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# Hospital Treatment Rates and Spill-over Effects: Does Ownership Matter?

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## Abstract

This paper studies the effect of hospital ownership on treatment rates allowing for spatial correlation among hospitals. Competition among hospitals and knowledge spillovers generate significant externalities which we try to capture using the spatial Durbin model. Using a panel of 2342 hospitals in the 48 continental states observed over the period 2005 to 2008, we find significant spatial correlation of medical service treatment rates among hospitals. We also get mixed results on the effect of hospital ownership on treatment rates that depends upon the market structure where the hospital is located and which varies by treatment type.

**JEL No.** I10 and C21

**Key Words:** Spatial Lag,Hospital ownership, Spillover Effects; Panel data

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## 1. Introduction

The quality and cost effectiveness of the health care system in the U.S. are two of the major concerns of the Affordable Care Act (ACA). According to World Health Organization (WHO), the total health expenditure of the U.S. accounted for 17.9% of the national GDP in 2010, which was the highest in the world. Despite spending this high expenditure on health, the health outcomes were not significantly better than those of other countries. In this paper we focus on ownership of the hospitals and their treatment rates. We distinguish between three types of hospital ownership: For-profit, not-for-profit, and government owned hospitals. There is an extensive literature focusing on hospital ownership, see for example Sloan (2000), McClellan and Staiger (2000), Sloan et al. (2001), Kessler and McClellan (2002), Horwitz and Nichols (2009), Bayindir (2012), to mention a few. A brief review of the different ownership theories and the empirical evidence is given in section 2. The empirical studies have mixed results. Both not-for-profit and government hospitals enjoy tax exemptions and financial advantages. They may have the luxury of using their profits to finance less profitable services. Sloan (2000) finds that not-for-profit hospitals provide better overall quality to the community. Bayindir (2012) suggests that not-for-profit hospitals are more likely to treat uninsured patients and patients with public health insurance than for-profits hospitals. Some studies indicate that for-profits are profit-seeking and have more financial incentives to provide better treatment and attract patients, while other studies suggest that there is no difference in quality between not-for-profits and for-profits hospitals. On the demand side, Jung, Feldman, and Scanlon (2011) find that hospitals with better reputation and higher quality of health care tend to increase patients' willingness to revisit. Moscone, Tosetti, and Vittadini (2012) suggest that information from neighbors along with patients' previous experience and hospital characteristics play important roles in their choice of hospitals in Italy. Porell and Adams (1995) survey the literature and report that patients are more likely to choose hospitals with better health outcomes. The health care market is based on the interactions between hospitals and patients. We explore how this market generates externalities among hospitals. In particular, we study how the treatment rates of one hospital may be affected by the treatment rates and competition from other neighboring hospitals.

The competition level of the market may be affected by the distance between hospitals, the hospital's reputation and the quality of hospitals[1]. Tay (2003) suggests that patients have a tradeoff between the quality of the hospital and the distance to other hospitals[2]. Hospitals improve their quality to attract patients from other neighborhoods[3]. Horwitz and Nichols (2009) find that not-for-profit hospitals are more likely to provide relatively profitable services in a market with a higher proportion of for-profit admissions. Government hospitals are the least likely to offer profitable services and the most likely to offer unprofitable services.

Knowledge spillovers may also contribute to externalities of health care**.** "A large medical literature has documented the important role of social networks in physician adoption of new technologies, suggesting that knowledge externalities are the source of the productivity spillovers." See Chandra and Staiger (2007, p.133). Physicians may learn from each other and possibly transfer to another hospital, especially when a new technology or equipment is introduced. Agglomeration economies also suggest firms (hospitals) have stronger technology spillovers or faster learning process of a new innovation in a high firm density area (Breschi and

[1] We do not argue that price of medical services is negligible, but most patients have insurance (Tay, 2003). Insurance companies cover a major part of medical expense. Moreover, patients who are aged 65 and above are most likely covered by Medicare. The out-of-pocket payments from patients are relatively low (Sloan, 2000). Porell and Adams (1995) indicate that studies do not find significant price effects when they use gross charges as the price measure.

[2] While almost half of acute myocardial infarction (AMI, or heart attack) patients are admitted to the closest hospital from home, more than 50% of the patients are willing to travel four to five miles further on average for better quality health care.

[3] However, using mortality rates, other empirical studies show mixed results of the effects of the competition on quality (see Gaynor, 2006).

Lissoni, 2001; Cohen and Morrison Paul, 2008; Baicker and Chandra, 2010). Hence, it is important to take into account the possible spillovers from one hospital to its neighboring hospitals.

These spillovers create a spatial correlation of quality, which is presented in Figure 1. The maps present the geographic distribution of the summary Hospital Compare quality scores by hospital referral region[4] (HRR) in the United States in 2005 (The Dartmouth Atlas of Health Care). The scores indicate the average percentages of heart attack, heart failure, and pneumonia clinical processes that are given to patients in the HRR. Figure 1a shows the spatial patterns of the overall score. The treatment rates are above 90% in many HRRs in the middle and north eastern United States. One may argue that these HRRs are wealthier urban areas. Therefore, their overall medical quality is higher than the national average. The geographic clusters suggest heterogeneity of health care across the country. However, we also find geographic clusters of high treatment rates in some less wealthy HRRs, such as those in North Carolina. This confirms the results by Skinner (2012) that demographic variables cannot fully explain the geographic variations in health care. The clusters may also indicate that the medical quality of one HRR is correlated with that of its neighboring HRRs. Focusing on the treatment rates by illness condition, we find the geographic patterns of heart attack and heart failure treatments in Figures 1b and 1c to be similar to that of the overall treatments. The geographic pattern of pneumonia treatments in Figure 1d is slightly different from heart disease treatments, but a spatial correlation persists.

When examining the interaction among hospitals, most studies utilize the Herfindahl-Hirschman Index (HHI) or similar market share variables as measures of competition level or market structure. While these indices are good measures of the aggregate competition level of

[4] Dartmouth Atlas defines the hospital referral regions by the regional market of health care. Patients are able to transfer or be referred to another hospital for major cardiovascular surgical procedures and for neurosurgery in the same HRR. One HRR can cross different counties and states.

the market, they do not take distances between hospitals into consideration. A market with three hospitals close to each other is considered to have the same competition as one with three hospitals spread out.

In this paper, we utilize a spatial Durbin model of hospital treatment rates. This spatial model is able to identify the intensity of geographic correlations**.** Other studies using spatial analysis in health care include Mobley et al. (2006) who studied elderly access to primary care services. They use the spatial lag model, which includes the spatial lagged dependent variable to model spillovers. They find a strong and positive spatial correlation for hospital treatments. However, they do not consider hospital ownership as an aspect of quality disparity.

In addition to spillover effects, the spatial Durbin model allows us to examine whether the market structure affects the treatment rates. The market of medical services is composed of hospitals with different characteristics, such as ownership and size. As suggested by Horwitz and Nichols (2009), hospitals have different treatment decisions based on the market structure they are facing. We cannot assume the spillover effects are the same for all types of markets. Operational strategies of hospitals may not only differ by the type of ownership but may also respond to the type of ownership of neighbors.

We use clinical process treatment rates from Hospital Compare as our dependent variable. Compared to other measures, like the mortality rate or the length of hospital stays, the process treatment rates are less noisy and reflect real hospital medical services. Our study finds strong and positive spillover effects among hospitals for heart attack patients. The spillover effects are even stronger for less acute illness conditions like heart failure and pneumonia. We find some evidence that not-for-profit hospitals provide better medical services than government and for-profit hospitals, but the treatments also differ by the market structure. Hospitals in a market with stronger intensity of not-for-profit hospitals are more likely to provide medications at discharge but less likely to perform percutaneous coronary intervention (PCI) in time. Moreover, the treatment rates of hospitals decrease if they are surrounded by large hospitals. The overall effect depends on the characteristics of the hospital, the spillover effects, and the market structure.

## 2. Literature Review

Unlike most of the industries that are composed of for-profit firms, about 60% of the non-federal hospitals in the United States were not-for-profit and only 20% were for-profit in 2010. As Horwitz and Nichols (2009, p.925) summarize in their Table 1, there are four theories of not-for-profit hospitals: (1) maximizing own output (Newhouse, 1970): not-for-profits are profit-seeking and maximize profitable services as for-profits do. They will offer more health care until profits are driven to zero; (2) maximizing the community output (Lee and Weisbrod, 1977): the goal of not-for-profits is to benefit the whole community and to maximize market output including unprofitable services; (3) for-profit in disguise (Pauly and Redisch, 1973): nonprofits would be essentially identical to for-profit hospitals in equilibrium, with economic profits counted as costs (salaries or perquisites accruing to staff physicians); and (4) a mixture of (1) and (2) (Hirth, 1997): not-for-profits behave depending on the competition level of the market. They are profit-seeking when facing competition.

The empirical studies have mixed results. Tax exemptions allow not-for-profit and government hospitals to provide better quality to the community or more medical care to uninsured patients (Sloan, 2000; Bayindir, 2012). Clement et al. (2002) note that for-profit hospitals provide less charity care than not-for-profits. McClellan and Staiger (2000) also suggest that not-for-profit hospitals treat elderly patients with heart disease slightly better than for-profits hospitals. Sloan et al. (2001) find that for-profit hospitals are more likely to use high-tech procedures with higher costs, while Kessler and McClellan (2002) find that areas with for-profit hospitals have lower hospital expenditures, but virtually the same patient health outcomes. They conclude that for-profit hospitals have important spillover benefits for medical productivity. Geweke, Gowrisankaran, and Town (2003) use a Bayesian model to estimate hospital quality in Los Angeles County. Focusing on elderly pneumonia patients, they find that there is not a definitive difference in mortality rates by hospital ownership. This is in line with the results of Sloan et al. (2001) and Sloan and Taylor (1999). These studies find weak evidence that the mortality rate of Medicare patients and the probability of readmission differ by hospital ownership.

However, when competition and market structure are taken into consideration, several studies suggest that the first or the last theory has more support. Horwitz and Nichols (2009) find not-for-profit hospitals are more likely to provide profitable services in a high for-profit market (15% of for-profit admissions or higher). The spillovers of medical services provided make not-for-profit hospitals behave more like for-profits in a high for-profit market. The role of hospital ownership is less important when the competition level increases. Not-for-profits compete with for-profit hospitals by providing better quality of health care (Sloan, 2000). McClellan and Staiger (2000) also suggest that the growing difference in mortality rates of the elderly AMI patients between for-profit and not-for-profit hospitals may be attributed to various factors, including location. Hospitals compete by providing better quality even though improving quality can be very costly (Morey et al., 1992). Fournier and Mitchell (1992) and Robinson and Luft (1985) suggest that increased competition is usually associated with increased cost. Propper, Burgess, and Green (2004) on the other hand argue that increased competition may lower hospital quality[5]. The treatment decisions may depend on the competition level of the market the hospitals are located in.

Besides competition, knowledge spillovers among physicians could also cause spatial correlations. Physicians are more likely to practice intensive treatments in a market with advanced medical technologies. Chandra and Staiger (2007) find that spillovers of technology increase the treatment rate in the market. Cardiac catheterization rate of AMI patients is higher in a market with a higher propensity for intensive treatments. Physicians learn practice skills from other physicians, and possibly transfer these skills to other hospitals due to job movement or due to these physicians working at multiple hospitals. About 40% of physicians with inpatient duty work at more than one hospital (Fisher et al., 2007). This mobility increases the probability of exchanging knowledge among physicians. Therefore, interactions and spatial correlations of treatments among hospitals should not be neglected when we examine hospital treatment rates.

A similar perspective from urban economists is agglomeration. Firms (hospitals) may operate more efficiently with geographical concentration due to economies of scale or technology spillovers (Breschi and Lissoni, 2001; Cohen and Morrison Paul, 2008; Baicker and Chandra, 2010). The geographical clusters of firms may be due to “labor pooling”. Firms (hospitals) may lower costs due to a larger and better pool of labor (Cohen and Morrison Paul, 2008). In addition, firms (hospitals) adopt new innovation more rapidly when this innovation has high financial incentives (Baicker and Chandra, 2010). Cohen and Morrison Paul (2008) use data on hospitals in Washington State and find that clustering reduces labor costs in several treatment centers. Baicker and Chandra (2010) examine the “high-value care” with Hospital Compare

[5] There are other studies that suggest competition improve cost-effectiveness and generate economy of scale (Dranove, Shanley, and Simon, 1992; Kessler and McClellan, 2000, Zwanziger and Melnick, 1988). Bloom et al. (2010) find that competition increases management quality of the public hospitals in the U.K.

treatment rates and "low-value care" with end-of-life spending of Medicare beneficiaries. Their results suggest that hospital quality is positively associated with neighbors' quality even though they do not control for the distance between the hospitals and only measure the overall treatment score.

Mobley et al. (2006) study this geographic correlation of health care in the U.S. They use Admissions for Ambulatory Care Sensitive Conditions (ACSCs) among elderly patients in the late 1990s as the preventive care utilization measure. ACSCs are preventable admissions and therefore can be an indicator of *poor quality*. They use a spatial lag model with both maximum likelihood and two stage least squares methods. They find strong and positive spatial correlations. More ACSCs in neighboring hospitals are associated with an increase in ACSCs for the hospital itself. The utilization rates are not significantly different between the elderly living in poor rural areas and those living in urban areas.

## 3. Data and methodology

We model hospital treatment rates using the spatial Durbin panel model given by

$$y_t = \lambda W y_t + H_t \gamma_1 + X_t \beta + W H_t \gamma_2 + \varepsilon_s + \tau_t + u_t \qquad t=1,2,..,T$$

$$u_{it} = \mu_i + v_{it} \qquad i=1,2,..,N$$

where $y_t$ is an (Nx1) vector of treatment rates for N hospitals at time t. W is an (NxN) spatial weight matrix, whose diagonal elements are zero and whose off diagonal elements are the normalized inverse distance from hospital i to hospital j. This weight matrix is row-normalized, i.e., the elements in each row sum to one, $\sum_{j=1}^{N} w_{ij} = 1$. $Wy_t$ is the spatial lagged dependent variable, which presents the weighted average treatment rates of neighboring hospitals. As we mentioned earlier, the treatment rates of own hospital may be affected by the treatment rates of neighboring hospitals through competition or knowledge spillovers. $\lambda$ thus measures the spillover effect of hospital treatment rates. $H_t$ is an (Nxk) matrix of hospital characteristics, and $X_t$ is an (Nxc) matrix of county demographic variables where hospital i is located. $\varepsilon_s$ and $\tau_t$ are state and year fixed effects. $u_t$ is an (Nx1) vector of error component disturbances. As the second equation shows, the typical element of $u_{it}$ is the hospital random effect $\mu_i$ and a remainder classical disturbance $v_{it}$. $\mu_i$ is assumed to be i.i.d. $(0, \sigma_\mu^2)$ and $v_{it}$ is assumed to be i.i.d. $(0, \sigma_v^2)$. $\mu_i$ and $v_{it}$ are independent of each other and the regressors $H_t$ and $X_t$.

Our panel data consists of all hospitals in the 48 continental states that reported their treatment rates every year from 2005 to 2008. Neighboring hospitals are those within a 30 miles radius. Thirty miles may seem arbitrary, but Horwitz and Nichols (2007) indicate that 90% of the discharges are from a mean radius of 21.5 miles of non-rural hospitals, compared to 25.2 miles for rural hospitals. Therefore, 30 miles seems reasonable to cover the potential market. In order to measure the spillover effects, we only include hospitals with at least one neighbor within the 30-mile radius. The maximum number of hospital neighbors is 109 and the average number of neighbors for each hospital is 20.56.

Our dependent variables are the treatment rates from Hospital Compare of the Centers for Medicare and Medicaid Services. This data set was released in 2004. The treatment rates are the percentages of the eligible adult patients who were actually given seven clinical processes of care for heart attack treatments[6]. Instead of examining the spillover effects on each of the seven AMI clinical processes separately, we combine them into four categories: (1) overall treatment rate; (2) giving aspirin and/or beta blockers at arrival; (3) prescribing aspirin/beta blockers/angiotensin

[6] Hospital Compare includes 17 clinic processes of care in total for heart attack, heart failure, and pneumonia.

converting enzyme (ACE) inhibitors at discharge; and (4) giving percutaneous coronary intervention (PCI) within 120 minutes of arrival[7]. The first category refers to the average of all treatments offered to AMI patients. The medications are similar in the second and third categories, but the timing of prescriptions indicates different treatment purposes. The second category indicates timely treatments that can relieve the conditions. The third category implies preventive treatments to reduce the probability of readmissions. These three categories are obtained using a weighted average where the weights are the number of cases in each process. PCI is a coronary angioplasty. It is a relatively high intensity treatment, which requires skilled staff and equipment.

A heart attack is a very acute condition, and patients need immediate medical care. They are most likely to be taken to hospitals in distinct local markets[8]. This precludes patients from travelling long distances to seek care and in turn being less likely to select the hospital they like. In addition, hospitals need to treat patients who check in to the emergency room, regardless of their insurance type. Focusing on heart attack processes allow us to reduce the selection issue between patients and hospitals. As Chandra and Staiger (2007, p.117) put it: "markets for heart attack treatment are geographically distinct…mobility is limited, and it is possible to observe production in many distinct local markets." One may argue that the competition or spillover can be limited due to this reason. However, the interactions between hospitals should have an impact on overall quality or specialized fields, rather than only on specific treatments or illness condition.

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[7] Smoking consultation is also included in the overall treatment receiving rate.

[8] Even if patients travel four to five miles for better treatments as suggested by Tay (2003), these hospitals may still be within one market according to our definition of neighborhood.

There are several advantages of using Hospital Compare as our quality measures. First, the processes reflect the real medical services that are delivered to patients in a timely manner. Even though using health outcomes, such as mortality rate, as quality measures can cover unobservable factors, they could be noisy due to relatively low mortality probability (McClellan and Staiger, 2000). The processes in Hospital Compare are timely and effective for patients. Many of the processes for AMI patients are recommended in the ACC/AHA Guidelines for the Management of Patients with Acute Myocardial Infarction (1999). Second, most of these processes are not intensive or require advanced technologies. Hospitals should be able to provide the treatments regardless of the size and the specialization of the hospital. We acknowledge that these are the basic treatments, which can be achieved easily. One hospital with lower treatment rates may not guarantee a worse overall quality. It may focus on other medical and non-medical services that are not included in the data, such as open heart surgery. However, these non-intensive treatments, such as giving beta blockers, serve as a marker of the quality of non-intensive medical management in a hospital, see Chandra and Staiger (2007, p.118). Heidenreich and McClellan (2001) and Rogers et al. (2000) find that giving aspirin/beta blockers/ACE inhibitors is the major reason for increasing survival rate following AMI. Third, these measures only include patients who are appropriate for the treatments. One limitation of our data is that it is at the hospital level. Without patient-level data, we have no information about the characteristics and illness severity of patients.

Data for the hospital characteristics are taken from the AHA Guide and Provider of Services File and the Centers for Medicare and Medicaid Services, which includes: indicators of not-for-profit hospitals, for-profit hospitals, teaching hospitals[9], and locating in an MSA; number of beds; number of nurses per bed; HHI; and CMI. Herfindahl-Hirschman Index (HHI) is the sum of squares of each hospital's market share based on the number of beds within its neighborhood. HHI is an indicator of market concentration/competition. A larger index indicates a lower concentration of the health care market. The market may be dominated by one large hospital and few small hospitals. To overcome one of the shortages of the Hospital Compare data, we use Case Mix Index (CMI) to control for the average severity of the patients in the hospital. CMI indicates the average cost per patient. A larger CMI means more complicated processes/treatments are offered to patients. The spatial lagged hospital characteristics, $\mathrm{WH}_t$, include indicators of for-profit, not-for-profit, and teaching hospitals; number of beds; and number of nurses per bed. $\gamma_2$ represents the spillover effects of neighboring hospitals' characteristics.

The characteristics of potential patients are controlled by county demographic variables, which are from the American Community Survey of the U.S. Census Bureau. This data set includes only counties with a population of 65,000 and above in 2005 and 2006. Therefore, hospitals in our data are located in relatively more urbanized areas. We control for percentages of never married individuals age 15 and above, high school dropouts, high school graduates, male, Hispanic, black, and elderly (age 65 and above); median earnings; and population density per square mile. One may argue the disparity of health care quality is due to geographic heterogeneity. Patients receive better treatment because they are located in an area with better

[9] Teaching hospitals include hospitals with Council of Teaching Hospitals designation, hospitals approved to participate in residency and/or internship training by the Accreditation Council for Graduate Medical Education, and those with medical school affiliation reported to the American Medical Association.

medical care resources. These county demographic variables are good proxies for geographical heterogeneity.

Table 1 presents the descriptive statistics of our data. The treatment rates of the four heart attack treatment categories have large means and small minimum values. This suggests that the distributions of treatment rates are skewed. Out of 2342 hospitals in our sample, 18.5% are for-profit, 68.7% are non-profit hospitals. The proportion of non-profit hospitals is slightly higher than the national average but closer to that in the non-rural areas (Horwitz and Nichols, 2007). Of these hospitals, 41.2% have teaching status and 89.4% are located in MSAs. The average number of beds is 263 and the average number of nurses per bed is 1.1. The average (median earnings) is $33,790 and the average population density is 2,230 individuals per square mile. Among the potential patients, 30.9% are never-married, 44% have at most a high school degree, 12.5% are elderly, 14.5% are Hispanic and 12.5% are black.

## 4. Empirical Results

We estimate our spatial Durbin panel data model using the generalized moments (GM) estimator[10] with random effects. See LeSage and Pace (2009) for a nice introduction of the spatial Durbin model and Kapoor, Kelejian and Prucha (2007) for details on the GM methodology. Also, Mutl and Pfaffermayr (2010) for an extension of the GM methodology to the spatial lag model and Debarsy (2012) for the spatial Durbin model. See also Elhorst (2003) for maximum likelihood estimation of spatial lag panel models, and Lee and Yu (2010) and Baltagi (2011) for recent surveys of spatial panels.

[10] We use the full set of moment conditions, see Millo and Piras (2012) for details. We also estimate the model using maximum likelihood estimation (MLE) using XSMLE: Stata module for spatial panel data model estimation, see Belotti, Hughes, and Mortari (2013). The MLE results were similar to those using the GM estimator except for smaller estimates of lambda. However, all the lambda estimates were statistically significant at the 1% significance level. These results are available upon request from the authors.

Table 2 presents the spillover effects of the heart attack treatment rates using a GM estimator. Some of the diagnostics performed include testing the joint significance of the state dummies as well as the time dummies. These were jointly significant for all models considered. Similarly, the hospital random effects are significant for all models. The first two columns show the GM estimation of the overall heart attack treatment rate. Without controlling for the market structure in the first column, we find that not-for-profit hospitals provide similar health care to heart attack patients as government hospitals. Surprisingly, the treatments in for-profit hospitals are significantly worse than not-for-profit and government hospitals. The number of beds, the number of nurses per bed, and being a teaching hospital are all positively associated with hospital quality. These are in line with the studies of Keeler et al. (1992) and Geweke, Gowrisankaran, and Town (2003). Yuan et al. (2000) also find that teaching not-for profit hospitals have lower mortality rates and infer that they provide over-all better quality of care. Aiken et al. (2002) report that a higher patient-per-nurse ratio increases the mortality rate of AMI. A hospital located in a less concentrated market lowers its treatment rates and offers better treatments if it generally has higher CMI, i.e., higher average cost per patient. We find little evidence that demographic variables affect hospital treatments. Hospitals provide lower quality in an area with more Hispanics and blacks, given everything else held constant.

The estimate of lambda indicates the magnitude of spillover effects among hospitals. For the overall treatment rate in column (1), the spatial correlation coefficient estimate is 0.263 without the measures of market structure. This suggests that when the average heart attack treatment rate of neighboring hospitals increases by 1%, the hospital’s treatment rate also increases by 0.263%. This effect is not trivial but smaller than the results found by Mobley et al. (2006).

After adding the market structure variables in column (2), the estimation results are similar to those in column (1). However, the effect of blacks is no longer significant. The lambda estimate increases to 0.381. Ownership of neighboring hospitals does not impact its own quality. Hospitals provide fewer treatments in a market with teaching hospitals and larger neighboring hospitals. The significance of market structure variables suggest that ignoring these may generate biased results. In addition, these results suggest that the treatment decisions of hospitals may be associated with a higher quality of neighbors rather than the distribution of hospital ownership in the market. Larger hospitals provide more health care, but when a hospital is close to larger hospitals, its treatment rates are lower. Columns (3) to (8) decompose the overall treatment into more specific heart attack treatments. Focusing on the estimation with market structure variables, we find evidence that for-profit hospitals provide fewer medications to patients after they arrive and before they are discharged than government hospitals. Not-for-profit hospitals have a higher PCI treatment rate than government hospitals. We find that number of beds, number of nurses per bed, and teaching status are positively associated with the medication treatment rates at both arrival and discharge, but not with PCI. The number of nurses per bed has relatively strong effects, but the number of beds is not significant. On the other hand, the number of nurses has little effect on medication at discharge. Teaching hospitals are more likely to give medications to heart attack patients. This is in line with the suggestion of Sloan (2000) that major teaching hospitals have better quality and non-teaching government hospitals have the worst outcome for elderly patients. What is interesting is that teaching status is negatively associated with the PCI treatment rate. This could be because teaching hospitals have longer waiting time to perform PCI than other hospitals (Nallamothu et al, 2005).

A hospital located in a less concentrated market gives fewer medication to heart attack patients at arrivals and it offers more of all the heart attack treatments if it generally has larger CMI. Hospitals provide fewer PCI treatments in areas with high never-married population and high school graduates.

The lambda estimates range from 0.233 to 0.464. Focusing on estimation with market structure, a 1% increase in average treatment rate of each category in neighboring hospitals is associated with an increase of 0.31%, 0.41%, and 0.46%, respectively, in the hospital's own treatment rate. The spillover effect of PCI is relatively larger than other treatments. The strong and positive spatial correlation of PCI confirms the results of Chandra and Staiger (2007). Hospitals are more likely to perform these treatments in a market with a high propensity of intensive treatments.

Except for the number of beds, market structure has different impacts on each treatment category. With not-for-profit hospitals in the market, a hospital is more likely to prescribe medications at discharge but less likely to perform PCI. All the treatments decrease when there are larger hospitals nearby. Interestingly, a hospital prescribes fewer medications at discharge when there are teaching hospitals in its neighborhood.

## 5. Spillover Effects on Other Illness Conditions

Hospital Compare also includes four processes of heart failure and six processes of pneumonia[11]. These two illness conditions are less acute in the sense that patients have more

[11] The processes of heart failure include an evaluation of the left ventricular systolic function, ACE inhibitor, discharge instructions, and smoking cessation advice during a hospital stay. The processes of pneumonia include giving initial antibiotic within 4 hours of arrival, screening for pneumococcal vaccination status, giving oxygenation, performing blood culture prior to the first hospital dose of antibiotics, giving smoking cessation advice, and giving appropriate initial antibiotics to immune-competent patients with pneumonia during the first 24 hours after arrival.

likelihood to travel further for treatments, or for preferred physicians, or for insurance reasons. Hence, we expect the effects of competition among hospitals and the geographic heterogeneity to be stronger. We combine these treatments for each illness condition and apply the previous spatial panel Durbin model to the average treatment rates of heart failure and pneumonia.

The GM estimation results are presented in Table 3. The first two columns are the estimation of heart failure treatments and the latter two columns are for pneumonia treatments. Focusing on the estimation with market structure, the results in column (2) suggest that not-for-profit hospitals provide more treatments than government hospitals. When the average severity of patients (CMI) in the hospitals is high, hospitals provide better treatments to heart failure patients. The lambda estimate indicates that when neighboring hospitals increase their heart failure treatment rate by 1% on average, it increases its own hospital treatment rate by around 0.553%. Similar to heart attack treatments, larger hospitals in the neighborhood decrease the treatment rates of own hospital. The severity level of patients (CMI) in the neighboring hospitals lowers the heart failure treatment rates in own hospitals.

Column (4) suggests that both for-profit and not-for-profit hospitals provide more pneumonia treatments than government hospitals. Teaching hospitals, however, are less likely to provide these pneumonia treatments. Hospitals also provide fewer treatments to areas with high minority populations. The lambda estimate indicates that when neighboring hospitals increase their pneumonia treatment rates by 1% on average, it increases its own hospital treatment rate by around 0.54%. Hospitals have lower treatment rates when they have for-profit and not-for-profit hospitals in their neighborhoods.

## 6. Discussion

Our results suggest that not-for-profit hospitals provide better quality, especially for cardiac treatments. One of the possible explanations is that for-profit hospitals are more aggressive on cost control. Eggleston and Shen (2011) find that the mortality rate for elderly heart attack patients is higher in for-profit hospitals, because they have more restrictive budget constraints. McKay and Deily (2008) also suggest that reductions in costs are associated with adverse consequences on health outcomes. In addition, not-for-profit hospitals enjoy tax exemptions. They are able to transfer the profit to services that are beneficial to patients. If the not-for-profit hospitals provide better services due to tax exemption, charitable obligations may benefit heart attack patients.

We find a tendency for some hospitals to favor high technologies or use intense treatments rather than less intense treatments as suggested in Skinner and Staiger (2009) and Chandra and Staiger (2007). Teaching hospitals provide more medication but less PCI. However, we are not able to draw a fine line based on ownership. For-profit hospitals are less likely to provide medication while not-for-profits favor PCI. In addition, the effect of ownership depends upon treatments and market structure. The results on PCI treatments suggest that not-for-profit hospitals provide better intense heart attack treatments in an inter-sectoral market. When a market has only for-profit or only not-for-profit hospitals, there is no significant effect or the effects are traded off. However, when a not-for-profit hospital is located in a high for-profit market, the PCI treatment rate is significantly higher. According to the study of Horwitz and Nichols (2009), PCI is a relatively profitable service. This result is in line with their study that not-for-profits provide more profitable services in a high for-profit market. On the other hand, when for-profit hospitals locate in a high not-for-profit market, they improve their quality by providing more medication before they discharge the patients. Not-for-profit hospitals provide better heart failure treatment regardless of the ownership composition in the market. Ownership of neighboring hospitals offset the high pneumonia treatment rates of for-profit and not-for-profit hospitals. Therefore, our results on hospital ownership are mixed.

Our results support the competition hypothesis. Hospitals have lower treatment rates when they compete with hospitals of better quality. Competition may generate both positive and negative externalities at the same time. Also, when a hospital has a larger neighbor, there is a higher probability of empty beds which is costly (Gaynor and Anderson, 1995). Hospitals with more beds have diseconomy of scale. The cost may increase with increasing beds (Keeler, Melnick, and Zwanziger, 1999). Hospitals may offer fewer treatments for financial reasons.

As expected, we also find that the spillover effect is stronger for less acute illness treatments than heart attack treatments. Less acute illnesses allow patients to travel further, making the competition among hospitals to increase. Positive externalities from competition and knowledge spillover improve medical services in the whole market. As an anonymous referee notes: “the type of competition in which hospitals engage is a local form of competition, among neighboring hospitals, as opposed to a global form of competition, where all hospital compete with each other regardless where they are geographically located and that could be valid for other types of disease, such as cancer”.

We also examine the sensitivity of our results to changing the radius from 30 miles to 25 and 35 miles. The results are given in Tables 4 and 5. The effects on own hospital characteristics remain similar. What is interesting is that the spillover effect and the effects of neighborhood characteristics are slightly stronger as we expand the market range, except for PCI treatment. When one hospital is considered to be able to affect another hospital at a further distance, the market power or knowledge spillover effect increases. One can argue that basic treatments are easy to obtain and learn from sources that are not bounded by geographical distance. However, PCI is “tacit knowledge” that is mainly transferred by face-to-face contact or hands-on apprenticeship. Tacitness has spatial limitation and the knowledge property regimes are fairly local (Breschi and Lissonni, 2001). Expanding the market makes the spillover relatively smaller.

Our results corroborate similar findings for France by Gobillon and Milcent (2012). These authors find that local composition of ownership and demographic variables have limited effects on spatial disparity of innovative treatments in France. They also find strong spillover effects and suggest that regional unobservable factors account for 20% of spatial disparities.

Since the overall effect depends upon the characteristics of the hospital itself, spillovers and market structure, this may explain why Gaynor (2006) suggests a mixed result for the effect of competition on hospital quality. Vickers and Yarrow (1988) also conclude that the competition level in the market could be a more important determinant of performance than type of ownership.

## 7. Conclusion

Our study employs a spatial Durbin panel data model to control for geographic correlation of treatments among hospitals. Our results suggest strong and positive spillover effects among hospitals. Our results should be tempered by the fact that we included basic treatments which were limited by data availability. Some hospitals may perform other effective treatments which are not available in our data set. In addition we only focused on three illness conditions. Some hospitals may provide better quality care treatments for other illness conditions not reported in our data set.

Our results on hospital ownership are mixed. While we find some evidence that hospitals have different operation strategies by ownership**,** this also depends on the market structure where the hospital is located. One thing that policy makers should not ignore is the effect of spillovers which we found to be strong and significant.

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Figure 1. Geographic Distribution of the Summary Hospital Compare Quality Score in Hospital Referral Regions

Figure 1a. Overall

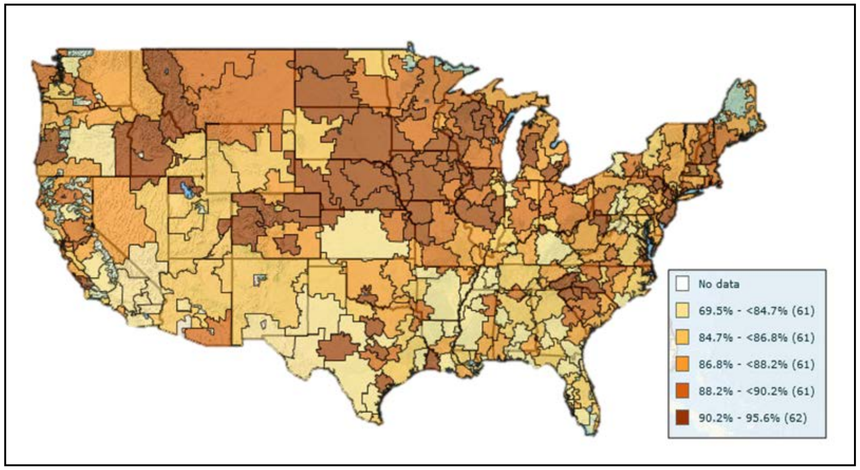



Figure 1b. Heart Attack

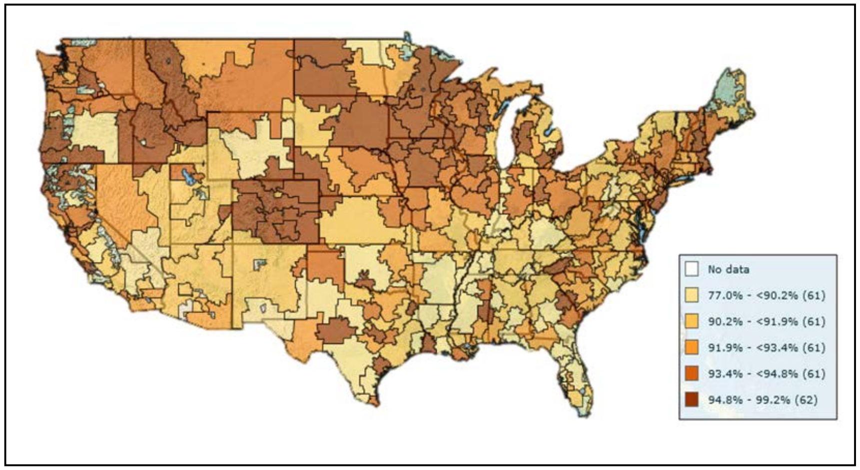



Figure 1c. Heart Failure

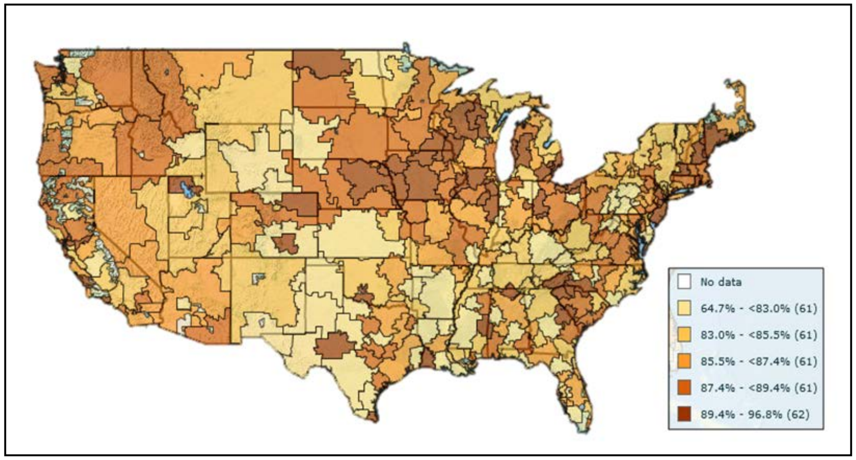
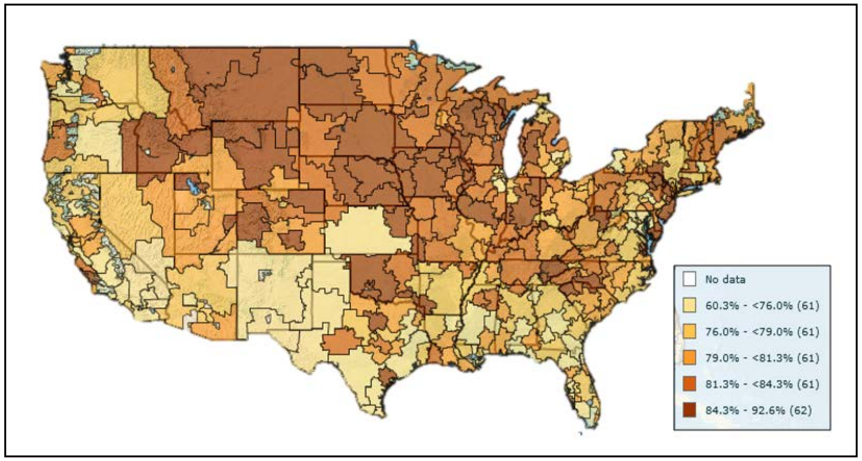



Figure 1d. Pneumonia




*Source: The Dartmouth Atlas of Health Care (The Dartmouth Institute for Health Policy and Clinical Practice).*

Table 1. Descriptive Statistics

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| *Dependent Variables:* | | | | |
| Heart Attack Treatments: | | | | |
| Overall | 0.921 | 0.065 | 0.257 | 1 |
| Medication at arrival | 0.934 | 0.063 | 0.28 | 1 |
| Medication at discharge | 0.917 | 0.086 | 0 | 1 |
| PCI | 0.627 | 0.197 | 0 | 1 |
| | | | | |
| Heart Failure Overall Treatments: | 0.797 | 0.129 | 0.05 | 1 |
| Pneumonia Overall Treatments: | 0.835 | 0.082 | 0.447 | 1 |
| | | | | |
| *Independent Variables:* | | | | |
| For-profit | 0.185 | 0.389 | 0 | 1 |
| Not-for-profit | 0.687 | 0.464 | 0 | 1 |
| Number of beds (in 100's) | 2.632 | 2.103 | 0.04 | 22.07 |
| Nurses per bed | 1.102 | 0.522 | 0.2 | 7.04 |
| Teaching Status | 0.412 | 0.49 | 0 | 1 |
| Located in an MSA | 0.894 | 0.308 | 0 | 1 |
| HHI | 0.137 | 0.172 | 0.001 | 0.971 |
| CMI | 1.456 | 0.262 | 0.642 | 4.992 |
| % never married | 0.309 | 0.06 | 0.166 | 0.557 |
| % HS dropouts | 0.151 | 0.059 | 0.018 | 0.418 |
| % HS grads | 0.29 | 0.067 | 0.116 | 0.55 |
| Median earnings (in 10,000's) | 3.379 | 0.061 | 1.741 | 6.09 |
| % male | 0.49 | 0.011 | 0.445 | 0.58 |
| % Hispanic | 0.145 | 0.159 | 0 | 0.951 |
| % black | 0.126 | 0.129 | 0 | 0.668 |
| % elderly | 0.125 | 0.033 | 0.046 | 0.335 |
| Population density (in 10,000's) | 0.223 | 0.668 | 0.001 | 0.716 |

Table 2. Estimates of Spillover Effects and Hospital Characteristics on Heart Attack Treatments

| Treatment | Overall | | Medication at arrival | | Medication at discharge | | PCI | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| For-profit | -0.008** | -0.008** | -0.011*** | -0.011*** | -0.012** | -0.012** | 0.011 | 0.015 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.018) | (0.019) |
| Not-for-profit | 0.005 | 0.004 | 0.001 | 0.000 | 0.002 | 0.000 | 0.057*** | 0.058*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.016) | (0.016) |
| Number of beds | 0.002*** | 0.003*** | 0.002*** | 0.002*** | 0.004*** | 0.004*** | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Nurses per bed | 0.007*** | 0.006*** | 0.006*** | 0.006*** | 0.004* | 0.004 | 0.035*** | 0.033*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.009) | (0.009) |
| Teaching Status | 0.008*** | 0.009*** | 0.008*** | 0.009*** | 0.013*** | 0.015*** | -0.024** | -0.024** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.010) | (0.010) |
| Located in an MSA | 0.002 | 0.004 | -0.001 | 0.001 | 0.002 | 0.005 | 0.026 | 0.025 |
| | (0.005) | (0.005) | (0.004) | (0.004) | (0.006) | (0.006) | (0.033) | (0.034) |
| HHI | -0.017* | -0.016* | -0.021** | -0.020** | -0.021* | -0.018 | -0.011 | -0.009 |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.012) | (0.012) | (0.050) | (0.050) |
| CMI | 0.043*** | 0.044*** | 0.042*** | 0.043*** | 0.067*** | 0.068*** | 0.040** | 0.045** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.006) | (0.006) | (0.020) | (0.020) |
| % never married | 0.043 | 0.047* | 0.034 | 0.036 | 0.053 | 0.056 | -0.323** | -0.296* |
| | (0.028) | (0.028) | (0.027) | (0.028) | (0.037) | (0.038) | (0.153) | (0.154) |
| % HS dropouts | -0.046 | -0.039 | -0.039 | -0.037 | -0.067 | -0.047 | -0.057 | -0.100 |
| | (0.031) | (0.031) | (0.030) | (0.031) | (0.042) | (0.043) | (0.174) | (0.176) |
| % HS grads | -0.001 | -0.007 | -0.003 | -0.009 | -0.029 | -0.035 | -0.259* | -0.230* |
| | (0.024) | (0.025) | (0.024) | (0.024) | (0.033) | (0.033) | (0.132) | (0.133) |
| Median earnings | 0.003 | 0.004 | 0.004 | 0.005 | 0.001 | 0.003 | -0.010 | -0.009 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.017) | (0.018) |
| % male | 0.040 | -0.000 | 0.119 | 0.091 | 0.056 | -0.017 | 0.594 | 0.647 |
| | (0.109) | (0.110) | (0.108) | (0.109) | (0.148) | (0.150) | (0.636) | (0.640) |
| % Hispanic | -0.023* | -0.009 | -0.009 | 0.001 | -0.037** | -0.015 | -0.078 | -0.066 |
| | (0.013) | (0.014) | (0.013) | (0.013) | (0.018) | (0.018) | (0.074) | (0.076) |
| % black | -0.033** | -0.023 | -0.020 | -0.012 | -0.037* | -0.024 | -0.144* | -0.117 |
| | (0.015) | (0.015) | (0.014) | (0.014) | (0.019) | (0.020) | (0.081) | (0.082) |
| % elderly | 0.030 | 0.040 | 0.037 | 0.045 | 0.071 | 0.084 | -0.045 | -0.105 |
| | (0.051) | (0.051) | (0.049) | (0.049) | (0.067) | (0.068) | (0.270) | (0.273) |
| Population density | -0.003 | -0.002 | -0.002 | -0.002 | -0.005* | -0.004 | -0.006 | -0.006 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.011) | (0.011) |
| **Spatial (λ)** | 0.263*** | 0.381*** | 0.233*** | 0.309*** | 0.246*** | 0.414*** | 0.373*** | 0.464*** |
| | (0.060) | (0.076) | (0.064) | (0.082) | (0.061) | (0.081) | (0.089) | (0.085) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Market Structure: | | | | | | | | |
| For-profit | | 0.001 | | 0.000 | | 0.008 | | 0.000 |
| | | (0.007) | | (0.007) | | (0.009) | | (0.028) |
| Not-for-profit | | 0.010 | | 0.009 | | 0.017** | | -0.058** |
| | | (0.006) | | (0.006) | | (0.008) | | (0.024) |
| Number of beds | | -0.003*** | | -0.003*** | | -0.004*** | | -0.007** |
| | | (0.001) | | (0.001) | | (0.001) | | (0.003) |
| Nurses per bed | | 0.001 | | 0.004 | | 0.002 | | -0.023 |
| | | (0.004) | | (0.004) | | (0.005) | | (0.016) |
| Teaching Status | | -0.006* | | -0.002 | | -0.011** | | 0.023 |
| | | (0.004) | | (0.004) | | (0.005) | | (0.015) |
| CMI | | -0.008 | | -0.010 | | -0.013 | | -0.014 |
| | | (0.009) | | (0.009) | | (0.011) | | (0.028) |
| State fixed effect? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| F-test for state fixed effects | 4.34*** | 3.49*** | 4.37*** | 3.63*** | 4.42*** | 3.27*** | 3.39*** | 3.38*** |
| F-test for year fixed effects | 88.06*** | 87.16*** | 63.6*** | 62.71*** | 77.96*** | 77.33*** | 21.24*** | 21.4*** |
| Number of hospitals | 2,056 | 2,056 | 2,056 | 2,056 | 2,056 | 2,056 | 935 | 935 |
| Observations | 8,224 | 8,224 | 8,224 | 8,224 | 8,224 | 8,224 | 3,740 | 3,740 |

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 3. Estimates of Spillover Effects and Hospital Characteristics on Heart Failure and Pneumonia Treatments

| Treatment | Heart Failure | | Pneumonia | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| For-profit | -0.006 | -0.005 | 0.010*** | 0.010*** |
| | (0.007) | (0.007) | (0.004) | (0.004) |
| Not-for-profit | 0.020*** | 0.020*** | 0.021*** | 0.022*** |
| | (0.006) | (0.006) | (0.003) | (0.003) |
| Number of beds | 0.001 | 0.002 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Nurses per bed | 0.010*** | 0.010*** | 0.001 | 0.001 |
| | (0.004) | (0.004) | (0.002) | (0.002) |
| Teaching Status | -0.002 | 0.001 | -0.008*** | -0.007*** |
| | (0.004) | (0.004) | (0.002) | (0.002) |
| Located in an MSA | -0.002 | 0.004 | 0.000 | 0.002 |
| | (0.009) | (0.009) | (0.005) | (0.005) |
| HHI | -0.029* | -0.028 | -0.008 | -0.010 |
| | (0.017) | (0.018) | (0.009) | (0.009) |
| CMI | 0.061*** | 0.063*** | -0.003 | -0.002 |
| | (0.008) | (0.008) | (0.004) | (0.004) |
| % never married | -0.078 | -0.064 | -0.007 | -0.003 |
| | (0.055) | (0.055) | (0.028) | (0.028) |
| % HS dropouts | -0.020 | -0.032 | 0.005 | 0.001 |
| | (0.058) | (0.059) | (0.029) | (0.029) |
| % HS grads | 0.046 | 0.023 | 0.019 | 0.017 |
| | (0.048) | (0.049) | (0.024) | (0.024) |
| Median earnings | 0.003 | 0.003 | 0.004 | 0.004 |
| | (0.006) | (0.006) | (0.003) | (0.003) |
| % male | -0.319 | -0.359* | -0.031 | -0.043 |
| | (0.206) | (0.209) | (0.106) | (0.106) |
| % Hispanic | 0.013 | 0.022 | -0.022* | -0.026** |
| | (0.024) | (0.025) | (0.013) | (0.013) |
| % black | -0.014 | -0.001 | -0.025* | -0.028* |
| | (0.028) | (0.029) | (0.015) | (0.015) |
| % elderly | 0.020 | 0.020 | 0.001 | 0.001 |
| | (0.098) | (0.099) | (0.050) | (0.051) |
| Population density | 0.001 | 0.001 | 0.001 | -0.001 |
| | (0.004) | (0.004) | (0.050) | (0.002) |
| **Spatial (λ)** | 0.482*** | 0.553*** | 0.608*** | 0.540*** |
| | (0.067) | (0.070) | (0.068) | (0.065) |

| | | | | |
|---|---|---|---|---|
| Market Structure: | | | | |
| For-profit | | -0.008 | | -0.018** |
| | | (0.014) | | (0.007) |
| Not-for-profit | | 0.000 | | -0.016*** |
| | | (0.012) | | (0.006) |
| Number of beds | | -0.004* | | -0.001 |
| | | (0.002) | | (0.001) |
| Nurses per bed | | -0.002 | | 0.001 |
| | | (0.007) | | (0.004) |
| Teaching Status | | -0.002 | | -0.005 |
| | | (0.007) | | (0.004) |
| CMI | | -0.033** | | -0.006 |
| | | (0.026) | | (0.008) |
| State fixed effect? | Yes | Yes | Yes | Yes |
| Year fixed effect? | Yes | Yes | Yes | Yes |
| F-test statistic for state fixed effects | 5.27*** | 4.84*** | 8.70*** | 7.99*** |
| F-test statistic for year fixed effects | 241.1*** | 240.7*** | 621.33*** | 623.75*** |
| Number of hospitals | 2,130 | 2,130 | 2,065 | 2,065 |
| Observations | 8,520 | 8,520 | 8,260 | 8,260 |

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 4. Estimates of Spillover Effects and Hospital Characteristics with a 25-mile market radius

| | Heart Attack | | | | Heart Failure | Pneumonia |
|---|---|---|---|---|---|---|
| Treatment | Overall | Medication at arrival | Medication at discharge | PCI | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| For-profit | -0.009** | -0.012*** | -0.012** | 0.011 | -0.006 | 0.010** |
| | (0.004) | (0.004) | (0.005) | (0.019) | (0.007) | (0.004) |
| Not-for-profit | 0.003 | -0.000 | -0.001 | 0.055*** | 0.020*** | 0.021*** |
| | (0.003) | (0.003) | (0.004) | (0.016) | (0.006) | (0.003) |
| Number of beds | 0.003*** | 0.002*** | 0.004*** | 0.001 | 0.002 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Nurses per bed | 0.006*** | 0.006*** | 0.004 | 0.034*** | 0.010** | 0.000 |
| | (0.002) | (0.002) | (0.003) | (0.010) | (0.004) | (0.002) |
| Teaching Status | 0.009*** | 0.009*** | 0.014*** | -0.023** | -0.002 | -0.007*** |
| | (0.002) | (0.002) | (0.003) | (0.010) | (0.004) | (0.002) |
| Located in an MSA | 0.002 | -0.000 | 0.002 | 0.018 | 0.002 | 0.002 |
| | (0.005) | (0.005) | (0.006) | (0.040) | (0.009) | (0.005) |
| HHI | -0.012 | -0.017** | -0.010 | -0.015 | -0.034** | -0.013 |
| | (0.009) | (0.009) | (0.012) | (0.048) | (0.017) | (0.009) |
| CMI | 0.042*** | 0.041*** | 0.065*** | 0.045** | 0.061*** | -0.003 |
| | (0.004) | (0.004) | (0.006) | (0.020) | (0.008) | (0.004) |
| % never married | 0.044 | 0.034 | 0.056 | -0.338** | -0.086 | -0.007 |
| | (0.029) | (0.028) | (0.039) | (0.160) | (0.057) | (0.029) |
| % HS dropouts | -0.042 | -0.037 | -0.047 | -0.176 | -0.032 | 0.009 |
| | (0.032) | (0.031) | (0.044) | (0.182) | (0.060) | (0.030) |
| % HS grads | 0.004 | -0.002 | -0.015 | -0.227 | 0.030 | 0.016 |
| | (0.025) | (0.025) | (0.034) | (0.139) | (0.050) | (0.025) |
| Median earnings | 0.005 | 0.005* | 0.005 | -0.013 | 0.002 | 0.004 |
| | (0.003) | (0.003) | (0.004) | (0.018) | (0.006) | (0.003) |
| % male | 0.058 | 0.156 | 0.033 | 0.713 | -0.351* | -0.039 |
| | (0.112) | (0.111) | (0.154) | (0.666) | (0.211) | (0.108) |
| % Hispanic | -0.010 | -0.001 | -0.012 | -0.046 | 0.015 | -0.030** |
| | (0.014) | (0.013) | (0.019) | (0.077) | (0.025) | (0.013) |
| % black | -0.020 | -0.010 | -0.020 | -0.097 | -0.001 | -0.029* |
| | (0.015) | (0.015) | (0.020) | (0.084) | (0.029) | (0.015) |
| % elderly | 0.046 | 0.046 | 0.096 | -0.071 | 0.015 | -0.002 |
| | (0.052) | (0.050) | (0.069) | (0.285) | (0.100) | (0.052) |
| Population density | -0.002 | -0.001 | -0.003 | -0.003 | 0.001 | -0.001 |
| | (0.002) | (0.002) | (0.003) | (0.011) | (0.004) | (0.002) |
| **Spatial (λ)** | 0.324*** | 0.215*** | 0.403*** | 0.480*** | 0.509*** | 0.495*** |
| | (0.077) | (0.083) | (0.081) | (0.086) | (0.068) | (0.065) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Market Structure: | | | | | | |
| For-profit | 0.007 | 0.006 | 0.013 | -0.017 | -0.007 | -0.015** |
| | (0.007) | (0.007) | (0.009) | (0.028) | (0.013) | (0.007) |
| Not-for-profit | 0.015** | 0.014** | 0.022*** | -0.077*** | -0.002 | -0.015** |
| | (0.006) | (0.006) | (0.008) | (0.024) | (0.011) | (0.006) |
| Number of beds | -0.003*** | -0.003** | -0.004*** | -0.006* | -0.004* | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.003) | (0.002) | (0.001) |
| Nurses per bed | 0.002 | 0.005 | 0.002 | -0.030* | -0.002 | -0.002 |
| | (0.004) | (0.004) | (0.005) | (0.016) | (0.006) | (0.003) |
| Teaching Status | -0.003 | 0.001 | -0.006 | 0.026* | -0.001 | -0.005 |
| | (0.004) | (0.004) | (0.005) | (0.015) | (0.007) | (0.004) |
| CMI | -0.002 | -0.003 | -0.009 | -0.014 | -0.021 | 0.001 |
| | (0.008) | (0.008) | (0.011) | (0.028) | (0.014) | (0.007) |
| State fixed effect? | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect? | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of hospitals | 2,016 | 2,016 | 2,016 | 908 | 2,092 | 2,029 |
| Observations | 8,064 | 8,064 | 8,064 | 3,632 | 8,368 | 8,116 |

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 5. Estimates of Spillover Effects and Hospital Characteristics with a 35-mile market radius

| | Heart Attack | | | | Heart Failure | Pneumonia |
|---|---|---|---|---|---|---|
| Treatment | Overall | Medication at arrival | Medication at discharge | PCI | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| For-profit | -0.011*** | -0.014*** | -0.015*** | 0.017 | -0.003 | 0.011*** |
| | (0.004) | (0.004) | (0.005) | (0.018) | (0.007) | (0.004) |
| Not-for-profit | 0.001 | -0.004 | -0.003 | 0.056*** | 0.021*** | 0.024*** |
| | (0.003) | (0.003) | (0.004) | (0.016) | (0.006) | (0.003) |
| Number of beds | 0.003*** | 0.002*** | 0.004*** | 0.002 | 0.002 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Nurses per bed | 0.004** | 0.002 | 0.003 | 0.034*** | 0.007* | -0.001 |
| | (0.002) | (0.002) | (0.003) | (0.009) | (0.004) | (0.002) |
| Teaching Status | 0.008*** | 0.008*** | 0.014*** | -0.018* | -0.000 | -0.007*** |
| | (0.002) | (0.002) | (0.003) | (0.010) | (0.004) | (0.002) |
| Located in an MSA | 0.002 | -0.001 | 0.004 | 0.018 | 0.001 | 0.001 |
| | (0.005) | (0.005) | (0.006) | (0.029) | (0.009) | (0.005) |
| HHI | -0.016 | -0.022** | -0.011 | 0.011 | -0.024 | -0.009 |
| | (0.010) | (0.010) | (0.013) | (0.049) | (0.019) | (0.010) |
| CMI | 0.050*** | 0.051*** | 0.073*** | 0.025 | 0.068*** | -0.002 |
| | (0.005) | (0.005) | (0.006) | (0.019) | (0.008) | (0.004) |
| % never married | 0.043 | 0.030 | 0.049 | -0.305** | -0.076 | -0.024 |
| | (0.029) | (0.029) | (0.039) | (0.142) | (0.055) | (0.028) |
| % HS dropouts | -0.037 | -0.041 | -0.033 | -0.124 | -0.019 | -0.012 |
| | (0.032) | (0.032) | (0.043) | (0.169) | (0.058) | (0.030) |
| % HS grads | 0.008 | 0.009 | -0.023 | -0.210 | -0.010 | 0.010 |
| | (0.026) | (0.026) | (0.034) | (0.128) | (0.049) | (0.025) |
| Median earnings | 0.004 | 0.005 | 0.005 | -0.009 | 0.001 | 0.003 |
| | (0.003) | (0.003) | (0.004) | (0.017) | (0.006) | (0.003) |
| % male | -0.034 | 0.035 | -0.042 | 0.567 | -0.291 | -0.077 |
| | (0.112) | (0.115) | (0.151) | (0.607) | (0.205) | (0.104) |
| % Hispanic | -0.014 | -0.006 | -0.016 | -0.077 | 0.020 | -0.021 |
| | (0.014) | (0.014) | (0.019) | (0.072) | (0.025) | (0.013) |
| % black | -0.021 | -0.013 | -0.021 | -0.130* | -0.004 | -0.029* |
| | (0.015) | (0.015) | (0.020) | (0.076) | (0.028) | (0.015) |
| % elderly | 0.021 | 0.022 | 0.061 | -0.185 | -0.003 | 0.002 |
| | (0.054) | (0.053) | (0.069) | (0.257) | (0.099) | (0.053) |
| Population density | -0.002 | -0.001 | -0.003 | -0.005 | 0.001 | -0.001 |
| | (0.002) | (0.002) | (0.003) | (0.011) | (0.004) | (0.002) |
| **Spatial ($\lambda$)** | 0.449*** | 0.346*** | 0.527*** | 0.375*** | 0.650*** | 0.587*** |
| | (0.079) | (0.084) | (0.084) | (0.085) | (0.073) | (0.064) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Market Structure: | | | | | | |
| For-profit | 0.005 | 0.004 | 0.012 | 0.002 | -0.012 | -0.020*** |
| | (0.008) | (0.008) | (0.010) | (0.028) | (0.014) | (0.007) |
| Not-for-profit | 0.014** | 0.015** | 0.020** | -0.057** | -0.001 | -0.013** |
| | (0.006) | (0.006) | (0.008) | (0.024) | (0.012) | (0.006) |
| Number of beds | -0.003*** | -0.003*** | -0.005*** | -0.007** | -0.004* | -0.002* |
| | (0.001) | (0.001) | (0.002) | (0.003) | (0.002) | (0.001) |
| Nurses per bed | 0.002 | 0.006 | 0.001 | -0.023 | -0.003 | 0.002 |
| | (0.004) | (0.004) | (0.006) | (0.017) | (0.007) | (0.004) |
| Teaching Status | -0.007* | -0.002 | -0.011** | 0.010 | -0.001 | -0.002 |
| | (0.004) | (0.004) | (0.005) | (0.015) | (0.008) | (0.004) |
| CMI | -0.016* | -0.016* | -0.027** | 0.002 | -0.038** | -0.006 |
| | (0.009) | (0.009) | (0.012) | (0.003) | (0.015) | (0.008) |
| | | | | | | |
| State fixed effect? | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect? | Yes | Yes | Yes | Yes | Yes | Yes |
| | | | | | | |
| Number of hospitals | 2,110 | 2,110 | 2,110 | 993 | 2,158 | 2,153 |
| Observations | 8,440 | 8,440 | 8,440 | 3,972 | 8,632 | 8,612 |

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.