Induced Physician-Induced Demand*

Kei Ikegami† **Ken Onishi**‡ **Naoki Wakamori**§

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Abstract

Physicians may change their practices when introducing advanced medical equipment, and, in particular, they tend to overuse it. We investigate further inefficiency arising from physicians at surrounding hospitals. Using the panel data on Japanese hospitals, we find that there exists a business-stealing effect: Hospitals lose their patients because of MRI adoption by nearby public hospitals, and, to compensate for the loss of patients, physicians take more MRI scans per patient. Our results suggest that the decision to adopt medical equipment should be made collectively rather than individually to avoid not only excessive adoption but also further physician-induced demand.

JEL Classification: I11, I12, I19.
Keywords: Physician-induced demand, Business-stealing effects, Externalities.

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†Department of Economics, New York University, 19 West 4th Street, 6th Floor, New York, NY 10012, USA. Email: ki2047@nyu.edu.

‡Federal Reserve Board, 20th Street and Constitution Avenue N.W., Washington, DC 20551, USA. Email: ken.t.onishi@frb.gov.

§(Corresponding Author) Graduate School of Economics, The University of Tokyo, Hongo 7-3-1, Bunkyo-ku, Tokyo 113-0033 JAPAN. Email: nwakamo@gmail.com.

1 Introduction

Increasing medical expenditure has attracted attention in many developed countries. In particular, there is a growing concern about the excessive introduction and use of advanced medical equipment. Though such advanced equipment certainly enhances the quality of healthcare, physicians may use it more than necessary, a practice typically known as *physician-induced demand* or *supplier-induced demand*. Their opportunistic behavior is driven by the high reimbursement price for physicians, whereas the usage cost and the burden on patients (patients' out-of-pocket expense) are low. As discussed in Baker (2010), physician-induced demand may become more prominent when hospitals newly adopt medical equipment. This paper investigates further inefficiencies arising from the local competition among hospitals. When a hospital purchases medical equipment, the patients attending the surrounding hospitals may switch to that hospital. This is known as a *business-stealing effect* in the industrial organization literature. This business stealing may strengthen the incentive of physician-induced demand at the surrounding hospitals to compensate for their loss of revenue. We call this class of physician-induced demand *induced physician-induced demand*, and investigate it in the context of magnetic resonance imaging (MRI) adoption and usage. Physician-induced demand through this channel is important, because ignoring the indirect effects on the surrounding institutions underestimates the social cost of adoption and taking this channel into account allows us to shed light on designing better healthcare policies.

To this end, we use the administrative data on all medical institutions in Japan, which provide an ideal environment to investigate such a new mechanism of physician-induced demand thanks to its institutional features. First, as Japan has offered universal health coverage since the 1960s, all citizens can go to any medical institution in Japan and receive medical service at the same price for the same treatment, regardless of their choice of medical institution. Together with the panel structure of the data which allows us to calculate the change in the number of MRI scanners within a 1-kilometer radius of each medical institution, this institutional feature enables us to examine how MRI adoptions at nearby hospitals affect the numbers of patients and MRI scans taken. Second and, again, related to the first feature, our environment is free from any endogeneity concern about prices. Because medical prices are fixed and regulated by the government under the Japanese health insurance system, physicians cannot adjust prices flexibly in response to changes in demand.

We take advantage of these institutional features, and seek to verify our hypothesis, by first examining whether the business-stealing effect exists in the MRI scanning market. Our estimation results show that a hospital's patient count can drop by up to 4 percentage points for an additional MRI scanner purchased by the surrounding hospitals. These business-stealing effects are found only for MRI purchases by public hospitals. We then investigate whether the hospitals that lose their patients take MRI scans more often to compensate for the reduction in patients. To provide such evidence, we define the *conversion rate* as the fraction of patients who receive MRI scans, and we demonstrate that the conversion rate increases after surrounding public hospitals purchase MRI scanners, which confirms the existence of *induced physician-induced demand.* In particular, our estimation results show that hospitals take roughly the same number of MRI scans, regardless of the change in the number of patients. One may worry that this induced physician-induced demand might be overestimated, if increases in both the conversion rate and the number of surrounding MRI scanners are driven by the increase in local demand, which is unobserved. However, our data reveal that purchases of MRI scanners by public hospitals are not correlated with the change in local demand, which circumvents the endogeneity concern in our analysis. Taking advantage of those findings, we further quantify physician-induced demand in a more general sense: how physicians change their behavior when the number of patients changes, exogenously. We take an instrumental variable (IV) approach, using the MRI purchases of public hospitals as an instrument for the number of patients, and confirm that physicians take MRI scans more often when the number of patients decreases. We further quantify the increase in healthcare expenditure due to this physician-induced demand. Our estimates suggest that total annual healthcare expenditure increases up to ¥11 billion (Japanese yen).

This paper contributes to two strands of literature. First, we contribute to the literature on supplier-induced demand by adding eloquent evidence of its existence and by revealing a new mechanism, externalities from the surrounding medical institutions, which has not yet been explored in previous studies. Supplier-induced demand has been studied extensively both in the context of the healthcare industry (Kessler and McClellan, 1996; Chandra and Staiger, 2007; Geruso and Layton, forthcoming) and outside of the healthcare industry (Balafoutas et al., 2013). Debate on the magnitude of induced demand and even on its existence is still ongoing (Dranove and Wehner, 1994; Chandra and Staiger, 2007; Currie and MacLeod, 2008). We provide a new piece of evidence of physician-induced demand and quantify its economic significance by investigating the MRI scanning market, where Baker (2010) and Clemens and Gottlieb (2014) also find physician-induced demand. We also exploit the unique features of the Japanese healthcare system to quantify its existence and magnitude, as Iizuka (2012) and Shigeoka and Fushimi (2014) do. In terms of the mechanism, Johnson (2014) classified the existing studies into three groups based on the sources of identification: (i) physicians' income shocks (Fuchs, 1978; Cromwell and Mitchell, 1986; Gruber and Owings, 1996), (ii) changes in physicians' fees (Rice, 1983; Nguyen and Derrick, 1997; Dafny, 2005), and (iii) variations in patient information (Currie et al., 2011; Angott et al., 2019). Our paper falls into the first category, as we focus on the exogenous change in the number of patients. In particular, the closest paper to ours is Gruber and Owings (1996). They exploit the exogenous change in the number of patients caused by the fall in the fertility rate as a source of physician-induced demand for C-sections. Although all existing studies, including Gruber and Owings (1996), view physician-induced demand as a phenomenon at each institution, this paper attempts to identify physician-induced demand that stem from interactions and competition among medical institutions. Theoretically, our definition of physician-induced demand follows Dranove (1988): Physicians exploit information asymmetries/advantages to induce patients to consume more care than necessary. In terms of modelling, we consider a similar model to that of Xiang (2020) and use the changes in conversion rates as outcome variables.

The second strand of literature that this paper contributes to focuses on hospital competition. Many studies have been conducted on how hospital competition affects healthcare quality. Katz (2013) summarizes them. For example, Dranove, Shanley and Simon

(1992); Kessler and McClellan (2000); and Bloom, Propper, Seiler and Van Reenen (2015) find that hospital competition increases healthcare quality. Though the business-stealing effect is a central issue related to competition and is studied intensively both theoretically (Mankiw and Whinston, 1986) and empirically (Davis, 2006), not much attention has been paid to the business-stealing effect in the healthcare industry. This paper, therefore, is the first to establish some evidence that hospital competition creates business-stealing effects, which further induces physician-induced demand.

This paper is organized as follows. Section 2 describes the institutional background and the data. We use the Japanese MRI scanning market to show in the first part of Section 3 that there are business-stealing effects associated with MRI purchases at surrounding hospitals and these business-stealing effects cause further physician-induced demand there, which verifies our induced physician-induced demand hypothesis. Taking advantage of our finding in the first half of Section 3, we attempt to identify more broadly defined physician-induced demand in the subsequent section. Section 4 provides various robustness check to address some concerns in our approach taken in Section 3. Section 5 concludes.

2 Institutional Background and Data

2.1 Institutional Background

Healthcare System in Japan. Since 1961, Japan has offered universal health coverage, like many Organization for Economic Co-operation and Development countries. Under the Japanese healthcare system, every citizen in Japan is insured, and two types of insurance programs are available in Japan. If a citizen's employer offers its own insurance program, the employee enrolls in it. This is called "Employer-based Health Insurance" (*Kenko-Hoken*). Dependents of the employee may also enroll in the program. Citizens not enrolled in Employee Health Insurance must enroll in so-called "National Health Insurance" (*Kokumin-Kenko-Hoken*). Both insurance programs offer the same insurance, and, regardless of their insurance program, when the insureds (patients) receive medical services at medical institutions, only 30% of the healthcare fee is paid by the patients. Their insurers cover the remainder.[1] The Japanese health care system has two notable features: (i) "free access," and (ii) fee-for-service (FFS) payment.

First and most important, patients have free access, which means they can go to any medical institution in Japan. This is unlike the U.S. healthcare system which, in principle, only allows patients to go only to medical institutions belonging to the network of their health insurer. Furthermore, unlike countries such as France, the United Kingdom, and the Netherlands, there is no general practitioner system in Japan and, thus, people generally go directly to specialized medical institutions when they get sick. These aspects are particularly relevant to this paper, as patients may change their choices of medical institution because of MRI adoption by nearby hospitals. Second, healthcare fees are regulated in Japan and are set by the government with biannual revisions, and the government sets a fixed fee for each medical treatment in an FFS payment system, patients pay for each medical treatment they receive, and physicians receive payment for each treatment they provide. Since 2003, some hospitals have adopted the DPC (Diagnosis Procedure Combination) payment system, where patients' payment is based on diagnosis categories and diagnosis groups rather than on each treatment they receive, as in FFS. Healthcare service providers are paid a flat-rate prospective fee per day of an inpatient hospital stay for certain DPC services and are paid FFS for non-DPC services. The Japanese government encourages hospitals to shift from FFS to DPC to reduce medical expenses. However, throughout our sample period, the FFS payment system remains the most popular payment system . We discuss this point thoroughly in Section 4.2.[2]

In Japan, medical institutions are formally divided into two main categories, hospitals and clinics, depending on their number of beds. A medical institution with fewer than 20 beds is classified as a clinic. Otherwise, it is classified as a hospital. In general, clinics provide basic treatment whereas hospitals provide advanced and specialized

[1] There are some exceptions. For example, the co-payment is 20% for patients aged 70 or older. Furthermore, insurers subsidize some expensive medical treatments.

[2] In 2008, 2011, and 2014, the fractions of DPC hospitals were 8.2%, 16.8%, and 18.7%, respectively, based on the *Survey on Assessment of DPC Introduction* and *Static Survey of Medical Institutions*. Although the fraction sharply increased between 2008 and 2011, it has demonstrated a marginal rise since 2014, reaching 19.8% in 2017.

treatment. Thus, from a patient's viewpoint, hospitals and clinics may not be close substitutes for each other. Moreover, more than three-quarters of MRI scanners are owned by hospitals, which draws our attention to hospitals rather than clinics. Furthermore, in terms of the ownership of medical institutions, there are 28 classifications in the Japanese official statistics, based on the hospital's founder, such as some national government organizations, local municipalities, medical corporations and so on. We re-classify them as either public or private based on ownership information.[3] Notice that, despite such variations in the ownership of medical institutions, the insureds must pay the same fees for the same medical treatment in Japan, regardless of their medical institution choices.

The MRI Scanning Market MRI is one of the medical imaging techniques that enables the scanning of body tissues. In particular, it is a useful tool for identifying diseases in the brain, other organs and soft tissues. It is used mainly in neurosurgery, neurology, and orthopedics.[4] Thus, the average patient whose co-payment is 30% must pay approximately ¥7,000 ($65) for a high tesla MRI scanning service and ¥5,800 ($ 54 USD) for a low-tesla MRI scanning service.[5] This feature may change physicians' incentive of physician-induced demand and thus we discuss it thoroughly in Sections 4.2 and 4.4.

Lastly, there are no regulations or subsidies that affect medical institutions' MRI adoption. According to Ho, Ku-Goto and Jollis (2009), the United States is in a similar situation where there is no effective regulation on MRI adoption. On the other hand, many European countries, including France and Germany, have regional restrictions to discourage

[3] We classify medical institutions as public if they are owned by the Japanese government, local municipalities, or any public institutions. Otherwise, we classify them as private.

[4] MRI scanners use magnetic fields and radio waves and thus, naturally, one of the most important characteristics of an MRI is the field strength of its magnet, which is measured in tesla. Although there are some exceptions, a higher-tesla machine is basically better than one with lower tesla, because a higher-tesla machine allows doctors to take higher-quality images in less time. Although the most popular MRI is a 1.5-tesla machine, the field strength varies by machine, typically ranging from 0.2 to 3 tesla. In the MRI treatment market, the regulated reimbursement price depends on the MRI's tesla. If an MRI's magnetic strength is 1.5 tesla or higher, medical institutions typically receive about ¥23,400 for each treatment. Otherwise, the reimbursement price is ¥19,200. Here, the reimbursement prices are imputed in the following way: First, if the MRI field strength is less than 1.5 tesla, the sum of the fee for undergoing an MRI scan and the standard consultation fee is ¥19,200. For a high-tesla MRI, the fees typically include more components and it is not clear how to calculate the average reimbursement price. Thus, we calibrate these high-tesla fees by matching the average reimbursement prices to those reported in Imai, Ogawa, Tamura and Imamura (2012).

[5] 1 U.S. dollar = ¥108.3 as of February 2, 2020.

excessive adoption of expensive medical equipment (see König, 1998, for details of the regulations).

2.2 Data

2.2.1 Overview

We use the administrative data on Japanese medical institutions, called the *Static Survey of Medical Institutions*. The Japanese Ministry of Health, Labor and Welfare conducts this survey every three years. In the data, we observe basic information on all medical institutions in Japan, such as address, establishing organization (ownership), number of beds, clinical specialty, and numbers of outpatients, inpatients, and doctors for each clinical speciality. In addition, we observe data on MRI ownership and usage.[6] Our sample period is from 2005 through 2014, and Table 1 describes summary statistics for the variables employed in this paper. We can see that of the 9,223 hospitals in 2005, 3,004 owned at least one MRI scanner, whereas of the 8,632 hospitals in 2014, 3,033 owned at least one MRI scanner.[7] The data also identify the number of inpatients and outpatients for each medical department, separately. Throughout this paper, we focus on patients in the neurosurgery, neurology and orthopedics departments, unless otherwise noted.[8] The second and third rows show the average number of patients, the sum of inpatients and outpatients, that each private and public hospital admit. In our sample, public hospitals tend to attract more patients. Note that private hospitals own about two-thirds of the MRI scanners. The aggregate number of MRI scanners is stable over time. However, at the hospital level, adoption and abandonment happened frequently. The seventh row shows the fraction of hospitals that experienced any change in the number of MRI scan-

[6]The survey is conducted in September, and the units for the numbers of outpatients, inpatients, and so on are person per month.

[7]As the number of hospitals monotonically decreases over our sample period, one may be concerned that this reduction is caused by hospital mergers. However, according to Furuta, Isogawa and Ohashi (2017) who study the effects of public hospitals' mergers, there were only 39 merger cases between 2005 and 2014.

[8]The choice of the three medical departments follows Baker (2001). Baker (2001) states that "MRI is a diagnostic tool for producing high resolution images of body tissues, most frequently the brain and spinal cord." The three departments we focus in our paper are the main departments handling symptoms related to the brain and spinal cord.

Table 1: Descriptive Statistics

	2005	2008	2011	2014
Number of hospitals	9,223	9,047	8,814	8,632
Average number of patients				
at private hospitals	2,174	2,002	1,941	1,890
at public hospitals	2,854	2,514	2,413	2,354
Number of hospitals equipped with MRIs	3,004	2,990	3,124	3,033
Number of private hospitals equipped with MRIs	1,897	1,896	2,036	1,995
Number of public hospitals equipped with MRIs	1,107	1,094	1,088	1,038
Fraction of hospitals adopting or abandoning MRIs	0.26	0.26	0.24	0.24
Number of MRI scans (per MRI scanner)				
Mean	189	198	195	193
25%	86	89	81	78
50%	169	175	176	170
75%	270	283	283	280

Note: This table provides summary statistics of the data on hospitals and MRI scanners for each sample year. The first seven rows in the upper panel show the number of hospitals, average number of patients visiting private hospitals, average number of patients visiting public hospitals, number of hospitals that own an MRI scanner, number of private hospitals that own an MRI scanner, number of public hospitals that own an MRI scanner, fraction of hospitals that change the number of MRI scanners they own between the current sample year and the previous sample year, respectively. The lower panel of the table shows the mean and the quartiles of the number of MRI scans per MRI among the hospitals in the data.

ners among hospitals that owned MRI scanners in the survey year or the previous survey year. We find that about 25% of the hospitals adopt or abandon MRI scanners between each survey year.[9]

The lower panel of Table 1 shows the utilization of MRI scanners. Suppose a hospital operates 22 days per month, 8 hours a day, and one MRI scan takes 30 minutes to complete. Then, the maximum number of MRI scans per month (physical capacity) would be 352, which enables us to define the utilization rate of an MRI scanner as the number of monthly MRI scans divided by 352. Table 1 shows that the median utilization rate of an MRI scanner is slightly less than 50%. This low utilization of MRI scanners in Japan is consistent with the findings in Niki (1993) and Onishi, Wakamori, Hashimoto and Bessho (2016).[10]

[9] See Table B1 in Appendix B for the change in the number of MRIs at each hospital. In the data, the most frequent change comes from the new adoption of one MRI and a significant fraction of variation comes either from the change from no scanners to one, or one to none.

[10] More specifically, Niki (1993) finds that the weekly average number of MRI scans taken at Japanese hospitals was 35.7 in early 1990s. Using the more recent data from 2008, Onishi et al. (2016) find that the utilization rate depends on the quality of MRI scanners; The weekly average number of MRI scans for the hospitals with high-Tesla MRI scanners was 64.2, whereas the weekly average number of MRI scans for the hospitals with low-Tesla MRI scanners was 34.9 in 2008.

Furthermore, using address information, we calculate distances among hospitals—in particular, distances among hospitals that own MRI scanners. Table 2 shows the average number of MRI scanners within 1 kilometer of each hospital that is equipped with MRI scanners. In Panel (A), we look at all hospitals that are equipped with MRI scanners and count the number of MRI scanners within 1 kilometer (excluding their own scanners). We also show the breakdowns for the number of MRI scanners owned by public and private hospitals, separately. In Panels (B1) and (B2), we also compute the same statistics from the viewpoints of public and private hospitals equipped with at least one MRI scanner, respectively. In all panels, the standard deviations are reported in parentheses. Based on the fact that the numbers of MRI scanners within 1 kilometer are about 0.6 and the standard deviations are around 1 over our sample period in Panel (A), the number of MRI scanners within 1 kilometer is mostly 0, 1, or 2.[11]

Table 2 shows the difference in the MRI purchase patterns between private hospitals and public hospitals. First, the number of MRI scanners within 1 kilometer of a public hospital is smaller than that within 1 kilometer of a private hospital. We can see this distinction by comparing the numbers in the first rows of Panels (B1) and (B2). This difference implies that public hospitals purchase MRI scanners in regions where MRI scanners are sparse. For example, in 2005, a private hospital had 0.76 MRIs owned by other hospitals within 1 kilometer whereas a public hospital had only 0.50, on average. Furthermore, the ratios of the third row to the second row of Panels (B1) and (B2) tell us that the entry decision of public hospitals differs from that of private hospitals. For instance, in Panel (B1) of 2005, the number of MRI scanners owned by public hospitals within 1 kilometer of public hospitals equipped with MRI scanners is about one-third $\left(\frac{0.13}{0.37}\right)$ of the number of MRI scanners owned by private hospitals whereas the rate is about one-half $\left(\frac{0.24}{0.52}\right)$ when we focus on the Panel (B2). This observation implies that public hospitals tend to purchase MRI scanners in areas having a smaller number of MRI scanners—in particular MRI scanners owned by public hospitals.

[11] See B2 in Appendix B for the exact numbers of MRI scanners at surrounding hospitals.

Table 2: The Number of MRIs within 1 Kilometer (by Ownership)

	2005	2008	2011	2014
Panel (A): From hospitals equipped with MRI scanners				
Number of MRI scanners within 1km	0.66	0.63	0.69	0.60
	(1.29)	(1.35)	(1.44)	(1.18)
...owned by private hospitals	0.46	0.43	0.48	0.44
	(0.99)	(0.96)	(1.07)	(0.97)
...owned by public hospitals	0.20	0.20	0.21	0.17
	(0.61)	(0.71)	(0.72)	(0.54)
Panel (B1): From public hospitals equipped with MRI scanners				
Number of MRI scanners within 1km	0.50	0.44	0.49	0.43
	(1.08)	(1.06)	(1.09)	(0.98)
...owned by private hospitals	0.37	0.33	0.36	0.31
	(0.90)	(0.86)	(0.89)	(0.85)
...owned by public hospitals	0.13	0.11	0.14	0.12
	(0.47)	(0.50)	(0.54)	(0.45)
Panel (B2): From private hospitals equipped with MRI scanners				
Number of MRI scanners within 1km	0.76	0.74	0.80	0.69
	(1.40)	(1.48)	(1.59)	(1.27)
...owned by private hospitals	0.52	0.48	0.56	0.50
	(1.04)	(1.01)	(1.15)	(1.03)
...owned by public hospitals	0.24	0.25	0.25	0.19
	(0.67)	(0.80)	(0.79)	(0.58)

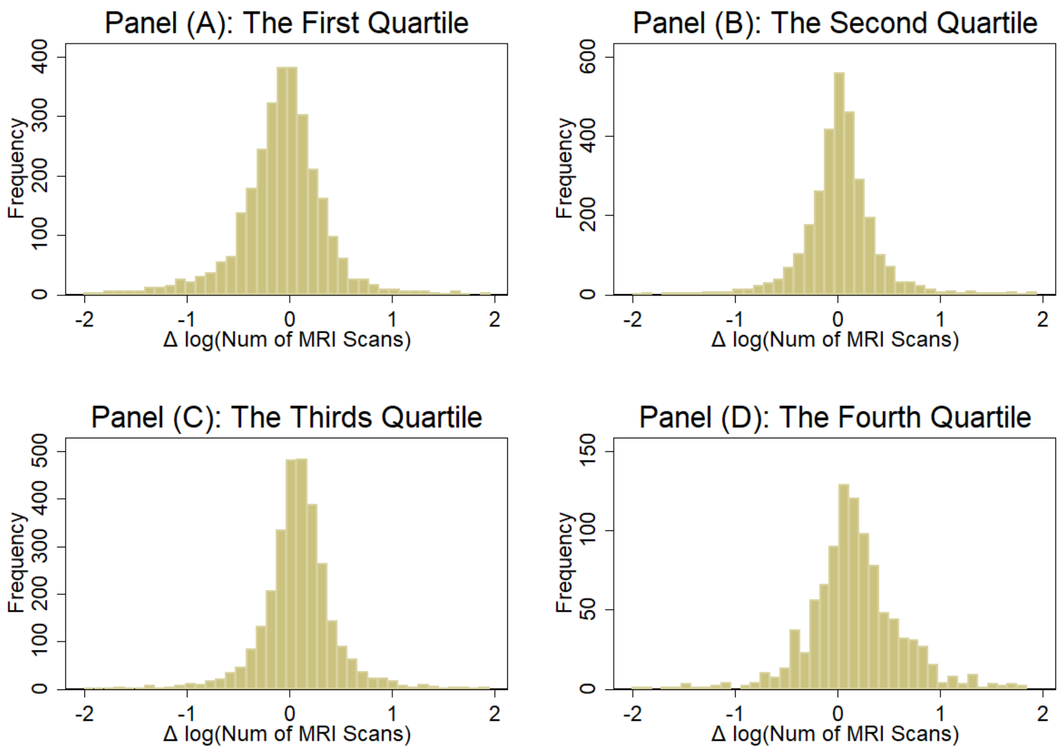
Note: This table provides summary statistics of the number of surrounding MRI scanners from each hospital. We compute the distances between hospitals using *geonear*, a STATA package established in Picard (2010). Panel (A) shows the average number of MRI scanners and its standard deviation (in parentheses) from each hospital that owns an MRI scanner. Panels (B1) and (B2) show the same statistics from each public hospital and private hospital, respectively. In each panel, the first row shows the total number of MRI scanners within 1 kilometer distance. The second and third rows show the number of MRI scanners within 1 kilometer distance owned by private hospitals and public hospitals, respectively.

2.2.2 Motivating Observations

To motivate our empirical analysis, we provide two pieces of evidence in this subsection for why we suspect that new purchases of MRI scanners by nearby hospitals may further induce physician-induced demand. Unfortunately, as discussed in the literature, identifying the *total* physician-induced demand is difficult because, given a set of patients, we do not know what the appropriate number of MRI scans would be and thus cannot determine how excessive the number of MRI scans taken in the observed data is. However, we may still be able to determine whether physicians engage in physician-induced demand by looking at the *changes* in the environment that are unrelated to the patients' conditions. If physicians change the number of MRI scans in response to such changes in the environment, it implies that physicians take MRI scans not to suit patients' interests but to suit their own, which allows us to quantify the induced demand. Our theoretical model, which is similar to those of Dranove (1988) and Xiang (2020), illustrates these points in Appendix A. We therefore focus on how physicians change their decisions on taking MRI scans. In the remainder of this section, we show descriptive evidence on how the MRI usage and conversion rate—defined as the percentage of patients that end up taking MRI scans—change when nearby hospitals purchase new MRI scanners. If the severity distribution of patients does not change before and after nearby hospitals purchase new MRI scanners, the increase in the conversion rate after the nearby introduction of MRI scanners supports our hypothesis of induced physician-induced demand. Subsection 4.1 thoroughly examines the assumption that the distribution of severity does not change.

Observation 1: Small pass-through from the number of patients to the number of MRI scans When a hospital faces a decreased number of patients compared with the previous period, does it proportionally take less MRI scans? To answer this question, we examine the relationship between the changes in the number of patients and the number of MRI scans. Here, we restrict the sample to hospitals that did not adopt or abandon MRI scanners between $t-1$ and t. We first compute the distribution of the change in the number of patients at each hospital, and then, using the quartile of this distribution, we

Figure 1: Changes in the Number of MRI Scans



Note: Each panel shows the distribution of the change in the logarithm of the number of MRI scans within each quartile group. The quartile group is defined based on the change in the number of patients at each hospital and Panels (A), (B), (C) and (D) correspond to the first, second, third and fourth quartile group, respectively.

classify the hospitals into Groups A, B, C, and D. Note that the quartiles of the distribution of the change in the logarithm of number of patients are negative 0.16, negative 0.03 and 0.09, implying that the hospitals in Group A experience a sharp decrease in the number of patients, whereas the hospitals in Group D experience an increase in the number of patients. Figure 1 shows the distribution of the change in the logarithm of the number of MRI scans in each group. The mean values for Groups A, B, C, and D are negative 0.38, negative 0.09, 0.03 and 0.38, respectively. Despite the large variation in the number of patients, Figure 1 shows that the number of MRI scans is centered around 0 for all groups. In fact, the medians of each group are negative 0.01, 0.04, 0.07 and 0.13, which have much smaller differences than negative 0.38, negative 0.09, 0.03 and 0.38. Those differences show that the extent of pass-through from the change in the number of patients to the number of MRI scans is small.

Observation 2: Changes in the conversion rate The first observation suggests that the fraction of patients who receive MRI scans is affected by the number of patients. To examine this possibility, we now look at the change in the MRI conversion between time $t-1$ and t in Figure 2. Here, the MRI conversion rate is defined as the fraction of patients who receive MRI scans. If there is no physician-induced demand, i.e., physicians take MRI scans based solely on the patients' condition, this conversion rate would not change unless the distribution of patients' severity changes.

For each of the eight panels in the figure, the horizontal axis shows the conversion rate in the previous period, and the vertical axis shows the conversion rate in the current period. The orange circles in the top four panels represent private hospitals, and the navy crosses in the bottom four panels represent public hospitals. The two panels in the first column use all hospitals, whereas the rest use only a subset of the hospitals to draw the scatter plots as data. The panels in the second, third, and fourth columns use the hospitals that face an increasing number of patients, a declining number of patients, and the increase in the number of MRI scanners owned by surrounding hospitals located within 1 kilometer, respectively.

From the panels in the first column, we can see that the conversion rate does not change over time on average, as most of the orange circles and the navy crosses are distributed symmetrically around the 45-degree line. In the next two panels where hospitals face increasing demand, we can again see that the conversion rates do not change over time. However, in the next two panels where hospitals face decreasing demand, we can see that many hospitals are above the 45-degree line, implying that they take more MRI scans per patient. Of course, one cannot interpret this observation solely as evidence of physician-induced demand, because we do not know why demand has decreased for these hospitals. So, we further plot the same graph for hospitals where at least one surrounding hospital located within 1 kilometer purchases MRI scanners. Now we can clearly see that most hospitals are above the 45-degree line, implying that physicians at these hospitals are likely to take more MRI scans, given the same number of patients. Perhaps these hospitals are likely to lose their patients due to the business-stealing effect, and, to maintain the same level of revenue from MRI scanning, they take more MRI scans than they did before.

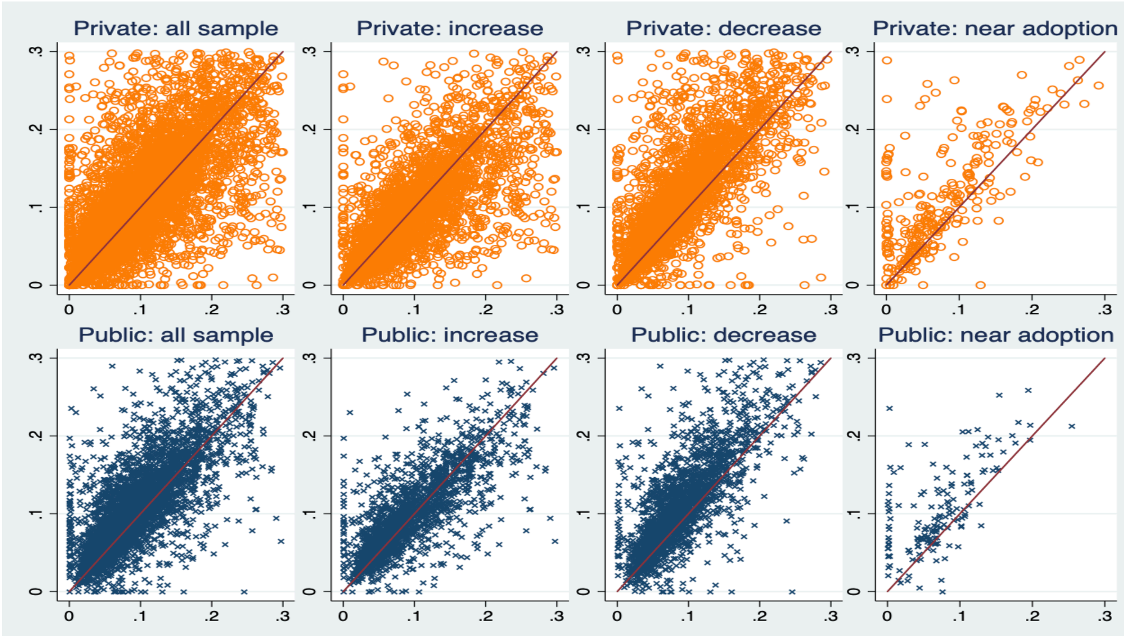
Of course, as mentioned earlier, there are several concerns about this graphical evidence. First, we do not control any hospital characteristics, and thus, in our main analysis, we include the hospital fixed effects to purely examine the effects caused by the MRI purchases of surrounding hospitals in Section 3.1. Second, there might be an endogeneity concern for MRI adoption of surrounding hospitals. This concern arises because if an unobserved factor increases the demand for the MRI scanning service in that area, it would affect both (i) the MRI conversion rates, as the number of MRI scans would increase, and (ii) the MRI adoption behavior of surrounding hospitals. Thus, we address such a concern in Section 3.1.3. Third, the severity distribution of patients could be different when surrounding hospitals purchase MRI scanners, because some patients who have a serious illness might tend to remain in the same hospital (as the early MRI adopter could be a good hospital), and thus, the MRI conversion rate could increase. To address such concerns, we conduct various robustness checks in Section 4.1.

3 Empirical Strategy and Results

The objective of this section is twofold. First, we show in Section 3.1 that there exists a phenomenon that we call *induced physician-induced demand*. Although there are many potential identification sources for physician-induced demand, such as changes in the reimbursement system and information structure, this paper proposes the externalities from nearby hospitals as a primary source of identification for physician-induced demand. More specifically, we focus on business-stealing effects: A hospital may lose its patients when nearby hospitals introduce MRI scanners and, in response to the decline in demand, the hospital may take more MRI scans per patient, even unnecessarily. We also address the endogeneity concern for the purchases of MRI scanners by surrounding hospitals.

Second, we quantify the physician-induced demand in a more general context as a phenomenon that physicians over-treat in response to a reduction in demand. Thoroughly examining our induced physician-induced demand hypothesis, we find that pub-

Figure 2: Changes in MRI Conversion Rates



Note: Each scatter plot shows the MRI conversion rate where the x-axis and y-axis show the MRI conversion rate at $t-1$ and t, respectively. Each dot represents a hospital. The scatter plots in the first and second rows show the conversion rate of private hospitals and public hospitals, respectively. The scatter plots in the first, second, third, and fourth columns show the conversion rate of all hospitals, hospitals facing an increasing number of patients between period $t-1$ and t, hospitals facing a decreasing number of patients between period $t-1$ and t, and hospitals facing new MRI adoption by surrounding hospitals.

lic hospitals' MRI purchase decisions are suitable for use as an instrument. We use this instrument and attempt to identify more broadly defined physician-induced demand in Section 3.2.

3.1 Testing Induced Physician-Induced Demand Hypothesis

3.1.1 Business-Stealing Effects

Throughout this paper, subscripts h and t denote the indices of each individual hospital and period, respectively. Let $M_{h,t}$ and $M_{-h,t}$ denote the number of MRI scanners owned by hospital h and by surrounding hospitals, respectively. Here, the hospitals surrounding hospital h are defined as the hospitals within a 1-kilometer radius of hospital h and we choose this distance so that the business-stealing effects are prominent enough to be detected.[12] Also, let $N_{h,t}$ denote the number of patients in the relevant medical departments, which we explain in Section 2, in hospital h at period t.

To examine the business-stealing effects of MRI purchases by surrounding hospitals, we use the following model:

$$\Delta \log \left(N_{h,t}\right) = \delta \Delta \log \left(M_{-h,t} + 1\right) + \text{controls} + \epsilon_{h,t}, \tag{1}$$

where ΔX_t denotes the first difference of X_t (i.e., $X_t - X_{t-1}$), and $\epsilon_{h,t}$ is an error term. As for control variables, we include year fixed effects, the change in the number of hospital beds, the number of MRIs that hospital h owns at $t-1$, the number of patients at the relevant medical department at $t-1$, and the number of MRI scans taken at hospital h at $t-1$.[13] We also include the lagged value and the first difference of the total number of hospital beds at the surrounding hospitals to capture the potential change in the quality of surrounding hospitals in a dimension other than their MRI adoption. We are interested in the coefficient for $\Delta \log \left(M_{-h,t} + 1\right)$, namely δ. A negative value of δ implies that more MRI scanners at surrounding hospitals negatively affect the patients from hospital h—i.e., there indeed is a business-stealing effect. Note that we add one to $M_{-h,t}$ when taking logarithm to avoid $\log(0)$ when constructing the variable.[14]

In addition to this baseline specification, we adopt another specification where we allow for a heterogeneous business-stealing effect. As it is natural to assume that the MRI adoption incentives differ between private hospitals and public hospitals, the resulting business-stealing effects may differ. Private hospitals may be closer to profit-maximizing entities and, thus, their adoption decisions may better reflect local demand for MRI scanning or they may have higher incentive to steal patients from nearby hospitals, which results in a larger or smaller business-stealing effect compared with the adoption of MRI at public hospitals. Also, the MRI adoption decisions of public hospitals may be less sen-

[12] We discuss this choice of 1 kilometer in more detail in Section 4.4.

[13] As we take first difference of the variables, we do not include hospital fixed effects, because hospital fixed effects are differenced out. This specification is more general than estimating a fixed-effect model on the level of the variables, as it allows for time-specific growth rate of the number of patients.

[14] Although this operation may seem to be arbitrary, we obtain similar results, qualitatively and quantitatively, when using the level specification. We discuss this issue again in Section 4.4

sitive to local demand, as they may care less about the profitability of MRI, which may result in a higher business-stealing effect. Depending on what effect exists/is dominant, we would expect a heterogeneous effect of the business-stealing effect determined by the owner of the MRI scanners. To capture this heterogeneity, let $M_{-h,t}^{Pub}$ and $M_{-h,t}^{Pri}$ denote the numbers of MRI scanners purchased by surrounding public hospitals and by surrounding private hospitals, respectively. We then estimate the following equation:

$$\Delta \log\left(N_{h,t}\right) = \delta_{pub}\Delta \log\left(M_{-h,t}^{Pub}+1\right)+\delta_{pri}\Delta \log\left(M_{-h,t}^{Pri}+1\right)+\text{controls}+\epsilon_{h,t}. \tag{2}$$

Note that we include the first difference of the number of beds to control for change in hospital size, and that inclusion of this variable may create a simultaneity issue. To address this concern, we run both ordinary least squares (OLS) regression and IV regression with the lagged value of the number of total outpatients, inpatients, and hospital beds as the instrument for the first difference of hospital beds.

Table 3 depicts the results. The first four columns present OLS estimation results, whereas the last four columns present IV estimation results. In the regression, we use only the hospitals that owned MRI scanners in periods $t-1$ and t. As we expected, public and private hospitals are affected differently by MRI adoption of surrounding hospitals and the substitution between public and private hospitals is different. The first and fifth columns show the baseline specification corresponding to Equation (1) by using all hospitals that own MRI scanners, whereas the rest of the columns correspond to Equation (2) where we estimate the business-stealing effect *on* public and private hospitals separately. The second and sixth columns show the results using observations only when h is a private hospital, the third and seventh columns show the results using observations only when h is a public hospital, and the fourth and eighth columns show the results using all hospitals, respectively.

First, the estimation results corresponding to Equation (1) show the negative and statistically significant effect of $\log\left(M_{-h,t}+1\right)$, suggesting that business-stealing effects exist. By comparing these results with the results corresponding to Equation (2), we can see that the business-stealing effect results from MRI scanner adoption of public hospitals.

Table 3: Business-Stealing Effects

Dependent Var: $\Delta \log(N_{h,t})$	(i) OLS All	(ii) OLS Private	(iii) OLS Public	(iv) OLS All	(v) IV All	(vi) IV Private	(vii) IV Public	(viii) IV All
$\Delta \log(M_{-h,t}+1)$	-.039**				-.039**			
	(.019)				(.019)			
$\Delta \log(M^{Pub}_{-h,t}+1)$		-.088**	-.123**	-.094***		-.094**	-.088	-.095***
		(.042)	(.051)	(.033)		(.042)	(.062)	(.033)
$\Delta \log(M^{Pri}_{-h,t}+1)$		-.002	-.016	-.003		-.001	-.020	-.004
		(.030)	(.026)	(.023)		(.030)	(.033)	(.023)
$\Delta \log(Beds_{h,t})$	.071***	.065**	.146**	.073***	.060	.166	-1.438***	.060
	(.023)	(.025)	(.060)	(.023)	(.144)	(.150)	(.471)	(.144)
Fixed Effects								
Time	√	√	√	√	√	√	√	√
N	9,780	6,258	3,522	9,780	9,780	6,258	3,522	9,780
R^2	.075	.066	.123	.076	.074	.062	.	.075

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include the number of MRI scanners hospital h owns at $t-1$, the number of patients at the relevant medical department at $t-1$, the number of MRI scans taken at hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables. In the last row, a '.' represents negative R^2.

Though estimated coefficients for specification Equation (2) have similar magnitude, the levels of significance are different. This difference may be due to the number of observations used in the estimation. It is natural to expect the statistics to have the highest power when more observations are used. In fact, the level of significance gets higher as the number of observations increases. Therefore, we believe that the results presented in the fourth and eighth columns are the most reliable.[15] The coefficient on the number of hospital beds is positive and statistically significant in the OLS specification but negative or statistically insignificant in the IV specification, which suggests that the size of the hospital is correlated with the number of patients in the relevant medical department but does not have any causal effect.

In terms of the economic significance, when the number of nearby public hospitals with MRI scanners increases from zero to one, the number of patients at the relevant

[15] One may worry that the business-stealing effects *on* public hospitals and *on* private hospitals are different. By comparing the results in the second and third columns, or the sixth and seventh columns, one may conclude that the former does not exist while the latter exists. We also performed a formal test using all observations but we could not reject the null hypothesis that the effect *on* public hospitals and the effect *on* private hospitals are the same.

medical department decreases by 6.6% ($\delta_{pub} \times (\log(2) - \log(1)) = 0.066$), which is a significant loss for hospitals. In the next subsection, we further examine how hospitals react to such a loss in patients.

3.1.2 Induced Physician-Induced Demand

Given our finding in the previous section that there are business-stealing effects caused by public hospitals' MRI purchases, we now become interested in how these business-stealing effects are translated into changes in the use of MRI scanners. Do the hospitals facing fewer patients due to the business-stealing effects take more MRI scans than they did before to compensate for their foregone revenue? To study this question, we define a new variable, the *MRI conversion rate*. Let $S_{h,t}$ denote the number of MRI scans taken in hospital h at time t, and the MRI conversion rate is defined as the fraction of patients that receive MRI scans—i.e.,

$$CR_{h,t}^{MRI} = \frac{S_{h,t}}{N_{h,t}}.$$

We use this conversion rate because our theoretical model in Appendix A motivates us to use it to capture *induced* physician-induced demand. Suppose the physicians take MRI scans based solely on the severity of the condition of patients, then the conversion rate should be constant regardless of other factors as long as the distribution of the severity remains the same. Therefore, we can test whether the business-stealing effect induces physician-induced demand by estimating the following two specifications:

$$\Delta CR_{h,t}^{MRI} = \beta_{pub}\Delta \log\left(M_{-h,t}^{Pub} + 1\right) + \beta_{pri}\Delta \log\left(M_{-h,t}^{Pri} + 1\right) + \text{controls} + \epsilon_{h,t}, \tag{3}$$

and

$$\begin{aligned} \Delta CR_{h,t}^{MRI} \quad = \quad & \beta_{pub}\Delta \log\left(M_{-h,t}^{Pub} + 1\right) + \beta_{pri}\Delta \log\left(M_{-h,t}^{Pri} + 1\right) \\ & + \gamma_{pub}\Delta \log\left(M_{h,t}^{Pub} + 1\right) \times P_h + \gamma_{pri}\Delta \log\left(M_{h,t}^{Pri} + 1\right) \times P_h + \text{controls} + \epsilon_{h,t}, \end{aligned} \tag{4}$$

where P_h is an indicator variable, taking a value of one if hospital h is a public hospital and of zero otherwise, and controls include P_h, the lagged values, values at $t-1$, of the number of hospital beds, MRI scans, patients in the relevant medical department, MRI scanners owned by hospital h, and the lagged value and the first difference of the total number of hospital beds at the surrounding hospitals. The signs of βs and γs allow us to test the existence of induced physician-induced demand. When estimating Equation (3), we separately run the regression using observation of private hospitals, public hospitals, and all hospitals, whereas we use all observations when estimating Equation (4). When we estimate the model, we restrict our sample to hospitals that owned and used MRI scanners in both periods $t-1$ and t. Furthermore, because the construction of CR_{ht}^{MRI} involves division, the variable contains extreme values. To avoid having the results be driven by those outliers, we drop 5% of the tail observations. Table 4 depicts the estimation results.[16]

Table 4: Induced Physician-Induced Demand

Dependent Var: $\Delta CR_{h,t}^{MRI}$	(i) Private	(ii) Public	(iii) All	(iv) All
$\Delta \log(M_{-h,t}^{Pub}+1)$	.018**	.012*	.008**	.009**
	(.008)	(.006)	(.003)	(.004)
$\Delta \log(M_{-h,t}^{Pri}+1)$	-.009	-.001	-.003	-.004
	(.006)	(.004)	(.002)	(.003)
Public $\times \Delta \log(M_{-h,t}^{Pub}+1)$				-.003
				(.005)
Public $\times \Delta \log(M_{-h,t}^{Pri}+1)$				.007
				(.004)
Fixed Effect				
Time	√	√	√	√
N	5,625	3,336	8,692	8,692
R^2	.	.	.052	.051

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include an indicator for public hospitals, the number of hospital beds at $t-1$, MRI scans at $t-1$, patients in the relevant medical department at $t-1$, and MRI scanners owned by hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables. In the last row, a '.' represents negative R^2.

The first three columns of Table 4 show the results corresponding to Equation (3) and present the results using observations when h is a private hospital, observations when h is a public hospital, and all observations, respectively. As in the results in Table 3, all

[16]Our estimation results are robust to the difference in the sample size between Tables 3 and 4. The results in Table 3 still hold when we restrict the sample to the same set of observations as in Table 4, which we show in Table B6 in Appendix B.

three columns show similar qualitative results with different significance levels. The results in those three columns clearly indicate that the adoption of MRI scanners at public hospitals has a statistically significant effect. However, it is hard to conclude whether private hospitals and public hospitals are affected differently. To examine this issue, we estimate the model corresponding to Equation (4). The fourth column presents the result. The coefficient on $\Delta M^{Pub}_{-h,t}$ is still estimated as positive and statistically significant at 5% level, and we cannot reject the hypothesis that the effect is the same on private and public hospitals.

The estimated value of β_{pub} suggests that the conversion rate increases 0.6% when the number of nearby public hospitals increases from zero to one ($\beta_{pub} \times (\log(2) - \log(1)) = 0.0062$). The average conversion rate conditional on having MRI scanners is 14.6%. Therefore, a 0.6% increase in conversion rate can be interpreted as a 4.2% increase from the average conversion rate (0.6%/14.6%). Together with the finding in Section 3.1.1, the estimated coefficients suggest that hospitals keep the number of MRI scans constant regardless of the number of patients visiting the hospitals—i.e., MRI adoption by nearby public hospitals reduces the number of patients but hospitals increase the conversion rate so that the number of MRI scans remains the same.

This observation is consistent with anecdotes from some documents published by public hospitals and/or interviews with physicians, indicating an implicit quota imposed by hospital managers for the number of MRI scans.[17] Therefore, to obtain similar results, we could alternatively use the number of MRI scans as a dependent variable, directly, to show that the number of MRI scans would not change in response to the change in the number of nearby MRIs. However, it is difficult to construct a rejectable hypothesis to test this claim statistically, which inspires us to use the conversion rates to investigate induced physician-induced demand.[18]

[17]Due to inefficient management and low profitability at public hospitals, the Japanese government implemented a policy called Reform of Local Public Hospitals. In the guidelines of the reform, the government required public hospitals to make their own action plans which often involve setting the target number of MRI scans per year, and to report their progress every year.

[18]Tables B7 and B8 in Appendix B present the estimation results corresponding to Tables 4 and 6 by replacing the conversion rate with the number of MRI scans as a dependent variable. We cannot reject the null hypothesis that the number of MRI scans is unchanged in response to the change in the number of MRIs at surrounding hospitals or the number of patients, which is consistent with the anecdotal evidence.

3.1.3 Addressing an Endogeneity Concern

The results presented in the previous sections may potentially suffer from the endogeneity of MRI purchases, because MRI purchases could be driven by unobserved changes in the demand for MRI scanning. For example, if a large-scale nursing home were built in one area, the elderly population would increase as would the demand for MRI scanning services. Expecting such an increase in demand, hospitals might purchase MRI scanners and, at the same time, the conversion rate might increase without any physicians' opportunistic behavior.

Such a mechanism would lead to biases in the estimation results we presented in the previous subsection. In particular, the estimated business-stealing effect in Table 3 and the estimated physician-induced demand in Table 4 may be upwardly biased, which may explain why new MRI purchases at private hospitals do not create a business-stealing effect. Private hospitals may care more about the profitability of MRI purchases and may take the local demand growth into their purchase decisions more than public hospitals do. However, even with such possible upward biases, we do find a business-stealing effect for new MRI purchases at public hospitals. The MRI purchase decisions of public hospitals may not be correlated with the local demand growth for a variety of reasons—e.g., local government may constrain the budget of public hospitals, public hospitals may have a more rigid decision process than private hospitals, the bureaucratic management structure at public hospitals means it may take longer to reach a decision, public hospitals are less sensitive to the profitability of a new purchase, etc.

Our estimation result in Table 3—that public hospitals steal patients from surrounding hospitals—is consistent with this possibility that public hospitals do not respond to the change in demand immediately when purchasing MRI scanners, which ends up with stealing patients from hospitals that enter the market beforehand. If the MRI purchase decision of public hospitals is not correlated with the change in unobserved local demand, at least, the results for the coefficients on the effect of public hospitals' MRI purchases in Table 3 and Table 4 are consistent.

To examine the validity of our results, we investigate the MRI adoption decisions of private and public hospitals. Let $D_{h,t}$ denote an indicator that takes a value of one if the difference of the number of MRI scanners owned by hospital h increases at period t—i.e., $D_{h,t} = 1$ implies new MRI adoption, takes a value of negative one if the difference of the number of MRI scanners owned by hospital h decreases at period t, and takes a value of zero if there is no change in the number of MRI scanners. We adopt the following empirical specification, and we estimate an ordered logit model with hospital random effects. Formally, a latent variable $D^*_{h,t}$ is specified as

$$D^*_{h,t} = \zeta_1 \log(N_{h,t-1}) + \zeta_2 M_{h,t-1} + \zeta_3 \log(N_{-h,t-1}) + \text{controls} + \mu_h + \epsilon_{h,t}, \tag{5}$$

where $N_{-h,t-1}$ denotes the number of patients at the surrounding hospitals of h at the relevant medical departments, μ_h denotes hospital random effects, and controls include $\Delta \log\left(M^{Pri}_{h,t-1} + 1\right)$, $\Delta \log\left(M^{Pub}_{h,t-1} + 1\right)$, the lagged value of the number of hospital beds, the lagged value of total outpatients and inpatients in all medical departments, the lagged value and the first difference of the total number of hospital beds at the surrounding hospitals, and the time-fixed effects. $D_{h,t}$ takes a value of either -1, 0, or 1, depending on the value of $D^*_{h,t}$ as

$$D_{h,t} = \begin{cases} -1, & \text{if } D^*_{h,t} \leq \underline{c}, \\ 0, & \text{if } \underline{c} < D^*_{h,t} < \bar{c}, \\ 1, & \text{if } D^*_{h,t} \geq \bar{c}. \end{cases}$$

The purpose of this specification is to infer the MRI purchase decisions of private and public hospitals to see whether an endogeneity issue exists. Our primary focus is to determine whether ζ_3 is estimated as significantly different from zero for pubic hospitals. If so, it rejects the hypothesis that public hospitals' MRI purchase decisions are not correlated to unobserved changes in demand in nearby hospitals, which violates the validity of our argument in previous sections.

Table 5 summarizes the results. Note that the sample size in Table 5 is smaller than the sample size in other tables, because the inclusion of $\Delta \log\left(M^{Pri}_{h,t-1} + 1\right)$ and $\Delta \log\left(M^{Pub}_{h,t-1} + 1\right)$ requires additional lagged values of the variables, $M^{Pri}_{h,t-2}$ and $M^{Pub}_{h,t-2}$, which are missing for the first year by construction. The first and third columns show the results with obser-

Table 5: MRI Purchase Decisions

	(i) Private	(ii) Public	(iii) Private	(iv) Public
$\log(N_{h,t-1})$	.271***	-.019	.278***	.010
	(.028)	(.066)	(.032)	(.078)
$M_{h,t-1}$	-1.880***	-1.808***	-1.918***	-1.685***
	(.061)	(.088)	(.070)	(.097)
$\log(N_{-h,t-1})$	-.020	-.001	-.015	.006
	(.014)	(.021)	(.017)	(.024)
$\Delta\log\left(M^{Pri}_{h,t-1}+1\right)$			-.142	.254
			(.143)	(.236)
$\Delta\log\left(M^{Pub}_{h,t-1}+1\right)$			.214	-.237
			(.197)	(.266)
Fixed Effect				
Year	√	√	√	√
N	14,396	5,178	10,349	3,703

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include the number of hospital beds at $t-1$, total inpatients and outpatients at all medical departments at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, time fixed effects and a constant term, as control variables.

vations only when h is a private hospital, whereas the second and the fourth columns show the results with observations only when h is a public hospital. ζ_3, the coefficient on $\log(N_{-h,t-1})$, is estimated not to be significantly different from zero for both private and public hospitals, which supports the argument we have made in previous sections. Furthermore, the coefficient on ζ_1, the number of patients in their own hospital, is estimated positive and statistically significant for private hospitals but not significantly different from zero for public hospitals. This observation further suggests that public hospitals do not respond to the change in the local demand immediately, which is consistent with our expectation that the MRI purchase decisions of public hospitals are constrained by non-economic factors, as purchasing MRI scanners involves various stakeholders' decisions. For example, when some doctors at a public hospital feel that it is necessary to purchase MRI scanners, they must first propose a purchase plan internally and, even if the purchase plan is approved there, the plan must be examined by a prefectural hospital organization and approval must be obtained from the city council or local government. Thus, compared with private hospitals, public hospital tend to respond more slowly to the local demand, which leads to our estimation results.

3.2 Generalized Physician-Induced Demand

In the previous sections, we quantify physician-induced demand caused by the MRI purchases of surrounding hospitals, which we defined as *induced physician-induced demand*. From the previous analysis, we now believe that MRI purchases by surrounding public hospitals can be used as an instrumental variable to the number of patients attending each hospital, because it satisfies exclusion restriction and relevance: Public hospitals do not respond to the potential demand immediately when they purchase MRI scanners and the number of patients would decrease because of the business-stealing effects. Taking advantage of this finding, we attempt to identify how physicians' behavior changes in response to the change in the number of patients.

To quantify this physician-induced demand, we adopt the following two stage least squared (2SLS) specification:

$$\Delta CR_{h,t} \quad = \quad \gamma_1 \Delta \log \left(N_{h,t}\right) + \gamma_2 \log(S_{h,t-1}) + \gamma_3 \log(N_{h,t-1}) + \text{controls} + \epsilon_{h,t}, \tag{6}$$

where $\Delta \log \left(N_{h,t}\right)$ is the endogenous variable and controls include $M_{h,t}$, the lagged number of hospital beds, the lagged number of outpatients and inpatients at all medical departments, the lagged value and the first difference of the total number of hospital beds at the surrounding hospitals, and time fixed effects. The first-stage regression for $\Delta \log \left(N_{h,t}\right)$ is specified as

$$\Delta \log \left(N_{h,t}\right) \quad = \quad \delta_1 \Delta M_{-h,t}^{Pub} + \text{controls}^{iv} + \varepsilon_{h,t},$$

where controls^{iv} include all control variables in Equation (6).

If γ_1 is negative, then the hospitals increase the conversion rate in response to an exogenous decrease in the number of patients, which constitutes evidence of physician-induced demand. As we discussed earlier, if physicians take MRI scans solely depending on the conditions of the patients, the conversion rate should remain constant when there is any exogenous change in the number of patients.[19]

[19] This argument relies on the assumption that the severity distribution does not change depending on the number of public hospitals with MRI scanners. We investigate whether this assumption is plausible in

Table 6: Physician-Induced Demand

Dependent Var: $\Delta CR_{h,t}$	(i) All	(ii) All	(iii) All	(iv) All
$\Delta\log(N_{h,t})$	-.076**	-.083**	-.089**	-.083**
	(.037)	(.038)	(.038)	(.037)
$\log(S_{h,t-1})$		-.006***	-.011***	-.013***
		(.001)	(.003)	(.002)
$\log(N_{h,t-1})$			.010*	.009
			(.006)	(.006)
Hospital-size related controls				√
Fixed effect				
Time	√	√	√	√
N	9,324	9,324	9,324	9,324
R^2	.220	.209	.198	.228
First-Stage $\Delta\log(M^{Pub}_{-h,t}+1)$	-.043*	-.042*	-.046**	-.046**
	(.022)	(.022)	(.021)	(.021)
First-Stage F Stats	13.86	12.86	41.06	34.34

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include an indicator for public hospitals, the number of MRI scanners owned by hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables. "Hospital size related controls" includes the number of hospital beds at $t-1$ and the total number of inpatients and outpatients at all medical departments at $t-1$.

Table 6 demonstrates the results for four different specifications with several different control variables. Regardless of the specifications, γ_1 is negative and statistically significant. The lagged value of the number of MRI scans is negative and statistically significant, which suggests regression toward the mean. The lagged value of the number of patients does not have any significant effect.

3.3 Implications

In the previous subsections, we qualitatively evaluate these two types of physician-induced demands in terms of the number of MRI scans. Given the estimation results in Sections 3.1 and 3.2, we are able to quantify the number of MRI scans generated by (induced) physician-induced demand. Then, we compute the total amount of reimbursement paid for the excessive MRI scans. As we explain in Section 2.2, healthcare expenditure for MRI scans ranges from ¥19,200 to ¥23,400 for each MRI scan, depending on the details of the

Section 4.1 more thoroughly.

actual treatment, and, thus, we use the average of ¥21,300 in the following calculation as the healthcare expenditure per MRI scan.

Panel (A) of Table 7 quantifies the number of MRI scans caused by induced physician-induced demand and associated healthcare expenditure. In Panel (B), we quantify the number of MRI scans caused by broadly defined physician-induced demand and associated healthcare expenditure. In general, a decrease in the number of patients caused by any mechanism unrelated to patients' condition induces physician-induced demand, as discussed in Section 3.2. To quantify this general effect, we use the estimation results from Table 6, where we find that a 1% decrease in the number of patients increases the conversion rate by 0.083%. Here, we look at hospitals that experienced a reduction in the number of patients and quantify their physician-induced demand caused by the changes in the number of patients.

Table 7: Monetary Value of Physician-Induced Demand

	2008	2011	2014
Panel (A): Induced PID			
Induced scans per month	648	902	455
Induced payment per month (in million JPY)	¥13.81	¥19.20	¥9.68
Induced payment per year (in billion JPY)	¥0.17	¥0.23	¥0.12
Panel (B): General PID			
Induced scans per month	41,307	28,683	21,800
Induced payment per month (in million JPY)	¥880	¥611	¥464
Induced payment per year (in billion JPY)	¥10.56	¥7.33	¥5.57

Note: This table provides qualitative evaluation of physician-induced demand. Panel (A) describes the estimated physician-induced MRI scans and resulting healthcare expenditure based on the estimates from Table 4, whereas Panel (B) describes the same statistics based on the estimates from Table 6.

Table 7 summarizes the results. Note that we can quantify physician-induced demand generated only by new MRI purchases in Panel (A) or the changes in the number of patients, meaning that we cannot quantify *pre-existing* physician-induced demand. In this sense, one can regard the reported amount as the lower bound of the total physician-induced demand that exists in the MRI scanning treatment. Panel (A) of Table 7 casts suspicion that induced physician-induced demand caused about 450 to 900 scans. These numbers may not seem to be economically significant, because they account for additional induced demand generated only by new MRI purchases of public hospitals, which does not occur frequently. On the other hand, when we calculate induced demand caused by reduced number of patients, Panel (B) of Table 7 shows that physician-induced demand caused about 22,000 to 41,000 MRI scans, which results in unnecessary additional healthcare spending of about ¥6 to ¥11 billion (Japanese yen). This healthcare spending could have been saved if MRI adoption decisions had been made collectively so that business-stealing effects and resulting physician-induced demand were minimal.

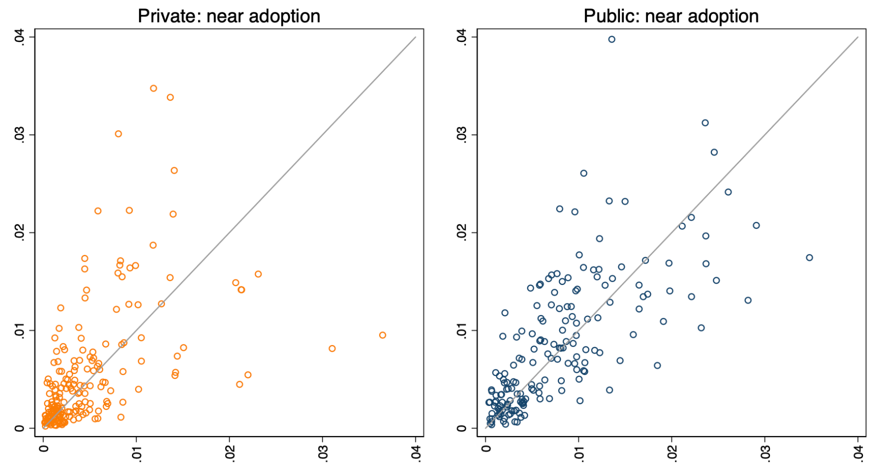
4 Robustness Check

4.1 Severity Sorting

In our previous analysis, we assume that the distribution of the severity of patients' condition would not change if nearby hospitals purchase MRI scanners. However, this assumption might not be true. For example, newly equipped hospitals may not yet have an established reputation and thus patients who exhibit more severe symptoms may remain at incumbent hospitals, some patients who exhibit more severe symptoms may want to visit a hospital that has new MRI scanners, or the MRI adoption decision of hospitals itself may depend on such unobserved changes in the severity distribution. In any case, the severity distribution of patients may not be independent of MRI adoption, which may result in upward or downward bias in our estimation results in Tables 4 and 6. Ideally, if we had patient-level data, we could directly test whether MRI adoption at the surrounding hospitals induces any severity sorting. However, we only have an access to hospital-level data.

To address these concerns without patient-level data, we first investigate the change in the *surgery conversion rate*, defined as the fraction of the number of all surgeries to the number of patients. This variable can be a proxy for the number of patients with severe symptoms. If patients with severe symptoms tend to remain at the same hospital, the surgery conversion rate would not change after MRI purchases by surrounding hospitals. As one can see from Figure 3, surgery conversion rates do not change for private or

Figure 3: Surgery Conversion Rates in $t-1$ and t



Note: Both scatter plots show the surgery conversion rate where the x-axis and y-axis shows the surgery conversion rate at $t-1$ and t, respectively, and each circle represents a hospital. The left panel shows the conversion rate of private hospitals facing new MRI adoption by surrounding hospitals, whereas the right panel shows the conversion rate of public hospitals facing new MRI adoption by surrounding hospitals.

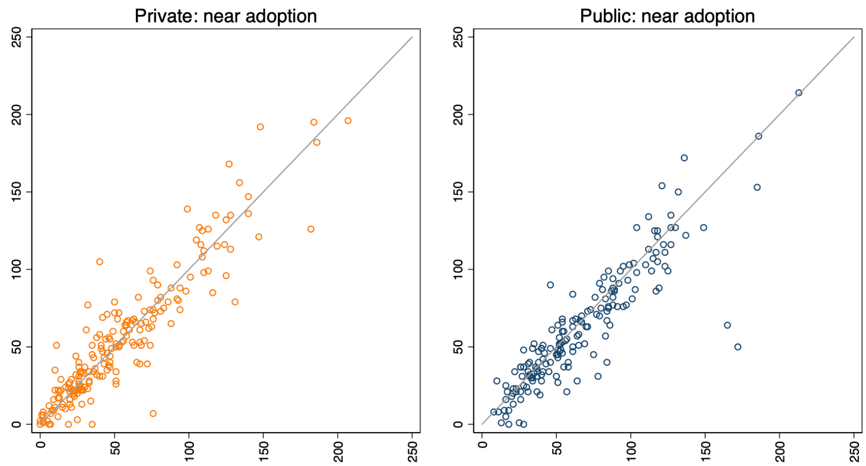
public hospitals, indicating that the severity distribution of attending patients does not change. We also check the robustness by comparing the number of inpatients, because this number can be another proxy for the number of patients with severe symptoms. Figure 4 shows the number of inpatients in $t-1$ and t. As one can see from the figure, they are symmetrically distributed with the 45 degree line, supporting our assumption.

More formally, we estimate a model similar to that in Equation (3)—i.e.,

$$\Delta y_{h,t} = \beta^{Pub} \Delta \log\left(M^{Pub}_{-h,t} + 1\right) + \beta^{Pri} \Delta \log\left(M^{Pri}_{-h,t} + 1\right) + \text{controls} + \epsilon_{h,t}, \tag{7}$$

where, as an explained variable, $y_{h,t}$, we use (i) the logarithm of the number of inpatients, (ii) the *computed tomography (CT) conversion rate*, (iii) the *cancer surgery conversion rate*, and (iv) the *all surgery conversion rate*, to check the robustness of our results. Those conversion rates are defined analogously to the conversion rate of MRI scans. Table 8 summarizes the estimation results. For all dependent variables, the coefficients on the change in the number of nearby MRI scanners are not significantly different from zero, which strongly supports our assumption that the severity distribution of patients is not

Figure 4: The Number of Inpatients in $t-1$ and t



Note: Both scatter plots show the number of inpatients where the x-axis and y-axis shows the number of inpatients at $t-1$ and t, respectively, and each circle represents a hospital. The left panel shows the number of inpatients at private hospitals facing new MRI adoption by surrounding hospitals, whereas the right panel shows the number at inpatients of public hospitals facing new MRI adoption by surrounding hospitals.

correlated with the MRI adoption of nearby hospitals.

4.2 Introduction of Diagnosis Procedure Combination

To prevent over-treatment by doctors, the DPC system has existed since 2003 in Japan. Though not many hospitals adopted the DPC system in our sample period initially, the result could be affected, because these hospitals may not have any incentive to engage in creating physician-induced demand. The best way to address this concern would identify DPC hospitals in our data, divide the full sample into DPC hospitals and non-DPC hospitals, and then redo our analysis separately. However, our data do not allow us to identify whether or not a hospital employs DPC payment scheme. Therefore, instead of doing so, in order to address this concern, we focus on the number of outpatients, instead of the total number of patients, because the DPC system is applied only to inpatients. We then redo the same empirical exercises, replacing the number of total patients with the number of outpatients, and obtain the same results, both qualitatively and quantitatively.

Table 8: Severity of Patients' Condition

	(i) log(Inpatients)	(ii) CR^{CT}	(iii) $\text{CR}^{CancerSurgery}$	(iv) $\text{CR}^{AllSurgery}$
$\Delta \log(M^{Pub}_{-h,t}+1)$	-.012	.001	.000*	-.000
	(.014)	(.002)	(.000)	(.001)
$\Delta \log(M^{Pri}_{-h,t}+1)$	-.000	-.002	.000	-.000
	(.009)	(.002)	(.000)	(.000)
Fixed Effect				
Time	√	√	√	√
N	8,649	8,672	5,096	8,672
R^2	.033	.015	.002	.106

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include an indicator for public hospital, the number of hospital beds at $t-1$, MRI scans at $t-1$, patients in the relevant medical department at $t-1$, and MRI scanners owned by hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables.

4.3 Pre- and Post-Trends

The specification we adopt in this paper is similar to difference-in-differences models. As in the standard difference-in-differences research design, one typical concern is that the treatment group and control group have different time trends. To address this concern and to show that our results are not driven by differential trends, we re-estimate Equations (2) and (4) with lagged and forward values of the "treatment" variable. Formally, we define $Treatment^{Pub}_{h,t} = \Delta \log\left(M^{Pub}_{-h,t}+1\right)$ and $Treatment^{Pri}_{h,t} = \Delta \log\left(M^{Pri}_{-h,t}+1\right)$, and run the following regression:

$$\begin{aligned}\Delta y_{h,t} &= \sum_{\tau=-2}^{2}\left(\beta_{Pub,\tau} Treatment^{Pub}_{h,t+\tau}\right) \\ &\quad + \sum_{\tau=-2}^{2}\left(\beta_{Pri,\tau} Treatment^{Pri}_{h,t+\tau}\right) + \text{controls} + \epsilon_{h,t},\end{aligned}$$

replacing $Treatment^{Pri}_{h,t+\tau}$ with 0 if it is missing. Table 9 presents the result. The only coefficients that are statistically different from 0 are $\beta_{Pub,0}$ with the same sign as in Tables 3 and 4. The insignificance of the other coefficients indicates that there are no significant pre-trends or post-trends that could bias our results in Section 3.

Table 9: Lagged and Future Value of the Change in the Number of MRIs

Specification Dependent Variable	Table 3 (viii) $\Delta\log(N_{h,t})$	Table 4 (iv) $\Delta CR^{MRI}_{h,t}$
$\Delta\log(M^{Pub}_{-h,t-2}+1)$	.007	.011
	(.053)	(.007)
$\Delta\log(M^{Pub}_{-h,t-1}+1)$	-.008	-.005
	(.024)	(.004)
$\Delta\log(M^{Pub}_{-h,t}+1)$	-.090***	.007**
	(.028)	(.004)
$\Delta\log(M^{Pub}_{-h,t+1}+1)$	.056	-.002
	(.047)	(.006)
$\Delta\log(M^{Pub}_{-h,t+2}+1)$	-.048	-.005
	(.046)	(.006)
$\Delta\log(M^{Pri}_{-h,t-2}+1)$	-.027	-.002
	(.030)	(.003)
$\Delta\log(M^{Pri}_{-h,t-1}+1)$	-.011	.002
	(.023)	(.002)
$\Delta\log(M^{Pri}_{-h,t}+1)$	-.003	-.003
	(.023)	(.003)
$\Delta\log(M^{Pri}_{-h,t+1}+1)$	.031	.004
	(.031)	(.003)
$\Delta\log(M^{Pri}_{-h,t+2}+1)$	.032	-.002
	(.032)	(.004)
N	9,780	8,692
R^2	.076	.079

Note: Standard errors in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications follows the same specification and use the same control variables as in the corresponding tables.

4.4 Discussions on Other Issues

4.4.1 Choice of 1 kilometer radius

We expect the business-stealing effects to be larger when hospitals are located near to each other. For our analysis, the definition of "surrounding hospitals" needs to be close enough for the business-stealing effects to exist and significantly affect the outcomes. To examine whether the choice of 1 kilometer is appropriate, we additionally include the number of MRI scanners at the surrounding hospitals by different distance bins when estimating the business-stealing effects, i.e., the number of MRIs within a 1-kilometer radius, between 1 kilometer to 2-kilometers away, and so on. Table B3 in Appendix B presents the estimation results of Equations (1) and (2) with two distance bins. The results suggest that the business-stealing effects would become undetectable when hospitals are more than 1 kilometer away. Therefore, we choose a 1-kilometer radius to investigate induced physician-induced demand.

4.4.2 Logarithm vs. Level

The primary variation we utilize in the regressions is the change in the number of MRIs at the surrounding hospitals. Table B2 in Appendix B shows the transition of this variable. As Table B2 shows, a large fraction of the variation comes from single-unit changes, from 0 to 1 and 1 to 0. Therefore, an analysis based on the logarithm and an analysis based on the level would not be very different, qualitatively and quantitatively. We present the estimation results of Equations (2), (3), and (4) with level variables in Tables B4 and B5. We believe, however, that using logarithm would better address the potential non-linearity of the effect of MRI scanners owned by the surrounding hospitals. This is because we would expect the business-stealing effects to be larger when the number of MRI scanners changes from 0 to 1 than from 3 to 4, for example.

4.4.3 Symmetricity of the Effects

We implicitly assume that the effects of induced physician-induced demand are symmetric, i.e., the conversion rate decreases (increases) at the same degree when surrounding hospitals divest (purchase) MRI scanners. To check the validity of this assumption, we first define two new variables, $\Delta \log \left(M^x_{-h,t}+1\right)^+ = \max\left\{\Delta \log \left(M^x_{-h,t}+1\right), 0\right\}$ and $\Delta \log \left(M^x_{-h,t}+1\right)^- = \min\left\{\Delta \log \left(M^x_{-h,t}+1\right), 0\right\}$, to allow for potentially asymmetric effects and re-estimate Equations (3) and (4). Table B9 presents the estimated coefficients on these variables. The results suggest that physician-induced demand is not symmetric. The effect is larger when the number of nearby MRI scanners increases, compared with cases when the number of nearby MRI scanners decreases. However, when we conduct a formal statistical test, we cannot reject the hypothesis that the coefficients on $\Delta \log \left(M^x_{-h,t}+1\right)^+$ and $\Delta \log \left(M^x_{-h,t}+1\right)^-$ are the same.

We further investigate why the effects are seemingly asymmetric. To do so, we re-estimate Equations (1) and (2) with the same variables. Table B10 presents the estimation results. The results suggest that the increses and decreases in the number of nearby MRIs have asymmetric effects, which explains the seemingly asymmetric effect in Table B9, i.e., physicians change the conversion rate in response to the change in the number of MRIs but not in response to the number of nearby MRIs *per se*. Again, we conduct statistical tests but we cannot reject the hypothesis that the coefficients on $\Delta \log \left(M^{x}_{-h,t}+1\right)^{+}$ and $\Delta \log \left(M^{x}_{-h,t}+1\right)^{-}$ are the same.

In summary, the results in Tables B9 and B10 show that the effect of the change in the number of *nearby MRIs* on the conversion rate is seemingly asymmetric but that of the change in the number of *patients* is seemingly symmetric as well, which is consistent with the primary focus of our paper.

4.4.4 Intensive Margin

As explained in Section 2, the price of a high-Tesla MRI scan is higher than that for a low-Tesla MRI scan. Thus, when a hospital that owns both types of MRI scanners experiences a loss of patients due to the business-stealing effects from the surrounding hospitals, the hospital might shift to utilizing a high-Tesla MRI scanner, which brings in more revenue, instead of utilizing a low Tesla MRI scanner. In our data, for example, 571 hospitals (about 18% of 3,124 MRI-equipped hospitals) owned multiple MRI scanners in 2011. When we investigate their portfolios of MRI scanners—a composition of high- and low-Tesla MRI scanners—it turns out that only 101 hospitals (about 3% of 3,124 MRI-equipped hospitals) owned both types of MRI scanners. Therefore, though such an intensive margin is an interesting and important topic to study, it would not affect our conclusions and studying it requires more observations, hospitals equipped with both MRI types, and variations in the data.

5 Conclusion

We investigate the adoption and usage of MRI scanners, often used as examples of expensive medical equipment, using panel data on all Japanese medical institutions. We find that MRI adoption creates business-stealing effects on nearby hospitals, further inducing physician-induced demand there. In particular, public hospitals do not take into account the local demand for MRI scans when making their MRI purchase decisions. As a result, their MRI purchases cause business-stealing effects and induce physician-induced demand at nearby hospitals. Our results suggest that the decision to adopt expensive medical equipment needs to be made collectively rather than individually to avoid not only excessive adoption but also unnecessary physician-induced demand.

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Appendix A A Theoretical Model

We model the MRI scanning process as a game between a physician and patients. The timing of this game is as follows;

1. At time t, physician h observes the number of patients N. Given the number of patients, the physician solves an ex ante utility maximization problem to find the optimal recommendation strategy, σ, as a function of the severity condition of the patients.

2. A patient i arrives at the hospital and meets physician h. Then the physician observes the severity of patient i, θ_i, that the patient cannot directly observe.

3. Physician h decides whether or not to take MRI scans based on the recommendation strategy $\sigma(\theta_i)$. The recommendation is denoted by r_i.

4. Each patient observes r_i and decides whether to accept the recommendation or to reject it. Then the payoffs of the patient and of the physician realize.

Here, we normalize $\theta \in \Theta = [0,1]$, and the recommendation strategy is a function from Θ to $\{0,1\}$ where 0 denotes "to recommend not to take an MRI scan" and 1 denotes "to recommend to take an MRI scan."

Now, we describe the physician's problem in detail. First, we define the payoff of patient i with severity θ_i, $U(\theta_i)$, as

$$U(\theta_i) = \begin{cases} u(W-P) + \pi(\theta_i), & \text{if } i \text{ takes an MRI scan, and} \\ u(W), & \text{otherwise,} \end{cases}$$

where $u(\cdot)$ denotes the utility from wealth, W denotes the wealth of the patients, p denotes the price of an MRI scan, and $\pi(\theta_i)$ denotes the utility from taking an MRI scan as a function of the severity. Given the payoff of patients and assuming that the patients accept the recommendation, we can define the ex ante utility of physician h as

$$\Pi(\sigma) = p \times N \times \int \sigma(\theta) g(\theta) \mathrm{d}\theta - c\left(N \times \left\{\int \sigma(\theta)\, g(\theta) \mathrm{d}\theta - \int \sigma^{opt}(\theta)\, g(\theta) \mathrm{d}\theta\right\}\right),$$

where p denotes the price of one MRI scan, $g(\theta)$ denotes the density of the severity, $G(\theta)$ denotes its distribution function with support $[0,1]$, σ^{opt} denotes the socially optimal recommendation strategy, and $c(\cdot)$ denotes the cost of "excess" MRI scans. There are two important notes. First, in reality, the Japanese medical association publishes a guideline for MRI scanning. We assume that such guidelines correspond to σ^{opt}. Second, we assume $c'(\cdot) > 0$. This function expresses the negative impact of excess scans such as bad reputation, physicians' psychological costs associated with deviating from σ^{opt}, costs of persuading healthy patients, and so on.

We assume that the patients know $g(\cdot)$ and $G(\cdot)$ but they do not observe θ_i directly. The patients accept the recommendation if

$$\mathrm{E}[u(W-P) - u(P) - \pi(\theta)|\sigma(\theta) = 1] \geq 0.$$

Using this condition, the physician's optimization problem is summarized as follows;

$$\max_{\sigma} \; p \times N \times \int \sigma(\theta)\, g(\theta) \mathrm{d}\theta - c\left(N \times \left\{\int \sigma(\theta)\, g(\theta)\mathrm{d}\theta - \int \hat{\sigma}(\theta)\, g(\theta)\mathrm{d}\theta\right\}\right),$$

$$\text{s.t.} \qquad \mathrm{E}[u(W-P) - u(P) - \pi(\theta)|\sigma(\theta) = 1] \geq 0.$$

Following Dranove (1983, 1988), we can constraint the recommendation strategy to the cutoff strategy when we solve the physician's problem above. Let θ^{opt} denotes the socially optimal cutoff and $\kappa = u(W) - u(W-P)$. Then we can rewrite the problem as follows;

$$\max_{\theta} \; P \times N \times (1 - G(\theta)) - c\left(N \times \left\{G\left(\theta^{opt}\right) - G(\theta)\right\}\right),$$

$$\text{s.t. } \mathrm{E}\left[\pi(\theta') \mid \theta' > \theta\right] \geq \kappa.$$

Before we proceed, we define two conditional expectation functions; $h(x) \equiv \mathrm{E}\left[\pi(\theta) \mid \theta > x\right]$ and $l(x) \equiv \mathrm{E}\left[\pi(\theta) \mid \theta < x\right]$. We assume that θ^{opt} satisfies

$$l(\theta^{opt}) \leq \kappa \leq h(\theta^{opt}).$$

This condition assures that the patients follow the physician's recommendation when the physician follows the socially optimal recommendation strategy.

Given these notations, we can further rewrite the optimization problem of the physician as

$$\max_{\theta} \; P \times N \times (1 - G(\theta)) - c\left(N \times \left\{G\left(\theta^{opt}\right) - G(\theta)\right\}\right)$$

$$\text{s.t. } h(\theta) \geq \kappa.$$

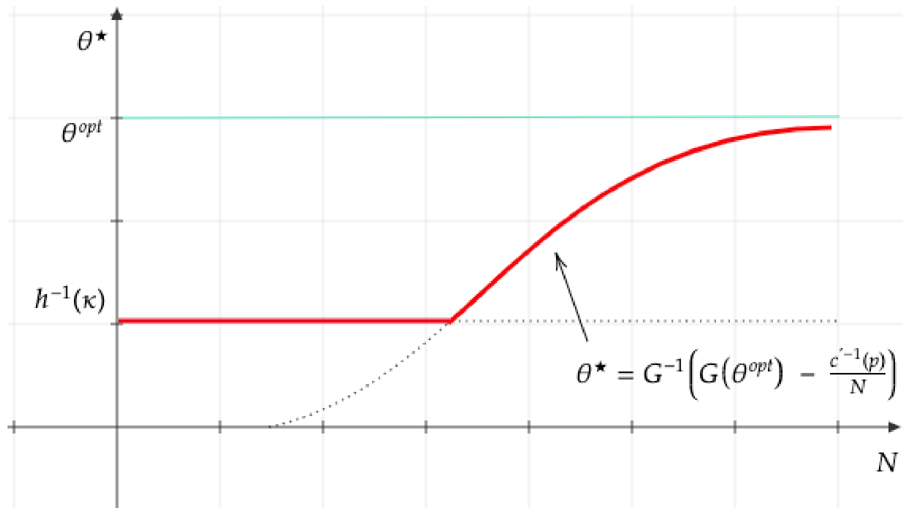

Figure 1: The solution to the optimization problem for each number of patients.

The solution to this optimization problem, θ^*, is

$$\theta^* = \max\left\{G^{-1}\left(G(\theta^{opt}) - \frac{c'^{-1}(p)}{N}\right), h^{-1}(\kappa)\right\}.$$

Figure 1 shows the solution as a function of the number of patents. The physician's payoff-maximizing cutoff is an increasing function of N with a lower bound $h^{-1}(\kappa)$. This model has a testable implication that "the conversion rate decreases as the number of patients increases," which is exactly what we test in this paper.

Appendix B Tables

Table B1: Transition of MRI Adoption/Abandonment

		MRIs_t				
		0	1	2	2+	Total
MRIs_{t-1}	0	20,741	1,322	86	15	22,164
	1	501	8,644	279	6	9,430
	2	42	232	1,112	94	1,480
	2+	7	16	76	269	368
	Total	21,291	10,214	1,553	384	33,442

Table B2: Transition of the Number of MRI Scanners at the Surrounding Hospitals

		MRIs_t				
		0	1	2	2+	Total
MRIs_{t-1}	0	6,356	191	21	1	6,569
	1	172	1,431	113	83	1,799
	2	38	106	493	89	726
	2+	74	36	77	638	825
	Total	6,640	1,764	704	811	9,919

Table B3: Marginally Larger Surrounding Areas

Dep. Var: $\Delta \log(N_{h,t})$	(i) OLS All	(ii) OLS Private	(iii) OLS Public	(iv) OLS All	(v) IV All	(vi) IV Private	(vii) IV Public	(viii) IV All
$\Delta \log(M_{-h,t}^{1km}+1)$	-.042**				-.043**			
	(.020)				(.020)			
$\Delta \log(M_{-h,t}^{1\sim2km}+1)$	-.014				-.015			
	(.019)				(.020)			
$\Delta \log(M_{-h,t}^{Pub,1km}+1)$		-.089*	-.137***	-.095**		-.093*	-.126**	-.096***
		(.049)	(.052)	(.037)		.049	.063	.037
$\Delta \log(M_{-h,t}^{Pub,1-2km}+1)$		-.041	.026	-.021		-.038	.008	-.020
		(.030)	(.029)	(.023)		(.030)	(.035)	(.023)
$\Delta \log(M_{-h,t}^{Pri,1km}+1)$		-.004	-.004	-.004		-.004	.012	-.004
		(.033)	(.031)	(.026)		(.033)	(.036)	(.026)
$\Delta \log(M_{-h,t}^{Pri,1-2km}+1)$		.005	-.018	.002		.007	-.044	.001
		(.027)	(.023)	(.020)		(.027)	(.027)	(.020)
Fixed Effects								
Time	√	√	√	√	√	√	√	√
N	9,780	6,258	3,522	9,780	9,780	6,258	3,522	9,780
r2	.075	.066	.123	.076	.074	.062	.25	.075

Note: Standard errors are reported in parentheses and significance levels are denoted by <.1 (*), <.05 (**), and <.01 (***). All specifications include the number of MRI scanners hospital h owns at $t-1$, the number of patients at the relevant medical department at $t-1$, the number of MRI scans taken at hospital h at $t-1$, and a constant term, as control variables.

Table B4: Business-Stealing Effects

Dependent Var: $\Delta \log(N_{h,t})$	(i) OLS All	(ii) OLS Private	(iii) OLS Public	(iv) OLS All	(v) IV All	(vi) IV Private	(vii) IV Public	(viii) IV All
$\Delta M_{-h,t}$	-.008				-.008			
	(.005)				(.005)			
$\Delta M_{-h,t}^{Pub}$		-.027*	-.047***	-.031**		-.028*	-.035*	-.031**
		(.016)	(.017)	(.012)		(.016)	(.021)	(.012)
$\Delta M_{-h,t}^{Pri}$		-.000	-.002	.000		.000	.001	.000
		(.011)	(.008)	(.008)		(.010)	(.009)	(.008)
$\Delta \log(Beds_{h,t})$	.071***	.064**	.145**	.072***	.058	.166	-1.434***	.060
	(.023)	(.025)	(.060)	(.023)	(.145)	(.150)	(.470)	(.145)
Fixed Effects								
Time	√	√	√	√	√	√	√	√
N	9,780	6,258	3,522	9,780	9,780	6,258	3,522	9,780
R^2	.075	.065	.122	.076	.074	.061	.	.075

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include the number of MRI scanners hospital h owns at $t-1$, the number of patients at the relevant medical department at $t-1$, the number of MRI scans taken at hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables. In the last row, a '.' represents negative R^2.

Table B5: Induced Physician-Induced Demand

Dependent Var: $\Delta CR^{MRI}_{h,t}$	(i) Private	(ii) Public	(iii) All	(iv) All
$\Delta M^{Pub}_{-h,t}$	.004*	.005**	.003**	.002*
	(.002)	(.002)	(.001)	(.001)
$\Delta M^{Pri}_{-h,t}$	-.002	-.001	-.001	-.000
	(.001)	(.001)	(.001)	(.001)
Public $\times \Delta M^{Pub}_{-h,t}$				.002
				(.005)
Public $\times \Delta M^{Pri}_{-h,t}$				-0001
				(.004)
Fixed Effect				
Time	√	√	√	√
N	5,625	3,336	8,692	8,692
R^2	.	.	.	.

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include an indicator for public hospitals, the number of hospital beds at $t-1$, MRI scans at $t-1$, patients in the relevant medical department at $t-1$, and MRI scanners owned by hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables. In the last row, a '.' represents negative R^2.

Table B6: Business-Stealing Effects

Dependent Var: $\Delta\log(N_{h,t})$	(i) OLS All	(ii) OLS Private	(iii) OLS Public	(iv) OLS All	(v) IV All	(vi) IV Private	(vii) IV Public	(viii) IV All
$\Delta\log(M_{-h,t}+1)$	-.044***				-.045***			
	(.017)				(.019)			
$\Delta\log(M^{Pub}_{-h,t}+1)$		-.042	-.124**	-.064**		-.052	-.108*	-.067**
		(.035)	(.058)	(.029)		(.042)	(.062)	(.033)
$\Delta\log(M^{Pri}_{-h,t}+1)$		-.020	-.028	-.019		-.021	-.024	-.019
		(.024)	(.026)	(.019)		(.030)	(.033)	(.023)
$\Delta Beds_{h,t}$	.046**	.038	.113**	.047**	.129	.223	-.760**	.127
	(.020)	(.023)	(.049)	(.020)	(.144)	(.150)	(.372)	(.144)
Fixed Effects								
Time	√	√	√	√	√	√	√	√
N	8,692	5,625	3,336	8,692	8,692	5,625	3,336	8,692
R^2	.075	.068	.118	.075	.073	.054	.	.073

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include the number of MRI scanners hospital h owns at $t-1$, the number of patients at the relevant medical department at $t-1$, the number of MRI scans taken at hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables.

Table B7: Induced Physician-Induced Demand

Dependent Var: $\Delta S_{h,t}$	(i) Private	(ii) Public	(iii) All	(iv) All
$\Delta \log(M^{Pub}_{-h,t}+1)$	-.000	.025	-.020	.004
	(.052)	(.123)	(.047)	(.049)
$\Delta \log(M^{Pri}_{-h,t}+1)$	-.048	.001	-.039	-.048
	(.035)	(.069)	(.028)	(.036)
Public $\times \Delta \log(M^{Pub}_{-h,t}+1)$				-.070
				(.071)
Public $\times \Delta \log(M^{Pri}_{-h,t}+1)$				.033
				(.053)
Fixed Effect				
Time	√	√	√	√
N	5,625	3,336	8,692	8,692
R^2	.068	.	.073	.073

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include an indicator for public hospitals, the number of hospital beds at $t-1$, MRI scans at $t-1$, patients in the relevant medical department at $t-1$, and MRI scanners owned by hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables. In the last row, a '.' represents negative R^2.

Table B8: Physician-Induced Demand

Dependent Var: $\Delta S_{h,t}$	(i) All	(ii) All	(iii) All	(iv) All
$\Delta \log(N_{h,t})$	.458	.298	.252	.319
	(.411)	(.416)	(.400)	(.388)
$\log(S_{h,t-1})$		-.092***	-.203***	-.247***
		(.011)	(.035)	(.032)
$\log(N_{h,t-1})$			.194***	.185***
			(.068)	(.070)
Hospital-size related controls				√
Fixed effect				
Time	√	√	√	√
N	9,324	9,324	9,324	9,324
R^2	.075	.105	.153	.180
First-Stage $\Delta \log(M^{Pub}_{-h,t}+1)$	-.043*	-.042*	-.046**	-.046**
	(.022)	(.022)	(.022)	(.022)
First-Stage F Stats	13.86	12.86	41.06	34.34

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include an indicator for public hospitals, the number of MRI scanners owned by hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term, as control variables. "Hospital size related controls" includes the number of hospital beds at $t-1$ and the total number of inpatients and outpatients at all medical departments at $t-1$.

Table B9: Induced Physician-Induced Demand

Dependent Var: $\Delta CR^{MRI}_{h,t}$	(i) Private	(ii) Public	(iii) All	(iv) All
$\Delta\log(M^{Pub}_{-h,t}+1)^{+}$	.037**	.005	.016***	.016***
	(.016)	(.010)	(.005)	(.006)
$\Delta\log(M^{Pub}_{-h,t}+1)^{-}$	.015*	.015**	.005	.005
	(.009)	(.007)	(.004)	(.004)
$\Delta\log(M^{Pri}_{-h,t}+1)^{+}$	.002	.000	-.003	-.004
	(.011)	(.008)	(.004)	(.004)
$\Delta\log(M^{Pri}_{-h,t}+1)^{-}$	-.013	-.002	-.003	-.003
	(.008)	(.005)	(.003)	(.003)
Fixed Effect				
Time	√	√	√	√
N	5,625	3,336	8,692	8,692
R^2	.	.	.051	.050

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include an indicator for public hospitals, the number of hospital beds at $t-1$, MRI scans at $t-1$, patients in the relevant medical department at $t-1$, and MRI scanners owned by hospital h at $t-1$, the number of hospital beds at the surrounding hospitals around h at $t-1$, the change in the hospital beds at the surrounding hospitals around h at t, and a constant term as control variables. In the last row, a '.' represents negative R^2.

Table B10: Business-Stealing Effects

Dependent Var: $\Delta\log(N_{h,t})$	(i) OLS All	(ii) OLS Private	(iii) OLS Public	(iv) OLS All	(v) IV All	(vi) IV Private	(vii) IV Public	(viii) IV All
$\Delta\log(M_{-h,t}+1)^{+}$	-.005				-.049			
	(.039)				(.039)			
$\Delta\log(M_{-h,t}+1)^{-}$	-.035				-.035			
	(.023)				(.023)			
$\Delta\log(M_{-h,t}^{Pub}+1)^{+}$		-.144	-.227	-.167**		-.152	-.208	-.171**
		(.092)	(.143)	(.078)		(.093)	(.147)	(.078)
$\Delta\log(M_{-h,t}^{Pub}+1)^{-}$		-.066	-.084	-.064*		-.070	-.045	-.064*
		(.047)	(.040)	(.035)		(.047)	(.058)	(.035)
$\Delta\log(M_{-h,t}^{Pri}+1)^{+}$		-.005	-.015	-.003		-.003	-.026	-.004
		(.047)	(.050)	(.038)		(.047)	(.074)	(.038)
$\Delta\log(M_{-h,t}^{Pri}+1)^{-}$		-.008	-.026	-.014		-.008	-.028	-.014
		(.043)	(.031)	(.031)		(.043)	(.035)	(.031)
Fixed Effects								
Time	√	√	√	√	√	√	√	√
N	9,780	6,258	3,522	9,780	9,780	6,258	3,522	9,780
R^2	.075	.066	.123	.076	.074	.062	.	.075

Note: Standard errors are reported in parentheses and significance levels are denoted by <0.1 (*), <0.05 (**), and <0.01 (***). All specifications include the number of MRI scanners hospital h owns at $t-1$, the number of patients at the relevant medical department at $t-1$, the number of MRI scans taken at hospital h at $t-1$, and a constant term, as control variables. In the last row, a '.' represents negative R^2.