative and significant in the OLS model, but is insignificant in the fixed effects model. Many hospitals did not change their for-profit/non-profit status for the duration of my sample. This may explain why the variable is not significant in the fixed effects model.

The dummy variables for teaching and transplant hospitals are also significant in the OLS model but not in the fixed effects model. Hospitals change their teaching or transplant status infrequently, which again may explain why these variables are not significant in the fixed effects model. These coefficients are also negative, which is unexpected given that the correlation coefficients between total operating expenditures and both of these variables are actually positive. These coefficients also are contrary to expectations because being either a teaching or transplant hospital would usually raise costs. However, the regressions include interaction terms for both of these variables with total beds, and these terms are positive. They may be picking up some of the effects of the teaching and transplant dummy variables. In addition, the correlation coefficients indicate that both the teaching and transplant dummy variables are highly correlated with many of the other variables on the right-hand side of the regression. As a result, the negative signs on the coefficients for the teaching and transplant variables may reflect multicollinearity.

The next regressions use the log of per capita total operating expenses as the dependent variable, with adjusted patients as the denominator. These regressions include the same right-hand side variables as before, but exclude the log of total inpatient admissions and the log of total outpatient visits because they are already represented in adjusted patients. I keep the log of average inpatient stay as a control variable in these regressions, because the length of stay is likely to affect costs per patient. The results are reported in models 1 and 2 in Table 12. The coefficient on ISM in the OLS regression is 0.0231 and statistically significant, but the coefficient in the fixed effects regression is much smaller and negative at -0.00241 and is not statistically significant. Clearly, the effect of ISM is smaller in the regressions for the log of per capita total operating expenses than in the regressions for the log of total operating expenses.

I next use a translog specification as a robustness test with the log of total operating expenses as the dependent variable. Table 13 contains the results. In the OLS regression (model 1), the coefficient on ISM is 0.0384 and statistically significant. The coefficient falls to 0.0101 in the fixed effects regression (model 2), but remains statistically significant. A comparison of the results in Table 13 with the Cobb-Douglas specifications in models 4 and 5 in Table 5 shows that the coefficient on ISM in the OLS regression falls. Most but not all of the squared and interactions terms are significant in the translog models, and the R^2 increases. Even in the translog specification, which includes additional control variables, I still find positive effects of ISM.

I also estimate a translog specification with the log of per capita total operating expenses as the dependent variable. Models 3 and 4 in Table 12 report the results for the OLS and fixed effects regressions. The coefficient on ISM is positive and significant in the OLS regression but very small, negative, and insignificant in the fixed effects regression. In addition, a comparison of these results with the Cobb-Douglas specification (models 1 and 2 in Table 12) shows that the estimated coefficients and significance levels change very little when the additional control variables in the translog specification are included.

The results thus far indicate that fully integrated hospitals do not have lower costs than hospitals that are not fully integrated. Some specifications suggest that integrated hospitals may have higher costs. I next investigate whether the potentially higher costs might be explained by integrated hospitals attracting more patients who are less healthy, or by providing a higher quality of care.

For the next set of regressions, I return to the Cobb-Douglas specification and use the log of adjusted patients as the dependent variable. I use the same right-hand side variables as in the regressions that used the log of per capita total operating expenses. Table 14 reports the results. For the OLS regression in model 1, the coefficient on ISM is 0.0644 and highly statistically significant. In the fixed effects regression in model 2, ISM falls to 0.0209 and remains highly significant. These results show that fully integrated hospitals have more patients. If the additional patients are higher cost or lower cost than the previous average patient, this could affect the coefficients on ISM in the cost regressions. For example, if costs increase due to vertical integration, this result from doctors admitting less healthy patients who the doctors would have sent elsewhere previously. .

The next regressions utilize the four quality of care measures as dependent variables, with the same right-hand side variables as in the Cobb-Douglas specification for the log of total operating expenses. Tables 15-18 contain these results. In the OLS regressions, the coefficient on ISM is positive and significant for heart failure mortality and readmissions, but the coefficient, is insignificant for pneumonia mortality and readmissions. In the fixed effects regressions, the coefficient on ISM is significant only in the regression for pneumonia readmissions, and the coefficient is negative.

Overall, there is little evidence in these data that being fully integrated is associated with higher quality healthcare. Two regressions suggest a decrease in the quality of care (higher readmission and mortality rates), one regression suggests the opposite, and the rest of the regressions show no significant effects.

6.1.2. Results for the Sample with the Other Organizational Form Variables

I estimated all of the above regressions from the main sample again for the second sample, which contains the other organizational form variables in addition to ISM. These variables are CPHO, OPHO, and IPA. Given that this sample has fewer observations, I first needed to discern the effect of the smaller sample size before adding the other organizational form variables to the regressions. I therefore reran OLS and fixed effects regressions for the log of total operating expenses using the same Cobb-Douglas specification as I used for the main sample. These results, reported in models 1 and 3 in Table 19, are similar to the earlier results reported in models 4 and 5 in Table 5 that included only ISM and the control variables for the main sample. The coefficients on ISM are slightly higher in the second sample than in the main sample, but overall the results for ISM are consistent with the earlier estimates. I will focus next on the results for the three additional organizational forms.

Using the log of total operating expenses as the dependent variable, in the OLS regression (model 2 in Table 19), CPHO and IPA are significant but OPHO is not. However, CPHO has a small positive coefficient and IPA has a small negative coefficient. In the fixed effects regression (model 4 in Table 19), CPHO remains positive and significant, although with a lower coefficient. The coefficient on IPA becomes positive and is statistically significant only at the 10% level. The coefficient on OPHO remains insignificant. These results suggest that CPHO in particular, which is the organizational form that is closest to full integration, is associated with increased costs, just as for ISM. There is mixed evidence about IPA, and the evidence does not support an association between OPHO and hospital costs.

As a robustness test, I use a translog specification for the log of total operating expenses using the same right-hand side variables as in the prior translog model, but now include the other organizational form variables. These results are reported in models 5 and 6 in Table 19. I find that in the OLS specification, CPHO is again positive and significant, and IPA is again negative and significant. OPHO remains insignificant. IPA and CPHO are significant at the 10% level in the fixed effects model, and the coefficient estimates are positive. Overall, the results for the organizational form variables in the translog models are similar to those in the Cobb-Douglas models, although the absolute values of the estimated coefficients are smaller in the translog models.

Table 20 reports the results using the log of per capita total operating expenses as the dependent variable. I first compare the results for ISM in this sample with the results in the main sample that use the Cobb-Douglas specification. Models 1 and 3 in Table 20 report results for OLS and fixed effects regressions that do not include the other organizational forms. The coefficients on ISM are very similar to the earlier coefficients in the main sample (models 1 and 2 in Table 12). Models 2 and 4 in Table 20 add the other organizational form variables using the Cobb-Douglas specification. In OLS, OPHO has a small positive and significant coefficient. IPA is highly significant but has a negative coefficient. CPHO is not significant. None of these three organizational forms are significant in the fixed effects regression. Turning to the translog specifications for OLS and fixed effects in models 5 and 6 in Table 20, the results for the three organizational form variables are similar to the Cobb-Douglas results in the same table. However, in the OLS regression, the coefficient on OPHO is only significant at the 10% level, and CPHO becomes significant at the 10% level.

Overall, the evidence of an impact on costs of the other organizational forms (reported in Tables 19 and 20) is somewhat inconsistent across different specifications and measures of costs, and it is difficult to draw strong conclusions. The inclusion of the other organizational form variables has relatively little effect on the estimated coefficients on ISM.

For the log of adjusted patients, (results reported in Table 21), I first compare the results for ISM in this sample with the results in the main sample that use the Cobb-Douglas specification. Models 1 and 3 in Table 21 report results for OLS and fixed effects regressions that do not include the other organizational forms. The coefficients on ISM are almost identical to the earlier coefficients in the main sample (models 1 and 2 in Table 14). Models 2 and 4 in Table 21 add the other organizational forms. The coefficient on CPHO in the OLS regression is small but positive and is statistically significant. The coefficients on OPHO and IPA are not significant. In the fixed effects specification, CPHO is still positive but much smaller, and is significant at only the 10% level. The coefficients on OPHO and IPA remain insignificant. The results for CPHO suggest that hospitals that enter into these agreements also take on more patients, similar to the results for ISM.

The regressions that utilize the quality of care measures as dependent variables, with the same right-hand side variables as in the Cobb-Douglas specification, are reported in Tables 22-25. Models 1 and 3 in each of these tables report results for OLS and fixed effects without including the other organizational form variables. The coefficients for ISM generally have similar signs and significance levels when compared to the same specifications using the main sample (reported in Tables 15-18). For the other organizational forms, as shown in models 2 and 4 in Tables 22-25, the coefficient on OPHO is negative and significant in two of the OLS regressions (although only at the 10% level in one of the regressions). The coefficient on IPA is positive and significant at the 10% level in only one of the OLS models. For the fixed effects models, the coefficient on OPHO is positive and significant in one regression at the 10% level. Overall, there is little evidence that the other organizational forms have a systematic impact on the quality of care. Moreover, the results in both this sample and the main sample provide little evidence that ISM has a systematic impact on the quality of care.

6.2. Results Using Matched Samples

Next I use matching models to analyze the impact of a change in ISM status on the log of total operating expenses and on log of per capita total operating expenses, using the approach explained in section 5.5. Tables 26 and 27 contain the results of these analyses., which use the main sample. The first set of models, reported in Table 26, analyzes the change in ISM from not fully integrated (ISM equal to 0) to fully integrated (ISM equal to 1). The treatment variable in these models is ISM0to1. The second set of models, reported in Table 27, analyses the change in ISM from fully integrated to not fully integrated. The treatment variable in these models is ISM1to0. The "lag" prefix used in the names of most of the matching variables indicates that the variables are lagged one year.

For hospitals that became fully integrated, the results in Table 26 show that the coefficient on ISM0to1 is 0.0699 for the log of total operating expenses as the dependent variable. The coefficient is 0.0421 for the log of per capita operating expenses as the dependent variable. Both coefficient estimates are significant. When the one-year difference in the log of total operating expenses is used as the dependent variable, the coefficient on ISM0to1 falls to 0.0182 but is statistically significant. However, for the one-year difference in the log of per capita total operating expenses, the coefficient on ISM0to1 is insignificant.

For hospitals that disintegrated (shown in Table 27), for the log of total operating expenses as the dependent variable, the coefficient on ISM1to0 is -0.0392 and significant at the 5% level. The coefficient on ISM1to0 is also negative for the log of per capita total operating expenses, but is not statistically significant. For the one-year difference in the log of total operating expenses, the coefficient on ISM1to0 is again negative and statistically significant. The coefficient on ISM1to0 is negative but not statistically significant for the one-year difference in the log of per capita total operating expenses.

Overall, the results of the matching analyses for the change in ISM status from not fully integrated to full integration (ISM0to1) are consistent with the results for ISM in the regression analyses using the Cobb-Douglas specification. Depending on the dependent variable used in the matching analysis, adopting full integration has either a positive and significant effect or an insignificant effect on costs. This provides additional support for the regression results. It is interesting that in the matching analyses for the change in ISM status from full integration to not fully integrated (ISM1to0), some of the estimates are negative and statistically significant. These results, together with the results for ISM0to1, suggest that costs may fall when hospital disintegrate and costs may rise when hospitals integrate. The finding that hospitals may have lower costs when they disintegrate adds support to the results showing that integrated hospitals may have higher costs. The matching analyses also suggest that at best, integration and disintegration have no statistically significant effect on hospital costs.

7. Conclusion

In this thesis, I have examined the relationship between hospital-physician integration and hospital costs. As discussed in the review of the theoretical literature, different economic theories make different predictions about the effect of vertical integration on costs. Some theories predict lower costs and other theories predict higher costs. I therefore conducted an analysis to test these predictions empirically. The different theoretical arguments also have different implications for the quality of care. Therefore, I empirically investigated the impact of hospital-physician integration on the quality of care, in addition to the impact of integration on hospital costs. As described in the methods section, I controlled for a large number of factors other than hospital-physician integration, using both Cobb-Douglas and translog specifications in the cost regressions. I estimated fixed effects regressions to control for unobserved time-constant factors specific to individual hospitals. I also used matching analyses to account for potential endogeneity.

The results of the empirical analysis show that, contrary to the predictions of transaction cost theory, hospital-physician integration is not associated with lower hospital costs. All of the regressions that used costs as the dependent variable (either total costs or per capita costs) show that integrated hospitals have higher or equivalent costs, excluding physician salaries, than non-integrated hospitals. In the specifications that used the log of total operating costs as the dependent variable integrated hospitals had statistically significantly higher costs than non-integrated hospitals, even when accounting for fixed effects. These effects were much smaller in the fixed effects regressions and in the regressions that used the translog specification, but even a small positive percentage increase in costs per hospital could translate into large dollar amounts for the hospitals. The regressions that used the log of per patient costs also showed smaller effects of full integration, and the coefficient estimates on ISM using fixed effects were not statistically significant.

In addition, I conducted analyses that matched hospitals on characteristics prior to a change in integration (ISM) status, in an effort to control for endogeneity. For example, hospitals that were expecting higher costs might have integrated in order to combat these costs—so costs might have been even higher if the hospitals had not integrated. However, the results of the matching analyses showed that after hospitals became integrated their costs were no higher than those of hospitals with similar characteristics that did not integrate. In some specifications, hospitals that integrated had higher costs. Moreover, hospitals that disintegrated had either lower costs or no change in costs after they took this action. Both sets of results from the matching analyses suggest that hospital-physician integration does not lower costs.

All of the cost estimates together suggest that at best, the costs of integrated hospitals are on par with those of non-integrated hospitals. The regressions that included other types of organizational forms also did not show any consistent effect of these vertical relationships on hospital costs. In addition, the results of the quality regressions showed no consistent effects of full vertical integration or other organizational forms on the quality of care. Thus, I did not find evidence consistent with the argument derived from transaction cost theory that improvements in coordination lead to better hospital healthcare quality. These results also suggest that any increases in costs that may stem from hospital-physician integration are not due to higher quality care. Overall, the results for both the cost and quality of care analyses do not support the predictions of transaction cost theory that integration improves coordination, and thereby lowers costs and increases the quality of care.

Although my results showed that hospital-physician integration is not associated with lower costs and higher quality in the sample as a whole, it is possible that these results could mask heterogeneity among hospitals. Some hospitals may implement vertical integration more effectively than others, such as by using procedures, monitoring, and incentives that lead to lower costs and more effective coordination. The results for lower cost and higher cost integrated hospitals could offset each other. This could also be true for the quality of care. It would be important for future research to investigate possible heterogeneity among hospitals and the effects on costs and quality.

Another issue that might affect my results concerns the reporting of hospital costs. Although reported hospital costs are supposed to exclude all physician costs, it may be difficult for hospitals to clearly separate all costs of supporting physician practices from hospital costs. For example, some administrative costs might be shared between hospitals and physician practices. In addition, hospitals may not clearly separate other costs such as health insurance that are likely to be shared across all hospital employees, including physicians. If hospitals allocate some costs of physician practices to hospital costs, this would raise the reported costs of integrated hospitals even though actual costs may not be as high. This could create a positive bias in the estimated effect of full integration on costs.

It would also be important for future research to further investigate the potential impact of endogeneity of the vertical integration decision. The impact of hospital size on integration is an important factor to consider. My results showed that integration is associated with larger hospital size. If integration leads to higher costs, this might occur because integrated hospitals have more patients who are also more costly. Although I controlled for the number of patients in several ways—as a control variable, as the denominator in the dependent variable for per patient costs, and as a matching covariate—I cannot completely rule out that any cost increases due to integration may stem from a larger number of patients. In particular, if the additional patients are higher cost or lower cost than the previous average patient, the estimated effects of full integration in the cost regressions could reflect this. For example, physicians might admit sicker patients who they would have referred to another hospital in the past. This would cause costs to increase as a result of vertical integration.

My results showing that hospital-physician integration may either increase costs or have no effect on costs (or the quality of care) raises the question of why hospitals would undertake such a major organizational change. One possible explanation is that hospitals integrate for other reasons. In particular, hospitals may integrate in order to increase their revenues, which could more than offset any increase in costs. For example, hospital-employed physicians might order more hospital lab tests or scans. Hospitals that are integrated may also have greater bargaining power with insurers because the hospitals would have greater control over the supply of physicians that insurers may want to include in their provider networks. And hospitals might be able to benefit from vertical foreclosure, and thereby gain market power and raise prices. For example, hospitals that integrate may be able to control a larger portion of the supply of physicians in a local geographic area, and physicians that are employed by hospitals may refer more of their patients to the hospitals that employ them. This makes it harder for non-integrated hospitals to obtain referrals from physicians if many of the physicians in an area are employed by hospitals. Whether hospital-physician integration has anticompetitive effects is also relevant for antitrust evaluations of hospital acquisitions of physician practices. Future research on hospital-physician mergers could investigate the impact of these mergers on revenues relative to the impact on costs.

Finally, my results may have implications for public policy. Notably, the overall results of my cost analyses are similar to those of Cuellar and Gertler (2006), who found no effect on hospital costs of full integration or other vertical relationships with physicians. Even with a more recent and much larger sample of hospitals in all geographic regions of the U.S., the evidence thus far does not point to lower costs as a benefit of hospital-physician integration. I also found no consistent impact of integration on the quality of care. Other possible consequences of hospital-physician integration—such as increased bargaining power with insurers or greater market power versus other hospitals—would tend to increase hospital prices and contribute to the already rising cost of healthcare. Although vertical integration is sometimes viewed as a way to stem rising healthcare costs, the evidence suggests that this may not be the case.

References

Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica, 74*(1), 235-267. doi:10.1111/j.1468-0262.2006.00655.x

Abadie, A., & Imbens, G. W. (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics, 29*(1), 1-11. doi:10.1198/jbes.2009.07333

American Hospital Association. (2017, February 23). TrendWatch Chartbook. Retrieved from http://www.aha.org/research/reports/tw/chartbook/index.shtml

Baker, J. B. (1999). Policy watch: Developments in antitrust economics. *Journal of Economic Perspectives, 13*(1), 181-194. doi:10.1257/jep.13.1.181

Baker, L. C., Bundorf, M. K., & Kessler, D. P. (2014). Vertical integration: Hospital ownership of physician practices is associated with higher prices and spending. *Health Affairs, 33*(5), 756-763. doi:10.1377/hlthaff.2013.1279

Baum, C. F. (2013, April). *Propensity score matching regression discontinuity limited dependent variables*. Lecture presented at EC 823: Applied Econometrics in Boston College, Boston. Retrieved from http://fmwww.bc.edu/EC-C/S2013/823/EC823.S2013.nn12.slides.pdf

Bresnahan, T. F., & Levin, J. D. (2013). Vertical integration and market structure. In R. Gibbons & J. Roberts (Authors), *The handbook of organizational economics* (pp. 853-890). Princeton: Princeton University Press.

Burns, L. R., & Pauly, M. V. (2002). Integrated delivery networks: A detour on the road to integrated health care? *Health Affairs, 21*(4), 128-143. doi:10.1377/hlthaff.21.4.128

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*(1), 31-72. doi:10.1111/j.1467-6419.2007.00527.x

Capps, C., Dranove, D., & Ody, C. (2016). The effect of hospital acquisitions of physician practices on prices and spending. *Working Paper,* 1-65. Retrieved April 15, 2018, from http://www.kellogg.northwestern.edu/faculty/directory/dranove_david.aspx#research

Christensen, L. R., & Greene, W. H. (1976). Economies of scale in U.S. electric power generation. *Journal of Political Economy, 84*(4, Part 1), 655-676. doi:10.1086/260470

Ciliberto, F., & Dranove, D. (2006). The effect of physician-hospital affiliations on hospital prices in California. *Journal of Health Economics, 25*(1), 29-38. doi:10.1016/j.jhealeco.2005.04.008

Ciliberto, F. (2006). Does organizational form affect investment decisions? *Journal of Industrial Economics, 54*(1), 63-93. doi:10.1111/j.1467-6427.2006.00276.x

Cuellar, A. E., & Gertler, P. J. (2006). Strategic integration of hospitals and physicians. *Journal of Health Economics, 25*(1), 1-28. doi:10.1016/j.jhealeco.2005.04.009

Fulton, B. D. (2017). Health care market concentration trends in the United States: Evidence and policy responses. *Health Affairs, 36*(9), 1530-1538. doi:10.1377/hlthaff.2017.0556

Gal-Or, E. (1999). The profitability of vertical mergers between hospitals and physician practices. *Journal of Health Economics, 18*(5), 623-654. doi:10.1016/s0167-6296(99)00013-2

Gaynor, M., Ho, K., & Town, R. (2014). The industrial organization of health care markets. *Journal of Economic Literature, 53*(2), 235-284. doi:10.3386/w19800

Goldsmith, J., Burns, L. R., Sen, A., & Goldsmith, T. (2015, February). Integrated delivery networks: In search of benefits and market effects. Retrieved from https://www.nasi.org/research/2015/integrated-delivery-networks-search-benefits-market-effects

Hart, O., & Holmstrom, B. (2010). A theory of firm scope. *Quarterly Journal of Economics, 125*(2), 483-513. doi:10.1162/qjec.2010.125.2.483

Hart, O., Tirole, J., Carlton, D. W., & Williamson, O. E. (1990). Vertical integration and market foreclosure. *Brookings Papers on Economic Activity. Microeconomics, 1990*, 205. doi:10.2307/2534783

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics, 86*(1), 4-29. doi:10.1162/003465304323023651

Koch, T. G., Wendling, B. W., & Wilson, N. E. (2017). How vertical integration affects the quantity and cost of care for Medicare beneficiaries. *Journal of Health Economics, 52*, 19-32. doi:10.1016/j.jhealeco.2016.12.007

Kocher, R., & Sahni, N. R. (2011). Hospitals' race to employ physicians - The logic behind a money-losing proposition. *New England Journal of Medicine, 364*(19), 1790-1793. doi:10.1056/nejmp1101959

Madison, K. (2004). Hospital-physician affiliations and patient treatments, expenditures, and outcomes. *Health Services Research, 39*(2), 257-278. doi:10.1111/j.1475-6773.2004.00227.x

Neprash, H. T., Chernew, M. E., Hicks, A. L., Gibson, T., & Mcwilliams, J. M. (2015). Association of financial integration between physicians and hospitals with commercial health care prices. *JAMA Internal Medicine, 175*(12), 1932. doi:10.1001/jamainternmed.2015.4610

Physicians Advocacy Institute. (2016, September). Physician practice acquisition study: National and regional employment changes. Retrieved from http://www.physiciansadvocacyinstitute.org/Portals/0/assets/docs/PAI-Physician-Employment-Study.pdf

Post, B., Buchmueller, T., & Ryan, A. M. (2017). Vertical integration of hospitals and physicians: Economic theory and empirical evidence on spending and quality. *Medical Care Research and Review,* 107755871772783. doi:10.1177/1077558717727834

Robinson, J. C. (1997). Physician-hospital integration and the economic theory of the firm. *Medical Care Research and Review, 54*(1), 3-24. doi:10.1177/107755879705400101

Unruh, L. Y., Fottler, M. D., & Talbott, L. L. (2003). Improving nurse staffing measures: Discharge day measurement in "adjusted patient days of care". *INQUIRY: The Journal of Health Care Organization, Provision, and Financing, 40*(3), 295-304. doi:10.5034/inquiryjrnl_40.3.295

U.S. Centers for Medicare and Medicaid. (2017, May 12). ACO Overview. Retrieved from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/ACO/

U.S. Centers for Medicare and Medicaid. (2018, January 08). National health accounts historical. Retrieved from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical.html

Williamson, O. E. (1975). *Markets and hierarchies: Analysis and antitrust implications, a study in the economics of internal organization*. New York, NY: The Free Press.

Williamson, O. E. (1985). *The economic institutions of capitalism*. New York, NY: The Free Press.

Table 1 Hospital-Physician Organizational Forms

Table 1
Characteristics of physician–hospital vertical relationships

	Independent Practice Association	Open Physician Hospital Organization	Closed Physician Hospital Organization	Management Services Organization	Fully Integrated Organization
Contracting w/managed care plans	x	x	x	x	x
Administrative services		x	x	x	x
Coordinate care			x	x	x
Physicians exclusive to hospital			x	x	x
Fully integrated ownership				Some	x
Physicians salaried					x
Provide insurance					Some

Source: Cuellar and Gertler (2006, p. 7)

Table 2 Variables

Variable Name	Description	Underlying Data Source
lTotOpExp	Log of Total Hospital Operating Expenses	HCRIS
lPerCapitaTotOpExp	Log of Per Capita Total Operating Expenses, ln(Total Operating Expenses Divided by Number of Adjusted Patients)	HCRIS
lAdjPatients	Log of Adjusted Patients (Adjusted Patients = Number of Inpatients +[Number of Inpatients x Outpatient Revenue/ Inpatient Revenue])	HCRIS
ISM	Dummy variable (0,1) indicating full hospital-physician vertical integration	AHA
IPA	Dummy variable (0,1) indicating IPA participation	AHA
OPHO	Dummy variable (0,1) indicating OPHO participation	AHA
CPHO	Dummy variable (0,1) indicating CPHO participation	AHA
lTotInpatAdmis	Log of Total Inpatient Admissions , equal to ln(total number of inpatient discharges)	HCRIS
lAvgInpatStay	Log of Average Number of Days per Inpatient Stay	HCRIS
lOutpatNum	Log of Number of Outpatients	AHA
lTotBeds	Log of Total Number of Beds	HCRIS
lSpecBeds	Log of Number of Specialty Beds	HCRIS
lNurseWagesZip	Log of Average Hourly Nurse Wages, at the zip code level	BLS

Teach1Yes	Dummy variable (0,1) indicating a teaching hospital	HCRIS
Trans1Yes	Dummy variable (0,1) indicating a transplant hospital	HCRIS
ForProfit1	Dummy variable (0,1) indicating a for-profit hospital	HCRIS
Urb1Rur0	Dummy variable (0,1) indicating urban location	HCRIS
Mort_30_HF	30 day mortality, heart failure (Number of deaths within 30 days of admission for heart failure/total number of admissions for heart failure)	IQR
Mort_30_PN	30 day mortality, pneumonia (Number of deaths within 30 days of admission for pneumonia/total number of admissions for pneumonia)	IQR
Readm_30_HF	30 day readmission, heart failure (Number of readmissions within 30 days of admission for heart failure/total number of admissions for heart failure)	IQR
Readm_30_PN	30 day readmission, pneumonia (Number of readmissions within 30 days of admission for pneumonia/total number of admissions for pneumonia)	IQR

Table 3 Trends in Vertical Integration, 2000-2013

Year	Percentage of Hospitals That Are Vertically Integrated
2000	17.94%
2001	20.01%
2002	22.07%
2003	23.93%
2004	25.04%
2005	26.62%
2006	28.73%
2007	30.38%
2008	35.57%
2009	37.47%
2010	39.30%
2011	41.16%
2012	41.96%
2013	43.13%

Source: American Hospital Association Survey, 2000-2013

Note: The calculations are based on the main sample that contains a total of 32,742 observations covering 3,575 hospitals.

Table 4 Base Regression, Cobb-Douglas Cost Function, Excluding Nurse Wages

Dependent Variable: lTotOpExp

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
lSM	0.0490***	0.0127**	0.0149***
	(0.00431)	(0.00522)	(0.00509)
lTotInpatAdmis	0.474***	0.503***	0.528***
	(0.0142)	(0.0346)	(0.0293)
lAvgInpatStay	0.108***	0.313***	0.301***
	(0.0144)	(0.0361)	(0.0302)
lOutpatNum	0.165***	0.0431***	0.0592***
	(0.00656)	(0.00647)	(0.00781)
lTotBeds	0.108***	0.0489***	0.0782***
	(0.0124)	(0.0174)	(0.0132)
lSpecBeds	0.0974***	0.0299***	0.0589***
	(0.00502)	(0.00805)	(0.00879)
Teach1Yes	-0.146**	-0.115	-0.174**
	(0.0584)	(0.0880)	(0.0785)
Trans1Yes	-0.278***	-0.0133	0.0657
	(0.104)	(0.159)	(0.150)
InteractlTotBedsTeach	0.0591***	0.0301*	0.0491***
	(0.0109)	(0.0174)	(0.0157)
InteractlTotBedsTrans	0.102***	0.0157	0.0159
	(0.0176)	(0.0265)	(0.0252)
ForProfit1	-0.0172***	-0.0592**	-0.0664***
	(0.00613)	(0.0234)	(0.0175)
Urb1Rur0	0.190***		0.352***
	(0.00615)		(0.0305)
Constant	11.48***	12.25***	12.13***
	(0.316)	(0.339)	(0.274)
Observations	32,742	32,742	32,742
R-squared	0.937	0.782	
State by Year FE	YES	YES	YES
Hospital FE	NO	YES	NO
Hosptial RE	NO	NO	YES
Number of hospitals	3,575	3,575	3,575

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 Main Sample, Cobb-Douglas Cost Function, With and Without Nurse Wages

Dependent Variable: lTotOpExp

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ISM	0.0568***	0.0134**	0.0165***	0.0575***	0.0134**	0.0165***
	(0.00455)	(0.00548)	(0.00537)	(0.00453)	(0.00548)	(0.00536)
lTotInpatAdmis	0.449***	0.475***	0.498***	0.443***	0.475***	0.498***
	(0.0147)	(0.0363)	(0.0311)	(0.0147)	(0.0363)	(0.0310)
lAvgInpatStay	0.0969***	0.294***	0.285***	0.0938***	0.294***	0.285***
	(0.0151)	(0.0376)	(0.0319)	(0.0150)	(0.0376)	(0.0318)
lOutpatNum	0.165***	0.0447***	0.0597***	0.168***	0.0447***	0.0600***
	(0.00688)	(0.00687)	(0.00818)	(0.00703)	(0.00687)	(0.00820)
lTotBeds	0.127***	0.0614***	0.0935***	0.128***	0.0614***	0.0937***
	(0.0129)	(0.0177)	(0.0141)	(0.0128)	(0.0177)	(0.0141)
lSpecBeds	0.102***	0.0348***	0.0627***	0.104***	0.0348***	0.0632***
	(0.00529)	(0.00830)	(0.00912)	(0.00524)	(0.00830)	(0.00913)
Teach1Yes	-0.141**	-0.133	-0.185**	-0.136**	-0.133	-0.186**
	(0.0631)	(0.0901)	(0.0817)	(0.0616)	(0.0902)	(0.0818)
Trans1Yes	-0.296***	-0.00695	0.0987	-0.224**	-0.00640	0.0923
	(0.107)	(0.164)	(0.154)	(0.103)	(0.164)	(0.154)
InteractlTotBedsTeach	0.0580***	0.0332*	0.0510***	0.0551***	0.0332*	0.0511***
	(0.0117)	(0.0180)	(0.0164)	(0.0114)	(0.0180)	(0.0164)
InteractlTotBedsTrans	0.105***	0.0156	0.0110	0.0911***	0.0155	0.0124
	(0.0181)	(0.0275)	(0.0259)	(0.0175)	(0.0274)	(0.0259)
ForProfit1	0.0253***	-0.0588**	0.0730***	0.0309***	-0.0588**	0.0731***
	(0.00640)	(0.0247)	(0.0187)	(0.00636)	(0.0247)	(0.0186)
Urb1Rur0	0.192***		0.344***	0.139***		0.336***
	(0.00640)		(0.0320)	(0.00639)		(0.0322)
lNurseWagesZip				0.617***	-0.00416	0.0622*
				(0.0237)	(0.0349)	(0.0324)
Constant	11.25***	12.45***	12.20***	9.283***	12.46***	11.99***
	(0.0880)	(0.350)	(0.299)	(0.113)	(0.381)	(0.325)
Observations	29,886	29,886	29,886	29,886	29,886	29,886
R-squared	0.934	0.785		0.935	0.785	
State by year FE	YES	YES	YES	YES	YES	YES
Hospital FE	NO	YES	NO	NO	YES	NO
Hospital RE	NO	NO	YES	NO	NO	YES
Number of hospitals	3,031	3,031	3,031	3,031	3,031	3,031

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6 Main Sample, Cobb-Douglas Cost Function, With and Without Case Mix Index

Dependent Variable: lTotOpExp

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
lSM	0.0611***	0.00720	0.0646***	0.00733
	(0.00469)	(0.00515)	(0.00444)	(0.00512)
lTotInpatAdmis	0.481***	0.580***	0.443***	0.577***
	(0.0186)	(0.0233)	(0.0186)	(0.0230)
lAvgInpatStay	0.131***	0.395***	0.166***	0.392***
	(0.0206)	(0.0255)	(0.0205)	(0.0253)
lOutpatNum	0.156***	0.0389***	0.151***	0.0391***
	(0.00701)	(0.00685)	(0.00771)	(0.00687)
lTotBeds	0.146***	0.0512***	0.129***	0.0512***
	(0.0164)	(0.0150)	(0.0162)	(0.0149)
lSpecBeds	0.0832***	0.0303***	0.0554***	0.0287***
	(0.00555)	(0.00764)	(0.00491)	(0.00766)
Teach1Yes	-0.0190	-0.0784	-0.00820	-0.0747
	(0.0654)	(0.0859)	(0.0613)	(0.0871)
Trans1Yes	-0.290***	0.0732	-0.770***	0.0518
	(0.101)	(0.147)	(0.0929)	(0.145)
InteractlTotBedsTeach	0.0318***	0.0211	0.0200*	0.0204
	(0.0122)	(0.0166)	(0.0114)	(0.0168)
InteractlTotBedsTrans	0.101***	-0.000370	0.164***	0.00335
	(0.0172)	(0.0245)	(0.0157)	(0.0240)
ForProfit1	-0.0440***	-0.0460*	-0.0785***	-0.0448*
	(0.00632)	(0.0237)	(0.00574)	(0.0238)
Urb1Rur0	0.126***		0.0401***	
	(0.00627)		(0.00592)	
lNurseWagesZip	0.622***	-0.00577	0.659***	-0.00854
	(0.0244)	(0.0362)	(0.0226)	(0.0360)
lCMI			1.002***	0.101**
			(0.0187)	(0.0398)
Constant	9.024***	11.59***	9.159***	11.61***
	(0.127)	(0.241)	(0.114)	(0.241)
Observations	25,371	25,371	25,371	25,371
R-squared	0.928	0.836	0.943	0.837
State by year FE	YES	YES	YES	YES
Hospital FE	NO	YES	NO	YES
Number of hospitals	2,427	2,427	2,427	2,427

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7 Main Sample, Cobb-Douglas Cost Function, With and Without Hospital System Variable

Dependent Variable: lTotOpExp

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
lSM	0.0545***	0.0139**	0.0553***	0.0140**
	(0.00468)	(0.00574)	(0.00468)	(0.00573)
lTotInpatAdmis	0.462***	0.478***	0.461***	0.478***
	(0.0153)	(0.0409)	(0.0153)	(0.0409)
lAvgInpatStay	0.121***	0.307***	0.120***	0.306***
	(0.0162)	(0.0425)	(0.0162)	(0.0425)
lOutpatNum	0.161***	0.0422***	0.161***	0.0422***
	(0.00742)	(0.00701)	(0.00744)	(0.00701)
lTotBeds	0.106***	0.0723***	0.107***	0.0723***
	(0.0129)	(0.0186)	(0.0129)	(0.0186)
lSpecBeds	0.100***	0.0349***	0.0999***	0.0349***
	(0.00564)	(0.00896)	(0.00562)	(0.00896)
Teach1Yes	-0.312***	-0.119	-0.305***	-0.119
	(0.0594)	(0.0949)	(0.0593)	(0.0949)
Trans1Yes	-0.164	-0.00668	-0.179*	-0.00662
	(0.104)	(0.161)	(0.104)	(0.161)
InteractlTotBedsTeach	0.0881***	0.0299	0.0864***	0.0299
	(0.0110)	(0.0191)	(0.0110)	(0.0191)
InteractlTotBedsTrans	0.0770***	0.0166	0.0796***	0.0166
	(0.0176)	(0.0270)	(0.0176)	(0.0270)
ForProfit1	-0.0520***	-0.0474*	-0.0564***	-0.0479*
	(0.00646)	(0.0266)	(0.00649)	(0.0267)
Urb1Rur0	0.139***		0.136***	
	(0.00683)		(0.00683)	
lNurseWagesZip	0.603***	0.0173	0.603***	0.0174
	(0.0250)	(0.0371)	(0.0250)	(0.0371)
Sys1Yes			0.0474***	0.00399
			(0.00672)	(0.0106)
Constant	9.327***	12.34***	9.294***	12.34***
	(0.123)	(0.432)	(0.123)	(0.433)
Observations	26,389	26,389	26,389	26,389
R-squared	0.937	0.789	0.937	0.789
State by year FE	YES	YES	YES	YES
Hospital FE	NO	YES	NO	YES
Number of hospitals	2,967	2,967	2,967	2,967

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Descriptive Statistics, Main Sample, 2000-2013, Excluding Quality of Care Variables

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
ISM	29,886	0.306	0.461	0	1
lOutpatNum	29,886	11.37	1.232	0	15.46
lTotOpExp	29,886	18.21	1.234	13.57	22.21
lPerCapitaTotOpExp	29,886	9.027	0.482	5.462	14.55
PerCapitaTotOpExp	29,886	9,921	22,199	235.6	2.092e+06
AdjPatients	29,886	15,987	16,099	2.270	255,255
TotOpExp	29,886	1.621e+08	2.343e+08	779,104	4.435e+09
TotBeds	29,886	154.1	149.8	1	1,880
TotInpatAdmis	29,886	9,101	10,154	1	135,352
ForProfit1	29,886	0.194	0.396	0	1
Teach1Yes	29,886	0.310	0.462	0	1
Urb1Rur0	29,886	0.651	0.477	0	1
Trans1Yes	29,886	0.0646	0.246	0	1
AvgInpatStay	29,886	5.387	7.878	1	342.9
NurseWagesZip	29,886	27.20	5.384	14.29	61.38
lTotInpatAdmis	29,886	8.429	1.382	0	11.82
lAvgInpatStay	29,886	1.567	0.365	0	5.838
OutpatNum	29,886	157,974	214,136	1	5.153e+06
lTotBeds	29,886	4.590	1.009	0	7.539
SpecBeds	29,886	26.72	38.82	1	468
lSpecBeds	29,886	2.404	1.455	0	6.148
lAdjPatients	29,886	9.183	1.128	0.820	12.45
lNurseWagesZip	29,886	3.285	0.191	2.660	4.117

Table 9 Descriptive Statistics, Main Sample, 2009-2013, for Sub-sample with Quality of Care Variables

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
ISM	9,298	0.410	0.492	0	1
lTotOpExp	9,298	18.56	1.170	14.46	22.21
lPerCapitaTotOpExp	9,298	9.172	0.396	6.156	13.14
PerCapitaTotOpExp	9,298	10,500	7,404	471.5	509,250
AdjPatients	9,298	18,627	18,335	99.40	255,255
TotOpExp	9,298	2.190e+08	3.030e+08	1.897e+06	4.435e+09
TotBeds	9,298	165.9	163.5	3	1,880
TotInpatAdmis	9,298	9,875	11,032	5	130,497
ForProfit1	9,298	0.155	0.362	0	1
Teach1Yes	9,298	0.318	0.466	0	1
Urb1Rur0	9,298	0.634	0.482	0	1
Trans1Yes	9,298	0.0699	0.255	0	1
Mort_30_HF	9,298	11.44	1.600	6.600	18.10
Mort_30_PN	9,298	11.71	1.835	6.700	24.50
Readm_30_HF	9,298	24.29	2.096	17.10	33.80
Readm_30_PN	9,298	18.18	1.644	13	27.60
AvgInpatStay	9,298	4.901	2.610	1.032	161.1
NurseWagesZip	9,298	30.77	5.245	19.44	61.38
lTotInpatAdmis	9,298	8.551	1.283	1.609	11.78
lAvgInpatStay	9,298	1.544	0.271	0.0317	5.082
OutpatNum	9,298	190,024	254,068	1	5.153e+06
lOutpatNum	9,298	11.63	1.076	0	15.46
lTotBeds	9,298	4.664	0.996	1.099	7.539
SpecBeds	9,298	31.52	45.26	1	468
lSpecBeds	9,298	2.580	1.450	0	6.148
lAdjPatients	9,298	9.393	1.009	4.599	12.45
lNurseWagesZip	9,298	3.413	0.159	2.967	4.117

Table 10 Descriptive Statistics, Sample with Other Organizational Forms, 2000-2013, Excluding Quality of Care Variables

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
ISM	28,507	0.311	0.463	0	1
lPerCapitaTotOpExp	28,507	9.029	0.479	5.462	14.55
PerCapitaTotOpExp	28,507	9,924	22,394	235.6	2.092e+06
AdjPatients	28,507	16,173	16,080	2.270	255,255
TotOpExp	28,507	1.645e+08	2.363e+08	779,104	4.435e+09
TotBeds	28,507	155.4	149.0	1	1,764
TotInpatAdmis	28,507	9,205	10,130	1	135,352
ForProfit1	28,507	0.188	0.391	0	1
Teach1Yes	28,507	0.313	0.464	0	1
Urb1Rur0	28,507	0.647	0.478	0	1
Trans1Yes	28,507	0.0654	0.247	0	1
IPA	28,507	0.111	0.315	0	1
OPHO	28,507	0.161	0.367	0	1
AvgInpatStay	28,507	5.397	7.850	1	342.9
NurseWagesZip	28,507	27.20	5.359	14.29	61.38
lTotOpExp	28,507	18.23	1.231	13.57	22.21
lTotInpatAdmis	28,507	8.450	1.375	0	11.82
lAvgInpatStay	28,507	1.570	0.362	0	5.838
OutpatNum	28,507	160,514	216,367	1	5.153e+06
lOutpatNum	28,507	11.39	1.227	0	15.46
lTotBeds	28,507	4.604	1.004	0	7.475
SpecBeds	28,507	26.95	38.86	1	468
lSpecBeds	28,507	2.420	1.451	0	6.148
lAdjPatients	28,507	9.201	1.124	0.820	12.45
CPHO	28,507	0.110	0.313	0	1
lNurseWagesZip	28,507	3.285	0.190	2.660	4.117

Table 11 Descriptive Statistics, Sample with Other Organizational Forms, 2009-2013, for Sub-sample with Quality of Care Variables

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
ISM	8,919	0.415	0.493	0	1
lPerCapitaTotOpExp	8,919	9.171	0.397	6.156	13.14
PerCapitaTotOpExp	8,919	10,500	7,505	471.5	509,250
AdjPatients	8,919	18,607	18,162	99.40	255,255
TotOpExp	8,919	2.193e+08	3.043e+08	1.897e+06	4.435e+09
TotBeds	8,919	165.7	161.4	3	1,764
TotInpatAdmis	8,919	9,857	10,897	5	127,314
ForProfit1	8,919	0.151	0.358	0	1
Teach1Yes	8,919	0.320	0.466	0	1
Urb1Rur0	8,919	0.630	0.483	0	1
Trans1Yes	8,919	0.0700	0.255	0	1
IPA	8,919	0.102	0.303	0	1
OPHO	8,919	0.154	0.361	0	1
Mort_30_HF	8,919	11.44	1.604	6.600	18.10
Mort_30_PN	8,919	11.72	1.842	6.700	24.50
Readm_30_HF	8,919	24.31	2.097	17.10	33.80
Readm_30_PN	8,919	18.19	1.649	13	27.60
AvgInpatStay	8,919	4.920	2.654	1.032	161.1
NurseWagesZip	8,919	30.71	5.229	19.44	61.38
lTotOpExp	8,919	18.56	1.175	14.46	22.21
lTotInpatAdmis	8,919	8.548	1.287	1.609	11.75
lAvgInpatStay	8,919	1.548	0.272	0.0317	5.082
OutpatNum	8,919	191,208	255,559	1	5.153e+06
lOutpatNum	8,919	11.64	1.079	0	15.46
lTotBeds	8,919	4.666	0.995	1.099	7.475
SpecBeds	8,919	31.35	44.82	1	468
lSpecBeds	8,919	2.576	1.449	0	6.148
lAdjPatients	8,919	9.391	1.013	4.599	12.45
CPHO	8,919	0.105	0.307	0	1
lNurseWagesZip	8,919	3.412	0.159	2.967	4.117

Table 12 Main Sample, Cobb-Douglas Cost Function, Log of Per Capita Total Operating Expenses

Dependent Variable: lPerCapitaTotOpExp

	(1)	(2)	(3)	(4)
VARIABLES	Model 1	Model 2	Model 3	Model 4
ISM	0.0231***	-0.00241	0.0223***	-0.00209
	(0.00442)	(0.00562)	(0.00442)	(0.00563)
lAvgInpatStay	0.590***	0.698***	0.746***	0.894***
	(0.0123)	(0.0341)	(0.216)	(0.210)
lTotBeds	-0.0790***	-0.0445**	-0.0714***	-0.0461***
	(0.00731)	(0.0182)	(0.00718)	(0.0178)
lSpecBeds	0.0468***	-0.00141	0.0499***	-0.00307
	(0.00390)	(0.00719)	(0.00392)	(0.00725)
Teach1Yes	-0.178***	-0.0805	-0.182***	-0.0846
	(0.0410)	(0.0937)	(0.0402)	(0.0957)
Trans1Yes	-0.0799	0.0686	-0.0454	0.0645
	(0.0921)	(0.180)	(0.0920)	(0.179)
InteractlTotBedsTeach	0.0553***	0.0176	0.0558***	0.0183
	(0.00780)	(0.0183)	(0.00764)	(0.0187)
InteractlTotBedsTrans	0.0570***	-0.0134	0.0511***	-0.0127
	(0.0154)	(0.0294)	(0.0154)	(0.0292)
ForProfit1	0.0405***	-0.0208	0.0365***	-0.0193
	(0.00584)	(0.0260)	(0.00576)	(0.0260)
Urb1Rur0	0.0993***		0.0929***	
	(0.00612)		(0.00608)	
lNurseWagesZip	0.628***	0.00308	0.797***	0.0411
	(0.0244)	(0.0363)	(0.113)	(0.114)
lAvgInpatStaySQ			0.0483***	-0.0287
			(0.0104)	(0.0249)
IntlAvgInpatStaylNW			-0.109	-0.0242
			(0.0670)	(0.0665)
Constant	6.353***	7.819***	5.964***	7.595***
	(0.121)	(0.163)	(0.376)	(0.384)
Observations	29,886	29,886	29,886	29,886
R-squared	0.543	0.618	0.545	0.619
State by year FE	YES	YES	YES	YES
Hospital FE	NO	YES	NO	YES
Number of hospitals	3,031	3,031	3,031	3,031

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13 Main Sample, Translog Cost Function

Dependent Variable: lTotOpExp

VARIABLES	(1) Model 1	(2) Model 2
ISM	0.0384***	0.0101**
	(0.00387)	(0.00486)
lTotInpatAdmis	0.613***	0.121
	(0.0602)	(0.0782)
lAvgInpatStay	-0.824***	0.254
	(0.175)	(0.187)
lOutpatNum	-0.178***	-0.119**
	(0.0671)	(0.0593)
lTotBeds	-0.00403	0.0252**
	(0.00824)	(0.0128)
lSpecBeds	0.0493***	0.0166**
	(0.00384)	(0.00666)
Teach1Yes	0.310***	0.0540
	(0.0535)	(0.0710)
Trans1Yes	0.232**	0.197
	(0.0969)	(0.133)
InteractlTotBedsTeach	0.0469***	-0.00675
	(0.0101)	(0.0138)
InteractlTotBedsTrans	-0.000150	-0.0263
	(0.0163)	(0.0222)
ForProfit1	0.0162***	-0.0505**
	(0.00533)	(0.0231)
Urb1Rur0	0.0705***	
	(0.00504)	
lNurseWagesZip	2.680***	1.180***
	(0.167)	(0.171)
lTotInpatAdmisSQ	0.0616***	0.0522***
	(0.00248)	(0.00310)
lAvgInpatStaySQ	0.127***	0.0175
	(0.00995)	(0.0146)
lOutpatNumSQ	0.0169***	0.00525***
	(0.00113)	(0.000674)
IntlTotInpatAdmislAvgInpatStay	0.128***	0.0851***
	(0.00821)	(0.00925)
IntlTotInpatAdmislOutpatNum	0.0371***	-0.0107***
	(0.00339)	(0.00337)
IntlAvgInpatStaylOutpatNum	0.00712	-0.00455
	(0.00664)	(0.00666)
IntlTotInpatAdmislNW	-0.229***	-0.110***

	(0.0170)	(0.0178)
IntlAvgInpatStaylNW	-0.135***	-0.155***
	(0.0520)	(0.0476)
IntlOutpatNumlNW	0.0884***	0.0473***
	(0.0199)	(0.0155)
Constant	5.911***	11.34***
	(0.577)	(0.628)
Observations	29,886	29,886
R-squared	0.949	0.813
State by year FE	YES	YES
Hospital FE	NO	YES
Number of hospitals	3,031	3,031

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14 Main Sample, Adjusted Patients

Dependent Variable: lAdjPatients

VARIABLES	Model 1	Model 2
ISM	0.0644***	0.0209***
	(0.00500)	(0.00620)
lAvgInpatStay	-0.788***	-0.704***
	(0.0114)	(0.0310)
lTotBeds	0.718***	0.296***
	(0.00836)	(0.0261)
lSpecBeds	0.224***	0.119***
	(0.00465)	(0.0104)
Teach1Yes	0.325***	-0.128
	(0.0513)	(0.142)
Trans1Yes	0.166	-0.144
	(0.104)	(0.273)
InteractlTotBedsTeach	-0.0547***	0.0350
	(0.00963)	(0.0277)
InteractlTotBedsTrans	-0.0214	0.0497
	(0.0173)	(0.0439)
ForProfit1	-0.218***	-0.0551*
	(0.00698)	(0.0317)
Urb1Rur0	0.0287***	
	(0.00690)	
lNurseWagesZip	0.0249	0.00226
	(0.0278)	(0.0443)
Constant	6.139***	8.515***
	(0.105)	(0.189)
Observations	29,886	29,886
R-squared	0.892	0.380
State by year FE	YES	YES
Hospital FE	NO	YES
Number of hospitals	3,031	3,031

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 15 Main Sample, Quality of Care, Heart Failure Mortality

Dependent Variable: Mort_30_HF

VARIABLES	(1) Model 1	(2) Model 2
ISM	0.0836**	-0.0205
	(0.0332)	(0.0910)
lTotInpatAdmis	-0.0909*	-0.110
	(0.0470)	(0.118)
lAvgInpatStay	-0.160***	-0.239
	(0.0605)	(0.180)
lOutpatNum	0.233***	-0.000565
	(0.0239)	(0.0468)
lTotBeds	-0.108*	0.0813
	(0.0562)	(0.126)
lSpecBeds	0.00124	-0.197***
	(0.0277)	(0.0745)
Teach1Yes	0.737**	0.362
	(0.299)	(0.808)
Trans1Yes	1.146	-2.132
	(0.739)	(1.770)
InteractlTotBedsTeach	-0.164***	-0.0620
	(0.0568)	(0.156)
InteractlTotBedsTrans	-0.260**	0.339
	(0.122)	(0.303)
ForProfit1	-0.0149	0.229
	(0.0497)	(0.273)
Urb1Rur0	-0.0166	
	(0.0498)	
lNurseWagesZip	-2.448***	0.200
	(0.197)	(0.552)
Constant	20.17***	11.89***
	(0.963)	(2.319)
Observations	9,298	9,298
R-squared	0.203	0.101
State by year FE	YES	YES
Hospital FE	NO	YES
Number of hospitals	2,208	2,208

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 Main Sample, Quality of Care, Heart Failure Readmissions

Dependent Variable: Readm_30_HF

VARIABLES	(1) Model 1	(2) Model 2
ISM	0.0716*	-0.131
	(0.0420)	(0.114)
lTotInpatAdmis	0.283***	0.0623
	(0.0626)	(0.154)
lAvgInpatStay	0.0865	0.0121
	(0.0812)	(0.207)
lOutpatNum	-0.328***	-0.0276
	(0.0333)	(0.0614)
lTotBeds	0.121*	0.216
	(0.0678)	(0.199)
lSpecBeds	-0.233***	-0.0283
	(0.0366)	(0.101)
Teach1Yes	0.643	-0.257
	(0.397)	(1.178)
Trans1Yes	-3.969***	1.885
	(0.976)	(2.983)
InteractlTotBedsTeach	-0.149**	0.0470
	(0.0756)	(0.227)
InteractlTotBedsTrans	0.715***	-0.348
	(0.164)	(0.545)
ForProfit1	0.577***	0.229
	(0.0637)	(0.356)
Urb1Rur0	-0.440***	
	(0.0604)	
lNurseWagesZip	2.624***	-0.266
	(0.257)	(0.553)
Constant	14.75***	24.11***
	(1.017)	(2.684)
Observations	9,298	9,298
R-squared	0.272	0.330
State by year FE	YES	YES
Hospital FE	NO	YES
Number of hospitals	2,208	2,208

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17 Main Sample, Quality of Care, Pneumonia Mortality

Dependent Variable: Mort_30_PN

VARIABLES	(1) Model 1	(2) Model 2
ISM	0.0564	0.0460
	(0.0406)	(0.102)
lTotInpatAdmis	-0.170***	-0.109
	(0.0587)	(0.151)
lAvgInpatStay	-0.0547	-0.121
	(0.0785)	(0.231)
lOutpatNum	0.107***	0.0254
	(0.0278)	(0.0618)
lTotBeds	-0.226***	0.0142
	(0.0676)	(0.137)
lSpecBeds	0.199***	0.182**
	(0.0323)	(0.0898)
Teach1Yes	0.451	-0.410
	(0.340)	(0.856)
Trans1Yes	0.686	1.086
	(0.958)	(1.723)
InteractlTotBedsTeach	-0.115*	0.0241
	(0.0643)	(0.173)
InteractlTotBedsTrans	-0.149	-0.165
	(0.158)	(0.306)
ForProfit1	0.190***	-0.292
	(0.0618)	(0.353)
Urb1Rur0	-0.154***	
	(0.0586)	
lNurseWagesZip	-1.960***	-1.137*
	(0.230)	(0.606)
Constant	20.84***	15.71***
	(1.515)	(2.581)
Observations	9,298	9,298
R-squared	0.134	0.086
State by year FE	YES	YES
Hospital FE	NO	YES
Number of hospitals	2,208	2,208

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18 Main Sample, Quality of Care, Pneumonia Readmissions

Dependent Variable: Readm_30_PN

VARIABLES	(1) Model 1	(2) Model 2
ISM	-0.00315	-0.221**
	(0.0353)	(0.0904)
lTotInpatAdmis	0.398***	0.0835
	(0.0479)	(0.125)
lAvgInpatStay	0.0702	-0.0201
	(0.0654)	(0.174)
lOutpatNum	-0.239***	0.0153
	(0.0274)	(0.0489)
lTotBeds	0.0247	-0.0446
	(0.0540)	(0.121)
lSpecBeds	-0.190***	0.106
	(0.0282)	(0.0831)
Teach1Yes	-0.704**	-1.028
	(0.302)	(0.920)
Trans1Yes	-1.123	1.515
	(0.837)	(2.039)
InteractlTotBedsTeach	0.129**	0.202
	(0.0575)	(0.175)
InteractlTotBedsTrans	0.237*	-0.235
	(0.141)	(0.341)
ForProfit1	0.283***	-0.0303
	(0.0490)	(0.334)
Urb1Rur0	-0.182***	
	(0.0496)	
lNurseWagesZip	1.272***	0.291
	(0.205)	(0.498)
Constant	13.43***	16.24***
	(0.859)	(2.182)
Observations	9,298	9,298
R-squared	0.217	0.158
State by year FE	YES	YES
Hospital FE	NO	YES
Number of hospitals	2,208	2,208

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 19 Sample with Other Organizational Forms, Total Costs

Dependent Variable: lTotOpExp

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
ISM	0.0606***	0.0602***	0.0145***	0.0141**	0.0395***	0.0107**
	(0.00461)	(0.00462)	(0.00547)	(0.00548)	(0.00393)	(0.00483)
CPHO		0.0158***		0.0121**	0.0109**	0.00835*
		(0.00517)		(0.00522)	(0.00463)	(0.00498)
OPHO		-0.00516		0.00638	-0.00221	0.00577
		(0.00482)		(0.00688)	(0.00438)	(0.00636)
IPA		0.0198***		0.00938*	-0.0123**	0.00835*
		(0.00617)		(0.00539)	(0.00567)	(0.00491)
lTotInpatAdmis	0.437***	0.437***	0.452***	0.452***	0.496***	0.246***
	(0.0155)	(0.0155)	(0.0378)	(0.0378)	(0.0787)	(0.0736)
lAvgInpatStay	0.0956***	0.0959***	0.278***	0.278***	-1.159***	0.432**
	(0.0157)	(0.0157)	(0.0386)	(0.0386)	(0.215)	(0.184)
lOutpatNum	0.167***	0.167***	0.0451***	0.0450***	-0.169**	-0.211***
	(0.00718)	(0.00720)	(0.00711)	(0.00710)	(0.0811)	(0.0592)
lTotBeds	0.143***	0.143***	0.0674***	0.0674***	0.0124	0.0323***
	(0.0137)	(0.0137)	(0.0180)	(0.0181)	(0.00877)	(0.0125)
lSpecBeds	0.103***	0.103***	0.0346***	0.0346***	0.0491***	0.0179***
	(0.00541)	(0.00541)	(0.00847)	(0.00847)	(0.00399)	(0.00667)
Teach1Yes	-0.0998	-0.0995	-0.112	-0.113	0.377***	0.0754
	(0.0641)	(0.0641)	(0.0908)	(0.0907)	(0.0569)	(0.0717)
Trans1Yes	-0.259**	-0.270**	0.00935	0.00620	0.229**	0.146
	(0.106)	(0.107)	(0.172)	(0.172)	(0.0979)	(0.139)
InteractlTotBedsTeach	0.0477***	0.0476***	0.0295	0.0299*	0.0599***	-0.0104
	(0.0119)	(0.0119)	(0.0180)	(0.0180)	(0.0107)	(0.0138)
InteractlTotBedsTrans	0.0978***	0.0997***	0.0110	0.0115	-0.000580	-0.0190
	(0.0180)	(0.0181)	(0.0286)	(0.0285)	(0.0165)	(0.0231)
ForProfit1	0.0357***	0.0356***	-0.0625**	-0.0613**	0.0145***	-0.0540**
	(0.00648)	(0.00648)	(0.0256)	(0.0257)	(0.00551)	(0.0233)
Urb1Rur0	0.132***	0.131***			0.0778***	
	(0.00651)	(0.00651)			(0.00514)	
lNurseWagesZip	0.630***	0.633***	-0.0147	-0.0155	0.506***	-0.0142
	(0.0241)	(0.0242)	(0.0349)	(0.0349)	(0.0214)	(0.0326)
lTotInpatAdmisSQ					0.0608***	0.0506***
					(0.00285)	(0.00278)
lAvgInpatStaySQ					0.139***	0.0184
					(0.0106)	(0.0151)
lOutpatNumSQ					0.0173***	0.00520***
					(0.00113)	(0.000703)
IntlTotInpatAdmislAvgInpatStay					0.136***	0.0856***

					(0.00930)	(0.00875)
lntlTotInpatAdmislOutpatNum					0.0387***	-0.0105***
					(0.00372)	(0.00300)
lntlAvgInpatStaylOutpatNum					0.00793	-0.00868
					(0.00717)	(0.00623)
lntlTotInpatAdmislNW					-0.190***	-0.145***
					(0.0219)	(0.0182)
lntlAvgInpatStaylNW					-0.0694	-0.200***
					(0.0621)	(0.0463)
lntlOutpatNumlNW					0.0884***	0.0773***
					(0.0245)	(0.0160)
Constant	9.236***	9.239***	12.68***	12.68***	12.86***	14.93***
	(0.118)	(0.123)	(0.395)	(0.395)	(0.251)	(0.331)
Observations	28,507	28,507	28,507	28,507	28,507	28,507
R-squared	0.936	0.936	0.782	0.782	0.949	0.813
State by year FE	YES	YES	YES	YES	YES	YES
Hospital FE	NO	NO	YES	YES	NO	YES
Number of hospitals	2,780	2,780	2,780	2,780	2,780	2,780

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 20 Sample with Other Organizational Forms, Per Capita Costs

Dependent Variable: lPerCapitaTotOpExp

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
ISM	0.0246***	0.0248***	-0.00156	-0.00164	0.0242***	-0.00142
	(0.00447)	(0.00448)	(0.00548)	(0.00551)	(0.00448)	(0.00550)
CPHO		0.00827		0.00274	0.00890*	0.00271
		(0.00503)		(0.00588)	(0.00502)	(0.00588)
OPHO		0.0109**		-0.00204	0.00990*	-0.00230
		(0.00513)		(0.00745)	(0.00510)	(0.00743)
IPA		0.0230***		0.00558	0.0211***	0.00577
		(0.00660)		(0.00608)	(0.00660)	(0.00607)
lAvgInpatStay	0.593***	0.594***	0.698***	0.698***	0.648**	1.009***
	(0.0126)	(0.0127)	(0.0346)	(0.0346)	(0.262)	(0.218)
lTotBeds	0.0703***	0.0707***	-0.0430**	0.0431**	0.0644***	0.0452**
	(0.00744)	(0.00744)	(0.0183)	(0.0183)	(0.00732)	(0.0179)
lSpecBeds	0.0447***	0.0443***	-0.00231	-0.00229	0.0468***	-0.00426
	(0.00399)	(0.00399)	(0.00733)	(0.00733)	(0.00403)	(0.00734)
Teach1Yes	-0.168***	-0.173***	-0.0628	-0.0632	-0.178***	-0.0656
	(0.0422)	(0.0423)	(0.0987)	(0.0987)	(0.0415)	(0.101)
Trans1Yes	-0.135	-0.142	0.0675	0.0676	-0.107	0.0554
	(0.0927)	(0.0931)	(0.184)	(0.184)	(0.0926)	(0.182)
InteractlTotBedsTeach	0.0530***	0.0540***	0.0141	0.0142	0.0546***	0.0147
	(0.00802)	(0.00804)	(0.0191)	(0.0192)	(0.00789)	(0.0196)
InteractlTotBedsTrans	0.0667***	0.0681***	-0.0145	-0.0145	0.0620***	-0.0125
	(0.0155)	(0.0155)	(0.0301)	(0.0301)	(0.0155)	(0.0297)
ForProfit1	0.0369***	0.0381***	-0.0320	-0.0317	0.0347***	-0.0300
	(0.00593)	(0.00593)	(0.0229)	(0.0230)	(0.00586)	(0.0229)
Urb1Rur0	0.0910***	0.0910***			0.0867***	
	(0.00621)	(0.00621)			(0.00609)	
lNurseWagesZip	0.643***	0.646***	-0.00284	-0.00319	0.640***	-0.00251
	(0.0248)	(0.0249)	(0.0371)	(0.0371)	(0.0248)	(0.0371)
lAvgInpatStaySQ					0.0424***	-0.0312
					(0.0108)	(0.0254)
IntlAvgInpatStaylNW					-0.0700	-0.0557
					(0.0793)	(0.0682)
Constant	6.276***	6.262***	7.829***	7.830***	6.417***	7.703***
	(0.125)	(0.133)	(0.167)	(0.167)	(0.141)	(0.163)
Observations	28,507	28,507	28,507	28,507	28,507	28,507
R-squared	0.548	0.548	0.617	0.617	0.550	0.619
State by year FE	YES	YES	YES	YES	YES	YES
Hospital FE	NO	NO	YES	YES	NO	YES

Number of hospitals	2,780	2,780	2,780	2,780	2,780	2,780

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 21 Sample with Other Organizational Forms, Adjusted Patients

Dependent Variable: lAdjPatients

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ISM	0.0663***	0.0666***	0.0207***	0.0203***
	(0.00503)	(0.00502)	(0.00609)	(0.00611)
CPHO		0.0490***		0.0106*
		(0.00570)		(0.00628)
OPHO		-0.00879		0.00555
		(0.00560)		(0.00779)
IPA		0.00457		0.00875
		(0.00684)		(0.00736)
lAvgInpatStay	-0.784***	-0.784***	-0.705***	-0.705***
	(0.0113)	(0.0113)	(0.0310)	(0.0310)
lTotBeds	0.713***	0.712***	0.292***	0.292***
	(0.00861)	(0.00861)	(0.0268)	(0.0268)
lSpecBeds	0.224***	0.224***	0.112***	0.112***
	(0.00472)	(0.00472)	(0.0100)	(0.0100)
Teach1Yes	0.351***	0.358***	-0.117	-0.118
	(0.0523)	(0.0525)	(0.147)	(0.147)
Trans1Yes	0.189*	0.186*	-0.0957	-0.0984
	(0.107)	(0.106)	(0.285)	(0.284)
InteractlTotBedsTeach	-0.0596***	-0.0611***	0.0328	0.0332
	(0.00982)	(0.00985)	(0.0285)	(0.0285)
InteractlTotBedsTrans	-0.0249	-0.0244	0.0396	0.0401
	(0.0178)	(0.0177)	(0.0459)	(0.0458)
ForProfit1	-0.219***	-0.217***	-0.0433	-0.0422
	(0.00708)	(0.00709)	(0.0312)	(0.0313)
Urb1Rur0	0.0339***	0.0331***		
	(0.00697)	(0.00698)		
lNurseWagesZip	0.0349	0.0374	-0.00303	-0.00373
	(0.0278)	(0.0278)	(0.0451)	(0.0452)
Constant	6.117***	6.096***	8.576***	8.575***
	(0.106)	(0.0994)	(0.194)	(0.194)
Observations	28,507	28,507	28,507	28,507
R-squared	0.895	0.896	0.387	0.387
State by year FE	YES	YES	YES	YES
Hospital FE	NO	NO	YES	YES
Number of hospitals	2,780	2,780	2,780	2,780

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 22 Sample with Other Organizational Forms, Quality of Care, Heart Failure Mortality

Dependent Variable: Mort_30_HF

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ISM	0.104***	0.101***	-0.0380	-0.0444
	(0.0340)	(0.0341)	(0.0937)	(0.0942)
CPHO		0.0636		0.162
		(0.0526)		(0.0998)
OPHO		-0.0888*		0.0577
		(0.0458)		(0.105)
IPA		-0.0250		0.0208
		(0.0534)		(0.109)
lTotInpatAdmis	-0.0705	-0.0679	-0.106	-0.108
	(0.0484)	(0.0484)	(0.126)	(0.126)
lAvgInpatStay	-0.165***	-0.170***	-0.257	-0.267
	(0.0614)	(0.0615)	(0.188)	(0.188)
lOutpatNum	0.220***	0.218***	0.00977	0.0107
	(0.0239)	(0.0238)	(0.0464)	(0.0462)
lTotBeds	-0.135**	-0.133**	0.0782	0.0783
	(0.0581)	(0.0582)	(0.130)	(0.129)
lSpecBeds	-0.00898	-0.00772	-0.198**	-0.197**
	(0.0287)	(0.0288)	(0.0787)	(0.0796)
Teach1Yes	0.570*	0.594*	0.179	0.166
	(0.306)	(0.306)	(0.829)	(0.826)
Trans1Yes	1.697**	1.649**	-1.839	-1.882
	(0.783)	(0.783)	(1.854)	(1.884)
InteractlTotBedsTeach	-0.130**	-0.134**	-0.0327	-0.0302
	(0.0581)	(0.0581)	(0.160)	(0.159)
InteractlTotBedsTrans	-0.352***	-0.344***	0.279	0.288
	(0.129)	(0.129)	(0.318)	(0.324)
ForProfit1	-0.00951	-0.0144	0.296	0.306
	(0.0512)	(0.0514)	(0.292)	(0.294)
Urb1Rur0	-0.00439	-0.00257		
	(0.0508)	(0.0508)		
lNurseWagesZip	-2.354***	-2.361***	0.309	0.289
	(0.200)	(0.200)	(0.571)	(0.570)
Constant	19.94***	20.00***	11.42***	11.48***
	(0.973)	(0.953)	(2.441)	(2.440)
Observations	8,919	8,919	8,919	8,919
R-squared	0.205	0.205	0.101	0.101
State by year FE	YES	YES	YES	YES
Hospital FE	NO	NO	YES	YES
Number of hospitals	2,118	2,118	2,118	2,118

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23 Sample with Other Organizational Forms, Quality of Care, Heart Failure Readmissions

Dependent Variable: Readm_30_HF

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ISM	0.0792*	0.0847*	-0.105	-0.115
	(0.0431)	(0.0433)	(0.115)	(0.115)
CPHO		0.0691		-0.0221
		(0.0655)		(0.133)
OPHO		0.0256		0.211*
		(0.0593)		(0.122)
IPA		0.117*		-0.0633
		(0.0642)		(0.132)
lTotInpatAdmis	0.325***	0.323***	0.0550	0.0622
	(0.0661)	(0.0662)	(0.165)	(0.166)
lAvgInpatStay	0.0768	0.0776	0.0293	0.0336
	(0.0832)	(0.0833)	(0.215)	(0.215)
lOutpatNum	-0.342***	-0.344***	-0.0123	-0.00996
	(0.0345)	(0.0346)	(0.0629)	(0.0626)
lTotBeds	0.0989	0.0961	0.227	0.235
	(0.0711)	(0.0712)	(0.200)	(0.199)
lSpecBeds	-0.261***	-0.260***	0.0272	0.0271
	(0.0382)	(0.0383)	(0.101)	(0.101)
Teach1Yes	0.572	0.583	-0.402	-0.388
	(0.406)	(0.406)	(1.195)	(1.196)
Trans1Yes	-4.811***	-4.782***	2.311	2.438
	(0.993)	(0.989)	(2.930)	(2.944)
InteractlTotBedsTeach	-0.133*	-0.135*	0.0712	0.0695
	(0.0773)	(0.0772)	(0.230)	(0.230)
InteractlTotBedsTrans	0.858***	0.852***	-0.431	-0.454
	(0.167)	(0.167)	(0.538)	(0.540)
ForProfit1	0.579***	0.582***	0.222	0.221
	(0.0659)	(0.0662)	(0.359)	(0.359)
Urb1Rur0	-0.426***	-0.427***		
	(0.0616)	(0.0616)		
lNurseWagesZip	2.529***	2.520***	-0.584	-0.604
	(0.262)	(0.262)	(0.562)	(0.561)
Constant	15.08***	15.15***	24.87***	24.78***
	(1.034)	(1.033)	(2.771)	(2.772)
Observations	8,919	8,919	8,919	8,919
R-squared	0.271	0.271	0.320	0.320
State by year FE	YES	YES	YES	YES
Hospital FE	NO	NO	YES	YES
Number of hospitals	2,118	2,118	2,118	2,118

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24 Sample with Other Organizational Forms, Quality of Care, Pneumonia Mortality

Dependent Variable: Mort_30_PN

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ISM	0.0513	0.0400	0.0500	0.0483
	(0.0416)	(0.0416)	(0.104)	(0.104)
CPHO		0.0252		0.0680
		(0.0591)		(0.118)
OPHO		-0.200***		0.0215
		(0.0552)		(0.123)
IPA		-0.0741		-0.131
		(0.0650)		(0.130)
lTotInpatAdmis	-0.176***	-0.171***	-0.132	-0.130
	(0.0617)	(0.0616)	(0.162)	(0.162)
lAvgInpatStay	-0.0724	-0.0818	-0.205	-0.207
	(0.0801)	(0.0800)	(0.243)	(0.243)
lOutpatNum	0.0910***	0.0895***	0.0276	0.0270
	(0.0281)	(0.0281)	(0.0637)	(0.0637)
lTotBeds	-0.253***	-0.247***	0.0147	0.0162
	(0.0710)	(0.0710)	(0.140)	(0.139)
lSpecBeds	0.218***	0.221***	0.206**	0.209**
	(0.0335)	(0.0335)	(0.0955)	(0.0958)
Teach1Yes	0.330	0.374	-0.547	-0.547
	(0.349)	(0.349)	(0.870)	(0.870)
Trans1Yes	0.546	0.453	1.230	1.448
	(1.019)	(1.017)	(1.749)	(1.773)
InteractlTotBedsTeach	-0.0888	-0.0971	0.0487	0.0480
	(0.0661)	(0.0663)	(0.175)	(0.175)
InteractlTotBedsTrans	-0.128	-0.114	-0.182	-0.219
	(0.168)	(0.168)	(0.314)	(0.318)
ForProfit1	0.178***	0.164***	-0.262	-0.265
	(0.0637)	(0.0636)	(0.329)	(0.331)
Urb1Rur0	-0.132**	-0.129**		
	(0.0595)	(0.0594)		
lNurseWagesZip			-1.339**	-1.362**
			(0.614)	(0.614)
Constant	21.31***	21.41***	16.63***	16.69***
	(1.519)	(1.465)	(2.689)	(2.686)
Observations	8,919	8,919	8,919	8,919
R-squared	0.138	0.139	0.088	0.088
State by year FE	YES	YES	YES	YES
Hospital FE	NO	NO	YES	YES
Number of hospitals	2,118	2,118	2,118	2,118

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25 Sample with Other Organizational Forms, Quality of Care, Pneumonia Readmissions

Dependent Variable: Readm_30_PN

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ISM	-0.0192	-0.0203	-0.257***	-0.259***
	(0.0361)	(0.0363)	(0.0895)	(0.0900)
CPHO		0.0417		-0.0923
		(0.0538)		(0.101)
OPHO		-0.0408		0.0640
		(0.0469)		(0.123)
IPA		-0.0166		0.0812
		(0.0557)		(0.114)
lTotInpatAdmis	0.392***	0.394***	0.0979	0.0992
	(0.0502)	(0.0502)	(0.135)	(0.136)
lAvgInpatStay	0.0620	0.0595	-0.0218	-0.0167
	(0.0666)	(0.0667)	(0.182)	(0.182)
lOutpatNum	-0.237***	-0.238***	0.0268	0.0281
	(0.0280)	(0.0281)	(0.0509)	(0.0507)
lTotBeds	0.0417	0.0425	-0.0470	-0.0444
	(0.0565)	(0.0566)	(0.120)	(0.120)
lSpecBeds	-0.197***	-0.196***	0.103	0.100
	(0.0295)	(0.0296)	(0.0830)	(0.0836)
Teach1Yes	-0.791***	-0.780**	-0.997	-0.989
	(0.303)	(0.303)	(0.928)	(0.926)
Trans1Yes	-1.438*	-1.464*	1.159	1.034
	(0.870)	(0.873)	(2.072)	(2.058)
InteractlTotBedsTeach	0.148**	0.145**	0.196	0.195
	(0.0576)	(0.0577)	(0.176)	(0.176)
InteractlTotBedsTrans	0.291**	0.295**	-0.170	-0.150
	(0.146)	(0.146)	(0.350)	(0.349)
ForProfit1	0.281***	0.279***	-0.0255	-0.0246
	(0.0505)	(0.0507)	(0.343)	(0.340)
Urb1Rur0	-0.189***	-0.188***		
	(0.0507)	(0.0507)		
lNurseWagesZip	1.241***	1.238***	0.275	0.289
	(0.209)	(0.209)	(0.512)	(0.515)
Constant	13.53***	13.56***	16.07***	15.98***
	(0.874)	(0.867)	(2.304)	(2.306)
Observations	8,919	8,919	8,919	8,919
R-squared	0.221	0.221	0.152	0.152
State by year FE	YES	YES	YES	YES
Hospital FE	NO	NO	YES	YES
Number of hospitals	2,118	2,118	2,118	2,118

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26 Matching Analysis, Adoption of Full Integration

Treatment Variable	lTotOpExp	One-year Difference lTotOpExp	lPerCapitaTotOpExp	One-year Difference lPerCapitaTotOpExp
ISM0to1	0.0699***	0.0182***	0.0421***	0.00895
	(0.0161)	(0.00658)	(0.0161)	(0.00725)
Number of Observations	15,860	15,860	15,860	15,860

Exact Match variables: year, Urb1Rur0, laglSM0 (binary variable indicating ISM=0 in the previous year)
Continuous covariates for lTotOpExp variables: lagOutpatNum, laglAvgInpatStay, laglTotBeds, laglSpecBeds, lagForProfit1, laglTotInpatAdmis, laglNurseWagesZip
Continuous covariates for lPerCapitaTotOpExp DVs: laglAvgInpatStay, laglTotBeds, laglSpecBeds, lagForProfit1, laglNurseWagesZip

Abadie-Imbens standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27 Matching Analysis, Abandonment of Full Integration

Treatment Variable	lTotOpExp	One-year Difference lTotOpExp	lPerCapitaTotOpExp	One-year Difference lPerCapitaTotOpExp
ISM1to0	-0.0392**	-0.0263***	-0.201	-0.000613
	(0.0199)	(0.00769)	(0.0223)	(0.0102)
Number of Observations	6,894	6,894	6,894	6,894

Exact Match variables (all dependent variables): year, Urb1Rur0, lagISM1 (binary variable indicating ISM=1 in the previous year)

Continuous covariates for lTotOpExp DVs: lagOutpatNum, laglAvgInpatStay, laglTotBeds, laglSpecBeds, lagForProfit1, laglTotInpatAdmis, laglNurseWagesZip

Continuous covariates for lPerCapitaTotOpExp DVs: laglAvgInpatStay, laglTotBeds, laglSpecBeds, lagForProfit1, laglNurseWagesZip

Abadie-Imbens standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1