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Testing the Medical Arms Race Hypothesis: a Spatial Approach

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a Spatial Approach

by

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Dedication

To my family, especially Ramsey

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Abstract

The surgical robot experienced rapid uptake throughout hospitals in the US despite lack of clinical evidence that it is superior to existing methods and undeterred by its high cost. This type of technology may be a "weapon" in the medical arms race hypothesis which asserts that competition among hospitals may be welfare reducing wherein it encourages resource use that is not commensurate with beneficial health outcomes. This paper is a case-study of the diffusion of the surgical robot among hospitals in Florida. We address the medical arms race hypothesis directly by investigating whether a hospital's decision to adopt a robot is a function of the neighboring, competing hospitals' decisions to do so. Using a spatial autoregressive probit model, we find that the spatial coefficient is significant and negative. That is, when neighboring hospitals operate a robot, a given hospital is *less* likely to operate one. Indeed, hospitals appear to consider the behavior of rival hospitals, but not in a way that would be consistent with a medical arms race. Support is lent to the hypothesis that as more hospitals become providers of robotic-assisted surgery (RAS), the less profitable it becomes to enter the market.

1. Introduction

A primary driving force behind the extensive growth in healthcare spending in the US, the largest per-capita healthcare spender, is attributed to the use of medical technology in hospital services (Newhouse, 1992; Smith, Newhouse, & Freeland, 2009; Chandra, Holmes, & Skinner, 2013). This dissertation seeks to investigate the nature of competition on the adoption of medical technology by hospitals. More specifically, this is a case-study of the adoption of the surgical robot among hospitals in Florida. Since its FDA approval in 2000, the surgical robot has experienced rapid uptake across hospitals. The propensity toward the adoption of the surgical robot despite lack of clinical evidence that it is superior to existing methods together with its high cost has implicated the technology as a "weapon" in a medical arms race. The medical arms race hypothesis asserts that technology-based competition among hospitals may lead to excessive provision of medical technology or amenities.[1]

It has been suggested that there are two distinct forms of the medical arms race. Barros et al. (1999) propose it could be one of lack of coordination across providers. Under certain conditions relating to how strongly demand responds to technology and the costs associated with adoption, this may result in an overinvestment in medical technology. Another possible form of a medical arms race concerns signaling. Hospitals might invest in the latest technology to signal their quality to both potential patients and medical personnel (Barros & Martinez-Giraltb, 2013). This

[1] "Excessive" meaning sub-optimal or welfare reducing: the resource use is not commensurate with beneficial health outcomes, that is, at the "flat of the curve" in medicine; this would apply when a technology is overutilized or when less cost-effective technology is adopted).

real or perceived quality signal is useful to attract market volume (and physicians), as it is likely an important factor for patients (and physicians) when choosing among hospitals. If this largely explains the medical technology adoption phenomena, we expect that in most cases competition will increase robot adoption.

However, other phenomenon may occur in strategic interaction in which either no hospitals choose to adopt or some hospitals adopt the technology while others choose not to. The former case may arise if adoption costs are prohibitively high. In the latter case, for example, depending on the relative costs of adoption, those facing higher costs may choose not to adopt while for those facing lower costs, the technology may be adopted.[2] Alternatively, it has been noted that competition may have a limiting effect on technology adoption (Reinganum, 1981). Depending on how sensitive are patients to the presence of technology, as more hospitals adopt a technology the remaining market share diminishes. This results in smaller profit-margins from adopting the technology as time goes on. Thus, as hospitals learn of neighboring hospitals' decision to adopt the technology, i.e. the "first movers", this reduces the incentive for the neighboring hospitals to invest.

Whether support is lent to the medical arms race hypothesis or whether another phenomenon occurs is of empirical interest since understanding the behavior of hospitals interacting strategically informs healthcare policymakers and stakeholders. It is also in the interest of public health since technology can be beneficial but also comes with costs. Using a spatial autoregressive probit model, we address the effect of competition directly by investigating the nature of a hospital's decision to adopt a robot as a function of the neighboring, competing

[2] Costs may be related to unobservable characteristics of the hospital and/or physician quality which we cannot control for in this analysis.

hospitals' decision. A significant and positive spatial coefficient supports a medical arms race whereas a significant and negative spatial coefficient lends support to the market's limiting effect. An insignificant result indicates there is no underlying spatial relationship in the diffusion of the robot. This may suggest the technology diffusion is not driven by the behavior of rival hospitals or that it may be driven by some quality-cost differences unobservable to the researchers. We find that the spatial coefficient is significant and negative. That is, when neighboring hospitals operate a robot, a given hospital is *less* likely to operate one. Indeed, hospitals appear to consider the behavior of rival hospitals, but not in a way that would be consistent with a medical arms race. Support is lent to the hypothesis that as more hospitals become providers of robotic-assisted surgery (RAS), the less profitable it becomes to enter the market.

The dissertation is organized as follows: in section 2 we provide motivation and relevant background information related to the US healthcare market, the surgical robot, diffusion of technology in the hospital market and a review of the literature; in 3 we suggest a conceptual framework which motivates the empirical model; in section 4 we cover the econometric model, estimation strategy and data; in 5 we discuss results and robustness checks; and in section 6 we conclude.

2. Background

2.1. US healthcare system

Several distinguishing and interrelated aspects of US healthcare system facilitate or determine technology adoption: the presence of health insurance, uncertainty about efficacy of care and market structure.

2.1.1. Health insurance

One of the features of the US healthcare market is the presence of insurance and its reimbursement mechanisms. Since patients with health insurance are generally only expected to pay some portion of the total cost of medical care, out-of-pocket expenses are relatively low which may lead to price insensitivity when deciding how much healthcare to consume. Depending on the reimbursement mechanism, healthcare providers may also be insensitive to costs. This was particularly concerning when payments were made retrospectively, i.e. ex post, based on services rendered. Neither patients or hospitals had cost considerations that might limit the adoption or use of medical technology (or consumption of healthcare, more generally). In fact, even from an innovation perspective, it has been shown that insurance may increase the entry of (cost-increasing) medical technologies (Goddeeris 1984).

This overinvestment was potentially curbed in the early 1980s with some structural changes to the healthcare market. With the introduction of Medicare's Prospective Payment System (PPS), payments were no longer tied to actual costs but rather to a pre-determined amount according to the classification of the visit, i.e. diagnosis-related group (DRG). Since a hospital can retain the difference between the DRG payment and actual costs, this structure provides the incentive for hospitals to become more cost-conscious in their care decisions. Around the same time, managed care in US private healthcare insurance took roots with its various strategies aimed to cull costs. For example, in network-based managed care organizations, hospitals compete for selective contracting with insurance companies to have access to their network of patients. This competition puts downward pressure on hospitals' costs. In the mid-1990s, prompted by patients' complaints about lack of options and with the growth of consolidated hospital systems, health insurance companies lost some of their power against hospitals. These conditions, which describe the current healthcare environment, make it relatively more favorable for overinvestment in medical technology.

2.1.2. Efficacy of care

Many medical technologies have significantly enhanced the quality of our healthcare, improving diagnostics, minimizing invasiveness, abbreviating hospital duration, and in some cases, reducing costs. However, not all technologies perform the same, and in efforts to contain the rising cost of health care in the US, much attention has been drawn to identify high-cost, low-value technologies. Skinner et al. recognize a heterogeneity across medical technologies in terms of their productivity and find that, on a macroeconomic level, countries more likely to adopt low productivity technologies, particularly what they refer to as "category II & III" technologies, are also more likely to experience the most rapid growth in health care costs. Category II includes those medical technologies having less consistent health outcomes, being beneficial to some while not providing value to others, but are prone to overuse and thus caution should be applied (e.g. MRI and CT scans); category III are the medical technologies which are associated with incremental health benefits and may be very expensive, offering little to no value (2011). The relative scarceness of randomized clinical trials (RCT) compared to population-based, retrospective studies in the medical literature (due to the cost and ethical considerations necessary for RCT) makes it difficult to distinguish the efficacy of medical technologies. Thus, especially in the presence of health insurance, excessive adoption can occur.

Despite sometimes limited or conflicting information about efficacy of particular medical technologies, there are societal beliefs about the curative nature of medical technology. Marketing research finds that patient-consumers associate new and expensive technology with effectiveness (Korobkin, 2013); that limited use of such technology is perceived as a cost-saving decision, even when there is lack of evidence of the technology clinically surpassing traditional methods (Schleifer & Rothman, 2012); and that advertising is directed at patients (Brennan, 2006). Indeed, the makers of the surgical robot have taken a direct-to-consumer advertising approach, sometimes leading patients to demand RAS. Moreover, marketing for robotic procedures typically relies on the same positive aspects of traditional MIS, making it misleading.

2.1.3. Hospital market

While the above-mentioned market characteristics facilitate investment in medical technology, the focus of this dissertation is on the role of the market in particular. The hospital market structure in the US tends toward an oligopoly with strategic interaction occurring among hospitals as they aim to maximize profits. We expect that even non-profit hospitals behave similarly, which is standard in the literature. This was put forth by Newhouse (1970) in his theory of output maximization and empirically corroborated by Horwitz and Nichol (2007). They found that in the presence of for-profit hospitals, non-profit hospitals will aim to maximize profits, since the for-profit hospitals “cream skim” patients, leaving the non-profit hospitals with a patient mix that tends to lose money for the hospital. Survival requires a non-profit to act in profit-maximizing ways.

Strategic interaction is a defining characteristic of the oligopolistic market structure that the US hospital market most closely parallels. The existence of health insurance and the resulting insensitivity of most patients to price leads to the presence of non-price competition among hospitals as they compete to obtain greater market share. Higher market share leads to higher utilization rates, economies of scale and improved learning curves.

2.1.3.1. Medical arms race

Under certain conditions, the strategic interaction between hospitals may lead them to overinvest in medical technology. As presented by Barros et al. (1999), the medical arms race can be summarized in the following game. Suppose the cost of adoption of a particular technology differs across hospitals where the cost for hospital B exceeds the cost for hospital A, i.e. $C > c$. Further assume that there are N patients paying price p for the hospital visit. Patients are taken to be highly responsive to the presence of technology such that if the technology is present in both hospitals, the patients will be split evenly across the two hospitals whereas if one hospital has the technology and the other is a non-adopter, all patients will go to the hospital with technology. The hospitals' payoff matrix will be the following:

Table 1. Hospital payoff matrix

		Hospital B	
		Adopt technology	No technology
Hospital A	Adopt technology	$Np/2-c$, $Np/2-C$	Np-c, 0
	No technology	0, $Np-C$	$Np/2$, $Np/2$

A variety of outcomes may arise depending on the relationship between costs and expected patient-volume revenue. Assuming adoption costs are low so that $c < C < Np/2$, a prisoner's dilemma emerges. The optimal outcome is for neither hospital to adopt the technology, but due to lack of coordination between hospitals, both providers will invest in the technology, i.e. a medical arms race. The results rely on the underlying assumptions about the sensitivity of patients to the presence of technology: the first-mover obtains the market share. As mentioned above, patients do appear to be highly sensitive to medical technology. In a related continuous-time game framework put forth by Fudenberg & Tirole (1985), it has been shown that in a duopoly, rents are equilized in the presence of threats of preemption; however, in a broader oligopoly, the advantage of preemption is sufficiently small so that late adoption can occur in a symmetric equilibrium . The MAR has also been presented purely as a signaling theory (Barros et al., 1999). If the hospitals are using the technology to signal their underlying and unobserved quality, under certain conditions related to their true quality and costs of adoption, the perfect Bayesian Nash equilibrium may be that overinvestment occurs.

2.1.3.2. Other outcomes

However, other outcomes may arise. Maintaining the assumption of highly sensitive demand in the simultaneous game representation (i.e. coordination), if costs of adopting are sufficiently high, $C > c > Np/2$, the dominant strategy is for both hospitals not to adopt. On the other hand, if adoption costs are distinct across hospitals so that $C > Np/2 > c$, the interaction would result in the hospital facing higher costs, B, choosing not to adopt the technology while for the hospital A with lower costs, the technology will be adopted. A similar equilibrium may arise from signaling under certain conditions related to costs of adoption that distinguish high and low-quality doctors/hospitals. For example, high-quality doctors may have a shorter learning curve. In these cases, the market may function to counteract excessive adoption of medical technology. From a more dynamic perspective, there are several theoretical models that explain a process of technology diffusion in which an agent’s own payoffs and the payoffs of other agents in the network are known. As true payoffs are revealed, an efficient equilibrium will emerge (Bala & Goyal, 1998). Along the same line, Reinganum's (1981) model suggests that, at first, competition increases the diffusion of a technology as first-movers attempt to gain competitive advantage. However, the market share will decrease as more firms adopt the technology, thereby reducing the incentive to adopt the technology. Each of these results in a strategic interaction in which some hospitals adopt the technology (i.e., the true "high quality" or the "first-movers"), while others choose not to.

2.2. Surgical robot

Minimally invasive surgery (MIS), also referred to as laparoscopic surgery, can be performed through "keyhole" incisions and is associated with significant improvements over the comparable surgery performed traditionally, that is, open surgery. Advantages of MIS over traditional/open surgery include lessened complications and blood loss, reduced recovery times, shorter hospital duration and lessened post-operative pain and scaring rendering it a major leap forward in surgery. In 2000, the FDA approved the only surgical "robot" capable of performing MIS, Intuitive Surgical's da Vinci Surgical System, which is now used in adult and pediatric MIS/laparoscopic surgeries including general, cardiac, colorectal, gynecological, head and neck, thoracic and urologic. A breakdown of the primary procedure codes associated with the robotic surgeries performed at hospitals with the surgical robot in our sample. Approximately half of the RAS-performed procedures were prostatectomy and hysterectomy.

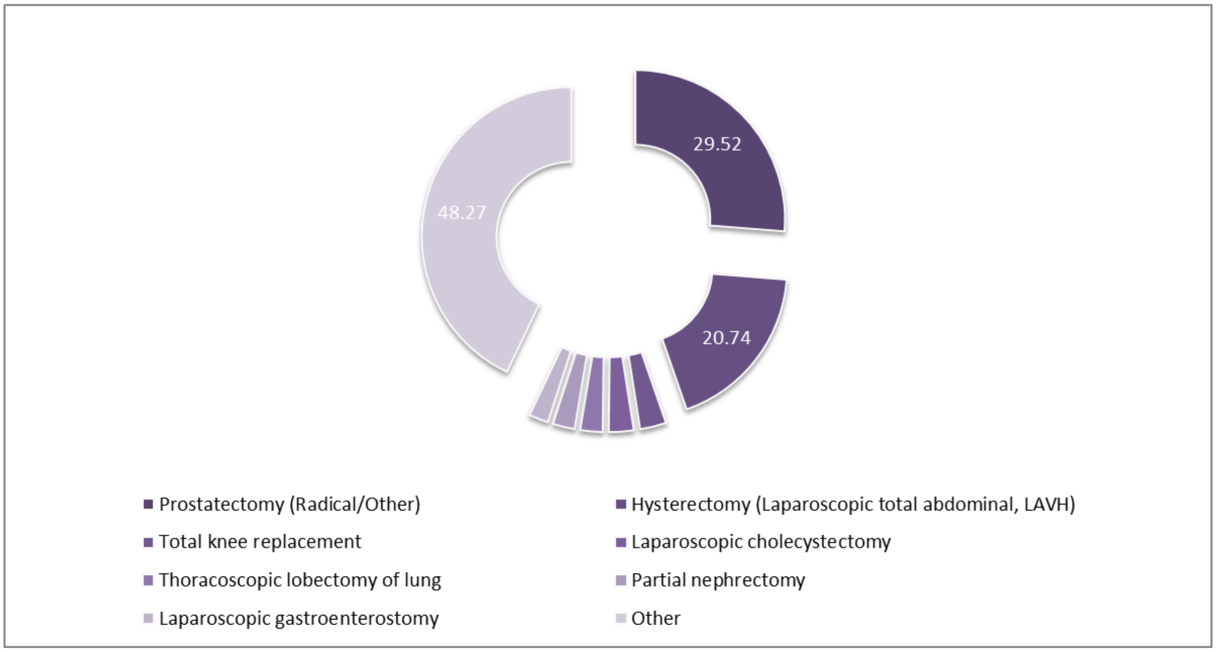

Figure 1. Primary procedures for which RAS was performed, all hospitals

The machine, which requires a dedicated operating room and costs approximately $2 million, allows a specially-trained surgeon to indirectly control surgical instruments attached to robotic arms suspended above the patient by way of a remote computer-control. The instruments are receptive to feedback allowing for smoother, tremor-free motions from the surgeon and greater range of motion. Although the overall surgery time generally exceeds that of traditional minimally-invasive methods, from the console the surgeons have better visualization via a magnified high-definition 3-D viewfinder and they can move more freely which may lead to better health outcomes when compared to traditional laparoscopic surgery.

As an iteration of MIS, RAS sometimes has clear advantages over traditional, open surgery. However, the clinical benefits of robotic-MIS over traditional MIS have not yet been clearly substantiated with the current population-based studies indicating minimal or no clinical advantages despite higher costs. Thus far, there has been a lack of randomized controlled trials assessing the traditional/open/conventional, conventional-laparoscopic/minimally invasive, and robotic-assisted laparoscopic approaches. The reliance on retrospective studies comparing these methods makes generalization difficult due to the inability to control for potentially important confounding factors such as surgeon training and ability.

There have been notable meta-analyses comparing these approaches in radical prostatectomy and gynecological/hysterectomy procedures with mixed conclusions. The population-based meta-analysis comparing traditional, conventional-laparoscopic and robotic-laparoscopic approaches to radical prostatectomy concludes that robotic prostatectomy performed at least as well as traditional or traditional-laparoscopic approaches based on primary outcomes (reduced blood loss, lower morbidity, positive surgical margins and safety) and secondary outcomes (transfusion rates, hospital length of stay and individual complication rates). The authors acknowledge that the large size of the study may lead to statistical significance without clinical significance. Further, no assessment of the costs was considered (Tewari et al., 2012).

Another large, population-based study compares RAS use in hysterectomy relative to conventional laparoscopic hysterectomy. The study, which makes use of propensity score matching, suggests robotic-MIS and traditional MIS perform similarly on measures of complication. Specifically, robotically-assisted hysterectomy slightly decreased the probability of hospital stay longer than two days but was associated with no difference in the need for transfusion or discharge to a nursing facility. Despite the similar outcomes, the RAS had an associated cost premium of $2,189. Yet, hysterectomies performed robotically, which were FDA-approved starting in 2005, have increased from 0.5 percent in 2007 to 9.5 percent in 2010

(Wright et al. 2013). Indeed, according to a systematic review of the literature on surgical treatments for gynecologic indications, there is no clear evidence to conclude RAS or traditional MIS provides superior outcomes (Gala et al., 2014). As of March 2015, the Committee on Gynecological Practice, Society of Gynecologic Surgeons, had the following opinion on RAS in the field:

> "Adoption of new surgical techniques should be driven by what is best for the patient, as determined by evidence-based medicine rather than external pressures. Well-designed randomized controlled trials or comparably rigorous nonrandomized prospective trials are needed to determine which patients are likely to benefit from robot-assisted surgery and to establish the potential risks."

While one such randomized controlled trial exists in the field of urology, it compares the clinical benefits of the RAS procedure to the procedure performed traditionally rather than conventional laparoscopically. The first stage of a randomized controlled trial comparing robotically-assisted prostatectomies (the most common use of the surgical robot) with traditional/open surgery localized prostate cancer treatment found similar outcomes at 12 weeks in terms of urinary and sexual function, post-operative complications and days missed from work. As would be expected, the prostatectomies performed via the robotic MIS were associated with less blood loss and less post-operative pain compared to the open surgery, but at 12 weeks, these differences leveled out. A second phase with long-term results is forthcoming (Yaxley et al., 2016).

Robotic-assisted MIS presents its own disadvantages including longer surgery times and mid and post-operative complications, some linked to deaths. In addition to the high fixed costs associated with the adoption of the surgical robot, high variable costs include an annual maintenance service contract with Intuitive costing $100,000-$170,000 and per-use disposables which increase the per-procedure cost $1,200-$2,000 relative to an equivalent MIS procedure. If hospital duration is reduced by RAS, then some of the variable cost can be offset.

Despite the large costs associated with this technology, hospitals are reimbursed the same regardless of the MIS method used, and thus the extensive costs mentioned provide an incentive for a recuperation of costs on the part of the hospital.[3] One way in which these higher costs are passed on in this reimbursement structure is by increasing the charges for the procedures or diagnoses for which surgical robots can be utilized either to account for the inability of some patients to fulfil their payments, particularly the uninsured, and/or to account for the replacement and updating of technology. Because Medicare and private-insurer reimbursement rates are determined by these procedure and diagnosis charges, the added costs related to the surgical robot are indirect (Barbash & Glied, 2010). High marginal costs may be offset through economies of scale as higher volume allows surgeons to become more proficient. It has been estimated that in order to offset the fixed and variable expense associated with the acquisition of the surgical robot through economies of scale, hospitals must perform 150-300 procedures each year for six years (Lee, 2014). Thus, the incentive exists to perform surgery with the technology rather than without, even if it is not clinically optimal for the patient, an occurrence known as "treatment creep". Eventually hospitals are assumed to earn profit from RAS, so increasing patient volume and/or performing a surgery that otherwise would not have occurred can return profits sooner.

[3] The Centers for Medicare & Medicaid Services (CMS) designates certain rural hospitals as "Critical Access Hospitals" (CMAs) and, as a function of Medicare beneficiaries at the hospital, these hospitals are eligible for varying subsidized capital expenditures including the da Vinci Surgical System. At the time of the analysis, 13 hospitals in Florida have been given this designation: Calhoun – Liberty Hospital, Campbellton-Graceville, Doctor's Memorial – Bonifay, Fishermen's, Florida Hospital Wauchula, George E. Weems, Hendry RMC, Lake Butler, Madison County Memorial and Mariners.

Figure 1 summarizes, for all relevant hospitals in Florida, the historical ratio of hospitals with the surgical robot to those without from 2008 to 2013. The figure reveals that the surgical robot has steadily increased in number and as a percentage of all hospital ownership, with 21 percent of hospitals having acquired a surgical robot in 2008 to over half having obtained one by the year 2013. In Florida, a certificate of need is not required for the purchase of the surgical robot.

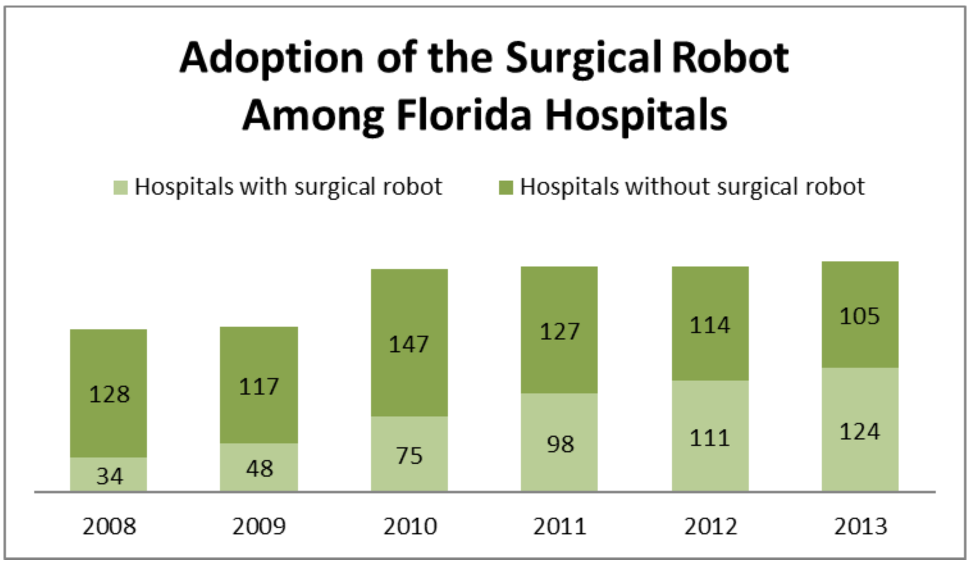

Figure 2. Adoption of the surgical robot; all long-term, acute care hospitals in Florida

From a geographical perspective, the spatial distribution of the hospitals in Florida that have acquired the surgical robot in 2008 and 2013 are displayed for comparison in Figure 2 and Figure 3. We seek to determine whether there is a spatial element to the presence of the surgical robot in hospitals across Florida. See Appendix B for further exploratory spatial analysis.

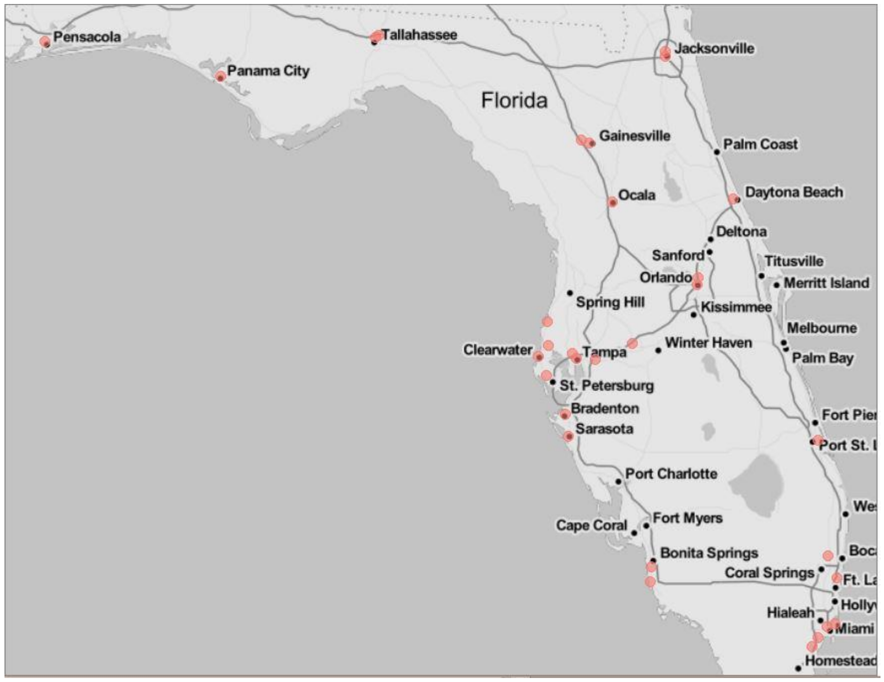

Figure 3. Spatial distribution of surgical robots in 2008

Figure 4. Spatial distribution of surgical robots in 2013

2.3. Literature review

Due to the impact of insurance on the behavior of healthcare providers, the literature can be segmented into "pre-managed care" and "post-managed care" sets and a more recent set of literature which encompasses the increase in hospital negotiating power as they consolidate into systems. The general consensus in the pre-managed care literature is that competition in the healthcare market leads to increased costs. That is, hospitals in less concentrated markets have higher costs per patient (Robinson & Luft, 1985; Noether, 1988), a higher employee/patient ratio (Robinson, 1988), and more high-tech services (Luft et al., 1986). Generally, the conclusion reverses, however, after the growth of managed care. Melnick & Zwanziger confirm the negative relationship between costs and concentration prior to the growth of managed care organizations and identify a loss of correlation post-PPO (1988). In another study, Zwanziger & Melnick find that after selective contracting, the rate of cost growth is smaller in less concentrated markets (1988). Taking advantage of the rollout of Medicare PPO in California, Dranove, Shanley, & Simon discover no relationship prior to managed care, but that post-managed care, more competition lead to a reduction in cost/price-margins (1992). Kessler & McClellan (1999) use a three-stage model in which a predicted measure of a hospital's patients are chosen based on a patient-level hospital choice model determined by such factors as demographics and distance from the patient's residence. Hospital market competitiveness is based on these predicted patient flows rather than the actual patient flows which breaks the endogeneity inherent in hospital selection and measures of HHI. Using this approach, they find that in the presence of managed care, competition reduced costs and adverse health outcomes.

Narrowing down the literature to technology adoption, in particular, many studies confirm a medical arms race hypothesis. James models the relative-size-weighted (that is, the number of hospital beds as a fraction of total hospital beds in the county) number of hospitals in a county that offer specific high-tech services as a function of the hospital demand and cost shift factors and a measure of competition. Her measure of weighting, she argues, emphasizes the ability of patients to have *access* to the treatment, and this distinction corresponds to the overprovision of a service causing an "unnecessary degree of access rather than a greater number of providers" (2002). Ladapo et al. study computed tomography, a type of imaging technology (2009). While controlling for clinical need and other hospital characteristics such as the operating margins, insurance reimbursement rates, whether related services were offered, and in particular a proxy for being a "first mover" / "technological leader" (i.e. adoption of PET), this article determines that early adoption is influenced by cardiac patient volume and hospital operating margins, but not by market competitiveness or insurance reimbursement. To assess the level of competitiveness in each hospital's market, a Hirschman-Herfindahl index (HHI) is constructed by summing the square of the hospital's admissions relative to the Hospital Referral Region/markets' admissions. Sethi (2014) finds that the adoption of endovascular aneurism repair adoption is associated with market forces – patients at more competitive hospitals are at increased odds of undergoing EVAR. He makes use of the Nationwide Inpatient Sample from the American Hospital Association annual survey, linked with Hospital Market Structure data for estimating HHI in a variable geographic radius defined by its encompass of 90 percent of discharged patients.

Studies with particular application to the adoption of surgical robots are more limited. Most recently, a patient-level study on the influence of market forces and hospital financial status (as measured by the operating margin) on the usage of surgical robots for certain procedures finds evidence that increased market competition (as measured by HHI) is correlated with increased usage. However, conditioned on having acquired a surgical robot, only one procedure type (partial nephrectomy) was (positively) associated with the hospital's operating margins. Wright et al. finds a positive correlation between more competitive regional markets (HHI-based) and an increased probability of patients receiving a RAS; however, they find also that once a hospital obtains the surgical robot, it is no more or less likely to provide RAS as a function of the competition (2016). Barbash, et al. (2014) study the determinants of robot adoption and conclude that factors associated with the adoption of a surgical robot include: increased proportion of other hospitals within the set geographic market area having already acquired a robot, hospitals with more than 300 beds, and teaching hospitals.

In Li et al. (2014), the researchers model a hospital's decision to acquire a surgical robot as a function of the nearest neighbor's previous decision to do so, teaching status, surgical volume, number of beds and urban setting. Using inpatient data from seven states between the years of 2001 and 2005, along with data from the robot manufacturer, Li et al. (2014) model this as a temporal and spatial decision using a two-state Markov chain method. They find evidence in support of the medical arms race which is to say that if the nearest neighboring hospital previously acquired a robot, a hospital was more likely to acquire one as well (OR 1.71, p=0.02). While the current study is similar in Li et al.'s direct approach in answering the medical arms race, their analysis is limited by assuming influence exists only from the nearest neighbors. The current study makes no such restriction and allows for a more comprehensive influence from nearby hospitals (subject to the assumptions made by the spatial weights matrix selection) as described in the empirical section. Additionally, as explained below, it may not be necessary to model the decision temporally since, under weak assumptions the simultaneous equilibrium outcome is encompassing.

3. Conceptual framework

We borrow the theoretical and empirical framework suggested by Mobley (2003) and used by Mobley, Frech, & Anselin (2009) and Gravelle, Santos, & Siciliani (2014) to ask whether provision of robotic surgery is a strategic complement, i.e. whether each hospital responds to rival hospitals' provision of robotic surgery with its own provision of that service. The hospital market is characterized as an oligopoly in which the equilibrium provision of robotic surgery is determined in simultaneous profit-maximizing decisions where each hospital's reaction function depends on the expected decision of nearby hospitals.

Empirically, this question can be answered using a spatial model in which the effect of neighboring hospitals' decisions to operate using robots depends on spatial proximity, i.e. the spatial autoregressive model. The spatial lag parameter (described later) is interpreted as the slope of the reaction function. Mobley (2003) and Mobley et al. (2009) apply this theoretical motivation for the corresponding empirical model to examine the effect of competition on price while Gravelle, Santos, & Siciliani (2014) do so for the effect of competition on quality.

The adapted theoretical model is as follows. The demand function of hospital *i* can be defined as $X_i = X(y_i, \boldsymbol{y_{-i}}; \delta_i)$, where y_i is the operation of robotic machines of hospital *i*, $\boldsymbol{y_{-i}}$ is the corresponding decision of neighboring rival hospitals, and δ_i are hospital demand parameters. We assume that hospitals receive a per-treatment price, *p*. Hospital cost parameters are denoted γ_i. The objective function of hospital *i* is to choose y_i to maximize

$$\pi_i = pX_i(y_i, y_{-i}; \delta_i) - C_i(X_i(y_i, y_{-i}), y_i; \gamma_i) - F_i$$

Assuming hospitals simultaneously choose robotic surgery provision, then maximizing the objective function above with respect to y_i, we obtain the first order condition for the Nash equilibrium

$$\frac{\partial \pi_i}{\partial y_i}(y_i^*, y_{-i}^*) = 0 \tag{1}$$

Further assuming the hospital objective function is strictly concave in its choice variable i.e.,

$$\frac{\partial^2 \pi_i}{\partial y_i^2}(y_i^*, y_{-i}^*) < 0$$

we have the Nash equilibrium: (y_i^*, y_{-i}^*). The system of two equations with two unknowns given in equation (1) can be solved for y_i to give the reaction function for hospital *i*

$$y_i^R = y_i^R(y_{-i}; \delta_i, \gamma_i)$$

We are interested in the effect of rivals' robotic surgery provision decisions on hospital *i*'s robotic surgery provision. By the implicit function theorem, we obtain the slope of the reaction function for hospital *i*,

$$\frac{\partial y_i^R}{\partial y_{-i}} = \frac{\partial^2 \pi_i / \partial y_i y_{-i}}{-\partial^2 \pi_i / y_i^2}$$

Where, given our second-order assumption, the sign of the cross-partial derivative determines whether robotic surgery provision is a strategic complement (positive), strategic substitute (negative), or independent. The cross-partial derivative represents the derivative of the hospital's marginal profit with respect to the rivals' choice.

The decision to adopt a surgical robot may not in fact be simultaneous, but rather conditioned on nearby decisions made in previous years. As noted in LeSage and Pace (2009) and LeSage et al. (2011), the simultaneous spatial autoregressive model can be interpreted as the steady state equilibrium for the dynamic process.[4] In other words, cross-sectional spatial dependence can capture the diffusion of the surgical robot over time; therefore, we have modeled the decision as a simultaneous one.

[4] As outlined in (Pace & LeSage, 2010; J. P. LeSage et al., 2011), we can begin by examining a dynamic spatial model omitting any simultaneous element and then showing that, under certain conditions, the model converges to the simultaneous version. Starting with spatiotemporal model that relies only on past data and omits any simultaneous spatial interaction, we have

$$y_t = Gy_{t-1} + X\beta + \varepsilon_t, \qquad \varepsilon_t \sim N(0_n, \sigma^2 I_n)$$

$$G = \tau I_n + \rho W$$

τ is a scalar parameter that represents the dependence over time for a given observation at time t and t-1 while ρ is the scalar parameter capturing the dependence between observation i at time t and observation j ($i \neq j$) at time t-1. The recursive relation after t time periods would be

$$y_t = G^t_{y_0} + (I_n + G + G^2 + \cdots + 6^{t-1})X\beta + u$$

$$u = G^{t-1}\varepsilon_t + \cdots + G\varepsilon_{t-1} + \varepsilon_t$$

After a large t has passed, we can find the steady-state equilibrium assuming $G^t \approx 0_n$ and zero expectation for the disturbance terms. That is,

$$E(y_t) \approx (I_n - G)^{-1}X\beta$$

$$E(y_t) \approx (I_n(1-\tau) - \rho W)^{-1}X\beta$$

$$E(y_t) \approx \left(I_n \frac{\rho}{1-\tau} W\right)^{-1} X \frac{\beta}{1-\tau}$$

This is a reparameterization of the simultaneous model where

$$E(y_t) = (1 - \rho^* W)^{-1} X\beta^*$$

$$\rho^* = \frac{\rho}{1-\tau}$$

$$\beta^* = \frac{\beta}{1-\tau}$$

Note that the $(1-\tau)^{-1}$ is the same long-run multiplier from time-series literature.

4. Empirical strategy

4.1. Empirical specification

It has been noted that improper measures of market competitiveness which rely on ad-hoc definitions of the hospital market may impart bias on the estimates (Kessler & McClellan, 1999). For example, measures of the market extent such as government-defined boundaries, hospital referral regions, and fixed and variable radii methods so often used in empirical studies related to market structure may not contain all relevant competitors and thus can bias the effects of competition measures which rely on these estimations (Sherer and Ross, 1990; Pindyck and Rubinfield, 1998).[5] The HHI, which sums the square of the shares of the market and is the most prevalent method of measuring market competitiveness, ignores the geographic distribution of hospitals within an area. Applied to hospitals, the shares may be computed as, for example, the number of hospital beds as a fraction of total hospital beds in the county (James, 1997) or a hospital's admissions relative to the Hospital Referral Region/markets' admissions (Ladapo, 2009). In any case, it is likely that the volume-shares which this measure relies on are a function of unobserved heterogeneity related to the hospital quality (real or perceived) which is itself a function of the technology it offers, that is, the HHI is endogenous. These bias the estimated relationship between HHI as a measure of market competitiveness and hospital costs and/or outcomes. It is worth noting that the underlying intuition behind the general approach outlined here is that hospitals are strategically interacting with each other although these methods do not

[5] The "fixed radii" method assumes that all hospital rivals exist within a given distance of a given hospital while the "variable radii" method assumes a hospital's rivals are any other hospital within a radius specific to the hospital such as one that contains some percentage of the hospital's patients.

test directly for this behavior. The spatial autoregressive framework introduced below allows us to mitigate much of the bias caused by these issues.

The spatial autoregressive probit model can be written structurally,

$$\boldsymbol{y}^* = \boldsymbol{X\beta} + \rho \boldsymbol{W} \boldsymbol{y}^* + \varepsilon, \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 \boldsymbol{I_N}) \tag{1}$$

Where $\boldsymbol{y}^*$, an $N\times 1$vector where *N* is the number of hospitals in the data set, is the underlying (net-profit) decision process with elements y_i^* that produces the observed binary outcome whether hospital *i* operates a robot, denoted as an element y_i of the $N\times 1$ vector $\boldsymbol{y}$. The relationship is established as

$$y_i = \begin{cases} 1, & y_i^* > 0 \\ 0, & y_i^* \leq 0 \end{cases}$$

As mentioned, the slope of the reaction function corresponds to the estimate of the spatial lag parameter, a scalar ρ, which measures the strength (and direction) of the dependence and is supported on [-1, 1]. Here, the spatial weights matrix $\boldsymbol{W}$ is specified as a function of distance. We have defined $\boldsymbol{W}$ to be a row-normalized, inverse-distance $N\times N$ matrix with each element, w_{ij}, expressing the degree of spatial proximity as:

$$w_{ij} = \begin{cases} \dfrac{d_{ij}^{-1}}{\sum_j d_{ij}^{-1}} \; for\ i \neq j\ and\ j\ is\ among\ the\ ten\ nearest\ neighbors \\ \qquad 0 \quad otherwise \end{cases}$$

Where d_{ij} is defined as the distance between hospital *i* and *j* and we have bounded the matrix at the ten nearest neighbors. [6,7] The inverse distance gives a lower weight to the decision of rivals

[6] See Appendix B for details about the construction of spatial weights matrices.

[7] The choice of ten neighbors was chosen after a model comparison using the Akaike information criterion (AIC) and experimenting with the ideal number of neighbors to include in order to optimize the

that are more distant from hospital i, pursuant to Tobler's First Law of Geography which states, "Everything is related to everything else, but near things are more related than distant things". The N diagonal elements, w_{ii}, take the value of zero. Thus, $\boldsymbol{W}\boldsymbol{y}^*$ is the spatial-weighted average decision process of neighboring hospitals. Note that the normalization of the spatial weights matrix along with the nearest-neighbors bound limit the allowable dependence. Finally, **X** captures hospital demand and cost variables (e.g. structural measures characterizing the hospital markets which ultimately determine the equilibrium provision of robotic technological services), and ε represents the unobserved factors.

The spatial model nests the standard probit model so that if $\rho = 0$, spatial dependence is not present and we can rely on non-spatial methods. However, if $\rho \neq 0$, as is often the case with units interacting in space, ignoring the neighboring outcomes by treating the model as non-spatial not only results in the omitted variable problem which biases the effects of the other variables and but also sacrifices information available to the researcher (Case, 1992). Similarly, a simultaneity exists due to the implied lack of independence; however, the current practice for applied spatial probit estimation is to ignore this shortcoming rather than to omit a crucial variable representing the underlying spatial interdependence. It has been shown that the bias caused by the omission of a statistically significant spatial interdependence is more concerning that the bias caused by these endogeneity concerns (Franzese & Hays, 2009).

4.2. Interpretation of estimates

In addition to the familiar non-linear aspect of the probit model, the potential dependence among observations allows a change in the ith observation's v^{th} explanatory variable, x_{iv}, to affect not

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underlying information. Our results are robust to these specifications. Full results for several of the specifications are provided in the Appendix.

only the *own*-y_i (expected probability of robot-adoption) but the *other*-y_j $(j \neq i)$ as well, returning additional non-linearity. Note that this is not a direct effect of x_{iv} on y_j, but rather the effect x_{iv}has on y_i which (potentially) affects y_j. In other words, hospital *i*'s decision to adopt a surgical robot may depend not only on its own hospital and market characteristics but also the neighboring hospitals' decisions which are a function of their own hospital and market characteristics. For example, a hospital's share of patients that are privately insured is expected to be a determinant of the hospital's decision to offer RAS; however, it is also possible that when making the decision, the hospital will consider the neighboring hospitals' decisions which are determined by the neighbors' own share of private insurance payers (i.e. a "spillover"). The parameter estimates in spatial models contain additional information about the underlying, potential spatial nature of the robot adoption decision process. Although not of particular interest for this dissertation, these estimates can inform policy-makers and hospital administrators about the nature of the spatial spillovers occurring across hospitals and their markets.

For simplification, let us begin by examining the differences between the marginal effects of the non-spatial linear model and the spatial autoregressive model with a continuous dependent variable.

Non-spatial / linear	Spatial autoregressive (continuous dep. var.)
$E(\partial y_i / \partial x_{iv}) = \beta_v$	$E(\partial y / \partial x'_v) = (I_n - \rho W)^{-1}(I_n \beta_v)$

Compared to the linear regression with its assumption of independence, we can see that the marginal effect is not simply equivalent to the parameter estimate but rather an *n*x*n* matrix with the following implication. The diagonal elements of this matrix contain the own-partial derivatives, $\partial y_i / \partial x'_{i,v}$. On the other hand, the off-diagonal elements consist of the cross-partial derivatives, $\partial y_i / \partial x'_{j,v}$ which capture the effect that changes in the neighboring explanatory variables can have on the hospital *i* through the neighboring outcomes; these effects can be thought of as the "spatial spillover". Again, note that there is no direct effect of neighboring hospital explanatory variables implied by the spatial autoregressive model. In fact, the effect is through the impact that the neighboring hospitals' explanatory variables have on these hospitals' decisions to adopt the surgical robot. More specifically, we assume no correlation between neighboring hospitals' characteristics and a hospital's error (Case, 1992). A scalar summary of both of these effects can be obtained by averaging the values across the observations, generating what is referred to as the *direct effect* and *indirect effect*, respectively. The sum of these effects produces the *total effect* (LeSage et al., 2011).

Below is a side-by-side comparison of marginal effects for a non-spatial probit regression and for a spatial probit regression which helps to illustrate the additional complexity introduced when considering the probit counterpart to the above.

Non-spatial probit	Spatial probit
$\partial E(y\|x_r)/\partial x_r = \phi(x_r\beta_r)\beta_r$	$\partial E(y\|x_r)/\partial x'_r = \phi[(I_n - \rho W)^{-1} I_n \bar{x}_r \beta_r] \odot (I_n - \rho W)^{-1} I_n \beta_r$

Where $\phi(\cdot)$ is the standard normal probability density function, $\bar{x}_r$is the mean value of the *r*th variable at which we evaluate the expression, and $\odot$ represents multiplication element-by-element. In the case of the non-spatial probit, the marginal effect consists of a scalar parameter estimate and the scaling expression by which it is multiplied. Analogously, the *spatial* probit marginal effect consists of a matrix term multiplied element-by-element to a matrix scaling term. It is from this expression that the diagonal elements are averaged to produce the *direct effect* and the off-diagonal elements are averaged to produce the *indirect effect* of the spatial probit estimation (LeSage & Pace, 2009).

4.3. Estimation technique

Even if we were estimating a continuous dependent variable, the presence of autocorrelation precludes estimation using OLS methods which requires independence of observations. Moreover, for modeling the discrete outcome, the implied lack of independence across observations is reflected in the likelihood being of *n* dimensions (cumulative normal) rather than *n* one-dimensional likelihoods, the integration of which (necessary to obtain individual parameter distributions) poses a challenge known as the “multidimensional integration issue”. Several estimation techniques have been created to deal with this concern, but it is becoming most common to estimate spatial probit using either frequentist recursive-importance sampling (RIS) or, most often, Bayesian methods. See Billé and Arbia (2013) and Franzese & Hays (2009) for a comprehensive review of spatial discrete choice estimation techniques. Bayesian methodology is also preferred for small sample inferences.

The Bayesian approach to the spatial probit is based on augmenting the data to include the latent vector, **y***, which describes the underlying continuous distribution and determines with certainty the discrete outcome, **y**. As LeSage and Pace (2009) note, Albert and Chib's (1993) treatment of Bayesian probit can be extended to the spatial model so that $p(\beta, \rho | y^*, W) = p(\beta, \rho | y^*, y, W)$. Thus, if we treat $\mathbf{y}^*$ as an additional vector of parameters, the conditional distribution will have the same form as in the Bayesian spatial autoregressive model with a continuous dependent variable.[8]

[8] See Appendix for the derivation of the full-conditional distributions for this model.

We will state the likelihood in terms of the latent $\mathbf{y}^*$. $L(\boldsymbol{y}^*, \boldsymbol{W}|\rho, \boldsymbol{\beta}) =$ $(2\pi)^{-1}\sigma^{-2(n/2)}|\boldsymbol{I}_n - \rho\boldsymbol{W}|e^{-\frac{1}{2\sigma^2}(\boldsymbol{\varepsilon}'\boldsymbol{\varepsilon})}$ where $\boldsymbol{\varepsilon} = (\boldsymbol{I}_n - \rho\boldsymbol{W})y^* - \boldsymbol{X\beta}$ and select the following independent diffuse prior distributions for parameters: $\boldsymbol{\beta} \sim N(c, T)$, where $c = 0$ and T is very large and $\rho \sim Beta(a1, a2)$, where $a1 = a2 = 1$.[9] To derive the parameter distributions, we wish to integrate over the joint posterior distribution (likelihood, priors) with respect to each of the parameters. Simulation methods provide a way in which we can numerically approximate the multi-dimensional integral. In Monte Carlo simulation methods, we cycle through random draws from the joint distribution collecting sample statistics. After sufficient samples are collected, population parameters can be approximated. Given the high dimensionality of the spatial probit likelihood, the joint posterior distribution is such that direct sampling from it is prohibitively complex. However, we can rely on Markov chain Monte Carlo methods which takes samples by "walking" around the distribution. From this distribution approximation, we can draw inferences on the parameter distributions. Of this family, the Gibbs sampling methods is most used. Rather than using independent draws from the joint distribution, Gibbs sampling relies on a sequence of draws from the set of parameter conditional distributions to approximate the distribution. We first derive individual conditional posterior distributions for each parameter: $p(\beta|\rho, y^*, y)$, $p(\rho|\beta, y^*, y)$, and $p(y^*|\beta, \rho, y)$ by selecting the parts of the joint distribution related to the particular parameter. After selecting arbitrary beginning values for the parameters β_0, ρ_0, y_0^*, we can then draw from the first parameter distribution conditional on the starting values of the other distributions, e.g. $p(\beta_1|\rho_0, y_0^*, y)$. The second parameter's new value is then drawn conditional on the new value of parameter one and the starting values of the remaining parameters, e.g. $p(\rho_1|\beta_1, y_0^*, y)$. Sampling through the conditional densities, sequentially, through some high

[9] Parameter ρ has limited support from [-1, 1].

number of iterations (we use 10,000 with a burn-in of 1,000 iterations), a convergent state is realized wherein all further draws would be from the targeted posterior joint distribution. In the application of MCMC to the Bayesian spatial probit, the conditional distributions for the parameters take the same form as in the Bayesian spatial autoregressive model with a continuous dependent variable:

$$p(\beta|\rho, y^*) \propto N(c^*, T^*)$$

$$c^* = (X'X + T^{-1})^{-1}(X'Ay^* + T^{-1}c)$$

$$T^* = (X'X + T^{-1})^{-1}$$

$$A = (I_n - \rho W)$$

and

$p(\rho|\beta, y^*) \propto |(I_n - \rho W)| exp(-0.5[Ay^* - X\beta]'[Ay^* - X\beta])$, a non-standard distribution due to the determinant of $(I_n - \rho W)$ that requires the Metropolis-Hastings within the Gibbs sampling. Very generally, Metropolis-Hastings requires that we generate a candidate sample from a proposal distribution, and per an acceptance probability, we accept the candidate sample as part of the posterior sample. Finally, given the observed y and the parameters, β and ρ, we have the following truncated multivariate distribution for latent y^*

$$y^* \sim TMVN\{(I_n - \rho W)^{-1} X\beta, [(I_n - \rho W)'(I_n - \rho W)]^{-1}\}$$

where as usual for identification, $\sigma_\varepsilon^2 = 1$. Sampling of y^* from the truncated multivariate normal distribution requires an *m*-step Gibbs sampling method proposed by Geweke (1991).

4.4. Data and descriptive characteristics

The dependent variable is whether hospital *i* offers service *m* in year *t*=2013, where *m*= {open robotic assisted procedures, laparoscopic robotic assisted procedures, percutaneous robotic assisted procedures, endoscopic robotic assisted procedures, thoracoscopic robotic assisted procedures, other and unspecified robotic assisted procedures}. These services are exclusive to hospitals and indicate the presence of a surgical robot.

Aside from the particular variable of interest, that is, the simultaneous spatially-weighted provision of robotic surgery for hospital *i*'s rivals, the model controls for hospital *i*'s cost and demand factors with the following variables: principal payer – percent of patients with Medicaid, percent of patients with Medicare, percent of patients with private insurance; for-profit status; number of licensed beds; and the following case-mix controls for the hospital market: percent male, percent white, percent with Bachelor degree, percent over the age of 65, population density (population per acre), median income (logged; $,000), and whether the hospital is located rurally.

Data Sources

Data comes from three main sources. The geographical Hospital Facilities in Florida (2013) originates from the University of Florida GeoPlan Center. It contains hospital facility addresses from seven different sources amounting to 341 hospitals in total. Since we compare only acute care hospitals, all other hospital categories have been excluded.[10] The remaining number of hospitals in this study totals 196. The geocoded hospitals are used in the calculation of the inverse-distance weighting matrix, $\boldsymbol{W}$.

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[10] Excluded hospital categories are: acute care/long term, children specialty, psychiatric, and rehabilitation.

Using a novel approach, we have constructed hospital-specific markets by aggregating Census block group polygons that have their centroid within the 60-minute drive times estimated in ArcGIS using all accessible streets.[11] From these markets, which represent the catchment areas, we estimate demographic market variables. In particular, we use 2010 US Census Bureau Block Groups for the State of Florida with fields from 2009-2013 American Community Survey (ACS). These data are at the block group level, where block groups are geographic entities consisting of census blocks that are contained within the same census tract. Block groups are the smallest census geography available which reduces the approximation error when apportioning to the markets. The ideal size of a block group is 1,500 people; however, they contain anywhere between 600-3000 individuals. ACS is collected annually; however, for block group it is provided in 5-year increments. Hospital-specific characteristics from these data include case-mix controls for the hospital's market as specified above: median income, percent male, percent with a Bachelor's degree, percent white, percent 65 or older, and population density. Note that this approach allows some overlapping of the market where hospitals draw their patients which underlies the competition among hospitals.

The Agency for Health Care Administration (AHCA) provides Florida hospital inpatient data including ICD-9-CM Procedure Codes. There are six ICD-9-CM Procedure Codes for robotic-assisted surgeries (RAS). Additionally, as mentioned above, the following hospital-specific cost characteristics, γ_i, are obtained from these data as hospital cost controls: percent of

[11] From ESRI ArcGIS: A drive-time polygon is a region that encompasses all accessible streets that lie within a specified drive time from that point. Drive-time polygons can be used to evaluate the accessibility of a point with respect to some other features. For example, one-, two-, and three-minute drive-time polygons around a grocery store can be used to determine which people are most likely to shop at the store.

patients with Medicare as principle payer, percent of patients with Medicaid as principle payer, percent of patients with private insurance as principle payer, non-profit status of the hospital, number of licensed beds and whether the hospital is in a rural locale.

Table 1 reports the descriptive characteristics of the sample hospitals and their markets. Hospitals with and without robotic-assisted technology generally have similar characteristics. Hospitals with the surgical robot are more likely to have a higher proportion of Medicaid and private insurance payors. These hospitals are also more likely to be non-profit. Market income is similar across hospitals with and without the robotic technology. Population density and the number of licensed beds are higher, on average, for hospitals with the technology. However, these hospitals are notably less likely to have Medicare payors and less likely to be in rural locales. The full distribution of the variables is available in Appendix A.

5. Empirical results

5.1. Results

Table 2 contains the estimation results from the spatial autoregressive probit estimation, SARP, (column 1), and the non-spatial probit estimation (column 2), both estimated using Markov chain Monte Carlo sampling. As discussed, the posterior means are not useful for interpreting quantitatively how changes in the independent variables affect the probability that a hospital will adopt a surgical robot; however, the signs will be informative. Moreover, from these effects we can assess the spatial coefficient which is the primary focus of this study. We also report the *direct*, *indirect* and *total* marginal effects, useful for interpreting the magnitude of the effects of changes in explanatory variables (including the spatial spillovers) on the dependent variable. These results are in Table 3.

5.1.1. Testing the MAR

First, we note that the spatial coefficient is significant, large, and negative which suggests that when neighboring hospitals operate a robot, a given hospital is *less* likely to operate one. In figure 3 are the distribution of draws from the random walk Metropolis-Hastings-within-Gibbs sampling required for the spatial parameter, ρ. An overwhelming majority of the draws exist in the negative space indicating a strong, negative spatial spillover effect from neighboring hospitals.

Rather than a spatial clustering of hospitals with the surgical robot, the negative spatial parameter indicates more of a checker board pattern in space where neighboring hospitals are less likely to adopt a surgical robot for a given hospital with the technology. Indeed, hospitals appear to consider the behavior of neighboring hospitals, but not in a way that would be consistent with a medical arms race. Instead, these results suggest an equilibrium of surgical robot acquisition at which point in time (i.e., at least by 2013) hospitals have determined that it is not a profit-maximizing decision to invest in this technology. This acts to counter overinvestment in the medical technology.

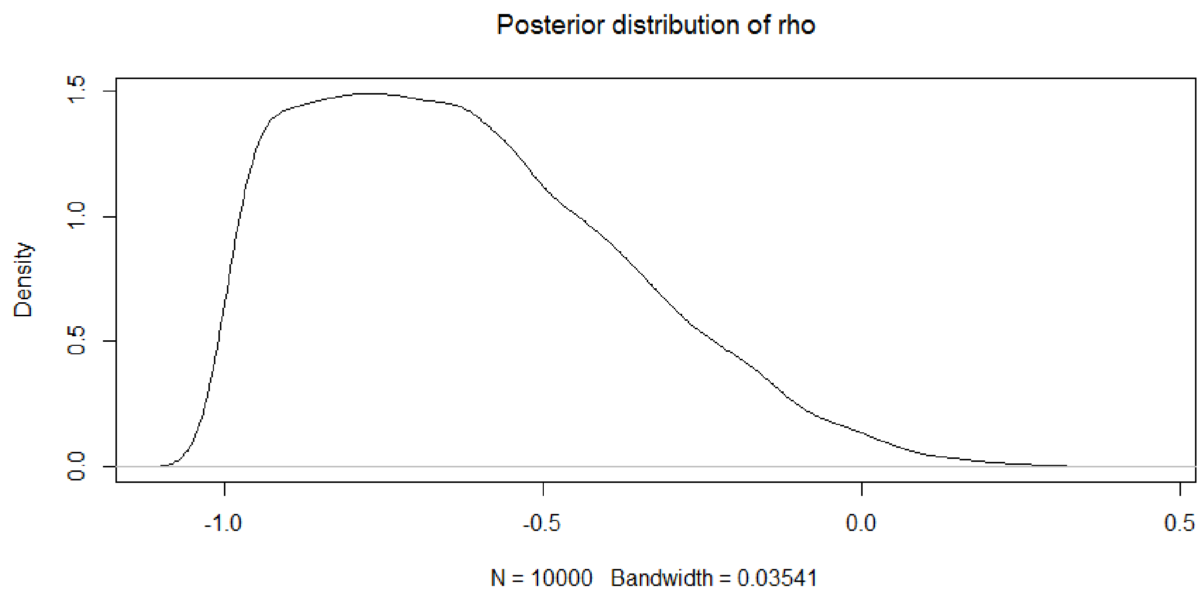

Figure 5. Posterior distribution of the spatial parameter, rho

Of the hospital characteristics, the proportion of private insurance payers is positively associated with the hospital's provision of RAS. The number of licensed beds is also positively associated with the probability of surgical robot adoption. Since the number of licensed beds is a proxy for hospital size, we expect that hospitals of larger size have wider scope. As for the market characteristics, rural hospitals are negatively associated with the decision to offer RAS.

The non-spatial probit model, also estimated using MCMC, indicates strong statistical significance for all independent variables. The estimated effects of Medicare and Medicaid are notably higher in the non-spatial probit model. Many of the market characteristics are inversely related to the dependent variable which is counter-intuitive. Given the significance of the spatial parameter in column 1, the omitted variable problem may suggest biased and inconsistent estimates in the non-spatial estimation.

5.1.2. Marginal effects

Next, we report the marginal impacts from which we can assess the magnitude of these effects and uncover underlying spatial spillovers from neighboring hospital characteristics through their impact on the hospitals' RAS decisions. Table 3 summarizes these results.

Private insurance has a strong total impact on the probability, increasing it by 66 percent for a one percent increase in private-payer share. This is after accounting for the 38 percent reduction when neighboring hospitals' private-payer share increases by one percent. Since the direct effect is positive and the spatial parameter is negative, we would expect that as neighboring hospitals' share of private insurance payers increases (and this increases the likelihood that the neighbors adopt the robot), hospital *i* would be less likely to invest in this technology.

A hospital located in a rural setting is 23 percent less likely to offer RAS compared to a hospital in a non-rural region. This is derived from a 37.2 percent reduction from the direct effect and a 13.8 percent increase from the indirect effect. This suggests that a hospital is less likely to have a surgical robot if the hospital is rural, but hospitals with rural neighboring hospitals are more likely to offer RAS. This would make sense since a rural hospital is less likely to have a surgical robot, but a hospital is more likely to have a surgical robot if the neighboring hospitals do not have a surgical robot.

5.2. Further analyses

5.2.1. Earlier period

Given the checker board spatial pattern observed in our sample of hospitals from 2013, we have suggested that we have observed an equilibrium as laid out in Reinganum (1981). That is, at first competition increases the diffusion of a technology as first-movers attempt to gain competitive advantage. As more firms adopt the technology the market share will decrease and along with it the incentive to adopt the technology. Given the dynamic nature of this explanation, as a robustness check we can perform the same analysis completed for 2013 data to an earlier period to identify whether in a period prior to 2013, competition is seen to enhance adoption of technology. A positive and significant spatial parameter from this estimation would support this theory. We have completed the earlier-period analysis for 2011. The results of this analysis are reported in table 4.

The negative and significant rho coefficient on the spatial lag indicates that the same spatial pattern occurs in 2011 as in 2013. A hospital is less likely to offer RAS if neighboring hospitals have done so. The rates of uptake outlaid in figure 1 indicate that an even earlier time-period may be more useful in establishing robustness to the theory. Perhaps in 2008 or 2009 competition was having a positive effect on the technology adoption. Unfortunately, 2011 is the earliest year for which we can obtain the necessary data for our geographical boundaries used in the construction of the hospital markets.

5.2.2. Hospital capacity

Hospitals with a surgical robot tend to be larger in terms of the number of licensed beds. It is possible that the reported results reflect the interaction between nearby hospitals that do not necessarily compete with each other due to difference in capacity. For example, a small hospital may not consider a neighboring large hospital to be a competitor for high-tech services and may indeed be less likely to offer those services once the larger hospital has established this service and the stated results may simply capture this effect. Although we control for the number of licensed beds, given that the Bayesian estimation allows for inferences on small samples, we consider a specification excluding hospitals with fewer than 75 licensed beds to test for these non-linear effects across hospital capacity. The results, found in column 2 of Table 5, corroborate what we have found using the full sample of hospitals indicating that even among just the larger hospitals, there is a reduced probability of offering RAS if a neighboring large hospital has the service. The -0.651 rho parameter for the $\boldsymbol{W}\boldsymbol{y}^{*}$ remains negative and significant.

5.2.3. Hospital networks

It may be important to distinguish hospitals that are part of a system from those who are stand-alone hospitals because networked or system hospitals may choose to provide certain services at one or a select number of locations since they can coordinate care across the different locations, that is, a within-network strategic interaction. Although not all networked hospitals may organize this way and other important factors may be involved, this provides a straight-forward way to distinguish a non-adoption decision due to strategic interaction across hospitals (or hospital-networks) from a non-adoption decision due to within-network strategy. Since some hospitals in our sample are in fact a part of a larger hospital network or system in which the delivery of services may be a coordinated effort, we have estimated a model including a dummy variable indicating those as such. The results from this specification appear in column 3 in Table 5. The consideration of the network has little effect on the spatial lag which is still strongly negative and significant.

5.2.4. Intensive margin

It may also be of interest to investigate whether, among hospitals that do have a surgical robot, there is a tendency for RAS to be performed more frequently when neighboring hospitals with the technology are performing high levels of RAS. This would provide some evidence of "treatment creep" which is the tendency for the unnecessary provision of health care services motivated by generating revenue, sometimes to recuperate extensive costs in the investment of expensive medical technologies. Given that the hospitals have a similar, even overlapping, market of patients from which to draw, we expect the levels of RAS intensity to be similar unless indicative of "treatment creep". We estimate a model as in (1) using the spatial autoregressive specification with a continuous dependent variable which represents the percentage of the hospital's procedures that were RAS. The results at the intensive margin are provided in column 4 of Table 5. Only private insurance has significance such that those hospitals with more private-insurance-payer patients are more likely to make use of the surgical robot. The spatial parameter is not statistically significant indicating that the intensity of robot usage is independent of the intensity of use at neighboring hospitals with the technology.

5.2.5. Traditional MAR

As a point of reference, we have estimated the model to reflect the conventional testing of the medical arms race hypothesis. That is, we have constructed a hospital-specific HHI by finding for each hospital the ratio of its licensed beds to the number of licensed beds in its market, then squaring these shares. For each hospital market, we identify and sum the four largest squared shares of licensed beds. The computed HHI ranges from 72.12 to 10,000 with a mean of 1,555 for the 196 hospitals for which this measure could be computed. Estimation was performed via MCMC probit with 10,000 iterations and a burn-in period of 1,000. Table 5, column 5 reports the results of this specification whose only difference from the SARP model is to replace the spatially-weighted average of nearest neighboring hospitals' provision of RAS with a more general construct of market competition, the HHI.

First, we note that the HHI is statistically significant and positive but negligible. This suggests that in more concentrated markets (i.e. less competitive), a hospital may be slightly more likely to offer RAS. This result contrasts with the post-managed care literature from Melnick & Zwanziger (1988) that identifies a loss of correlation between market concentration and hospital costs. Compared to the specification in which we control directly for competition via the spatially-weighted neighboring hospital robot decisions, many of the other variables have statistical significance although there is consistency regarding the signs and magnitudes of the coefficients for all except the proportion of Medicare payers which is here positively associated with the provision of the technology.

6. Conclusion

We conclude that a spatial strategic interaction among hospitals does exist and that the adoption of the surgical robot among hospitals in the state of Florida occurs not as a result of but in spite of the decision of competing hospital's decision to offer robotic-assisted procedures. In particular, it is more likely for non-neighboring hospitals to adopt the robotic technology. This particular spatial pattern we observe can be explained by Reinganum's (1981) theory that competition acts to limit the diffusion of the surgical robot. These results are not sensitive to restricting competition to hospitals of similar (large) capacity which might be more likely to consider each other rivals. Networks of hospitals were considered as well without substantially affecting our main results. The study lends support to the theory that competition does not necessarily lead to the overprovision of medical technology, an important finding for all healthcare stakeholders.

Compared to other studies on the adoption of the surgical robot that find less concentrated markets are associated with robot adoption (Wright et al. 2016; Barbash et al. 2014, Li et al. 2014), our study relies on a spatial approach to address the underlying mechanism through which competition may affect the decision to adopt the technology and we find that the strategic interaction underlying competition actually serves to limit the adoption of the technology. We also find that, conditional on robot ownership, a hospital is no more likely to use the robot if facing more competition. These results corroborate with Wright et al. (2016).

Limitations of the current study include the inability to claim causal statements given the cross-sectional nature of the data. Because we cannot control for time-invariant, unobservable characteristics of the hospital such as management style (a key factor in technology adoption, as mentioned in section 2), we cannot conclusively determine that the neighboring hospital's decision to offer robotic surgery *caused* a given hospital to not offer the surgical robot. We can say only that, in equilibrium, the decision is (negatively) related to the decision of neighboring hospitals or that a hospital is less likely to offer robotic surgery if neighboring hospitals do so, on average. The current approach also assumes that the strategic interaction determined by the analysis occurs between all pairs of hospitals whereas localized differences in strategic interaction are possible. Finally, it is worth noting that medical technology is subject to improvements and innovation. Furthermore, with regards to the cost side of welfare, throughout the period of this study, Intuitive is the monopolist in the surgical robot market. Some of the company's initial patents have expired. As more suppliers enter the market, we can expect the costs of the surgical robot, disposables and maintenance contracts will decline. The purpose of this study was to investigate whether hospitals were making the decision to procure technology (i.e. surgical robots) as a result of competitive pressures. It therefore took advantage of the timespan during which clinical evidence in support of the adoption was lacking to provide insight onto competition behavior in the hospital market with respect to welfare-reducing effects of less concentrated hospital markets.

In addition to the empirical findings which can shed light on the strategic interaction among hospitals with regard to medical technology adoption, this paper seeks to further the application of the spatial autoregressive model which can be useful for investigating social learning, learning from others and technological externalities (Foster and Rosenzweig, 1995; Conley and Udry, 2001; Foster and Rosenzweig, 2010). More importantly, we wish to contribute to the limited application of discrete choice spatial models specifically.

Further research relating to this topic may attempt to make more thorough consideration of the hospital networks which are growing, especially in response to structural changes in the healthcare market, and which pose a challenge for the current spatial methodologies. Additionally, in a future study we may be able to investigate whether hospitals respond to neighboring hospitals' technology procurement decisions by offering a strategic substitute medical technology. This can be accomplished using the spatial Durbin regression model, an extension of the spatial autoregressive model in which the neighboring hospital characteristics are also a weighted independent variable. The applications of the spatial approach to the healthcare market are vast, as the impact of competition is a topic of continuous study, especially as the healthcare market faces structural changes in our attempt to improve the healthcare system in this country.

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Table 2. Descriptive characteristics

Variable	Hospitals without surgical robot (n=84) Mean	SE	Min	Max
Medicare	0.565	0.174	0.001	0.857
Medicaid	0.156	0.137	0.000	0.683
private insurance	0.156	0.087	0.000	0.536
non-profit	0.357	0.482	0.000	1.000
market income (log; $,000)	3.374	0.199	3.000	3.987
market male	49.497	1.527	48.293	56.084
market bachelor	11.153	1.888	5.633	13.406
market white	76.861	5.483	67.376	90.302
market 65+	25.232	6.130	14.329	43.198
population density (per acre)	0.645	0.497	0.023	1.992
licensed beds	157.964	185.030	20.000	1493.000
rural	0.274	0.449	0.000	1.000

Variable	Hospitals with surgical robot (n=112) Mean	SE	Min	Max
Medicare	0.478	0.134	0.142	0.778
Medicaid	0.196	0.101	0.019	0.468
private insurance	0.208	0.080	0.085	0.462
non-profit	0.420	0.496	0.000	1.000
market income (log; $,000)	3.394	0.171	3.005	3.942
market male	48.883	0.791	48.228	54.235
market bachelor	11.847	1.291	6.212	13.458
market white	75.446	5.496	62.251	87.170
market 65+	25.157	5.313	16.030	40.503
population density (per acre)	0.871	0.483	0.104	2.097
licensed beds	356.732	216.899	62.000	1217.000
rural	0.027	0.162	0.000	1.000

Notes. The full sample consists of 196 long-term, acute-care hospitals in the state of Florida in 2013.

Table 3. Spatial and non-spatial probit estimation results

	(1) SARP	(2) Probit
Medicare	-0.003	0.340***
	(2.84)	(0.04)
Medicaid	0.717	1.208***
	(2.44)	(0.05)
private insurance	3.691*	3.777***
	(2.11)	(0.04)
non-profit	0.117	0.086***
	(0.23)	(0.00)
market income (log; $,000)	1.270	1.255***
	(1.08)	(0.02)
market male	-0.360	-0.317***
	(0.24)	(0.00)
market bachelor	-0.089	-0.128***
	(0.13)	(0.00)
market white	-0.027	-0.012***
	(0.04)	(0.00)
market 65+	-0.021	-0.024***
	(0.04)	(0.00)
population density (per acre)	-0.342	-0.502***
	(0.46)	(0.01)
licensed beds	0.002***	0.002***
	(0.00)	(0.00)
rural	1.315***	-1.167***
	(0.47)	(0.01)
Wy	-0.610**	
	(0.25)	
Observations	196	196

Notes. The dependent variable is whether the hospital provides a RAS procedure. Column 1 contains the estimates from the spatial autoregressive probit (SARP) model estimated using MCMC methods with diffuse priors. Reported estimates are the full conditional means based on 10,000 samples after 1,000-sample burn-in. Estimates in column 2 are from the non-spatial probit model estimated using MCMC. Standard errors of the means are in parenthesis. Coefficients that are significant at the 0.01, 0.05, and 0.1 percent levels are marked with ***, **, * respectively.

Table 4. Marginal effects from the SARP estimation

	(a) Direct effects			(b) Indirect effects			(c) Total effects		
	Lower	Posterior mean	Upper	Lower	Posterior mean	Upper	Lower	Posterior mean	Upper
Medicare	-1.010	0.001	1.016	-0.403	-0.001	0.396	-0.639	0.000	0.641
Medicaid	-0.936	0.205	1.347	-0.536	-0.076	0.363	-0.590	0.129	0.860
private insurance	0.069	1.044	2.010	-0.844	-0.383	0.005	0.044	0.662	1.316
non-profit	-0.076	0.033	0.142	-0.057	-0.012	0.029	-0.047	0.021	0.092
market income (log; $,000)	-0.142	0.359	0.854	-0.363	-0.132	0.053	-0.088	0.226	0.548
market male	-0.214	-0.102	0.008	-0.004	0.038	0.091	-0.138	-0.064	0.004
market bachelor	-0.087	-0.025	0.039	-0.015	0.009	0.035	-0.056	-0.016	0.024
market white	-0.026	-0.008	0.011	-0.004	0.003	0.011	-0.016	-0.005	0.007
market 65+	-0.023	-0.006	0.012	-0.005	0.002	0.009	-0.015	-0.004	0.007
population density (per acre)	-0.309	-0.096	0.121	-0.048	0.034	0.125	-0.199	-0.062	0.075
licensed beds	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.001
rural	-0.581	-0.372	-0.165	0.029	0.138	0.256	-0.382	-0.234	-0.102

Notes. Upper and lower refer to the 95% confidence interval.

Table 5. Earlier time-period

	(1) SARP 2013	(2) SARP 2011
Medicare	-0.003	1.939
	(2.84)	(2.21)
Medicaid	0.717	3.036
	(2.44)	(2.57)
private insurance	3.691*	6.730***
	(2.11)	(2.18)
non-profit	0.117	-0.043
	(0.23)	(0.24)
market income (log; $,000)	1.270	-0.372
	(1.08)	(1.19)
market male	-0.360	-0.099
	(0.24)	(0.23)
market bachelor	-0.089	0.077
	(0.13)	(0.14)
market white	-0.027	-0.003
	(0.04)	(0.04)
market 65+	-0.021	0.018
	(0.04)	(0.04)
population density (per acre)	-0.342	-0.257
	(0.46)	(0.45)
licensed beds	0.002***	0.002***
	(0.00)	(0.00)
rural	1.315***	-1.084**
	(0.47)	(0.52)
Wy	-0.610**	-0.619**
	(0.25)	(0.25)
Observations	196	196

Notes. The dependent variable is whether the hospital provides a RAS procedure. Column 1 contains the estimates from the spatial autoregressive probit (SARP) model estimated using MCMC methods with diffuse priors for 2013 and column 2 contains same for 2011. Reported estimates are the full conditional means based on 10,000 samples after 1,000-sample burn-in. Standard errors of the means are in parenthesis. Coefficients that are significant at the 0.01, 0.05, and 0.1 percent levels are marked with ***, **, * respectively.

Table 6. Other robustness checks

	(1) SARP 2013	(2) SARP - Large	(3) SARP Network	(4) LPM - Intensive	(5) HHI
Medicare	-0.003	-0.738	0.154	0.010	0.372***
	(2.84)	(2.72)	(2.17)	(0.02)	(0.05)
Medicaid	0.717	-0.227	0.875	-0.008	1.264***
	(2.44)	(3.07)	(2.44)	(0.02)	(0.05)
private insurance	3.691*	5.322*	4.024*	0.044**	3.806***
	(2.11)	(2.82)	(2.13)	(0.02)	(0.04)
non-profit	0.117	0.094	0.148	-0.001	0.091***
	(0.23)	(0.26)	(0.24)	(0.00)	(0.00)
market income (log; $,000)	1.270	2.337*	1.358	0.007	1.275***
	(1.08)	(1.20)	(1.08)	(0.01)	(0.02)
market male	-0.360	-0.243	-0.360	-0.002	-0.351***
	(0.24)	(0.28)	(0.24)	(0.00)	(0.01)
market bachelor	-0.089	-0.352**	-0.093	-0.001	-0.141***
	(0.13)	(0.17)	(0.14)	(0.00)	(0.00)
market white	-0.027	-0.047	-0.024	0.000	-0.012***
	(0.04)	(0.04)	(0.04)	(0.00)	(0.00)
market 65+	-0.021	-0.032	-0.024	0.000	-0.024
	(0.04)	(0.04)	(0.04)	(0.00)	(0.00)
population density (per acre)	-0.342	-0.403	-0.311	0.000	-0.458***
	(0.46)	(0.52)	(0.47)	(0.00)	(0.01)
licensed beds	0.002***	0.002**	0.002***	0.000	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
rural	-1.315***	-0.715	-1.303***	-0.002	-1.218***
	(0.47)	(0.73)	(0.47)	(0.00)	(0.01)
network			-0.179		
			(0.23)		
HHI					0.000***
					(0.00)
Wy	-0.610**	-0.651***	-0.612**	0.111	
	(0.25)	(0.25)	(0.25)	(0.23)	
Observations	196	164	196	112	196

Notes. The dependent variable is whether the hospital provides a RAS procedure. Column 1 contains the estimates from the spatial autoregressive probit (SARP) model for comparison. Estimates in column 2 correspond to the analysis excluding smaller hospitals. Column 3 adds a network dummy variable to the specification. The intensive margin is assessed for the hospitals with the surgical robot in column 4. Column 5 represents the HHI-based approach to competition on the technology adoption. Standard errors of the means are in parenthesis. Coefficients that are significant at the 0.01, 0.05, and 0.1 percent levels are marked with ***, **, * respectively.

Appendix A. Variables

Summary of variables, their calculation and the rationale for inclusion follows. Note that all market variables have been created by first establishing a hospital's market using DriveTime analysis in ArcGIS 10.3, which superimposes a polygon on the Census Block Groups (CBG) corresponding to 60-minute drive times using all current available, accessible roadways. Using the rule that the CBG will be included in the market if the polygon contains the population-weighted centroid of the CBG, we aggregate the variables of interest and calculate proportions. These hospital-specific market boundaries allow for both variation in market characteristics and overlapping of potential patients which underlies competition.

Table A.1. Table of variables

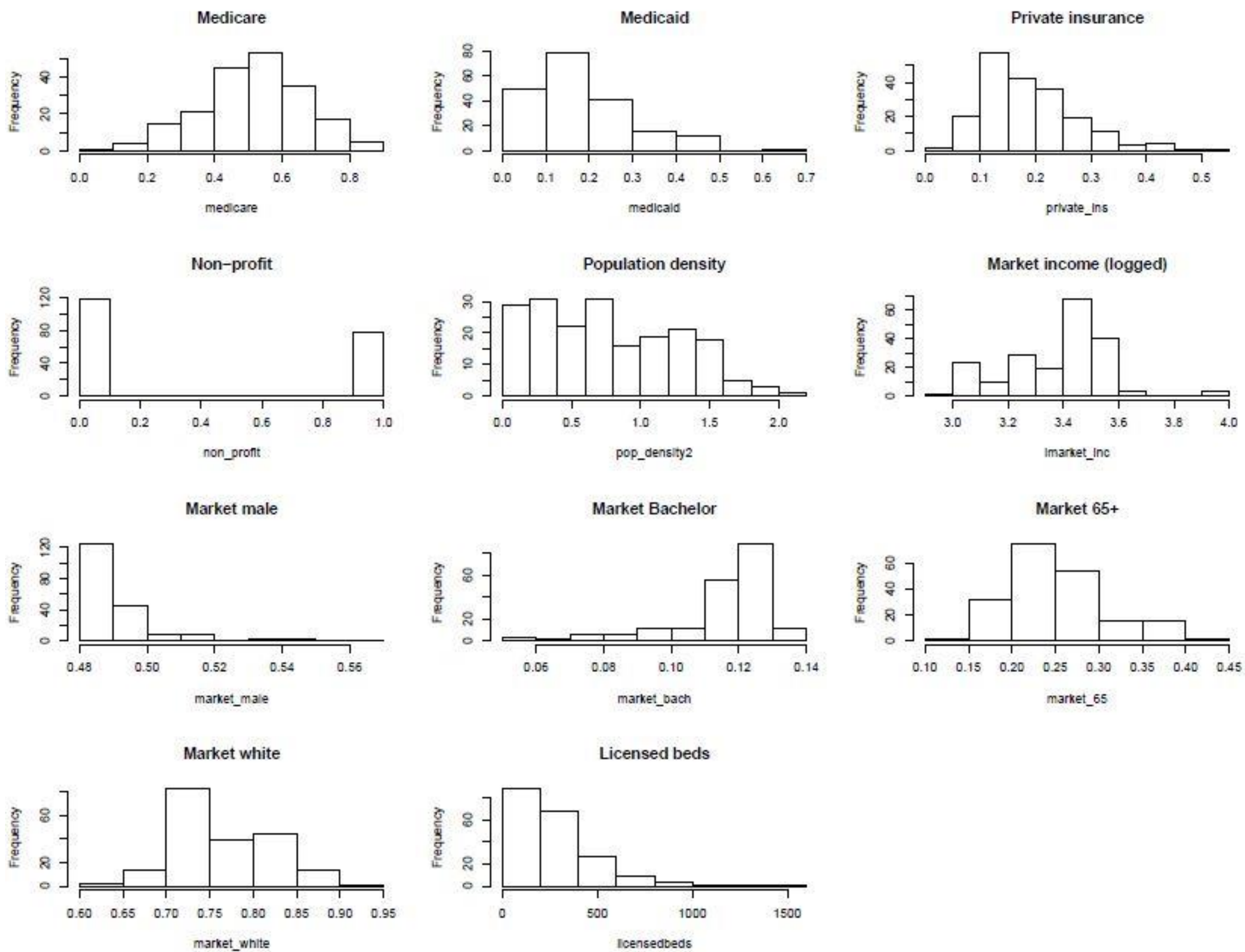
Variable	Description	Rationale for Inclusion
Dependent		
robot	a binary variable for whether hospital *i* offers service *m* where *m*= {open robotic assisted procedures, laparoscopic robotic assisted procedures, percutaneous robotic assisted procedures, endoscopic robotic assisted procedures, thoracoscopic robotic assisted procedures, other and unspecified robotic assisted procedures}	inconclusive evidence on the health outcomes of robotic-assisted surgery when compared to traditional methods, coupled with the expenses suggests robotic-assisted surgical procedures are a component of the "medical arms" in the arms race
Independent		

	spatial_lag	spatially-weighted linear combination of the decision of neighboring hospitals to provide robotic surgery	hospitals may interact strategically in a complementary way, providing specialized services that are unique to the market, or in a substitute manner, offering the same specialized services as neighboring hospitals; or strategic interaction may not exist at all
principle payer ('compositional variable'; omitted category is 'other')	medicare	percent of patients with Medicare insurance	insurance coverage and reimbursement rates may impact a hospital's decision to provide robot-assisted procedures
	medicaid	percent of patients with Medicaid insurance	
	private	percent of patients with private insurance	
	non_profit	a binary variable for whether hospital *i* is non-profit (omitted category includes: investor owned, Federal, public/government, State)	
	lmrkt_inc	hospital market median income	case-mix control; hospitals in wealthier markets may be incentivized to advertise and/or provide specialized services; alternatively, since correlated with bachelor, may reduce the need for certain specialized services given a reduced likelihood of disease
	mrkt_male	percentage of the GIS-defined hospital market population total that are male	case-mix control; certain diseases and therefore treatments vary by gender
	mrkt_bach	percentage of the GIS-defined hospital market population total with a Bachelor degree	case-mix control; certain diseases and therefore treatments vary by education
	mrkt_white	percentage of the GIS-defined hospital market population total that are white	case-mix control; certain diseases and therefore treatments vary by race

mrkt_65	percentage of the GIS-defined hospital market population total that are 65+ years in age	case-mix control; certain diseases and therefore treatments vary by age
pop_dens	hospital market population; market summed population over market summed acres	case-mix control; hospitals in larger markets may be themselves larger hospitals, offering more services
licensed beds	number of licensed beds in hospital	proxy for hospital size; larger hospitals may have more scope
rural	binary variable indicating whether hospital is located in rural area	

Below are the full histograms for the independent variables.

Table A.2. Histograms of independent variables



Appendix B. Spatial weights and exploratory spatial analysis

B.1. Spatial weights matrix

The spatial weighting matrix is the positive $N \times N$ matrix $\boldsymbol{W}$ where each element is a spatial weight, $w_{ij}: i, j = 1, \ldots, n$, that summarizes the spatial relations between the n units in space. The diagonal elements are conventionally set to 0 to indicate one is not a neighbor to itself, that is, $w_{ii} = 0$ for all $i = 1, \ldots, n$. The off-diagonal elements, $w_{ij}, j \neq i$, can be defined a number of different ways depending on the particular situation being modeled. For example, w_{ij}= 1 *if distance between i and j is* $\leq k$; alternatively, w_{ij}= 1 *for m nearest neighbors;* or another option is w_{ij}= 1 *if i and j are contiguous*. Estimating the spatial weights matrix elements precludes identification, so some assumption on the particular nature of the spatial relationship is required. We have defined $\boldsymbol{W}$ to be row-normalized, inverse-distance with each element, w_{ij}, expressing the degree of spatial proximity as:

$$w_{ij} = \begin{cases} \dfrac{d_{ij}^{-1}}{\sum_j d_{ij}^{-1}} \; for\ i \neq j\ and\ j\ is\ among\ the\ ten\ nearest\ neighbors \\ 0 \quad otherwise \end{cases}$$

Where d_{ij} is defined as the distance between hospital *i* and *j* and the *n* diagonal elements, w_{ii}, take the value of zero Thus, $\boldsymbol{Wy}$ is the spatial-weighted average of the neighbor outcomes.

A simple example will illustrate the above. The following table summarizes the relationship between three units in space. In parentheses are the distances between units.

Unit Neighbors (distance)

1	2 (2), 3(1)
2	1 (2), 3(3)
3	1 (1), 2(3)

This information can be summarized in an inverse-distance matrix wherein each element, d_{ij}^{-1}, represents the inverse of the distance between units *i* and *j*. For instance, $D =$

$$\begin{pmatrix} 0 & 1/2 & 1 \\ 1/2 & 0 & 1/3 \\ 1 & 1/3 & 0 \end{pmatrix}$$

We can then divide each element in the row by the sum of the row-elements to define the new elements of the row-normalized $\boldsymbol{W}$, $\sum_{j=1}^{n} d_{ij}^{-1}, = 1 , i = 1, .. , n$

$$\boldsymbol{W} = \begin{pmatrix} 0 & 1/3 & 2/3 \\ 3/5 & 0 & 2/5 \\ 3/4 & 1/4 & 0 \end{pmatrix}$$

If $\boldsymbol{y} = (y_1, y_2, y_3)'$ then $\boldsymbol{W}\boldsymbol{y} = \begin{pmatrix} 1/3\, y_2 + 2/3\, y_3 \\ 3/5\, y_1 + 2/5\, y_3 \\ 3/4\, y_1 + 1/4\, y_2 \end{pmatrix}$, a spatial-weighted average of neighboring response variables.

B.2. Moran's I

It is possible to measure the positive, negative, or nonexistent degree to which observations with location have similar attributes, that is, spatial autocorrelation. We first estimate a non-spatial regression and save the residuals. Then, a global spatial autocorrelation can be tested for using the Moran's I statistic which takes the form $I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2}$. Moran's I is asymptotically normal under the null hypothesis that no spatial autocorrelation exists, so for our sample we can interpret the test statistic $\frac{I-E[I]}{\sqrt{Var(I)}}$ as a p-value. Given the results below, we are unable to reject the null hypothesis that no global spatial autocorrelation exists. In other words, the data appear to exhibit overall complete spatial randomness. However, the Moran's I statistic is limited by being a global statistical measurement which means it is best for identifying a certain relationship pattern that exists across the whole study area and is incapable of identifying particular spatial clustering (Hongfei Li, Calder, & Cressie, 2007). Note that these results are a function of the form of $\boldsymbol{W}$ which means improperly specified weights may lead to a type II error. This statistic's limitations are not well established. For example, it has been shown that Moran's I is only an accurate measure of the spatial dependence if the spatial parameter is near zero.

Table B.1. Moran's I test statistic

Moran I statistic standard deviate = -0.2606, p-value = 0.7944
alternative hypothesis: two.sided
sample estimates:

Observed Moran I	Expectation	Variance
-0.0329	-0.0263	0.0006

Appendix C. Bayesian analysis

C.1. Derivation of the Bayesian SAR full conditionals

We include the derivation of the full conditional distributions from the spatial autoregressive model with a continuous outcome as estimated in the intensive margin analysis.

$$y = \rho Wy + X\beta + \varepsilon, \quad \text{where } \varepsilon \sim N(0, \sigma^2 I_n)$$

Note:

$$y - \rho Wy = X\beta + \varepsilon$$

$$y(I_n - \rho W) = X\beta + \varepsilon$$

$$y = (I_n - \rho W)^{-1}(X\beta + \varepsilon)$$

$$\varepsilon = Ay - X\beta$$

Where $A = I_n - \rho W$

Likelihood: $L(y, X, W|\beta, \sigma^2, \rho) = (2\pi)^{-\frac{n}{2}}(\sigma^2)^{-\frac{n}{2}}|A|\exp\{-0.5\sigma^{-2}(Ay - X\beta)'(Ay - X\beta)\}$

Prior distributions:

$$(\beta, \sigma^2) \sim NIG(c, T, a, b)$$

$$\pi(\beta, \sigma^2) = \pi(\beta|\sigma^2)\pi(\sigma^2) = N(c, \sigma^2 T)IG(a, b)$$

$$= (2\pi)^{-\frac{k}{2}}(\sigma^2)^{-\frac{k}{2}}|T|^{-\frac{1}{2}}\exp\{-0.5\sigma^{-2}(\beta - c)'T^{-1}(\beta - c)\} \times \frac{b^a}{\Gamma(a)}(\sigma^2)^{-(a+1)}exp\{-0.5\sigma^{-2}2b\}$$

Full posterior:

$$p(\beta, \sigma^2, \rho|y, X, W) \propto (\sigma^2)^{-(\frac{n}{2}+\frac{k}{2}+a+1)}|A|\exp\{-0.5(\sigma^2)^{-1}[(Ay - X\beta)'(Ay - X\beta) + (\beta - c)'T^{-1}(\beta - c) + 2b]\}$$

Expanding the terms within squared brackets,

$$y'A'Ay - y'A'X\beta - \beta'X'Ay + \beta'X'X\beta + \beta'T^{-1}\beta - \beta'T^{-1}c - c'T^{-1}\beta + c'T^{-1}c + 2b$$

$$= \beta'(X'X + T^{-1})\beta - \beta'(X'Ay + T^{-1}c) - (y'A'X + c'T^{-1})\beta + c'T^{-1}c + 2b + y'A'Ay$$

If we let

$$c^* = (X'X + T^{-1})(X'Ay + T^{-1}c)$$

$$T^* = (X'X + T^{-1})^{-1}$$

$$b^* = b + 0.5(c'T^{-1}c + y'A'Ay + y'A'X + c'T^{-1})$$

$$a^* = \frac{n}{2} + a$$

Then,

$$(\beta, \sigma^2, \rho | y, X, W) \propto (\sigma^2)^{-(a^* + \frac{k}{2} + 1)} |A| \exp\{-0.5(\sigma^2)^{-1}[(\beta - c^*)'(T^*)^{-1} (\beta - c^*) + 2b^*]\}$$

This posterior distribution is *close to* but not exactly a tractable form (i.e. the NIG prior is not a conjugate).

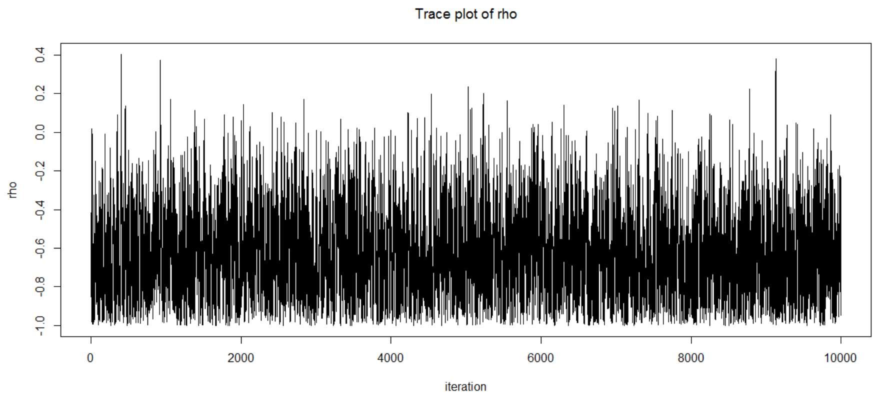
If $\rho = 0$ then $A = I_n$ and, indeed, $\beta, \sigma^2 | y, X, W \sim NIG[c^*, T^{*-1}, a^*, b^*]$

An uninformative prior, $a, b = 0;\ T^{-1} = 0$ allows us to simplify the posterior

$$\propto (\sigma^2)^{-\frac{n}{2}} |A| \exp\{-0.5\sigma^{-2}(Ay - X\beta)'(Ay - X\beta)\} p(\rho)$$

C.2. Convergence diagnostics for simulation-based Bayesian inference

Useful for determining convergence, the figure below displays the trace plot of the spatial parameter from the MCMC. The plot mixes across most of the distribution and centers/becomes stationary on -0.5 (i.e. the mean and variance are relatively constant), indicating it likely approximates the right posterior distribution of rho with the user-set burn-in period of 1000. The convergence diagnostics and posterior distributions for all parameters follow, each displaying proper convergence behavior.



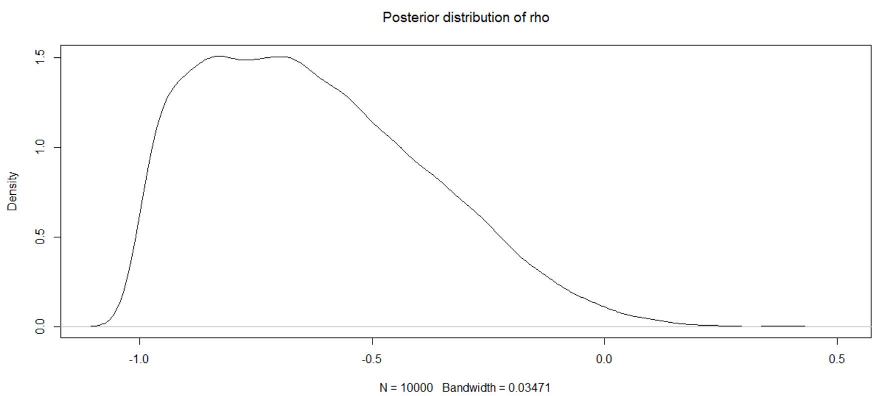


Figure 6. Trace plot and posterior distribution for the spatial parameter, rho

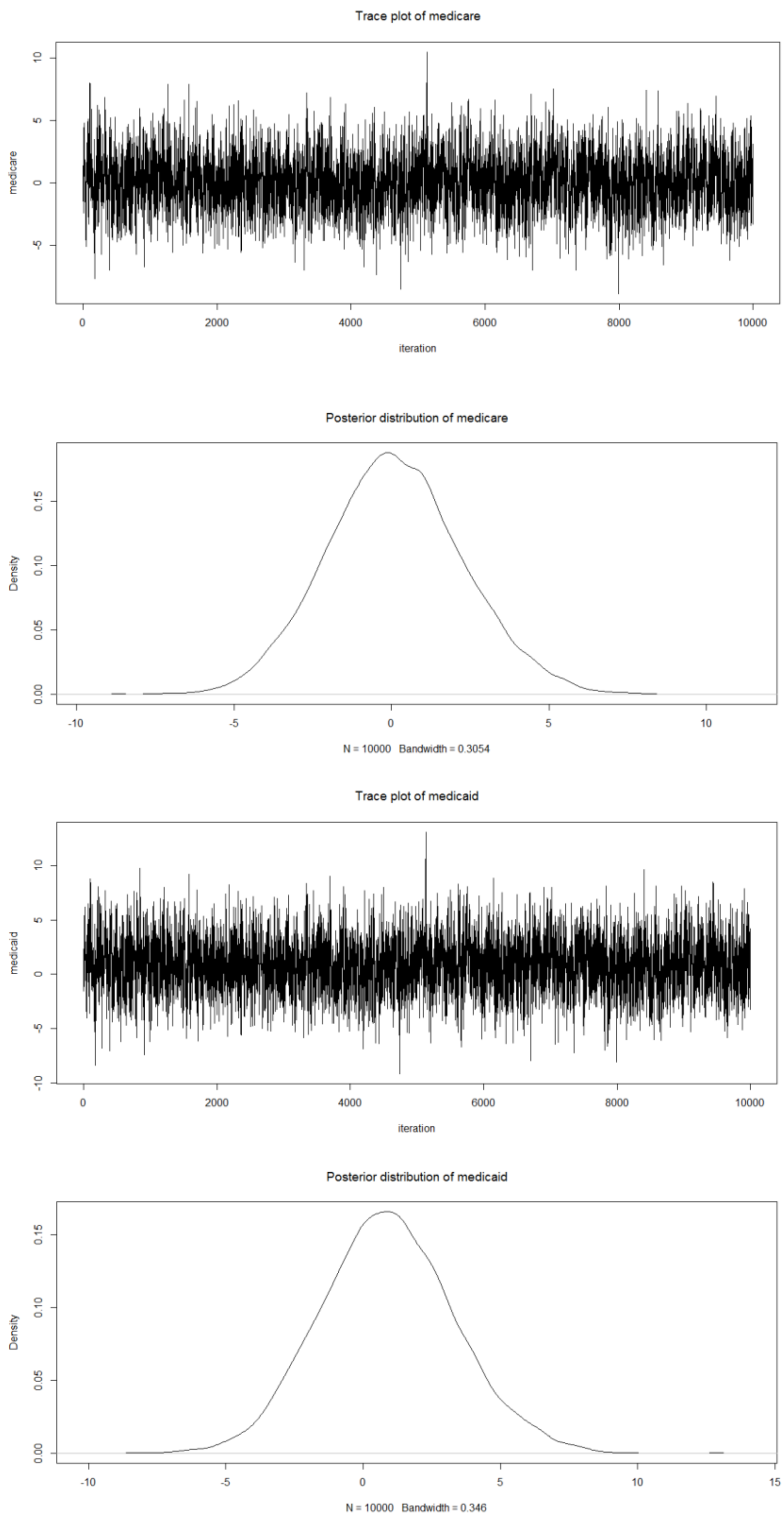


Figure 7. Trace plot and posterior distribution for independent variables (Continued on Next Page)

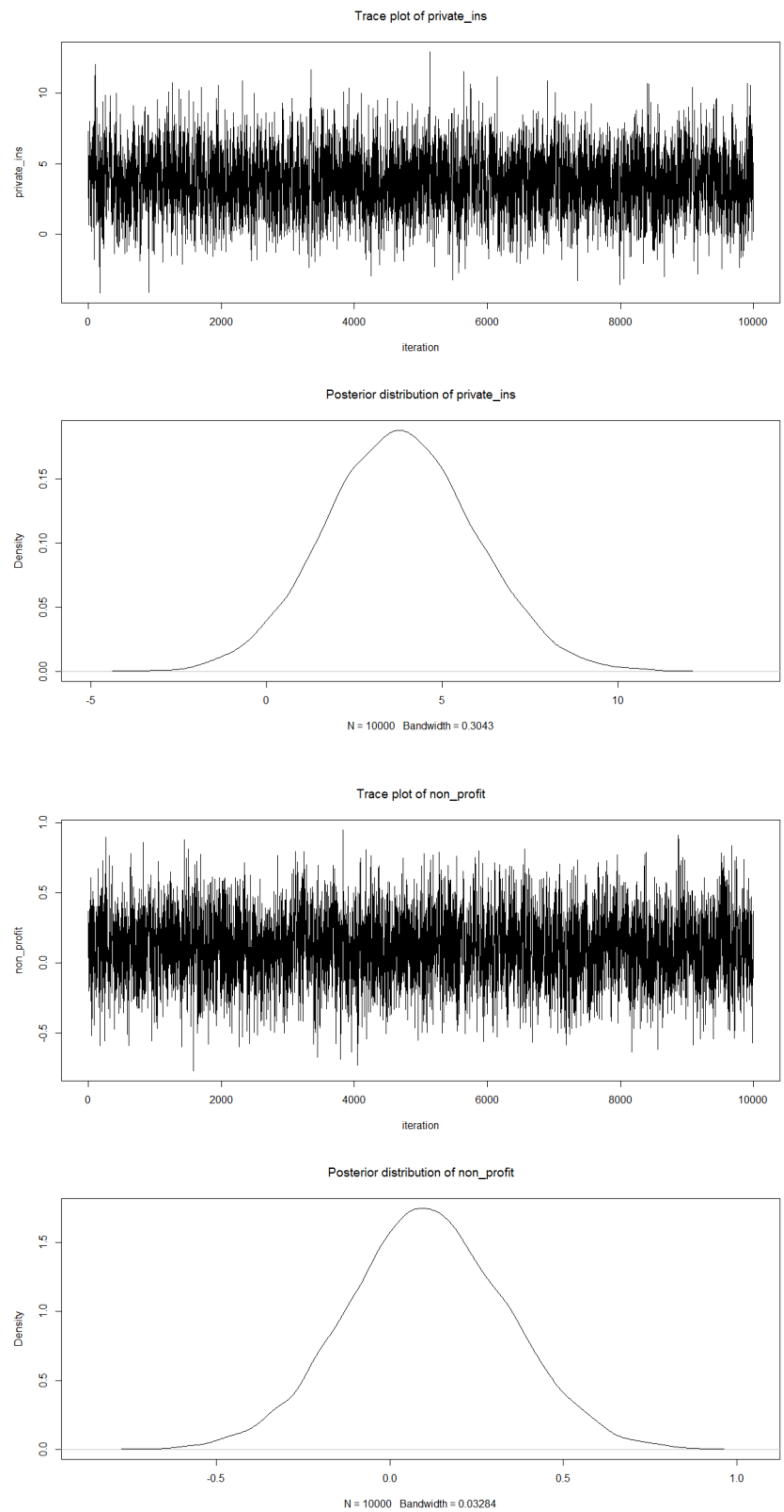


Figure 7. Trace plot and posterior distribution for independent variables (Continued on Next Page)

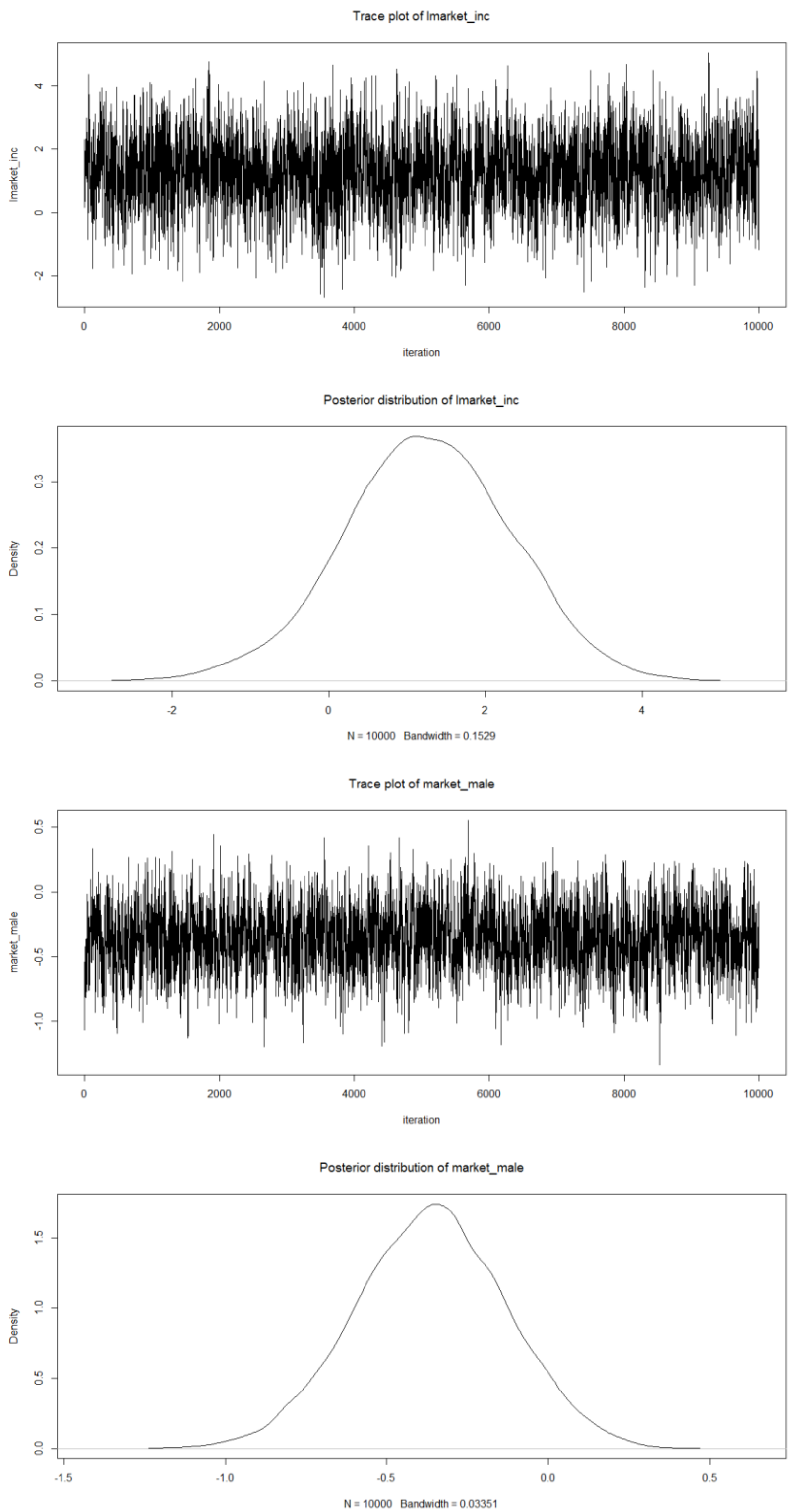


Figure 7. Trace plot and posterior distribution for independent variables (Continued on Next Page)

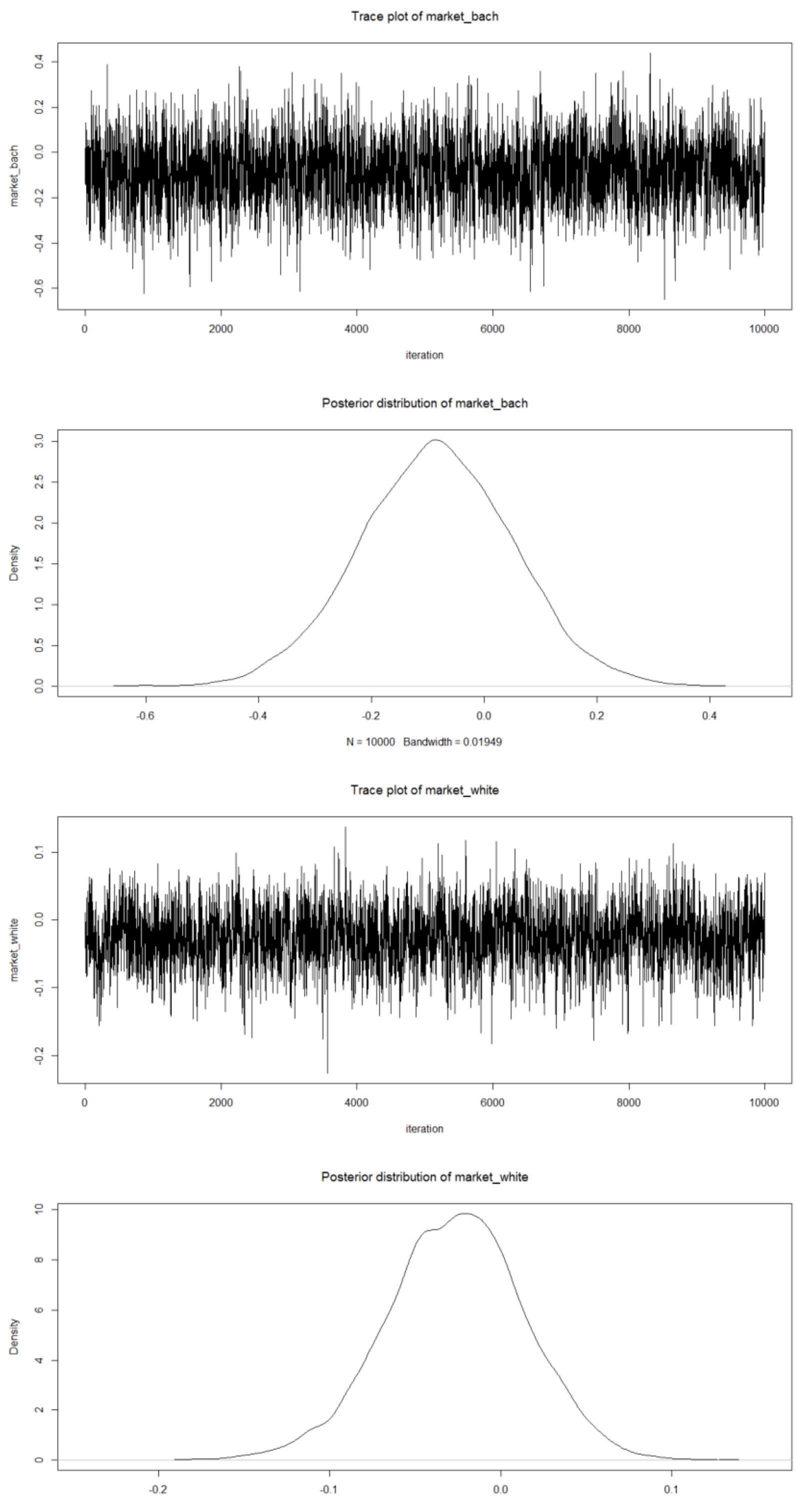


Figure 7. Trace plot and posterior distribution for independent variables (Continued on Next Page)

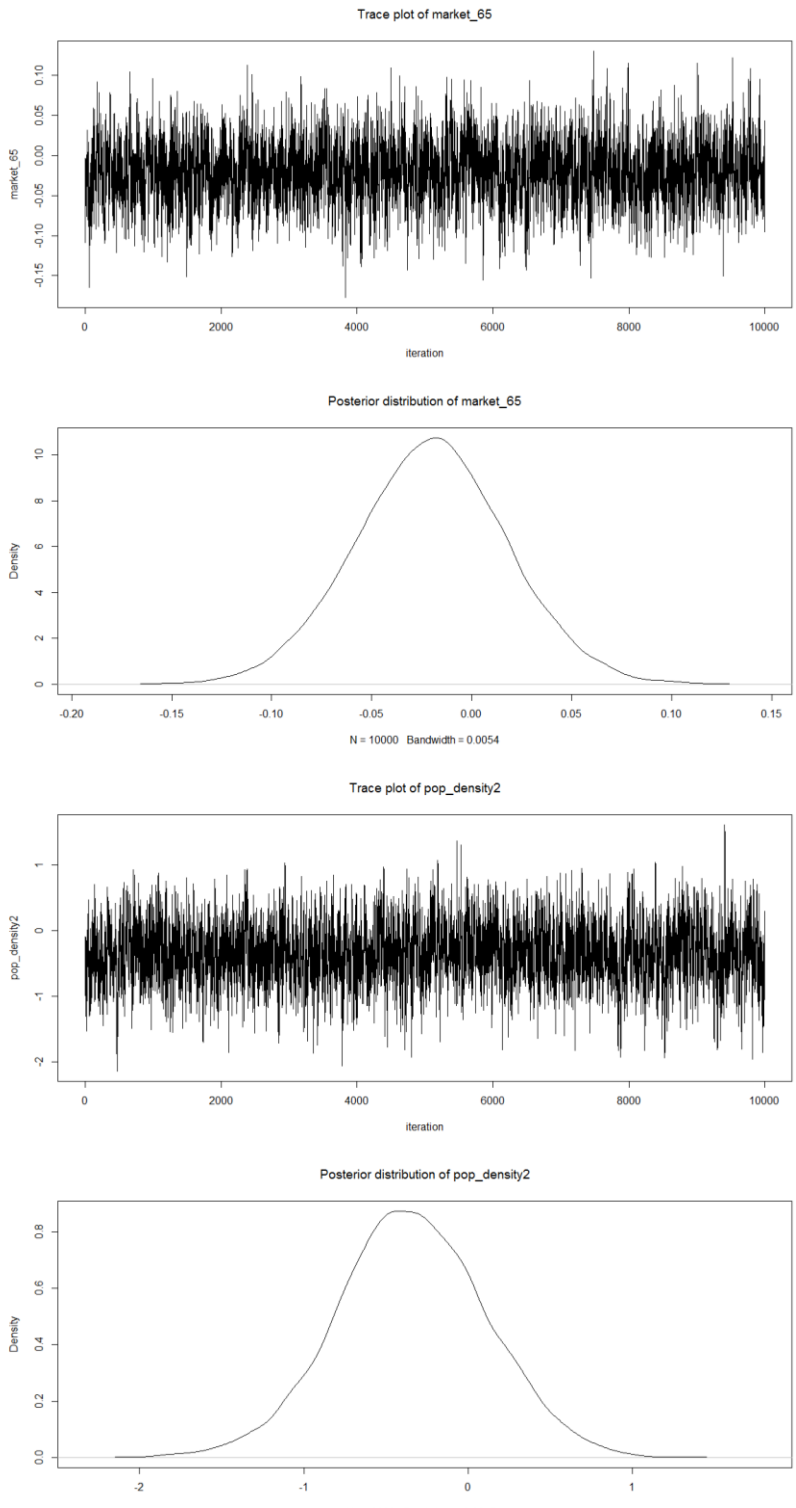


Figure 7. Trace plot and posterior distribution for independent variables (Continued on Next Page)

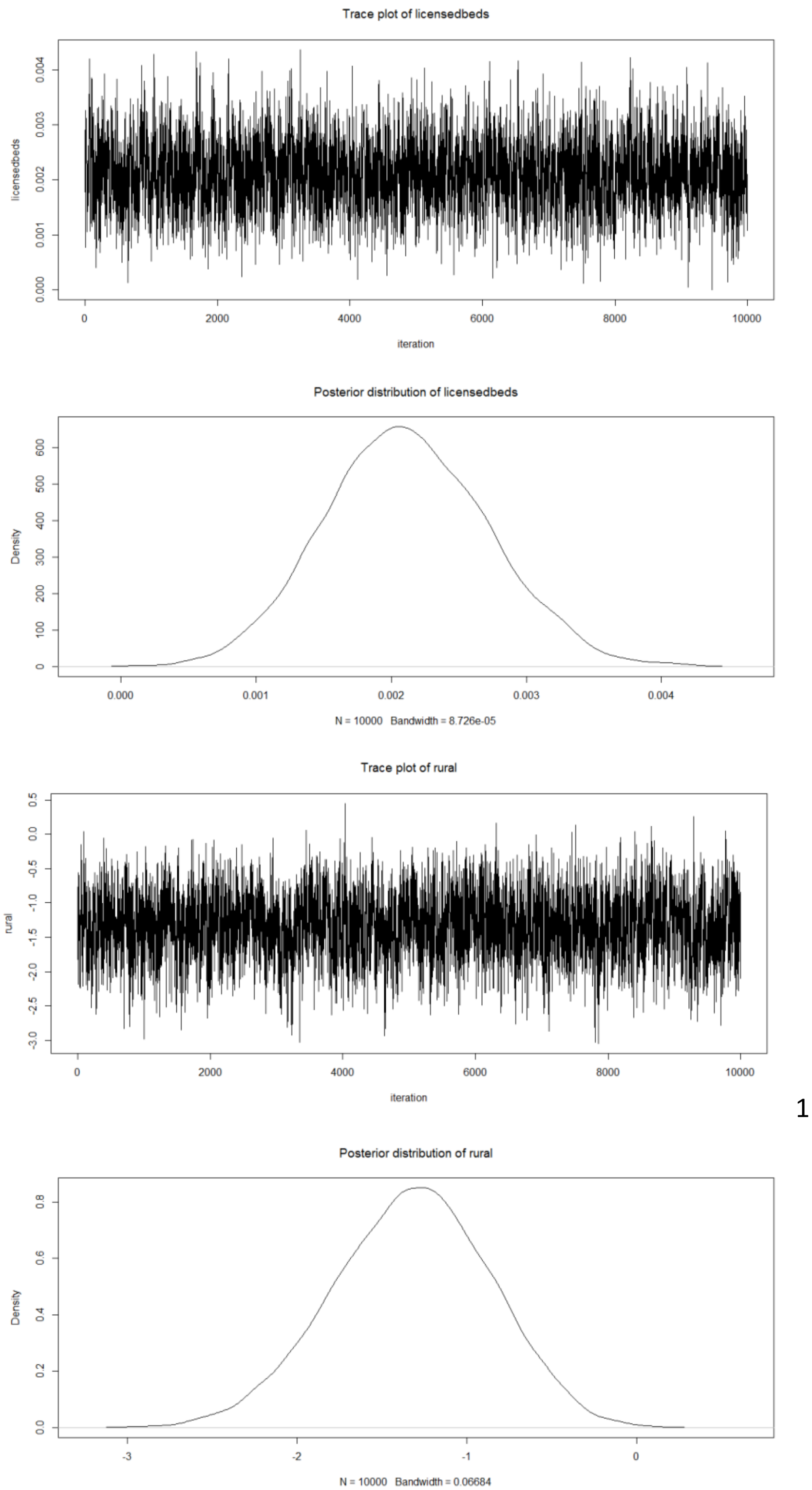


Figure 7. Trace plot and posterior distribution for independent variables (Continued on Next Page)

C.3. Selection of number of neighbors; AIC model comparison

In addition to specifying the elements of the spatial weights matrix, $\boldsymbol{W}$, to be of inverse-distance which assigns a greater weight to hospitals that are nearer in proximity, we also assume there is a limit to the number of hospitals a given hospital may consider a rival. Beyond this threshold, the w_{ij} will take the value of zero. This is a reasonable assumption since the hospital sample spans the entire state of Florida. Note that LeSage & Pace (2014) claim that a well-specified and properly interpreted spatial regression model is not sensitive to the assumed structure of the spatial relationship captured in $\boldsymbol{W}$. Nonetheless, to attempt to reveal the optimal number of rival hospitals for the spatial weights matrix, we estimate the model with several specifications of $\boldsymbol{W}$ using the *k* nearest neighbors. To determine the "stopping point", we then use the Akaike information criterion (AIC) which evaluates the fit of the specification while penalizing for overfitting to minimize loss of information. In this form of model comparison, the lower AIC reflects the optimal model. This criterion is similar to one utilized by Kostov (2010) in attempt to find the "optimal" weighting matrix. Results for several of the specifications are reported in Table C.1. There are minimal differences in the measure of AIC (as well as the posterior means estimates); for each value of *k* tested; however, we take the results to indicate the optimal number of neighbors for the leading model to be *k*=10. Note that the optimal *k* will vary depending on the specification and we adjust accordingly. These results provide some empirical robustness to the conclusion of LeSage and Pace (2014) about the lack of sensitivity in the estimates to assumptions in $\boldsymbol{W}$. Moreover, as explained by LeSage and Pace (2014), differences in estimates found while testing variations of the weighting matrix are likely the result of improper specification of the regression model which lends support to the specification described in Section 4.

Table C.1. Selection of the *k* nearest neighbors; AIC comparison

	SARP(k=8)			SARP (k=9)			SARP (k=10)			SARP (k=11)		
	Mean	Pr(>|z|)		Mean	Pr(>|z|)		Mean	Pr(>|z|)		Mean	Pr(>|z|)	
(Intercept)	18.885	0.119		17.026	0.149		16.361	0.166		15.007	0.181	
Medicare	0.167	0.940		0.073	0.974		0.096	0.965		0.168	0.939	
Medicaid	0.964	0.697		0.844	0.733		0.878	0.722		0.976	0.692	
Private insurance	4.010	0.065	.	3.719	0.084	.	3.802	0.073	.	3.691	0.086	.
Non-profit	0.109	0.642		0.104	0.658		0.103	0.659		0.105	0.647	
Log(med. income)	1.381	0.216		1.366	0.201		1.305	0.234		1.179	0.273	
Market male	-0.418	0.092	.	-0.380	0.116		-0.365	0.133		-0.334	0.147	
Market Bachelor's	-0.100	0.471		-0.091	0.511		-0.091	0.505		-0.097	0.469	
Market white	-0.027	0.512		-0.027	0.511		-0.026	0.514		-0.023	0.548	
Market 65+	-0.023	0.552		-0.023	0.553		-0.021	0.579		-0.020	0.589	
Population density	-0.356	0.458		-0.362	0.438		-0.332	0.483		-0.290	0.518	
Licensed beds	0.002	0.001	***	0.002	0.001	***	0.002	0.001	***	0.002	0.001	***
Rural	-1.297	0.007	**	-1.314	0.005	**	-1.317	0.005	**	-1.250	0.006	**
Wy (rho parameter)	-0.665	0.003	**	-0.599	0.017	*	-0.609	0.016	*	-0.560	0.047	*
AIC	231.318			231.641			231.220			232.493		

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1