Published in final edited form as:

Healthc (Amst). 2014 July ; 2(2): 152–157. doi:10.1016/j.hjdsi.2013.10.002.

Are hospitals “keeping up with the Joneses”? Assessing the spatial and temporal diffusion of the surgical robot

Huilin Li, Ph.D.^{1,2}, Mitchell H. Gail, M.D. Ph.D.³, R. Scott Braithwaite, M.D. MSc.¹, Heather T. Gold, Ph.D.^{1,2,4}, Dawn Walter, M.P.H.⁵, Mengling Liu, Ph.D.^{1,2}, Cary P. Gross, M.D.^{6,7}, and Danil V. Makarov, M.D. M.H.S.^{1,2,4,5,7}

¹Department of Population Health, New York University, New York, NY, 10016

²New York University Cancer Institute

³Division of Cancer Epidemiology and Genetics, Biostatistics Branch, National Cancer Institute, NIH, Rockville, MD, 20852-7242

⁴Robert F. Wagner Graduate School of Public Service

⁵Department of Urology, New York University School of Medicine

⁶Cancer Outcomes, Public Policy, and Effectiveness Research (COPPER) Center, and Division of General Internal Medicine, Yale University School of Medicine

⁷United States Department of Veterans Affairs

Abstract

Background—The surgical robot has been widely adopted in the United States in spite of its high cost and controversy surrounding its benefit. Some have suggested that a “medical arms race” influences technology adoption. We wanted to determine whether a hospital would acquire a surgical robot if its *nearest* neighboring hospital already owned one.

Methods—We identified 554 hospitals performing radical prostatectomy from the Healthcare Cost and Utilization Project Statewide Inpatient Databases for seven states. We used publicly available data from the website of the surgical robot’s sole manufacturer (Intuitive Surgical, Sunnyvale, CA) combined with data collected from the hospitals to ascertain the timing of robot acquisition *during year 2001 to 2008*. One hundred thirty four hospitals (24%) had acquired a surgical robot by the end of 2008. We geocoded the address of each hospital and *determined a hospital’s likelihood to acquire a surgical robot based on whether its nearest neighbor owned a surgical robot*. We developed a Markov chain method to model the acquisition process spatially

Corresponding author: Huilin Li Ph.D., Assistant Professor, Division of Biostatistics, Department of Population Health, School of Medicine, New York University, huilin.li@nyumc.org, Phone: (212) 263-8977, Fax: (212)263-8570, Office: 650 First Avenue, 547, New York, NY, 10016.

The views expressed in this article are those of the author(s) and do not necessarily represent the views of the Department of Veterans Affairs.

Author Contributions

H.L. and D.M. designed the study; C.G. and D.M. formed the cohort; D.M. R.S.B and H.G. set up the model for diffusion of technology, H.L., M.G. and M.L designed the analytic model and provided the statistical interpretation. H.L. and D.W. performed statistical analyses; H.L. and D. M. took primary responsibility for writing the manuscript.

and temporally and quantified the “neighborhood effect” on the acquisition of the surgical robot while adjusting simultaneously for known confounders.

Results—After adjusting for hospital teaching status, surgical volume, urban status and number of hospital beds, the Markov chain analysis demonstrated that a hospital whose nearest neighbor had acquired a surgical robot had a higher likelihood itself acquiring a surgical robot. (OR=1.71, 95% CI: 1.07–2.72, $p=0.02$).

Conclusion—There is a significant spatial and temporal association for hospitals acquiring surgical robots during the study period. Hospitals were more likely to acquire a surgical robot during the robot’s early adoption phase if their nearest neighbor had already done so.

1. Introduction

The surgical robot has been widely adopted in the United States in spite of its high cost and controversy surrounding its benefit (1, 2) *since its approval by the Food and Drug Administration in 2001. Facilitating the performance of laparoscopic procedures, robotic surgical devices allow a surgeon to operate remote-controlled robotic arms which can manipulate a patient’s tissues, while the surgeon is seated at a console in the operating room.* The surgical robot is very expensive: purchase prices range between \$1 million and \$2.25 million, an annual service contract costs \$140,000 and per case disposables cost over \$2000 (1, 3, 4). Published studies of the efficacy of robotic surgery have provided mixed results. Some studies have shown that robotic surgery results in benefits such as reduced length of stay and reduced intraoperative blood loss (5–8), as compared to open surgery or standard laparoscopy. However, other studies have shown robotic surgery outcomes to be similar to or even worse than outcomes associated with traditional *open or laparoscopic* procedures (9–12).

Given the high cost and uncertain benefit of surgical robots, the reasons for rapid adoption of this technology are unclear. Some have suggested that factors other than improving health outcomes, such as the robot’s utility in hospital marketing, played a role (13); a new literature has emerged focusing on hospital-intrinsic factors associated with the adoption of the surgical robot. Adopter institutions tend to have higher surgical volume and are larger; located in urban areas, and tend to be academic medical centers (13). In addition to intrinsic hospital factors, environmental factors, such as hospital competition for physician-recruits and patients may also play a role in the diffusion of the surgical robot (14–16). In this medical competition model, technology is more likely to be adopted when a hospital’s competitors acquire it. It is unknown whether such a neighborhood effect was important in the diffusion of the surgical robot.

We sought to determine whether a hospital was more likely to acquire a surgical robot if its neighbors acquired the technology. Because the surgical robot was diffusing throughout the US, a given hospital’s neighborhood could change through time depending upon whether and when its neighbors might have acquired robots. To account for this challenge, we developed a two-state Markov chain method to *determine the likelihood of a hospital adopting the surgical robot given whether the nearest neighbor hospital owned a robot or not.* This novel method is able to quantify the “neighborhood effect” which we define as the

likelihood of robot adoption as a function of local robot adoption. We hypothesized that having neighbor hospitals with surgical robots would increase the likelihood of a non-robot owning hospital's adoption of the same technology. If this hypothesis were true, it would suggest that a hospital's purchasing decisions, at least in part, are based on regional competition, rather than on clinical evidence alone. If we found no neighborhood effect, it might suggest that regional competition was less significant than the hospital's intrinsic characteristics when deciding to adopt new technology. Understanding the diffusion of the surgical robot is extremely valuable to policy makers, physicians and patients who should be aware of factors influencing hospital behavior and their adoption of new technology, especially when this technology may be costly and unproven.

2. Methods

2.1 Study Design and Data Source

We performed a retrospective study at the hospital level. We obtained data from the Healthcare Cost and Utilization Project (HCUP) Statewide Inpatient Databases (SID) for seven states (Arizona, Florida, Maryland, North Carolina, New York, New Jersey, and Washington) during the years 2001 and 2005 to determine *which hospitals were at risk of acquiring a surgical robot. While there are a wide range of procedures which are now performed with the assistance of a surgical robot, its initial diffusion was driven primarily by the desire to perform robotic-assisted radical prostatectomy* (2). Therefore, we used these data to identify 554 hospitals in which at least one radical prostatectomy had been performed in any year between 2001 and 2005; two of these hospitals were excluded from the neighborhood analyses because of missing data. We combined publicly available data from the website of the surgical robot's sole manufacturer (Intuitive Surgical, Sunnyvale, CA) with data collected from the websites and personnel of the hospitals, *who were contacted by telephone and email*, to ascertain the date of robot acquisition by hospitals during 2001 to 2008. These data were subsequently linked with data from the 2005 American Hospital Association Annual Survey to determine hospital characteristics.

2.2. Neighborhood Definition

We obtained the exact coordinates of each hospital using *its address* as reported in the AHA Annual Survey. We then geocoded each address and calculated the distance between any two hospitals. *We were primarily interested in the effect of a hospital's nearest neighbor (i.e. a hospital's neighborhood as defined by its nearest hospital). Considering various definitions of a hospital's neighborhood, we conducted sensitivity analyses using two basic definitions:* 1) the "Nearest K " Neighborhood; and 2) the "Circle" Neighborhood. For the Nearest K Neighborhood method, we defined a hospital's neighborhood by its nearest K hospitals. As K increases *more and more hospitals located in increasingly remote locations are included in the neighborhood and the neighborhood effect becomes progressively diluted*; therefore, in order to maintain a sensible neighborhood definition, K should not be too large. The Circle Neighborhood method defined a hospital's neighborhood by those hospitals within a specified radius *determined by the distance in miles from the reference hospital to its nearest neighbor plus K miles* (17). For both methods, we investigated $K=1, 2, \dots, 5$. Both definitions ensure that each hospital has at least one neighbor (18). In addition,

we restricted neighbors to being within the same state, except for NY and NJ, whose proximity led us to collapse them into a single region. In Figure 1, an artificial example is used to illustrate these two neighborhood definitions.

2.3 Description of confounding variables

In studying the neighborhood effect, we sought to eliminate the possible confounding effects of hospital teaching status, urban status, hospital size and surgical volume, *whose association with a hospital's time to adoption of the surgical robot has been previously described* (13). We adjusted *our model for these factors* as described in the next section. The distributions of surgical volume and hospital size were much skewed in the data, so we dichotomized a hospital's number of radical prostatectomies in 2001 (baseline) and number of beds using their respective medians.

2.4 Statistical Analysis

In order to quantify the neighborhood effect on diffusion of the surgical robot, we analyzed the diffusion process by looking at how one hospital is influenced by its neighbor. We used a two-state Markov chain model to model the dynamic spatial and temporal process of surgical robot adoption. We assumed that the potential influence of prior adoption events does not vary with the length of time since their occurrence (17). We modeled the probability of a hospital's having acquired a robot as a logistic function of calendar year, intrinsic hospital characteristics, and the robot ownership status of its neighbors during the prior year. The details of the modeling are given below.

Let $Y_i(t) = 1$ if hospital i at year t has a robot and 0 otherwise. Suppose at the initial year $Y_i(1)$ is given. Let $Z_i(t)$ denote the robot acquisition status of hospital i 's neighborhood at the end of year t . We considered two types of $Z_i(t)$: 1) the proportion of hospitals who had acquired robot(s) by the end of year t within the neighborhood of hospital i ; or 2) a binary number which indicates whether any of its neighbor(s) had robot ($=1$) or not ($=0$) by the end of year t . X_i is a vector of the non-time dependent variables for hospital i . The conditional probability that the i th hospital would have a robot at time t given its status at time $t-1$, neighborhood robot acquisition status at $t-1$, calendar year t and all the other time-invariant covariates X_i is given by

$$p_{it} = P(Y_i(t) | Y_i(t-1), X_i, Z_i(t-1)) = \begin{cases} 1 & \text{if } Y_i(t-1) = 1 \\ \frac{\exp(Y_i(t)\eta_i)}{1 + \exp(\eta_i)} & \text{if } Y_i(t-1) = 0 \end{cases}, \text{ where } \quad (1)$$

$$\eta_i = \beta X_i + \delta t + \gamma Z_i(t-1).$$

In the model, β is a vector of parameters representing the covariate effect of the hospital intrinsic characteristics. The parameter γ determines the degrees of spatial correlation or neighborhood effect. Taking the product of the conditional probabilities in model (1) yields

the likelihood function $L = \prod_{t=2}^T \prod_{i=1}^N p_{it}$, where $T=8$ and $N=552$. We obtain the estimates $\hat{\beta}$ and $\hat{\gamma}$ by maximizing the likelihood. Relevant statistical inferences such as the standard deviation and Wald test are based on the asymptotic normality of the maximum likelihood estimators.

Statistical analyses were performed using SAS 9.3 (SAS Institute, Cary, NC) and R (<http://www.r-project.org/>) software.

3. Results

We identified a cohort of 552 hospitals with complete covariates performing radical prostatectomy, and therefore “at risk” for surgical robot acquisition, from the HCUP SID from seven states (AZ, FL, MD, NC, NY, NJ, and WA). Most were urban hospitals (84%) and nonteaching hospitals (59%). The number of radical prostatectomies (RP) performed by hospitals in 2001 ranged from 0 to 1029, with a median (interquartile range) of 13 (5 to 29). The number of hospital beds ranged from 7 to 2163, with a median (interquartile range) of 239 (146 to 374). The distribution of these four variables between the non-adopter hospitals and adopter hospitals are all significant ($p < 0.001$). The detailed characteristics of the hospitals can be found in Table 1. One hundred thirty-five of these hospitals (24%) had acquired at least one surgical robot by the end of 2008. The yearly breakdown of the number of hospitals adopting the surgical robot is reported in Figure 2. The 10 hospitals reported in the year 2001 include all previous adopters. Overall, there is an increasing trend for robot adoption through time, including a sharp increase in 2005.

Table 2 gives the nearest neighbor effect (i.e. $K=1$) estimates along with the estimates for calendar year and adjusted for confounders, including teaching status, urban status, hospital size and surgical volume from the Markov chain model. We fitted the data from year 2001 up to a variable final year, between 2004 to 2008 (due to a paucity of events for the years 2001–2003, neither the neighborhood effect nor any of the confounders is significant). The first rural hospital adopted the surgical robot in 2006, thus we only adjusted for urban/rural location after 2005. The neighborhood effect is significant in the years up to 2006, 2007 and 2008 with odds ratios ranging between 1.71 and 1.98. At the same time, the effects of teaching, surgical volume and hospital size are strong and consistently significant across terminal years of analysis. Urban location, which was identified previously as a significant confounder (13), has a large but statistically insignificant effect. Similar results were found for urbanicity when other definitions of neighborhood were used (data not shown).

In table 3, we report the sensitivity analyses results considering the combinations of two definitions of neighborhood and two definitions of a neighborhood’s robot acquisition status, as described in section 2.2 and 2.4 respectively. The first two blocks (A and B) of Table 2 are the results for the neighborhood defined as the nearest K Neighborhood method. For block A, the robot acquisition status of neighborhood denoted by Z_i in model (1) is the proportion of robot adopters within the neighborhood and for block B, Z_i is a binary number indicating whether any neighbor hospital had a robot or not. The last two blocks (C and D) are the results for the Circle Neighborhood method with the same definition of Z_i as in block A and B. For each neighborhood definition, we considered $K=1, 2, \dots, 5$. When the neighborhood is defined as the nearest K hospitals (i.e. block A and B), for $K=1$, two definitions of Z_i are equivalent and the results are reported separately in Table 2.

For K greater than 1, a positive trend of the neighborhood effect is observed but does not achieve statistical significance, with odds ratios ranging between 1.02 and 1.48 for year

2008. For the second neighborhood definition [i.e. using the distance to the nearest hospital plus K miles as the neighborhood radius (block C and D)] a significant neighborhood effect is found for the data up to year 2007, with Z_i being the proportion of robot adopters within the neighborhood. The estimated odds ratios are 1.98 and 2.11 for $K=1$ and 2 separately. There is no statistically significant neighborhood effect observed in other final years or for K values using the Circle Neighborhood method (block C and D), although similar positive risks are observed. Thus after adjusting for hospital teaching status, surgical volume, urban status and number of hospital beds, a hospital whose nearest neighbor had acquired a surgical robot has a higher likelihood of itself acquiring a surgical robot. However, the result was sensitive to the definition of neighborhood.

4. Discussion

The surgical robot is an expensive, unproven medical technology which has been rapidly adopted for undetermined reasons. In this paper we assessed the spatial and temporal diffusion of the surgical robot through a novel *approach* analyzing the neighborhood effect on adoption of new technology. Using a Markov chain model for the dynamic robot acquisition process and adjusting for known confounders such as teaching status, urban status, hospital size and baseline surgical volume, we determined that hospitals were more likely to acquire surgical robots if their nearest neighbor hospitals had already done so. While a previous analysis (13) suggested that urban hospitals were more likely to be early adopters of the surgical robot, the neighborhood appears to confound this relationship. Perhaps it is not an intrinsic characteristic of urban hospitals which enables them to adopt new technology but rather their proximity to a *surfeit* of neighbors. Our result is *particularly* valuable for physicians, patients, healthcare administrators and policy makers, as it suggests that the diffusion of new medical technology may be driven at least in part by competition among neighboring hospitals rather than solely by the mission to provide optimal patient care.

One of this study's greatest challenges was determining how to define a hospital's neighboring hospitals. While we were primarily interested in the effect of a hospital's nearest neighbor, we also conducted sensitivity analyses using other definitions. When we considered $K=2,3,4$ or 5 neighboring hospitals, either by using the proportion of hospitals with robots or by noting whether any had at least one robot, the odds ratios all exceeded 1.0, although the associations were not always statistically significant (Table 3). For the circle neighborhood method, if we used the proportion of the hospitals with robots to define the neighborhood covariate, the odds ratios almost always exceeded 1.0 and the cumulative associations for data up to year 2007 were statistically significant for $K=1$ and 2, although others were not. If we defined the neighborhood covariate by whether any hospital had at least one robot, no statistical significance was found. Some directions of the associations also changed and decreased risk, but none was statistically significant (Table 3). Thus, the strength of evidence for the neighborhood effect is sensitive to the choice of definition of neighborhood, and there is no standard definition for this concept.

Technological innovation in healthcare plays an important role in driving cost, so understanding its diffusion into practice may help patients, physicians and policy makers

understand how to allocate scarce resources more efficiently and better manage the adoption process. Following Rogers's lead work (19), there have been several studies of the diffusion of medical technology. McClellan and Kessler (20) studied the diffusion of treatments for heart attack around the globe and found that the use of medical technology to treat myocardial infarction is strongly related to economic and regulatory incentives including the magnitude of out-of-pocket costs to patients, the generosity of reimbursement to physicians and hospitals, regulation of the use of new technologies or the supply of physicians, regulation of competition, and the structure of hospital ownership. Hashimoto et al (21) investigated the diffusion of stent technology in the early 1990s and confirmed Roger's diffusion of innovation theory that distinctive payment systems, practice norms and local patients' clinical characteristics are all factors affecting the process of innovation diffusion. However, these studies did not consider the role that geographic proximity of the adopters might have; most studies that have used geospatial models have studied the diffusion of non-medical technologies. Hamaoka (22) studied the diffusion of Electronic Toll Collecting transponders to 47 Japanese prefectures using the spatial panel model and found a regional association between diffusion of transponders among the geographic areas. Nyblom et al (23) found that the organic farming practices in Finland were more often found within the same neighborhoods and in the neighborhoods of earlier adopters. Coleman et al (24) studied the diffusion of a new prescription drug among physicians in four cities. Re-analyses of these data indicated that a physician's adoption of a new drug is affected by others' adoptions (23, 25, 26).

The methods cited have critical limitations. Nyblom et al (17) proposed a permutation test to identify the spatial and temporal association between adopters while controlling for confounding covariates and time by permuting within strata. This method has two limitations: 1) the number of strata increases rapidly with the number of covariates; and 2) the permutation test does not estimate effect size. Strang and Tuma (23) developed diffusion models that incorporate spatial and temporal heterogeneity within an event-history framework. However, their method neglected the interdependence between outcome and dynamic neighborhood status, which biased the maximum likelihood estimation. In our work we wished to overcome the limitations of these prior geospatial models and apply these new methods to understand the diffusion of medical innovation.

In order to address these limitations, we developed a two-state Markov chain model to study diffusion of the surgical robot. We characterized the adoption process as a sequence of binary variables as in Haining (27) and modeled the transition probability as a logistic function of previous neighborhood robot adoption, calendar year and time-invariant covariates (23, 27). Using this method, we estimated the effects of potential confounders and the neighborhood effect on the odds of acquiring a robot.

Our study has *other* important strengths. We updated a unique, population-based dataset that has information on the timing, location and characteristics of hospitals that acquired or did not acquire the surgical robot. These data allowed us to estimate parameters of the Markov model that characterize the joint effects of neighborhood, calendar year and other covariates on the chance of acquiring a robot.

Our study also has several limitations. Since this is an observational study, we can only determine the associations between our variables of interest; we cannot exclude the possibility that other unmeasured factors may account for the associations we found. However, it would not be possible to perform a prospective randomized trial to determine the patterns of hospital industry behavior. Secondly, the estimated neighborhood effect from the Markov model was statistically significantly positive for the association with the nearest hospital's robot status and with neighbor hospital's robot status by circle neighborhood definition for final year 2007. Associations with neighborhood were not as strong and not statistically significant for other definitions of neighborhood. This could potentially be the result of hospitals not defining their competitors as only local (28) and indicate the sensitivity of the neighborhood definition in the spatial diffusion study. *Working with claims data, there is no way for us to know which hospitals a given hospital perceives to be its competitors. There is no guarantee that neighboring hospitals are necessarily competitors, however, it is almost certain that there are at least some neighboring hospitals which are indeed competitors. We felt that studying neighboring hospitals was a conservative assumption because if there actually were no competitive relationship between hospitals, our results would be biased toward the null.* Additionally, our data only includes 7 states, 5 of which do not share borders with one another. States about whom we have no robot adoption information could have hospitals within them that are affected by hospitals within our study sample and vice versa. Future research will be necessary to expand the study sample so that we may overcome this bias toward the null. Lastly, our analyses are based on a one year timeframe and are unable to assess the influence among the hospitals who might have adopted the robot in the same year. This is a phenomenon that merits further study, but, like the previous limitation, represents a bias toward the null.

In summary, our analyses indicate that having neighbor hospital(s) with a surgical robot increases the probability that a given hospital will obtain its own robot, even after adjusting for hospital teaching status, urban location, hospital size and baseline surgical volume. More data over additional years are needed to obtain more precise estimates of the spatial and temporal neighborhood effect. By treating the adoption of surgical robot as the outcome of a spatial and social diffusion process, we can begin to understand the neighborhood effect on robot acquisition and plan further study of the social factors that influence the technology diffusion. Qualitative data from physicians, hospital administrators and patients may also help elucidate the process by which the surgical robot diffused into widespread medical practice. Our findings suggest that adoption of a technology may cluster near hospitals that are early adopters of new healthcare innovations, concentrating the costs and benefits of such technology within communities of competing hospitals. Policy makers should consider this tendency in allocating resources to achieve maximal population benefit or minimize its burdens.

Acknowledgments

The research reported/outlined here was supported by the Department of Veterans Affairs, Veterans Health Administration, Health Services Research and Development Service. Dr. Makarov is a VA HSR&D Career Development awardee at the Manhattan VA.

Other Funding Sources: NYU Cancer Institute, the Louis Feil Charitable Lead Trust

Bibliography

1. Carreyrou J. Surgical robot examined in injuries. Wall Street Journal. 2010
2. ALPERT, BILL. Robots in Search of Added Employment. [Online]. Jan 26. 2013 http://online.barrons.com/article/SB50001424052748703684904578259840108154794.html#articleTabs_article%3D2
3. Lotan Y, Cadeddu JA, Gettman MT. The new economics of radical prostatectomy: cost comparison of open, laparoscopic and robot assisted techniques. J Urol. 2004; 172:1431–1435. [PubMed: 15371862]
4. Kolata G. Results unproven, robot surgery wins converts. The New York Times. 2010; 2:14. <http://www.nytimes.com/2010/02/14/health/14robot.html>.
5. Menon M, Tewari A, Baize B, et al. Prospective comparison of radical retropubic prostatectomy and robot-assisted anatomic prostatectomy: the Vattikuti Urology Institute experience. Urology. 2002; 60:864–868. [PubMed: 12429317]
6. Menon M. Robotic radical retropubic prostatectomy. BJU Int. 2003; 91:175–176. [PubMed: 12580996]
7. Ahlering TE, Woo D, Eichel L, et al. Robot-assisted versus open radical prostatectomy: a comparison of one surgeon's outcomes. Urology. 2004; 63:819–822. [PubMed: 15134953]
8. Gettman MT, Blute ML. Critical comparison of laparoscopic, robotic, and open radical prostatectomy: techniques, outcomes, and cost. Curr Urol Rep. 2006; 7:193–199. [PubMed: 16770855]
9. Box GN, Ahlering TE. Robotic radical prostatectomy: long-term outcomes. Curr Opin Urol. 2008; 18:173–179. [PubMed: 18303539]
10. Hu JC, Gu X, Lipsitz SR, et al. Comparative effectiveness of minimally invasive versus open radical prostatectomy. JAMA. 2009; 302:1557–1564. [PubMed: 19826025]
11. Farnham SB, Webster TM, Herrell SD, et al. Intraoperative blood loss and transfusion requirements for robotic-assisted radical prostatectomy versus radical retropubic prostatectomy. Urology. 2006; 67:360–363. [PubMed: 16461085]
12. Weizer AZ, Ye Z, Hollingsworth JM, et al. Adoption of new technology and healthcare quality: surgical margins after robotic prostatectomy. Urology. 2007; 70:96–100. [PubMed: 17656216]
13. Makarov D, Li H, Gold HT, et al. Factors associated with the early acquisition of the surgical robot by non-federal, community hospitals in the United States. 2013
14. Dranove D, Shanley M, Simon C. Is hospital competition wasteful? Rand Journal of Economics. 1992; 23(2):247–62. [PubMed: 10119678]
15. Daniel, Kessler; McClellan, Mark. Is Hospital Competition Socially Wasteful. Quarterly Journal of Economics. 2000:577–615.
16. Meyer AD, Goes JB. Organizational Assimilation of Innovations- a Multilevel Contextual Analysis 4. 1988; 31:897–923.
17. Yblom J, Borgatti S, Roslakka J, Salo MA. Statistical analysis of network data—an application to diffusion of innovation. N2003. Social Networks. 25:175–195.
18. Gresenz, Carole Roan; Rogowski, Jeannette; Escarce, José J. Updated Variable-Radius Measures of Hospital Competition. Health Services Research. 2004; 392:417–430. [PubMed: 15032962]
19. Rogers, EM. Diffusion of Innovation. 5. New York: Free Press; 2003.
20. McClellan, Kessler. Technological Change in Health Care: A Global Analysis of Heart Attack. Ann Arbor: University of Michigan Press; 2002.
21. Hashimoto, Hideki; Noguchi, Haruko; Heidenreich, Paul; Saynina, Olga; Moreland, Abigail; Miyazaki, Shunichi; Ikeda, Shunya; Kaneko, Yoshihiro; Ikegami, Naoki. The diffusion of medical technology, local conditions, and technology re-invention: A comparative case study on coronary stenting. 2. Health Policy. 2006; 79:221–230. [PubMed: 16473435]
22. Yutaka, Hamaoka. Spatial Diffusion of Innovation: A Spatial Panel Analysis of Electronic Toll Collecting Transponders in Japan. 2010. Available at SSRN: <http://ssrn.com/abstract=1678806> or <http://dx.doi.org/10.2139/ssrn.1678806>

23. Strang, David; Tuma, Nancy B. Spatial and Temporal Heterogeneity in Diffusion. *American Journal of Sociology*. 1993; 99:614–39.
24. Coleman, James S.; Katz, Elihu; Manzel, Herbert. *Medical Innovation*. New York: Bobbs-Merrill; 1996.
25. Burt, Ronald S. Social Contagion and Innovation: Cohesion versus Structural Equivalence. *American Journal of Sociology*. 1987; 92:1287–1335.
26. Marsden, Perter V.; Podolny, Joel. *Dynamic Analysis of Network Diffusion Processes*. Social Networks through Time. 1990
27. Haining R. Spatial and spatial-temporal interaction models and the analysis of patterns of diffusion. *Transactions of the Institute of British Geographers*. 1993; 8:158–86.
28. Dale, Buss. *Forbes*. [Online]. Oct 8. 2012 <http://www.forbes.com/sites/dalebuss/2012/10/08/cleveland-clinic-ad-in-wsj-capitalizes-on-debate-praise/>
29. Barbash GI, Glied SA. New Technology and Health Care Costs — The Case of Robot-Assisted Surgery. *New England Journal Medicine*, p. 2010; 363:8.
30. Berwick DM. Disseminating innovations in health care. *JAMA*. 2003; 289(15):1969–75. [PubMed: 12697800]
31. Zweifel, P.; Eisen, R. *Versicherungsökonomie*. (Insurance Economics). 2. Heidelberg: Springer; 2003.
32. Skinner, J.; Staiger, D. *Technology Diffusion and Productivity Growth in Health Care*. 2009. NBER Working Paper No. w14865

K	Nearest K Neighborhood	Circle Neighborhood
1	1	1, 2
2	1,2	1, 2, 3, 4
3	1, 2, 3	1, 2, 3, 4, 5
4	1, 2, 3, 4	1, 2, 3, 4, 5
5	1, 2, 3, 4, 5	1, 2, 3, 4, 5, 6

Figure 1.
In the left figure, the empty diamond is the reference hospital and six solid dots are its neighbor hospitals. The numbers beside the solid dots indicate the degree of closeness to the reference hospital (1 is the closest). Five circles are circle neighborhoods with radius defined by the distance in miles from the reference hospital to its nearest neighbor plus K miles. Each ring is separated from its subsequent ring by one mile. The table at right lists the hospital number(s) defined as neighbor(s) of the reference hospital under the two neighborhood definitions for $K=1$ to 5.

Figure 2.
Surgical robot adopters

Table 1**Hospital Characteristics**

	All	Non-adopter	Adopter	Pvalue
Characteristics				
No. Hospitals in sample	554	419(75.6%)	135(24.4%)	
No. Hospitals in sample with complete covariates	552	417(75.5%)	135(24.5%)	
Teaching Status				<0.0001*
Teaching	227(41.1%)	138(33.1%)	89(65.9%)	
Nonteaching	325(58.9%)	279(66.9%)	46(34.1%)	
Urban Status				<0.0001*
Urban location	465(84.2%)	333(79.9%)	132(97.8%)	
Rural location	87(15.8%)	84(20.1%)	3(2.2%)	
No. hospital beds				<0.0001 [†]
Median(Interquartile)	239(146–374)	204(129–307)	397((282–622)	
Large hospital	274(49.6%)	163(59.5%)	111(40.5%)	
Small hospital	278(50.3%)	254(91.4%)	24(8.6%)	
RRP in 2001				<0.0001 [†]
Median(Interquartile)	13(5–29)	9(4–22)	40(20–68)	
High volume	271(49.1%)	161(59.4%)	110(40.6%)	
Low volume	281(50.9%)	256(91.1)	25(8.9%)	

* Chi-square test

[†] Wilcoxon test

Table 2

Nearest Neighborhood effect estimates along with covariate estimates from Markov chain model of surgical robot adoption for 552 hospitals using nearest one hospital as neighbor

Final Year*	Teaching	Surgical volume	Hospital size	Calendar year	Urban [‡]	Neighborhood
2004	OR (CI) pvalue	3.35(1.33, 8.43) 0.01	3.08(1.09, 8.68) 0.03	1.82(1.15, 2.88) 0.01	NA NA	0.46(0.06, 3.54) 0.46
2005	OR(CI) pvalue	3.62(1.77, 7.38) <0.01	3.24(1.43, 7.32) <0.01	1.71(1.31, 2.24) <0.01	NA NA	1.93(0.9, 4.14) 0.09
2006	OR(CI) pvalue	3.96(2.13, 7.36) <0.01	2.94(1.5, 5.74) <0.01	1.41(1.18, 1.69) <0.01	4.75(0.63, 35.8) 0.13	1.96(1.05, 3.65) 0.03
2007	OR(CI) pvalue	3.3(1.98, 5.51) <0.01	3(1.7, 5.29) <0.01	1.3(1.14, 1.48) <0.01	7.21(0.97, 53.69) 0.05	1.98(1.17, 3.36) 0.01
2008	OR(CI) pvalue	3.62(2.29, 5.73) <0.01	2.91(1.76, 4.79) <0.01	1.28(1.16, 1.42) <0.01	2.99(0.91, 9.84) 0.07	1.71(1.07, 2.72) 0.02

* The same model (1) was fitted 5 times, with successive fits based on all the years up to the final year indicated. Thus OR estimates are correlated across years.

[†] OR estimates are adjusted for teaching, surgical volume, hospital size, calendar year for final year 2004 and 2005, and the same plus urban for final year 2006–2008. Before 2006, all the adopters were from urban, so urban was not fitted.

[‡] Urban was only included in model (1) for data with final year 2006–2008. Before 2006, all the adopters were from urban, so no estimates of urban effect.

Table 3

Sensitivity analysis of neighborhood definitions.

K	1	2	3	4	5
A. Nearest K Neighborhood; $Z(t)$ is proportion of robot adopters within neighborhood					
Final Year *	OR [†] (CI)	p value	OR(CI)	p value	OR(CI)
2004	0.46 (0.06, 3.52)	0.46	1.83 (0.28, 12.04)	0.53	1.37 (0.11, 16.71)
2005	1.92 (0.9, 4.12)	0.09	2.42 (0.77, 7.56)	0.13	1.42 (0.29, 7.05)
2006	1.96 (1.05, 3.65)	0.03	1.65 (0.65, 4.14)	0.29	0.96 (0.27, 3.46)
2007	1.98 (1.17, 3.36)	0.01	1.67 (0.77, 3.59)	0.19	1.04 (0.37, 2.93)
2008	1.71 (1.07, 2.72)	0.02	1.61 (0.84, 3.1)	0.15	1.19 (0.5, 2.81)
B. Nearest K Neighborhood; $Z(t)$ is whether neighbor hospitals had robot or not					
Final Year	OR(CI)	p value	OR(CI)	p value	OR(CI)
2004	0.46 (0.06, 3.54)	0.46	1.48 (0.54, 4.05)	0.44	1.01 (0.37, 2.73)
2005	1.93 (0.9, 4.14)	0.09	1.72 (0.9, 3.28)	0.1	1.13 (0.59, 2.15)
2006	1.96 (1.05, 3.65)	0.03	1.45 (0.83, 2.52)	0.19	1 (0.58, 1.73)
2007	1.98 (1.17, 3.36)	0.01	1.44 (0.89, 2.31)	0.13	1.01 (0.63, 1.61)
2008	1.71 (1.07, 2.72)	0.02	1.33 (0.87, 2.01)	0.18	1.02 (0.68, 1.55)
C. Circle Neighborhood [‡] ; $Z(t)$ is proportion of robot adopters within neighborhood					
Final Year	OR(CI)	p value	OR(CI)	p value	OR(CI)
2004	1.31 (0.27, 6.23)	0.74	1.54 (0.26, 9.08)	0.63	1.47 (0.22, 9.92)
2005	2.14 (0.87, 5.25)	0.1	2.14 (0.75, 6.12)	0.16	1.64 (0.5, 5.34)
2006	1.87 (0.9, 3.9)	0.09	1.99 (0.86, 4.62)	0.11	1.83 (0.73, 4.6)
2007	1.98 (1.07, 3.67)	0.03	2.11 (1.04, 4.27)	0.04	1.74 (0.79, 3.84)
2008	1.59 (0.92, 2.75)	0.1	1.62 (0.87, 3.04)	0.13	1.43 (0.72, 2.86)
D. Circle Neighborhood; $Z(t)$ is whether neighbor hospitals had robot or not					
Final Year	OR(CI)	p value	OR(CI)	p value	OR(CI)
2004	1.31 (0.27, 6.23)	0.74	1.54 (0.26, 9.08)	0.63	1.47 (0.22, 9.92)
2005	2.14 (0.87, 5.25)	0.1	2.14 (0.75, 6.12)	0.16	1.64 (0.5, 5.34)
2006	1.87 (0.9, 3.9)	0.09	1.99 (0.86, 4.62)	0.11	1.83 (0.73, 4.6)
2007	1.98 (1.07, 3.67)	0.03	2.11 (1.04, 4.27)	0.04	1.74 (0.79, 3.84)
2008	1.59 (0.92, 2.75)	0.1	1.62 (0.87, 3.04)	0.13	1.43 (0.72, 2.86)

K	1	2	3	4	5					
2004	1.78 (0.7, 4.55)	0.23	1.75 (0.75, 4.09)	0.2	1.23 (0.53, 2.89)	0.63	1.1 (0.47, 2.58)	0.83	1.25 (0.56, 2.79)	0.58
2005	1.82 (0.96, 3.43)	0.07	1.45 (0.79, 2.68)	0.23	1.02 (0.55, 1.89)	0.94	0.9 (0.49, 1.67)	0.75	0.92 (0.51, 1.67)	0.78
2006	1.61 (0.93, 2.78)	0.09	1.31 (0.77, 2.22)	0.32	1.04 (0.61, 1.75)	0.9	0.9 (0.53, 1.52)	0.68	0.92 (0.55, 1.55)	0.76
2007	1.6 (1, 2.57)	0.05	1.29 (0.81, 2.04)	0.28	1.04 (0.65, 1.64)	0.88	0.89 (0.56, 1.41)	0.62	0.87 (0.55, 1.38)	0.56
2008	1.35 (0.88, 2.05)	0.17	1.11 (0.73, 1.67)	0.63	0.93 (0.62, 1.4)	0.73	0.85 (0.56, 1.28)	0.43	0.84 (0.56, 1.26)	0.4

* The same model (1) was fitted 5 times, with successive fits based on all the years up to the final year indicated. Thus OR estimates are correlated across years.

[†] OR estimates are adjusted for teaching, surgical volume, hospital size, calendar year for final year 2004 and 2005, and the same plus urban for final year 2006–2008. Before 2006, all the adopters were from urban, so urban was not fitted.

[‡] Radius equal to the distance in miles from the reference hospital to its nearest neighbor plus *K* miles