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ABSTRACT

Health care markets in developed countries have become increasingly concentrated, while at the same time there has been an increasing trend of mergers and acquisitions (M&As) in these markets. I study the impact of M&As in the diagnostic procedure market, a market that is an important part of the health care industry and patient care, but has received little attention in this context. I use detailed nationwide register data from the Finnish private health care sector. My difference-in-difference estimates show that M&As increased prices in blood tests in both the acquiring and acquired units, but not in X-rays and MRIs. I additionally estimate a patient demand model that reveals that prices have little impact on the choice of provider while the referring physician's influence is large, potentially contributing to the firms' ability to increase their price margins.

JEL Classification: L11, I11, J21, K21

Keywords: Diagnostic Services, Mergers and Acquisitions, Market Power, Private Health Care

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1 Introduction

The health care industry has become increasingly concentrated over the recent decades as the increasing trend of mergers and acquisitions (M&As) has affected the markets both in the Europe and in the US (Angeli and Maarse 2012; Fulton 2017). As health care is one of the most important industries, this consolidation has raised concerns about the functioning of these markets. Most of the focus in the policy discussion and empirical studies on M&As have so far been in the aggregate hospital prices, while the impacts on more micro-level sub-markets have received less attention. One example is the diagnostic service market, an understudied market that has been estimated to be globally worth around $40–45 billion (Morel et al. 2016), and that is arguably an important part of health care.

In this paper, I study the effects of M&As in the diagnostic service markets in the Finnish private health care with detailed procedure-level data. An interesting feature of the diagnostic procedures is that they are a good example of products that are quite homogeneous and standardized quality wise. The advantage of analyzing markets with standardized products is the easier inference of the effects of M&As on prices and consumer welfare as the product quality is controlled.

I start by estimating event study and difference-in-differences models to test whether a wave of mergers during the period of 2008–2017 led to increased prices in blood testing and imaging procedures. I use detailed register data that contain the exact prices of each procedure and cover the whole private health care sector thus allowing me to study the question in a detailed fashion. I test the heterogeneity of the effects for different types of procedures and separately for units that were part of the acquisitions and their rival units.

To overcome concerns of spillovers from the acquisitions in my setting, I compare health care units in the affected markets to control units in markets that were not exposed to acquisitions. To further validate my research design, I estimate event study specifications to test for the pre-trend assumption. The results indicate that, in the acquired units (target, hereafter), acquisitions increase the prices of blood tests by 6 to 9 percent, while for X-rays the prices do not change. For MRIs the estimates are more noisy and no conclusive evidence of either price increase or decrease can be found. The acquiring units (units owned by the acquiring firm in the same market) also increase their blood test prices by a similar amount. Interestingly, rival units do not react to this by changing their prices. The price increase in target units is only evident in in-market acquisitions, providing evidence for the market power hypothesis as the underlying mechanism.

One explanation for the heterogeneity of the results is that, as the markets were more concentrated in the pre-acquisition period in X-ray and MRI markets, the firms are already exploiting higher price margins. In addition, MRIs and X-rays are relatively more pricier products than blood tests and firms may have less leeway to increase their prices post-acquisition.

To obtain a more comprehensive idea of how the price increase in blood tests translates to changes in patient welfare, I proceed to estimate a patient demand model for health care units. A typical challenge in demand estimations is the unobserved product quality that can influence decision making. The homogeneity of the products in diagnostic service markets alleviates this problem.[1] My estimates show that the influence of prices in the choice is small and the referring physician's influence is large. The finding of the large influence of physicians on patients' choices is in line with the findings in the literature (Baker, Bundorf, and Kessler 2016; Carlin, Feldman, and Dowd 2016; Chernew et al. 2018). Similarly, recent literature has documented that the demand elasticity estimates on the intensive margin for various health care services are relatively low (Chandra, Gruber, and McKnight 2014; Dunn 2016; Prager 2020). Using these estimates I quantify the changes in the consumer surplus from the price increase. Because of the small price coefficient the change is, however, negligible.

The previous empirical literature has studied M&As mostly in the hospital markets in the US using proxies or approximated price levels (Dafny 2009; Lewis and Pflum 2017; Schmitt 2018; Dafny, Ho, and Lee 2019).[2] The common finding is that mergers and consolidation

[1] Although, firms can still differentiate their service quality.

[2] An exception is the study by Cooper et al. (2018) that use claims data covering 28 percent of individuals

increases hospital prices. Likewise, the scarce literature on mergers in physician markets have found price increases after a merger (Carlin, Feldman, and Dowd 2017; Koch and Ulrick 2020; Nurminen and Saxell 2020). Moreover, literature studying mergers in the public health care sector have found little evidence of service quality benefits (Gaynor, Laudicella, and Propper 2012; Avdic, Lundborg, and Vikström 2018). I contribute to the literature by studying M&As in an important branch of health care: diagnostic markets. To the best of my knowledge, this is the first paper that focuses on the impacts of M&As on prices in the diagnostic markets. Using the comprehensive data with precise price information, I am able to more effectively analyze the role of competition on prices. I also estimate a demand model specification that enables quantifying the role of price and physicians for patients' choice and the changes in consumer surplus from the price changes.

2 Institutional Setting

In Finland, the private health care exists alongside a large universal public health care sector. Whereas the public health care sector typically includes only small co-payments, the private health care sector is free market based.[3] Firms, health care units, and physicians compete with each other and set their prices according to the demand and level of competition. In this fee-for-service setting, a fraction, that is, a fixed amount of the out-of-pocket prices are also reimbursed by the National Health Insurance (NHI) scheme. The reimbursement rates are the same across Finland. Table A1 shows as an example the amounts allocated for different procedures across several years. The rates have decreased over time.

In addition to the NHI, the patient may also have private health insurance.[4] [5] In order

with employer sponsored health insurance in the US.

[3]Occupational health care is also part of the health care system in Finland. Employees are entitled to preventive occupational health care financed and arranged by the employer, but the provision of medical care is voluntary. Employers can provide occupational health care through the municipalities' (public) health care centers, private health care firms, or provide these services by themselves. As a sector of its own and lacking data from it, I omit the occupational health care from this study.

[4]Private health insurance does affect the prices I observe in the data (Section 4.1). Any external private health insurance would reimburse the leftover out-of-pocket price after NHI reimbursement.

[5]The share of patients having and getting their health care reimbursed by the private health insurance

to have coverage, patients with private insurance are not limited to any pre-determined list of providers that are within the network of the insurance contract—in contrast to the system in the US. Overall, private health care covered by the NHI accounts for approximately 10 percent of health care expenditures in primary and specialized (hospital) health care in Finland (THL 2019).

The focus of this paper is on the diagnostic services market in the private health care sector. Analyst estimates put the size of the global diagnostics market to be worth around $40–45 billion (Morel et al. 2016). Altogether in the EU countries in 2018, the market size of in vitro diagnostics was over 10 billion euros (MedTech Europe 2019). The diagnostic market in the Finnish private health care has considerably expanded during the last decade. Between 2006 and 2019, the number of laboratory tests and radiological examinations, respectively, have increased by 23 and 83 percent (Official Statistics of Finland 2020). During the same period, for laboratory tests, the overall charged amount for NHI reimbursed examinations has increased from 44 million euros to 83 million euros, an increase of 89 percent, while for radiological examinations, the increase has been from 75 million euros to 140 million euros, a similar increase of 87 percent (Official Statistics of Finland 2020).

Typically, a patient first visits a physician who then, after determining the patient need for a diagnostic procedure, writes a referral for one. After receiving the referral, the patient is free to choose the provider of the diagnostic service according to his or her preferences. Some firms also provide diagnostic procedures without a physician's referral. However, in this case the patient does not receive the NHI reimbursement and so it is uncommon to purchase a diagnostic service without a referral.

The diagnostic procedures themselves are fairly homogeneous consumption goods where the quality is standardized (Chernew et al. 2018). In the case of imaging tests, a medical report by a radiologist is usually included with the delivery of the results. Health care units typically provide both physician and diagnostic services. Although the physician visiting

is, however, low.

(office) prices typically vary from physician to physician even within health care units, the price does not depend on the referring physician; the list prices for the diagnostic procedures are the same for all patients. Physicians do not receive any direct profits if the patient chooses the same provider as where the referring physician works. Nevertheless, it is possible that the physician provides information only about the procedures within the firm. Additionally, the patient may have limited information on the providers of these services prior to visiting the physician. Thus, the physician may influence the patient in the choice of the provider.

3 Theoretical Background on M&As

In the relatively simple free market based institutional setting where the prices are determined by supply and demand, the basic merger theory arguably fits the institutional context well. The goal of this paper is to empirically analyze the different theoretical aspects that I go through in this section.

In the absence of any efficiencies, horizontal mergers tend to increase prices and reduce output (Deneckere and Davidson 1985; Farrell and Shapiro 1990; McAfee and Williams 1992). For the rivals of the merging parties, in Bertrand competition, the prices also increase as they internalize the externalities from the reduced competition (Deneckere and Davidson 1985). If synergies are involved between two merging firms, the efficiency may increase (Farrell and Shapiro 1990). This further decreases marginal costs which may lead to price decreases. Furthermore, economies of scale may be involved. In this case, mergers may lead to increased investments in (long-run) capacity, R&D, and new products. In the context of diagnostic procedure markets this may be realized as, for example, an increase in the laboratory capacity or reduced operating expenses through consolidation of administrative services.

Effects of mergers on the aggregate surplus depend on the net change between consumer and producer surplus (Williamson 1968). If the loss of consumer surplus from a price increase is larger than the increase in producer surplus from decreased costs, the merger is harmful for society. Conversely, if the increased producer surplus offsets the decrease in consumer surplus, the aggregate social surplus is higher after the merger. In practice, the anti-trust authorities mostly consider the consumer surplus (Whinston 2007). Also, this trade-off analysis does not take into account the benefits to consumers from any new products arising from increased investments in innovation. In the diagnostic procedure markets, mergers usually do not result in entirely new product innovations.

Many of the acquisitions in the Finnish private health care market have been between nationwide chains and small local firms. As the combined turnover in these acquisitions do not exceed the threshold of the Finnish Competition and Consumer Authority, the acquisitions need not be notified to the authorities. A similar finding has been documented in the US, where physician practice concentration has been driven by small acquisitions (Capps, Dranove, and Ody 2017).

4 Data

4.1 Data Sources and Variables

The administrative diagnostic service use data come from the Social Insurance Institution of Finland. The sample in this study covers the period 2008–2017 and contains all procedures in the private health care sector that were reimbursed by the NHI. Since all residents in Finland are entitled to NHI, the data is well representative of the Finnish private health care diagnostic service sector. Later, in Section 6 where I cover the patient demand model analysis, I also utilize private physician's visiting data to gather information on the referring physician. This data mirrors the diagnostic service use data. The data include the exact prices for the procedures, procedure codes, the date of testing and referral, health care unit names and zip codes, patient and physician IDs, patient zip code residency, and patient annual income (asset and salary separately).

I augment the data with variables for a patient case mix from two registers: the prescription drug special reimbursement register and the sickness allowance register, both maintained by the Social Insurance Institution of Finland. A patient can be entitled to a special reimbursement if a medical certificate is issued by a physician for a particular disease. Likewise, qualification for sickness allowance requires nine days of illness and a medical certificate. The purpose of the sickness allowance is to compensate for the loss of income due to an incapacity to work and is paid for a maximum of up to 300 working days. The special reimbursement register has its own coding for diseases and the sickness allowance register has ICD-10 coding. I merge these registers to the main data by patient IDs. I calculate the proportion of patients with these reimbursements for given diseases (diabetes, heart condition, cancer, ulcer, lung disease, and mental health disorder) purchasing a diagnostic service from a health care unit in a given quarter. See Table A2 for the identifying codes.

The diagnostic services I study in this paper are blood tests, X-rays, and MRIs. Because of the large number of different blood and imaging tests, for simplicity, I select a sample of the most common procedures that I observe consistently through the periods in the data. For blood tests I select C-reactive protein (CRP), complete blood count, thyrotropin, and lipid panel. For X-rays I select thorax, mammography, knee, and foot and toes. For MRIs I select knee and lower back. These subsets cover around 32, 49, and 50 percent of all blood tests, X-rays, and MRIs within their respective categories. Because of the large number of different types of blood tests—even with the large fraction of tests that have low frequency—the cumulative number of excluded tests is relatively larger than in imaging procedures. However, my results are robust to including all blood test codes. Table A1 shows the different procedures and codes.

The data for the acquisitions for the period 2008–2017 comes from annual reviews of the firms gathered from the Finnish Patent and Registration Office. The acquisition dates are merged with the main data by health care unit name and location.

A drawback in the procedure data is that for a fraction of observations, for health care units that do not have a direct reimbursement contract with the Social Insurance Institution of Finland, the location and the name of the unit are unobserved. As I identify different units by their name and location, and identifying these units is crucial for the purposes of this paper, I omit these observations from the data. Figure A1 shows the fraction of observations from these units over time. In the first years the proportion is around 20 to 30 percent but this steadily decreases to just a few percent in 2017 as health care units join the contract. To mitigate any bias that this would introduce into the price coefficient, I also estimate specifications that control for market specific Herfindahl-Hirschman indices (HHI) and hospital district specific time fixed effects. Additionally, because the data is claims data, I do not observe procedures that were not reimbursed by the NHI. This can occur if the patient does not have a physician's referral when purchasing the procedure. However, the proportion of these unobserved procedures is likely to be low.

To arrive at the final sample, I omit a few health care units that are non-profit, acquired units that had less than four quarters of observations before and after the acquisition, and units that were acquired more than once during the time period in the data. My results are robust to relaxing these sample restrictions. Finally, the MRI markets experienced a major shock during the last quarter of 2014 because of an entrant that had an aggressive pricing policy for MRI procedures. The firm entered different parts of Finland and the shock was nationwide. This shock cut MRI prices for all other firms by approximately 50 percent. Due to this major shock that complicates disentangling the effect of acquisitions from the entrant on prices, I omit all observations for MRIs starting from the last quarter of 2014.

4.2 Market Definition, Treatment and Control Group

I define the market area surrounding a health care unit to be a circle with a specific radius. All other units that fall within this circle belong to the health care unit's market area. A similar approach has been taken in the recent literature (Gaynor, Laudicella, and Propper 2012; Bloom et al. 2015; Lewis and Pflum 2017; Schmitt 2018; Beaulieu et al. 2020). The advantage of defining market areas this way instead of using geographical boundaries, such as municipality borders, is that two health care units that are located near the market border but on opposite sides still compete in the same market area.

I choose a radius of 30 kilometers for the circle. I calculate the distances using the centroids of the zip codes in which the units are located. I base the radius on the actual patient travelling distances from their residency zip codes to the health care units' zip codes. Figure A2 shows the cumulative share of patients travelling within specific distances. Most of the patients, around 80 to 90 percent, travel less than 30 kilometers. The share is slightly lower for MRIs but still considerable. In online Appendix A.3 I show that the results are robust to choosing a smaller or larger radii.

To obtain a more complete idea of the impacts of acquisitions, I estimate the effects not only for target units, but also for other units located within the target unit's market area: acquiring units (units that belong to the acquiring firm) and rivaling units. When I separately look at the target units, I omit all other units from the sample except the control units. I construct the control group from units that are outside the market area of acquired units. I do this to ensure that the control units are outside of any influence of changes in the competitive environment, and thus minimize potential spillovers from acquisitions to control group.

4.3 Summary Statistics

Figure 1 shows the price trends for the different diagnostic procedures over time. The mean price of blood tests has increased over time from 31 euros to over 36 euros. Similarly for X-rays, the mean price has increased from around 110 euros to nearly 130 euros. The figure shows the notable price drop in MRIs after 2014 due to the new entrant, as explained in Section 4.1.

Firms that have multiple units in different geographical regions typically adopt a uniform pricing strategy at the national level, likely due to menu costs. Although, for some imaging

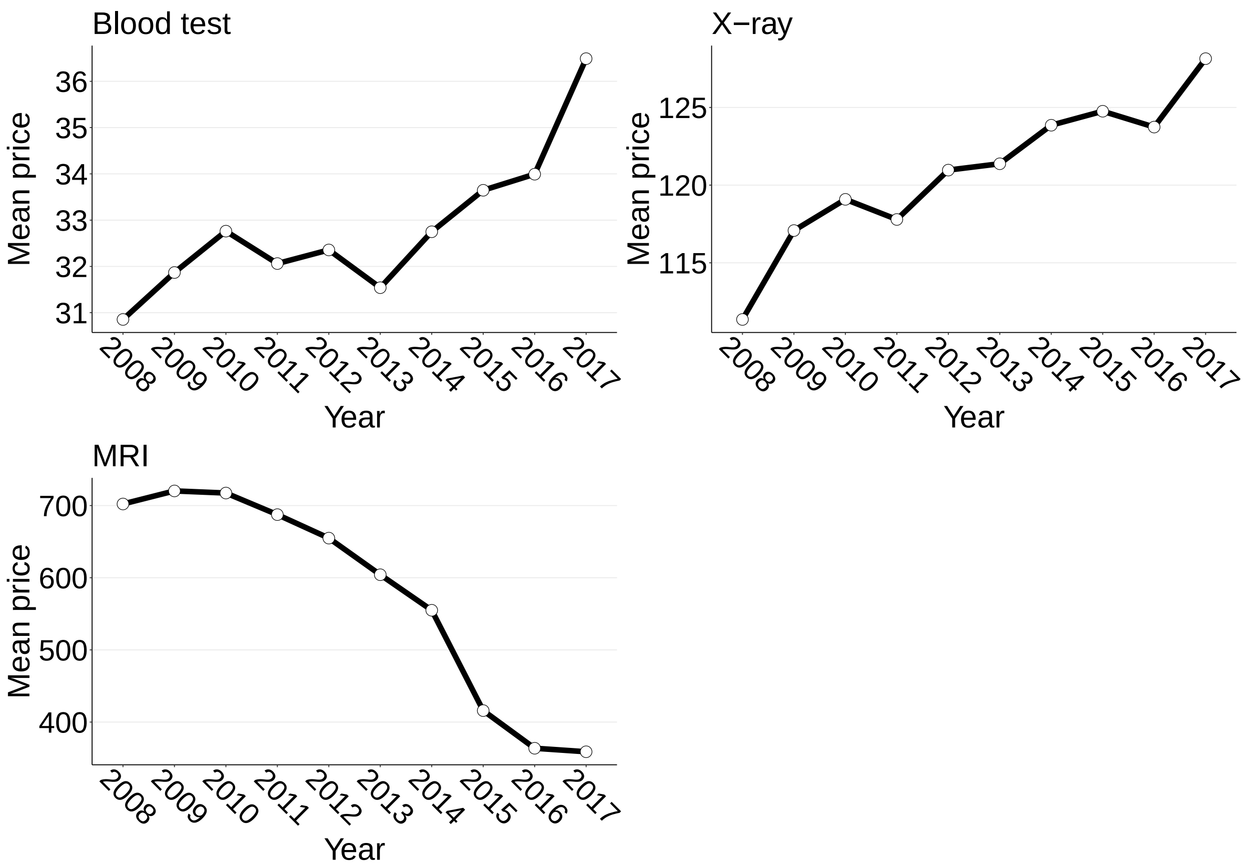

FIGURE 1: Price Trends

Note: The prices are deflated with CPI with 2017 as the base year.

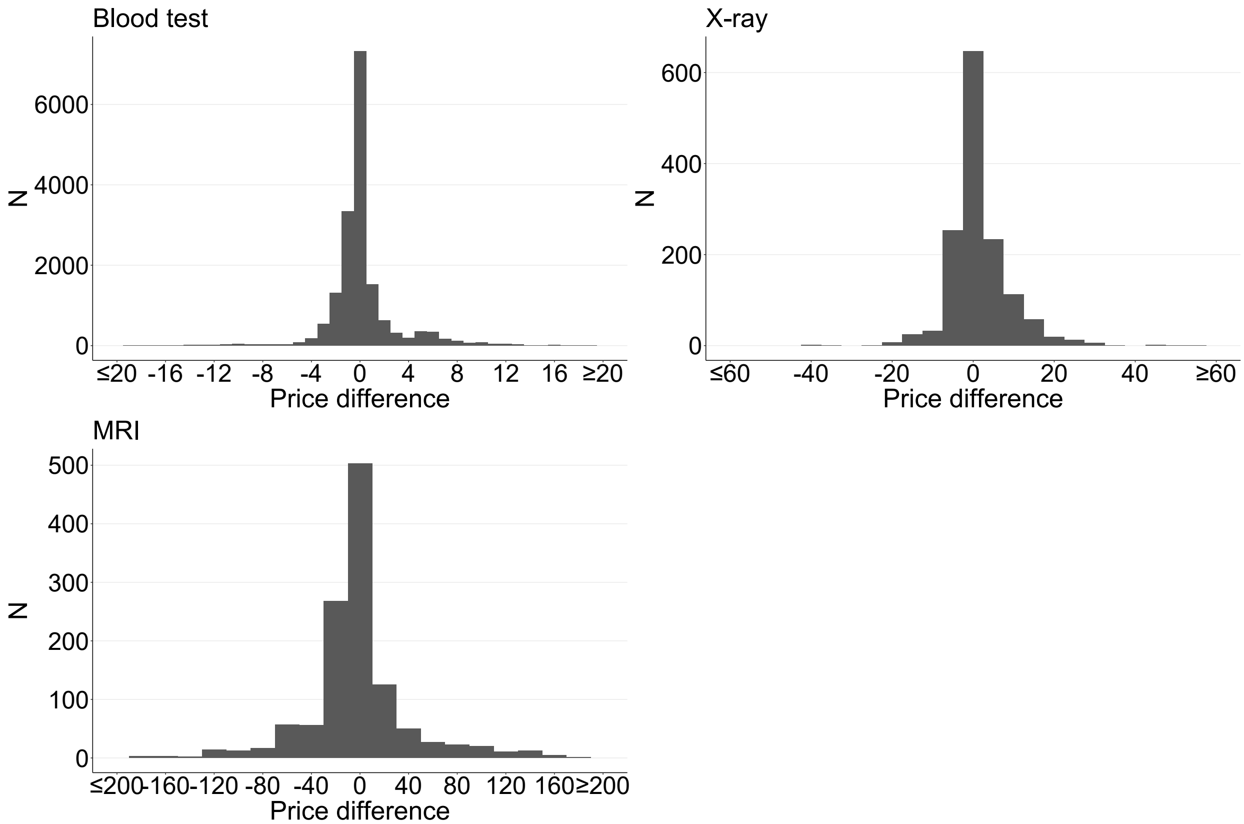

Figure 2: Within-firm Price Difference

Note: The x-axis is the within-firm difference between the mean monthly firm-level price and unit-level price for each procedure type. Only firms with at least two units are included in the figure. The width of the bins are 1, 5, and 20 for blood tests, x-rays, and MRIs, respectively.

procedures, mostly MRIs, these firms may engage in zone pricing. Figure 2 shows the distribution of the within-firm price difference by comparing the mean unit-level prices to the mean firm-level prices at the monthly-level. The prices are least dispersed in blood tests and most dispersed in MRIs. As expected, the largest spike is at the zero tick. Figure A3 shows the across-city and within-city price dispersion in three large geographically distant cities, Helsinki, Tampere, and Turku. The within-city prices vary slightly less than across-city prices, but overall the difference is small. Taken together, these figures raise support for the uniform pricing strategy for blood tests and X-rays, and more local pricing strategy for MRIs.

Figure 3 plots the HHI densities across the markets for years 2010 and 2017. Overall the

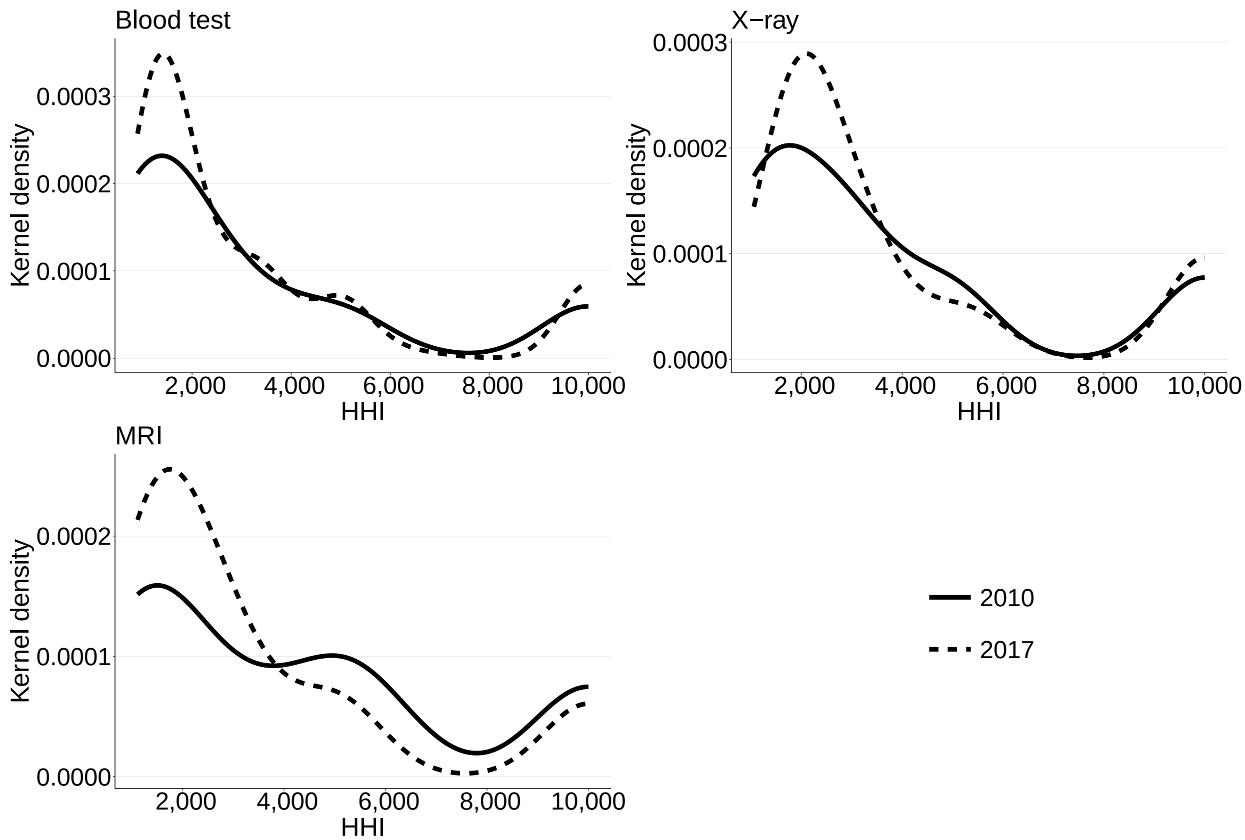

Figure 3: HHI Distribution Across Markets

markets are fairly concentrated as the bulk of the markets have HHIs well above 2,000. For example, the FTC in the US considers markets with HHIs above 2,500 as highly concentrated. Interestingly, the markets seem to be less concentrated in 2010. This is likely explained by the proportion of missing observations in the early periods in the data because of the way the locations are recorded in the data (see Section 4.1). This causes some health care units to appear later in the data which mechanically decreases the HHI in the latter years.

Table 1 shows the descriptive statistics for target units (acquired units) and control units in the analysis sample. The number of target units that provide blood testing is 57 while the number of target units that provide MRIs is rather low, only 13 (only 2008–2014). Most of the acquisitions are in-market acquisitions, i.e. ones where the acquiring firm already has at least one other unit in the market. In Section 5.2 I explore how the effects of acquisitions vary according to in-market versus out-of-market status.

Table 1: Summary Statistics for Target and Control Units

	Target			Control		
	Blood test	X-ray	MRI	Blood test	X-ray	MRI
Frequencies (2008 – 2017)						
Units	57	33	13	84	39	18
In-market acquisitions	38	31	11	0	0	0
Out-of-market acquisitions	19	2	2	0	0	0
Procedures (observations)	1,018,389	289,034	45,213	253,782	57,602	8,016
Referring physicians	7,185	6,117	1,724	2,918	1,794	472
Patients	358,324	205,407	40,083	89,347	41,732	7,336
Means (2009 or first year in data)						
Price (euros)	26.790	98.905	645.992	29.298	104.791	628.550
Referring physicians per unit	69.926	93.129	69.250	15.253	27.217	11.545
Procedures per unit	1,498.907	913.484	526.667	278.620	245.696	79.636
Procedures per physician per unit	17.605	9.091	6.808	29.682	5.366	4.311
Patient annual income (euros)	32,980.980	30,283.921	34,264.528	26,614.190	25,868.785	33,640.307
Patient age	44.535	49.545	44.425	49.494	52.200	47.100
Share diabetes	0.028	0.034	0.037	0.032	0.084	0.013
Share heart condition	0.056	0.051	0.039	0.062	0.083	0.052
Share cancer	0.018	0.020	0.014	0.012	0.011	0.005
Share ulcer	0.010	0.007	0.008	0.006	0.006	0.008
Share lung condition	0.047	0.074	0.060	0.061	0.106	0.044
Share mental health disorder	0.023	0.022	0.020	0.031	0.020	0.014

The target units seem to be larger in terms of the number of referring physicians and procedures. The prices are slightly higher in the control units for blood tests and X-rays. The annual income and patient age is also slightly higher for patients in the target units. The differences in the mean prices are small. The share of patients with different morbidities seem to be similar across the units. Table A3 shows the same comparison between acquiring and rival units. The prices are similar between these units but the volume is larger in the acquiring units in terms of number of procedures and number of referring physicians. Interestingly, the number of procedures per physician in the rival units is however over twice the number in the acquiring units.

Ideally, the control and treated units would be similar. One approach to decrease the gap in the variables is to use matching procedures. This, however, requires a larger number of health care units. As the number of health care units in the control group is not large enough, this approach is not feasible in my setting. In the next section where I describe the empirical approach, I lay out solutions to control for these differences.

5 Reduced Form Framework

5.1 Reduced Form Model Specification

To estimate the impact of mergers on diagnostic service prices, I use a difference-in-differences framework:

$$y_{ijkt} = \gamma_t + \alpha_i + \mu_k + \beta ACQ\left\{t \geq \tau\right\}_i + \epsilon_{ijkt}. \tag{1}$$

Here i indexes health care units, j indexes patients, k indexes procedures, t indexes time periods, and τ is the quarter of acquisition for an acquired units. The parameter of interest is β which measures the impact of the dummy the variable that gets value one after a unit has been acquired. γ, α, and μ are fixed effects for time, health care units, and procedures (finest coding level), respectively.

The empirical model uses variation in spatial and temporal dimensions in the identification of the parameter β. For a given acquisition, the identifying variation comes from the control units that are outside the target unit's market area and from the other target units that are acquired at a different time period in the data. I also estimate the effects for the acquiring and rival units using a specification that allows for different post-acquisition effects by including separate dummy variables for these units. When these units are included in the estimation, the identification additionally uses the variation in the timing of the treatment in these units. As there are likely to be correlation in unobservable components over time within the health care units, I cluster standard errors at the health care unit level.

To interpret the parameter β as causal, the timing and the targets of acquisitions need to be exogenous in this setting, i.e. ϵ_{ijkt} is uncorrelated with $ACQ\left\{t \geq \tau\right\}_i$, conditional on the controls. Unconditional correlation would arise if, for example, firms acquire units that have higher efficiency and higher prices. Another possibility is that firms acquire units in locations that are undergoing an economic boom that also affects price levels. The health care unit fixed effects control for any observed or unobserved differences in the levels across the units. To the extent that there are any time-varying unobserved confounding factors left, I also estimate specifications that include interactions between time and hospital district fixed effects that absorb area specific shocks.

Private firms have to compete with the public health care centers at least to some extent. Some areas may have better working public health care in terms of, for example, waiting times. This can put more competitive pressure on the private firms. The unit fixed effects also control for area specific differences in the competitive environment between the public and private sector.

It may still be of concern that the patient case mix changes after an acquisition. If more sick patients start to use the acquired unit's services, and these patients have lower price elasticity, the unit may be able to increase prices. To control for this, I also estimate specifications where I add a term θX_{it} that includes controls for shares of patients with different morbidities. This term also includes the health care unit's market HHI that accounts for shocks to the market area, such as exits or entries.

I directly test for the parallel trend assumption between the target and control units by estimating event study specifications of equation (1):

$$y_{ijkt} = \gamma_t + \alpha_i + \mu_k + \sum_{l=-9}^{9} \beta_l ACQ \left\{t = \tau + l\right\}_i + \epsilon_{ijkt}. \tag{2}$$

Here the difference-in-differences dummy is replaced by a set of indicators for pre-treatment and post-treatment periods. The pre-treatment event dummies reveal if there are any differences in the outcome trends and the post-treatment event dummies reveal if there are any dynamics in the treatment effect over time.

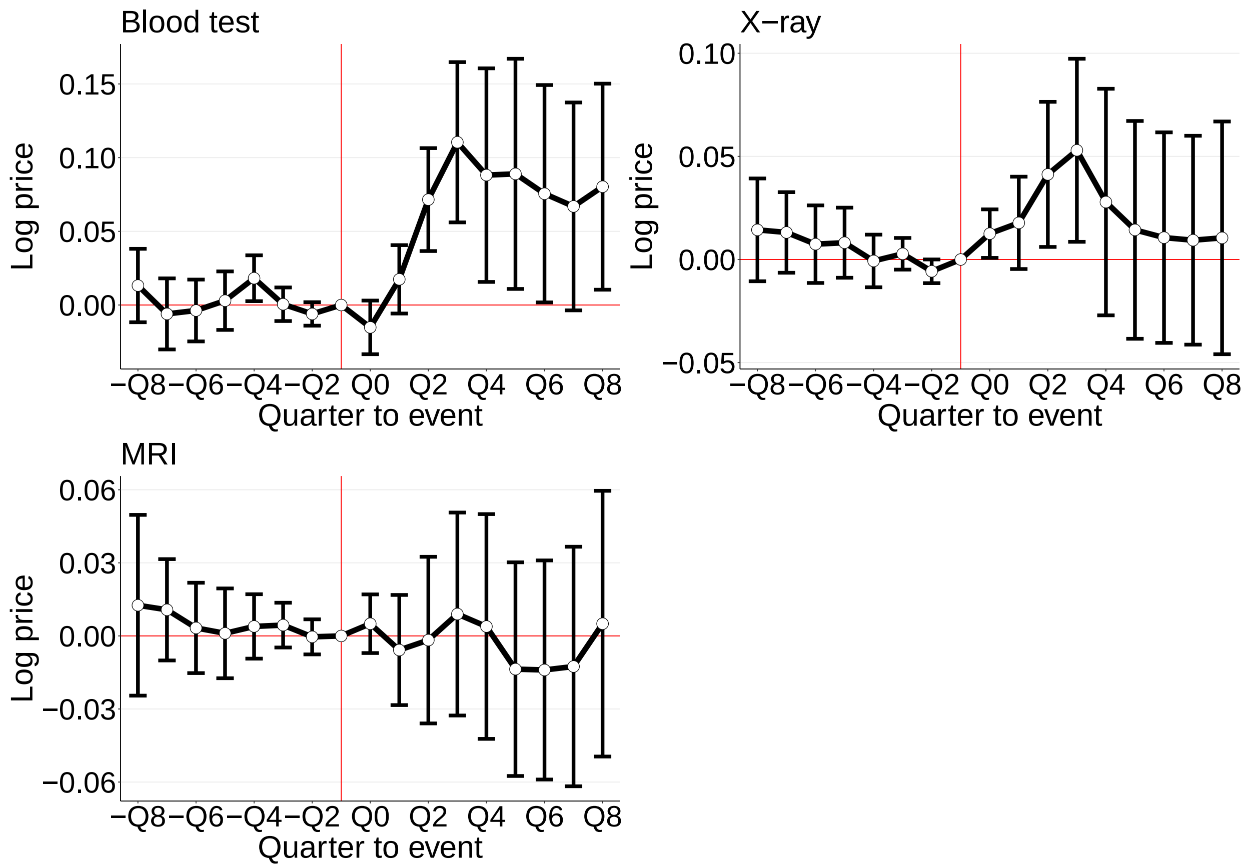

FIGURE 4: Event Study for Prices in Target Units

Notes: The figure plots the point estimates and confidence intervals from the event study regression. $-Q1$ is the omitted period. Controls include fixed effects for health care units, finer procedure type, and common time trend.

5.2 Reduced Form Results

Figure 4 shows the event study for prices in the target units. For the three procedures, there seem to be no pre-trend. For blood tests the prices increase after acquisition and seem to persist in the long run. For X-rays, there is a jump in the prices two quarters after the acquisition but the effect reverts after that. The acquisitions do not seem to affect MRI prices but the results are noisy. Table 2 shows the DiD results when the treatment effects are collected under one coefficient for different specifications. The increase in prices are robust to different specifications and around 7–9 percent for blood tests. Interestingly, for MRIs the coefficients show a slightly decreasing price effect of 3 to 4 percent.

Table 2: Effect of Acquisition on Prices in Target Units

	(1)	(2)	(3)	(4)	(5)
Blood test					
DiD	0.070***	0.068***	0.067***	0.086***	0.090***
	(0.020)	(0.018)	(0.020)	(0.025)	(0.022)
Observations	1,272,171	1,272,171	1,272,171	1,272,171	1,272,171
X-ray					
DiD	0.019	0.020	0.020	0.013	0.014
	(0.022)	(0.022)	(0.020)	(0.031)	(0.030)
Observations	346,636	346,636	346,636	346,636	346,636
MRI					
DiD	−0.031*	−0.034**	−0.030*	−0.040***	−0.040***
	(0.016)	(0.016)	(0.016)	(0.010)	(0.010)
Observations	53,229	53,229	53,229	53,229	53,229
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. "Add. controls" includes controls for shares of patients with diabetes, heart condition, cancer, ulcer, lung disease, and mental health disorder, based on diagnoses in sickness allowance register and special drug reimbursement register, purchasing a diagnostic procedure from a health care unit in a given quarter, and the market HHI. See Table A2 for the list of used codes in the diagnoses.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

As a robustness check, in Figures A4 and A5 I drop, respectively, treated and control units one by one from the regression. The figures show that the coefficient values are very stable across the samples, meaning that not one unit is driving the results. Additionally, online Appendix A.3 replicates the estimations shown in this section with 20 and 70 kilometer optional market radii, and shows that the results are very robust.

Similarly, Table 3 shows the results but now with the acquiring and rival units included in the regression and separated with their own indicators. This also serves as a robustness test for the target units as these regressions use variation from the acquiring and rival units as well. The point estimates for target units are very similar, except for MRIs where the estimates become close to zero and statistically insignificant. Overall, the noisiness in the point estimates for MRIs makes the results for these procedures rather inconclusive.

Why do acquisitions lead to price increases only in blood test markets? One potential reason is that the markets are already more concentrated imaging markets and firms have less room to increase their price margins. The absolute prices are also higher for imaging procedures than blood tests, which may lead to more price shopping and firms having less leeway to increase their markups. Patients may be less willing to price shop for relatively lower priced products and the referring physician may have greater influence on patients' choices—a topic I return to in the demand model estimation in Section 6.

Acquiring units seem to also increase blood testing prices by a similar amount after they acquire a unit from the same market. This is in line with the increased market power hypothesis. Maybe a little surprisingly, the rival units in the same market do not seem to increase their prices.

Next, to obtain a more clear idea of the underlying mechanism, I further divide the target units to in-market acquisitions and out-of-market acquisitions. By definition, only in-market acquisitions directly increase market concentration and thus market power. Because of the low number of out-of-market units in X-ray and MRI procedures, I focus on blood tests. Table 4 presents the results. The effect seems to come from in-market acquisitions.

Table 3: Effect of Acquisition on Prices in Target, Acquiring, and Rival Units

	(1)	(2)	(3)	(4)	(5)
Blood test					
DiD×Target	0.062***	0.062***	0.061***	0.064***	0.066***
	(0.022)	(0.021)	(0.023)	(0.021)	(0.020)
DiD×Acquirer	0.050***	0.046***	0.050***	0.046***	0.039**
	(0.012)	(0.012)	(0.012)	(0.015)	(0.016)
DiD×Rival	−0.002	−0.004	−0.000	0.006	0.004
	(0.017)	(0.015)	(0.017)	(0.021)	(0.019)
Observations	2,373,668	2,373,668	2,373,668	2,373,668	2,373,668
X-ray					
DiD×Target	0.013	0.009	0.013	0.008	0.007
	(0.023)	(0.022)	(0.021)	(0.027)	(0.026)
DiD×Acquirer	−0.018	−0.019*	−0.015	−0.021*	−0.021*
	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)
DiD×Rival	0.004	0.004	0.003	0.008	0.008
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	690,050	690,050	690,050	690,050	690,050
MRI					
DiD×Target	−0.008	−0.005	−0.008	0.019	0.018
	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)
DiD×Acquirer	−0.042*	−0.034*	−0.042*	−0.018	−0.016
	(0.024)	(0.020)	(0.024)	(0.015)	(0.016)
DiD×Rival	−0.030	−0.028	−0.030	−0.008	−0.008
	(0.021)	(0.020)	(0.021)	(0.015)	(0.016)
Observations	147,313	147,313	147,313	147,313	147,313
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. "Target" stands the acquired units, "Acquirer" stands for the units that are in the market area of the target units and belong to the acquiring firm, and "Rival" stands for the target unit's rivaling units in the same market area. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4: Effect of In-market and Out-Of-Market Acquisition on Blood Testing Prices in Target Units

	(1)	(2)	(3)	(4)	(5)
DiD×In-market	0.074***	0.073***	0.071***	0.090***	0.095***
	(0.021)	(0.019)	(0.021)	(0.026)	(0.023)
DiD×Out-of-market	0.007	−0.002	0.009	0.006	−0.003
	(0.055)	(0.052)	(0.056)	(0.077)	(0.073)
Observations	1,272,171	1,272,171	1,272,171	1,272,171	1,272,171
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. In-market acquisitions are acquisitions where the acquiring firm already has at least one unit in the market area. Out-of-market acquisitions are acquisitions where the acquiring firm does not have existing units in the target units market area. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

The price coefficient indicates a 7 to 9 percent increase in prices. The coefficients for out-of-market acquisitions are statistically insignificant and very close to zero. These results further strengthen the market power hypothesis.

Despite the price increase, acquisitions can improve efficiency if there are synergies involved. However, as is usually the case, I do not observe the marginal costs of firms. Instead, I measure what happens to the intensive margin of production. The intensive margin measures the number of procedures in the unit, given that the unit had production in that quarter. Increased efficiency may increase the production of these procedures. I aggregate the data to health care unit-quarter level. I weight the observations in the regressions by the population size in the market area in year 2014.[6]

It is important to note that this measurement is rather imperfect and volume may increase in a unit without any efficiency increases. For example, the demand may increase because of a brand effect or physicians may be instructed to write more referrals to diagnostic procedures.

[6] This information is from Statistics Finland.

Table 5: Effect of Acquisition on Volume in Target Units

	(1)	(2)	(3)	(4)
Blood test				
DiD	0.011	0.132	0.006	0.155
	(0.115)	(0.097)	(0.128)	(0.112)
Observations	3,726	3,726	3,726	3,726
X-ray				
DiD	−0.055	0.034	−0.021	0.046
	(0.155)	(0.036)	(0.176)	(0.038)
Observations	1,864	1,864	1,864	1,864
MRI				
DiD	−0.316*	−0.084	−0.189	−0.049
	(0.175)	(0.091)	(0.199)	(0.088)
Observations	567	567	567	567
Time FE	X	X	X	X
Unit FE	X	X	X	X
Add. controls		X		X
Time×Hospital district FE			X	X

Notes: The unit of observation is health care unit×quarter. The outcome is the log number of procedures. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Increased volume is a good proxy for increased efficiency in the case of excess demand where the supply side cannot meet pre-acquisition. I also omit the extensive margin analysis because of the selection into the sample with the direct reimbursement contract and because I require units to have one year of observations in the data before and after the merger (Section 4.1). These factors would mechanically bias the results upwards.

Table 5 shows the results. For blood tests the coefficient is positive but imprecisely estimated in specifications with additional time-varying controls. For X-rays and MRIs the coefficients are close to zero or even negative. Overall, the results do not provide conclusive evidence for increased efficiency.

6 Patient Demand Model

6.1 Model Specification

To obtain a more comprehensive idea of how the patients choose their provider for diagnostic testing and how prices and the referring physicians affect the choice, I estimate a demand model for health care units. I focus on blood testing because this is the procedure that was mostly affected by the acquisitions. In practice, the patient first chooses the physician after which the physician clinically evaluates the patient and decides whether to write a referral for testing. To reduce the complexity of the model, I partially abstract from the choice of the physician.

Patient i draws utility from having the blood test done in health care unit j in the market m in the following way (for brevity, I omit the time period t):

$$u_{ijm} = -\alpha p_{jm} + \beta X_{ijm} + \Phi ReferringFirm_{ijm} + \epsilon_{ijm}. \tag{3}$$

p_{jm} is the price of the procedure, X_{ijm} is a vector of unit characteristics and patient demographics and their interactions, and ϵ_{ijm} is the idiosyncratic unobserved part of the utility. The term $ReferringFirm_{ijm}$ is a dummy that attains the value of one when the referring physician's firm is the same as the firm in the choice set.[7] Thus the coefficient Φ measures the influence that the physician has on the patient's choice. However, some caution has to be taken when interpreting the parameter: it is also likely to capture some of the patient's convenience of having the procedure done within the same firm. As I only observe patients that actually purchase a blood test, the model does not contain an outside option.

The characteristic component X_{jm} includes the brand (firm) fixed effects, the distance

[7] I identify the referring physician's firm from the physician data by patient and physician IDs and the date of the referral. If there is no exact match on the date, I use a 30-day rolling window to match to the closest date. Not all procedures can be matched to a single physician in the data, however. This can happen, for example, if the patient gets the referral through a phone call, in which case there is no recorded visit to the physician in the data. Around 11 percent of the observations go unmatched. In that case the dummy gets value of zero in all of the patient's choices. The results are robust to increasing or decreasing the rolling window.

between the patient and the unit in the choice set, and the distance between the referring physician's unit and the unit in the choice set.[8] The latter variable is potentially important as patients may be reluctant to travel far from their treating physician.[9] I allow individual heterogeneity in the choice behavior by letting the characteristics depend on a rich set of patient demographics that include gender, age bins ($18-30$, $31-40$, ..., $60-70$, >70), yearly income bins ($0-20000$, ..., $80000-100000$, >100000), and morbidities (diabetes, heart condition, lung disease, ulcer, cancer, and mental health disorder). In the estimations I interact these demographics with the two largest brands and the distance.[10]

The price coefficient is usually subject to omitted variable bias. For example, unaccounted quality can bias the price coefficient upwards. However, in the context of diagnostic tests, the endogeneity of prices to quality is less worrisome as the procedures are highly standardized. Any differences that affect choice preferences can be attributed to service quality that are captured by the brand fixed effects and the dummy for referring physician's firm. Nevertheless, some unaccounted aspects of the service quality may be left that potentially bias the price coefficient upwards. In this sense, the estimated effects are conservative.

I assume that the unobserved part of the utility follows type I extreme value distribution. The probability that the patient i chooses unit j in market m is

$$P_{ijm} = \frac{\exp(v_{ijm})}{\sum_{j' \in m} \exp(v_{ijm})}, \tag{4}$$

where $v_{ijm} = -\alpha p_{jm} + \beta_i X_{jm} + \Phi ReferringFirm_{ijm}$. This logit probability is used to estimate the demand model using maximum likelihood.

The multinomial logit specification entails the independence of irrelevant alternatives (IIA) property. Estimating a mixed logit model with simulated random coefficients would

[8]One obvious characteristic that I am missing in the data is the average waiting times. However, for blood tests, the waiting times are typically very short and usually the procedure can be done during the same day.

[9]For the small fraction of observations that I do not observe the referring physician and his or her location, I input the distance as zero. The results are robust to using alternative values, for example to using an improbably high value.

[10]This specification is similar to (Polyakova 2016).

allow unrestricted substitution patterns, relaxing the IIA property. However, this model needs to be estimated through simulation, and thus is computationally quite burdensome. As I am not interested in the substitution patterns per se, I therefore choose to estimate the simpler conditional logit model and mitigate the IIA property through the interactions with the detailed patient characteristics.

I maintain the same market definition as in the reduced form analysis, but now defined from the patients' zip codes of residence. To reflect the preferences of consumers that are located in markets that are affected by acquisitions, I limit the sample to those markets that had an acquisition. To prevent the effect of the acquisitions themselves on the choice or referral preferences, I use a time window of one year before the acquisition in the market. I limit the markets to those that have at least two different units to choose from. I also exclude units that have a very low market share (< 0.001 or less than 30 observations) and patients that are under the age of 18.

I construct the prices of the other providers in the patient's choice set using provider-specific average prices during the same day. If there are no observations for a particular unit during the same day, I take the average, respectively, over the week, month, or quarter, depending on whether there are observations in the respective time frame. To reduce the computational burden I take a 20 percent random sample of patients from the data, leaving a final sample of over $645,000$ observations from $25,000$ choice situations.

6.2 Demand Model Results

The results are shown in Table 6, different columns depicting different specifications with the fixed effects and demographic interactions.[11] The price coefficient has the expected sign but the order of magnitude is very low across the specifications. Comparison of the price coefficient in column 1 and 2 shows the importance of including brand fixed effects. Both distance variables, the travelling distance between the choice and the patient and between

[11]See Table A4 for the full table with distance interactions with demographics.

the choice and the referring physician's unit, have negative and statistically significant coefficients, implying that patients dislike travelling.

In contrast to the price coefficient, the coefficient for the physician's referring firm has a strong positive impact on the choice probability. This finding is not unique in the literature and evidence suggests that the referring physicians have strong influence on patients' choices (Baker, Bundorf, and Kessler 2016; Carlin, Feldman, and Dowd 2016; Chernew et al. 2018). Column 4 additionally includes an interaction between the price and the dummy for the same referring firm. While the coefficient for this interaction is positive, implying that the price has lower influence in choices where the referring physician's firm is the same, it is low in magnitude and statistically insignificant.

The low influence of prices and high influence of the referring physician suggest that patients have low willingness to price-shop between different units for these procedures. This findings is not surprising in the context of diagnostic procedures. One potential explanation is that these procedures cannot always planned in advance which gives the patient little time and choice for provider shopping.

Another explanation is that the patient may have limited information on the available choices and the physician is not mandated to offer additional information on less expensive alternatives. Empirical studies of physician agency have documented that physicians can be insensitive to relatively small changes in patient out-of-pocket costs (Iizuka 2012; Carrera et al. 2018). Frictions to switch to another provider can be high and consumer search may be costly and time-consuming, see e.g. Brot-Goldberg et al. (2017) on evidence of limited price-shopping.

Moreover, the prices for blood tests are relatively low and the procedure itself is a very homogeneous product, making it harder for patients to differentiate between the available alternatives and leaving more room for the influence of the treating physician. It could be that consumers need to face substantial price differences and transparent prices to engage in price-shopping behavior (Robinson, Whaley, and Brown 2016). These prevailing frictions

Table 6: Logit Demand Estimates

	(1)	(2)	(3)	(4)
Price	-0.0018	-0.0085^{***}	-0.0088^{***}	-0.0108^{***}
	(0.0017)	(0.0024)	(0.0024)	(0.0029)
Referring firm	5.0446^{***}	5.2985^{***}	5.3278^{***}	5.1755^{***}
	(0.0570)	(0.0664)	(0.0672)	(0.1405)
Distance	-0.1975^{***}	-0.2630^{***}	-0.2420^{***}	-0.2419^{***}
	(0.0039)	(0.0047)	(0.0149)	(0.0149)
Referring unit distance	-0.4795^{***}	-0.4831^{***}	-0.4919^{***}	-0.4920^{***}
	(0.0062)	(0.0062)	(0.0063)	(0.0063)
Price×Referring firm				0.0049
				(0.0040)
Total observations	646,031	646,031	646,031	646,031
Choice situations	25,124	25,124	25,124	25,124
Log likelihood	-20,146.69	-17,211.3	-17,038.3	-17,037.54
Brand FE		X	X	X
Top-2 Brand×Demographics			X	X
Distance×Demographics				X

Notes: The demographics include dummies for diabetes, heart condition, cancer, ulcer, lung disease, and mental health disorder, sex, age ($18-30$, $31-40$, ..., $61-70$, > 70), and income ($0-20,000$, $20,001-40,000$, ..., $> 100,000$). The distances are measured in kilometers. The diagnoses are gathered from sickness allowance register and special drug reimbursement register. See Table A2 for the list of used codes in the diagnoses.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

may partly explain why the acquired units are able to extract higher prices under decreased competition.

6.3 Consumer Surplus

To quantify the changes in patient surplus from price increases due to acquisitions, I use the demand model estimates above. The change in expected consumer surplus for individual i is according to Small and Rosen (1981):

$$\Delta E[CS_i] = \frac{1}{\alpha}\left[\ln\left(\sum_{j\in m}\exp(v_{ijm})\right) - \ln\left(\sum_{j\in m}\exp(v_{ijm}^C)\right)\right], \tag{5}$$

Table 7: Change in Consumer Surplus (Euros)

Price increase	Mean	SD	P10	P90
Target	-0.825	0.864	-1.991	-0.000
Target + Acquiring	-1.138	0.794	-2.170	-0.008

Notes: The consumer surplus is calculated using equation (5) and the specification in column 3 of Table 6. The counterfactual prices are based on Tables 2 and 3.

where v_{ijm}^{C} is the same as above but with the counterfactual prices. I take the counterfactual prices from the reduced form estimates in Table 3. I increase the prices of target units by 6 percent and the prices of acquiring units by 5 percent.

The changes in consumer surplus over all patients are summarized in Table 7. On par with the small price coefficient, the changes in consumer surplus are negligible. On average, the decrease is 0.8 euros when the prices are increased in the target units, and 1.1 euros when prices are increased both in the target and acquiring units. At the higher end, for the 10th percentile patient, the loss is 2.2 euros.

Another useful exercise is to calculate the direct cost savings from choosing the least expensive alternative in the choice set (and ignoring any general equilibrium effects). Over the patient sample, this yields an average of 12.9 euro cost savings or 42.7 percent compared to the mean prices of the observed choices.

Overall, if consumers became more price sensitive and everything else remained fixed, the welfare losses would be larger from price increases. However, increased sensitivity may constrain mergers from increasing their markups. Increasing transparency and incentives to price-shopping could translate into significant cost savings for patients.

7 Discussion

In this paper, I study the effects of mergers in the markets for diagnostic procedures in Finland. Using detailed and comprehensive register data that cover the universe of the Finnish private health care sector, I estimate difference-in-differences models to examine how prices in target, acquiring, and rivaling units react to mergers. I find that prices for blood tests increase in target and acquiring units pre-merger by 6 to 9 percent but not in rival units. For X-ray and MRI procedures I do not find conclusive evidence of price changes.

The price increase in blood tests seems to stem from increased market concentration and decreased competition. In addition, measured by the procedure volume in the unit, my results do not provide evidence of increased efficiency. However, due to data limitations, I am not able to directly test whether marginal costs decrease in the merged parties.

I proceed to estimate a patient demand model for health care units and find that the patients are quite insensitive to prices and the referring physician has high influence on choices. Because of the small price coefficient, the changes in consumer surplus from price increases in merging parties are negligible. However, if patients chose the unit with the cheapest price in their choice set, the cost savings would be around 43 percent compared to the mean price.

A possible explanation for the finding of price increase only in blood tests is that the price elasticity is lower for these procedures, allowing firms to increase their price margins. Decreasing referring physician's influence in patient choice by increasing transparency in prices and choice options could incentivize patients to price-shop more. This can potentially decrease the opportunities of mergers to capitalize on market power. In the meanwhile, competition authorities should continue monitoring different sub-markets of health care, such as diagnostic service markets, as mergers can have impact on these, even though prices would not substantially increase at the aggregate level.

References

Angeli, F., and H. Maarse. 2012. "Mergers and acquisitions in Western European health care: Exploring the role of financial services organizations". *Health Policy* 105 (2): 265–272.

Avdic, D., P. Lundborg, and J. Vikström. 2018. *Mergers and Birth Outcomes: Evidence from Maternity Ward Closures.* IZA Discussion Papers 11772. Institute of Labor Economics (IZA). https://ideas.repec.org/p/iza/izadps/dp11772.html.

Baker, L. C., M. K. Bundorf, and D. P. Kessler. 2016. "The effect of hospital/physician integration on hospital choice". *Journal of Health Economics* 50:1–8.

Beaulieu, N. D., et al. 2020. "Changes in Quality of Care after Hospital Mergers and Acquisitions". *New England Journal of Medicine* 382 (1): 51–59.

Bloom, N., et al. 2015. "The Impact of Competition on Management Quality: Evidence from Public Hospitals". *The Review of Economic Studies* 82 (2): 457–489.

Brot-Goldberg, Z. C., et al. 2017. "What does a Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics". *The Quarterly Journal of Economics* 132 (3): 1261–1318.

Capps, C., D. Dranove, and C. Ody. 2017. "Physician Practice Consolidation Driven By Small Acquisitions, So Antitrust Agencies Have Few Tools To Intervene". PMID: 28874481, *Health Affairs* 36 (9): 1556–1563.

Carlin, C. S., R. Feldman, and B. Dowd. 2016. "The Impact of Hospital Acquisition of Physician Practices on Referral Patterns". *Health Economics* 25 (4): 439–454.

— . 2017. "The impact of provider consolidation on physician prices". *Health Economics* 26 (12): 1789–1806.

Carrera, M., et al. 2018. "Do Physicians Respond to the Costs and Cost-Sensitivity of Their Patients?" *American Economic Journal: Economic Policy* 10 (1): 113–52.

Chandra, A., J. Gruber, and R. McKnight. 2014. "The impact of patient cost-sharing on low-income populations: Evidence from Massachusetts". *Journal of Health Economics* 33:57–66.

Chernew, M., et al. 2018. *Are Health Care Services Shoppable? Evidence from the Consumption of Lower-Limb MRI Scans.* Working Paper, Working Paper Series 24869. National Bureau of Economic Research. http://www.nber.org/papers/w24869.

Cooper, Z., et al. 2018. "The Price Ain't Right? Hospital Prices and Health Spending on the Privately Insured". *The Quarterly Journal of Economics* 134 (1): 51–107.

Dafny, L. 2009. "Estimation and Identification of Merger Effects: An Application to Hospital Mergers". *The Journal of Law and Economics* 52 (3): 523–550.

Dafny, L., K. Ho, and R. S. Lee. 2019. "The price effects of cross-market mergers: theory and evidence from the hospital industry". *The RAND Journal of Economics* 50 (2): 286–325.

Deneckere, R., and C. Davidson. 1985. "Incentives to Form Coalitions with Bertrand Competition". *The RAND Journal of Economics* 16 (4): 473–486.

Dunn, A. 2016. "Health insurance and the demand for medical care: Instrumental variable estimates using health insurer claims data". *Journal of Health Economics* 48:74–88.

Farrell, J., and C. Shapiro. 1990. "Horizontal Mergers: An Equilibrium Analysis". *The American Economic Review* 80 (1): 107–126.

Finnish Institute for Health and Welfare (THL). 2019. *Health expenditure and financing in 2018 (in Finnish).* Statistical Report 15/2019. Finnish Institute for Health and Welfare. http://www.julkari.fi/handle/10024/138110.

Fulton, B. D. 2017. "Health Care Market Concentration Trends In The United States: Evidence And Policy Responses". *Health Affairs* 36 (9): 1530–1538.

Gaynor, M., M. Laudicella, and C. Propper. 2012. "Can Governments Do It Better? Merger Mania and Hospital Outcomes in the English NHS". *Journal of Health Economics* 31 (3): 528–543.

Iizuka, T. 2012. "Physician Agency and Adoption of Generic Pharmaceuticals". *American Economic Review* 102 (6): 2826–58.

Koch, T., and S. W. Ulrick. 2020. "Price effects of a merger: evidence from a physicians' market". *Economic Inquiry.*

Lewis, M. S., and K. E. Pflum. 2017. "Hospital systems and bargaining power: evidence from out-of-market acquisitions". *The RAND Journal of Economics* 48 (3): 579–610.

McAfee, R. P., and M. A. Williams. 1992. "Horizontal Mergers and Antitrust Policy". *The Journal of Industrial Economics* 40 (2): 181–187.

MedTech Europe. 2019. *European IVD Market Statistics Report.* `https://www.medtecheurope.org/resource-library/european-ivd-market-statistics-report-2019/`. Accessed: 25.8.2020.

Morel, C., et al. 2016. *Ensuring innovation in diagnostics for bacterial infection: implications for policy.* Observatory Studies Series No. 44. Copenhagen (Denmark): European Observatory on Health Systems and Policies.

Nurminen, M., and T. Saxell. 2020. *Physician Prices and Competition: Evidence from Acquisitions in the Private Health Care Sector.* Working Paper, VATT Working Papers 130. VATT Institute for Economic Research.

Official Statistics of Finland. 2020. *Statistics on reimbursements for medical expenses (web publication).* Reimbursements for examination and treatment charges: Number of recipients. Accessed: 2.10.2020. Helsinki: Kela. `http://raportit.kela.fi/linkki/76532207`.

Polyakova, M. 2016. "Regulation of Insurance with Adverse Selection and Switching Costs: Evidence from Medicare Part D". *American Economic Journal: Applied Economics* 8 (3): 165–95.

Prager, E. 2020. "Healthcare Demand under Simple Prices: Evidence from Tiered Hospital Networks". *American Economic Journal: Applied Economics* 12 (4): 196–223.

Robinson, J. C., C. Whaley, and T. T. Brown. 2016. "Association of Reference Pricing for Diagnostic Laboratory Testing With Changes in Patient Choices, Prices, and Total Spending for Diagnostic Tests". *JAMA Internal Medicine* 176 (9): 1353–1359.

Schmitt, M. 2018. “Multimarket Contact in the Hospital Industry”. *American Economic Journal: Economic Policy* 10 (3): 361–87.

Small, K. A., and H. S. Rosen. 1981. “Applied Welfare Economics with Discrete Choice Models”. *Econometrica* 49 (1): 105–130.

Whinston, M. D. 2007. “Chapter 36 Antitrust Policy toward Horizontal Mergers”, ed. by M. Armstrong and R. Porter, 3:2369–2440. Handbook of Industrial Organization. Elsevier.

Williamson, O. E. 1968. “Economies as an Antitrust Defense: The Welfare Tradeoffs”. *The American Economic Review* 58 (1): 18–36.

A Online Appendix

A.1 Tables

Table A1: NHI Reimbursement Rates And Codes

Procedure	Codes	2008	2011	2013	2017
Blood test					
CRP	1216, 4594, 1217	5	5	2	1
Complete blood count	2474, 2473	8	6	2	1
Lipid panel	2245, 6027	20	20	8	5
Thyrotropin	2832, 4831, 3669	8	8	3	2
X-ray					
Foot and toes	NH3AA	33	35	15	9
Foot and toes, extensive	NH3BA	40	40	17	11
Knee	NG1AA	33	35	15	9
Knee, extensive	NG1BA	40	40	17	11
Mammography	HA1AA	50	70	29	18
Mammography, extensive	HA1BA	70	100	41	26
Thorax	GD1AA	33	35	15	9
Thorax, extensive	GD1BA	40	40	17	11
MRI					
Knee and lower leg	NG1BG, NG1BM	400	350	145	73
Knee and lower leg (under 1.5 T)	NG1BF	250	250	104	
Knee and lower leg, (under 1.0 T)	NG1BH	200			
Knee and lower leg, extensive	NG1CG, NG1CM	500	450	186	93
Knee and lower leg, extensive (under 1.0 T)	NG1CH	300			
Knee and lower leg, extensive (under 1.5 T)	NG1CF	350	350	145	
Knee and lower leg, very extensive	NG1DG, NG1DM	600	550	228	114
Knee and lower leg, very extensive (under 1.0 T)	NG1DH	400			
Knee and lower leg, very extensive (under 1.5 T)	NG1DF	450	450		
Lumbar spine	NA3BG, NA3BM	400	350	145	73
Lumbar spine, (under 1.5T)	NA3BF	250	250	104	
Lumbar spine, extensive	NA3CG, NA3CM	500	450	186	93
Lumbar spine, extensive (under 1.5T)	NA3CF	350	350	145	
Lumbar spine, very extensive	NA3DG, NA3DM	600	550	228	114
Lumbar spine, very extensive (under 1.5T)	NA3DF		450	186	

Table A2: Codes for Morbidity

Morbidity	Code drug special reimbursement	ICD-10 sickness allowance
Diabetes	103, 215	E08–E11, E13
Heart condition	201, 206, 207	I20–I28, I30–I52
Cancer	115, 116, 117, 128, 130	C00–D49
Ulcer and Crohn's disease	208	K25–K28, K50–K52
Lung disease	203	J00–J99
Mental health disorder	112	F01–F99

Table A3: Summary Statistics for Acquiring and Rival Units

	Acquirer			Rival		
	Blood test	X-ray	MRI	Blood test	X-ray	MRI
Frequencies (2008 − 2017)						
Units	53	44	21	129	85	46
Procedures (observations)	467,815	131,285	39,720	633,682	212,129	54,364
Referring physicians	4,155	3,956	1,391	5,442	5,301	2,136
Patients	162,440	95,569	34,690	232,058	148,465	48,922
Means (2009 or first year in data)						
Price (euros)	29.815	106.303	647.276	29.956	115.395	582.826
Referring physicians per unit	49.375	54.324	69.200	23.681	51.965	52.968
Procedures per unit	866.271	401.297	557.000	411.412	394.228	289.806
Procedures per physician per unit	10.592	5.515	6.099	27.882	5.525	5.652
Patient annual income (euros)	35,849.050	30,926.044	41,152.750	31,991.215	32,183.124	37,368.782
Patient age	41.902	48.223	42.819	39.547	51.635	45.406
Share diabetes	0.034	0.034	0.037	0.030	0.038	0.066
Share heart condition	0.052	0.028	0.023	0.048	0.077	0.036
Share cancer	0.010	0.014	0.009	0.033	0.018	0.018
Share ulcer	0.008	0.007	0.005	0.008	0.011	0.004
Share lung condition	0.050	0.073	0.063	0.061	0.096	0.071
Share mental health disorder	0.045	0.028	0.014	0.027	0.018	0.016

Table A4: Full Table of Logit Demand Estimates

	(1)	(2)	(3)	(4)
Price	-0.0018	-0.0085^{***}	-0.0088^{***}	-0.0108^{***}
	(0.0017)	(0.0024)	(0.0024)	(0.0029)
Referring firm	5.0446^{***}	5.2985^{***}	5.3278^{***}	5.1755^{***}
	(0.0570)	(0.0664)	(0.0672)	(0.1405)
Distance	-0.1975^{***}	-0.2630^{***}	-0.2420^{***}	-0.2419^{***}
	(0.0039)	(0.0047)	(0.0149)	(0.0149)
Referring unit distance	-0.4795^{***}	-0.4831^{***}	-0.4919^{***}	-0.4920^{***}
	(0.0062)	(0.0062)	(0.0063)	(0.0063)
Price×Referring firm				0.0049
				(0.0040)
Distance×Morbidity				
Diabetes			0.0090	0.0088
			(0.0204)	(0.0204)
Heart condition			-0.0265	-0.0265
			(0.0197)	(0.0197)
Cancer			0.0694^{***}	0.0694^{***}
			(0.0257)	(0.0257)
Ulcer			-0.1079^{***}	-0.1079^{***}
			(0.0360)	(0.0360)
Lung condition			-0.0303	-0.0302
			(0.0190)	(0.0190)
Mental health disorder			-0.1361^{***}	-0.1362^{***}
			(0.0299)	(0.0299)
Distance×Female			-0.0101	-0.0101
			(0.0094)	(0.0094)
Distance×Income				
$20,000 < \text{Income} \leq 40,000$			0.0189	0.0189^{*}
			(0.0115)	(0.0115)
$40,000 < \text{Income} \leq 60,000$			0.0058	0.0059
			(0.0140)	(0.0140)
$60,000 < \text{Income} \leq 80,000$			0.0563^{***}	0.0562^{***}
			(0.0182)	(0.0182)
$80,000 < \text{Income} \leq 100,000$			0.0756^{***}	0.0756^{***}
			(0.0234)	(0.0234)

Income $> 100,000$			0.0702***	0.0701***
Distance×Age				
			(0.0182)	(0.0182)
$31 - 40$			0.0172	0.0172
			(0.0176)	(0.0176)
$41 - 50$			−0.0051	−0.0052
			(0.0174)	(0.0174)
$51 - 60$			0.0060	0.0059
			(0.0165)	(0.0165)
$61 - 70$			−0.0656***	−0.0656***
			(0.0171)	(0.0171)
> 70			−0.1598***	−0.1601***
			(0.0176)	(0.0176)
Total observations	646,031	646,031	646,031	646,031
Choice situations	25,124	25,124	25,124	25,124
Log likelihood	-20,146.69	-17,211.3	-17,038.3	-17,037.54
Brand FE		X	X	X
Top-2 Brand×Demographics			X	X

Notes: The demographics include dummies for diabetes, heart condition, cancer, ulcer, lung disease, and mental health disorder, sex, age ($18 - 30$, $31 - 40$, …, $61 - 70$, > 70), and income ($0 - 20,000$, $20,001 - 40,000$, …, $> 100,000$). The diagnoses are gathered from sickness allowance register and special drug reimbursement register. See Table A2 for the list of used codes in the diagnoses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

A.2 Figures

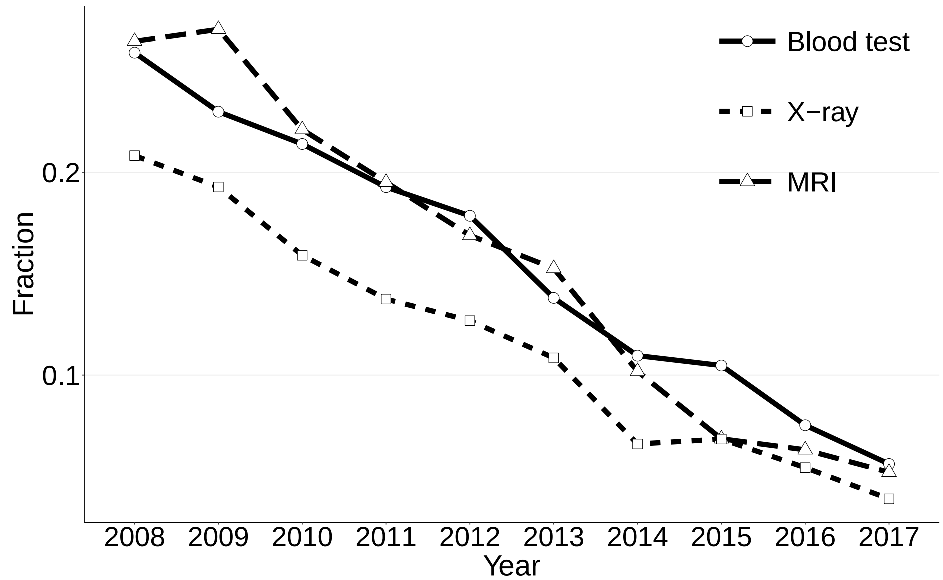

Figure A1: Fraction of Observations from Units With Missing Location

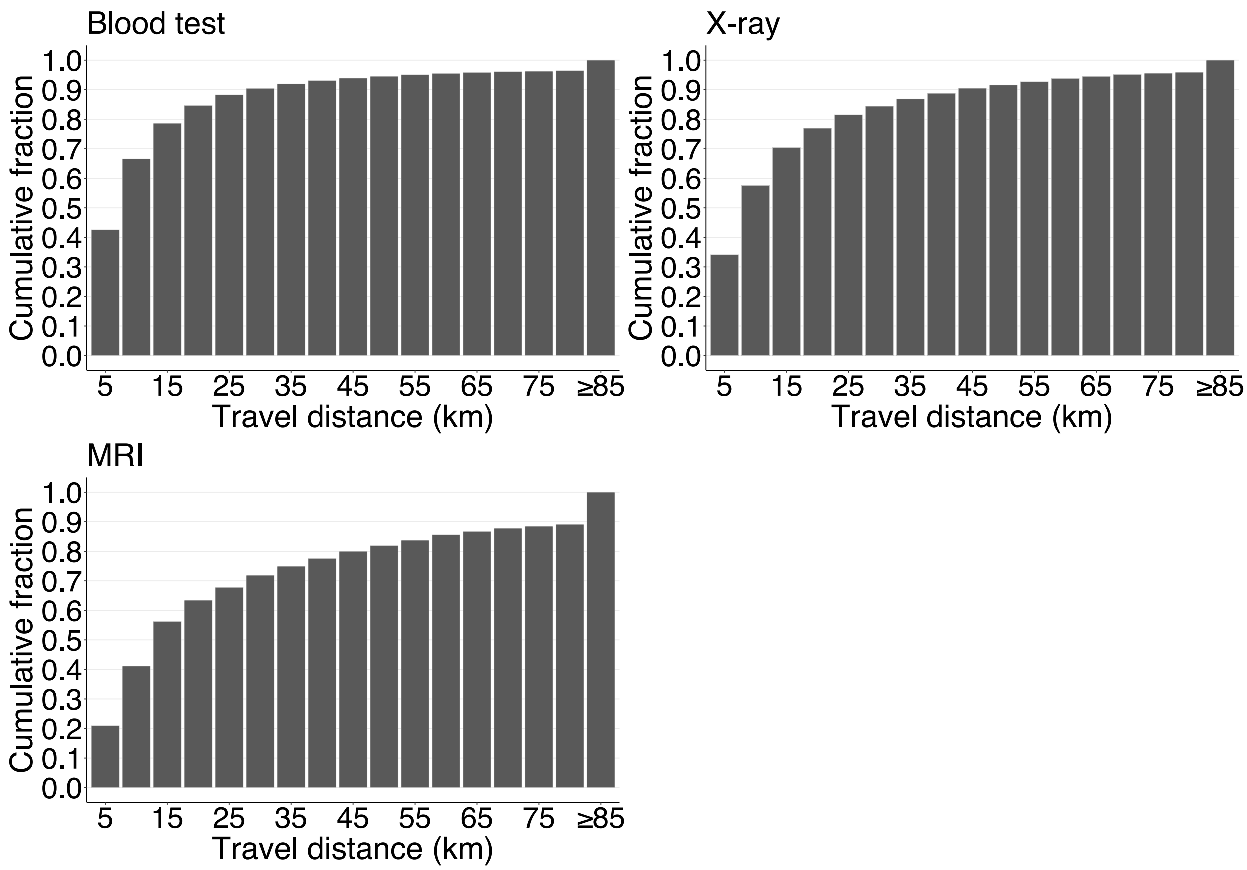

Figure A2: Patient Cumulative Travel Distance

Note: The x-axis is based on the distance between the centroids of the health care unit's zip code and the patient's zip code of residence.

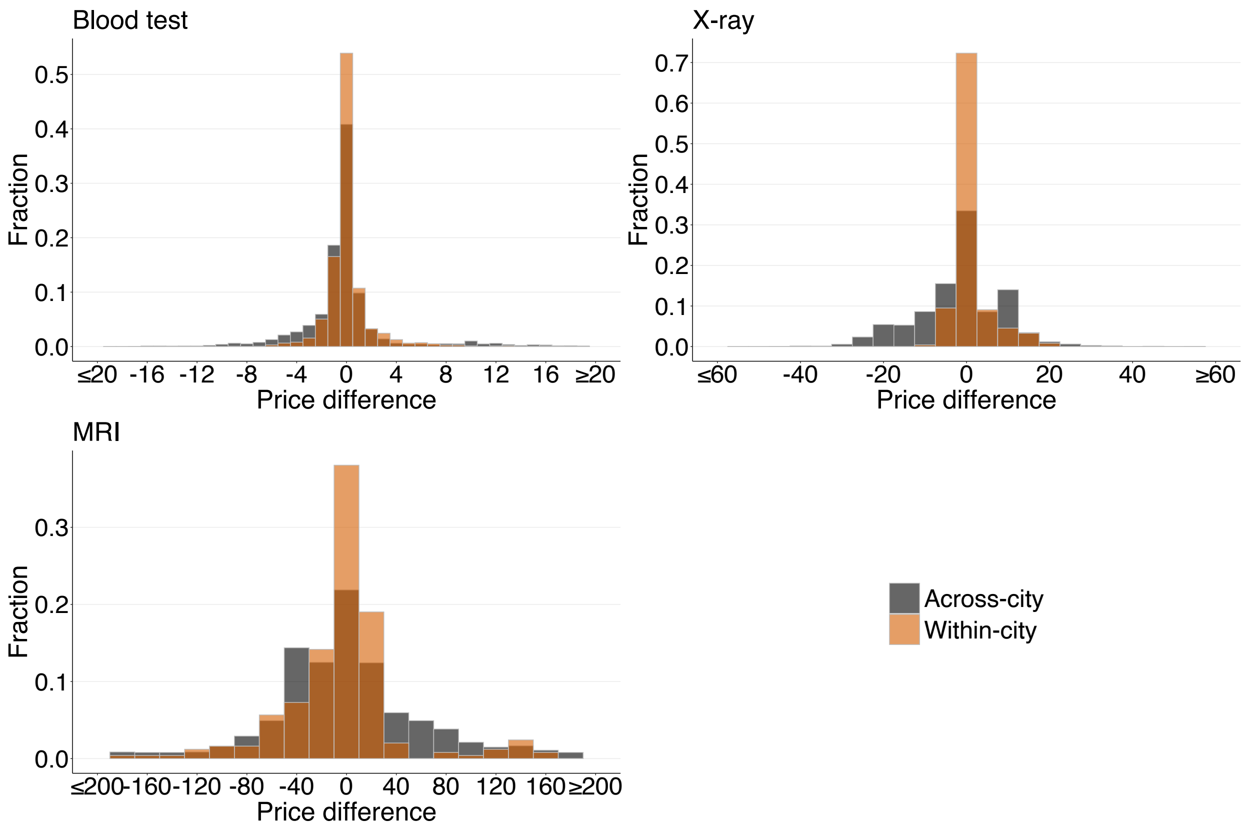

Figure A3: Within-Firm Within-City and Across-City Price Difference

Note: The x-axis is the within-firm difference between the mean monthly firm-level price and unit-level price for each procedure type. The figure includes observations from three big cities in Finland that are geographically distant: Helsinki, Tampere, and Turku. The "Across-city" category includes units that have at least one unit in two of the cities. The price difference is the difference in the procedure prices in these units. The "Within-city" category includes units that have at least two units in the same city. Y-axis shows the fraction on observations in each bin by group. The width of the bins are 1, 5, and 20 for blood tests, x-rays, and MRIs, respectively.

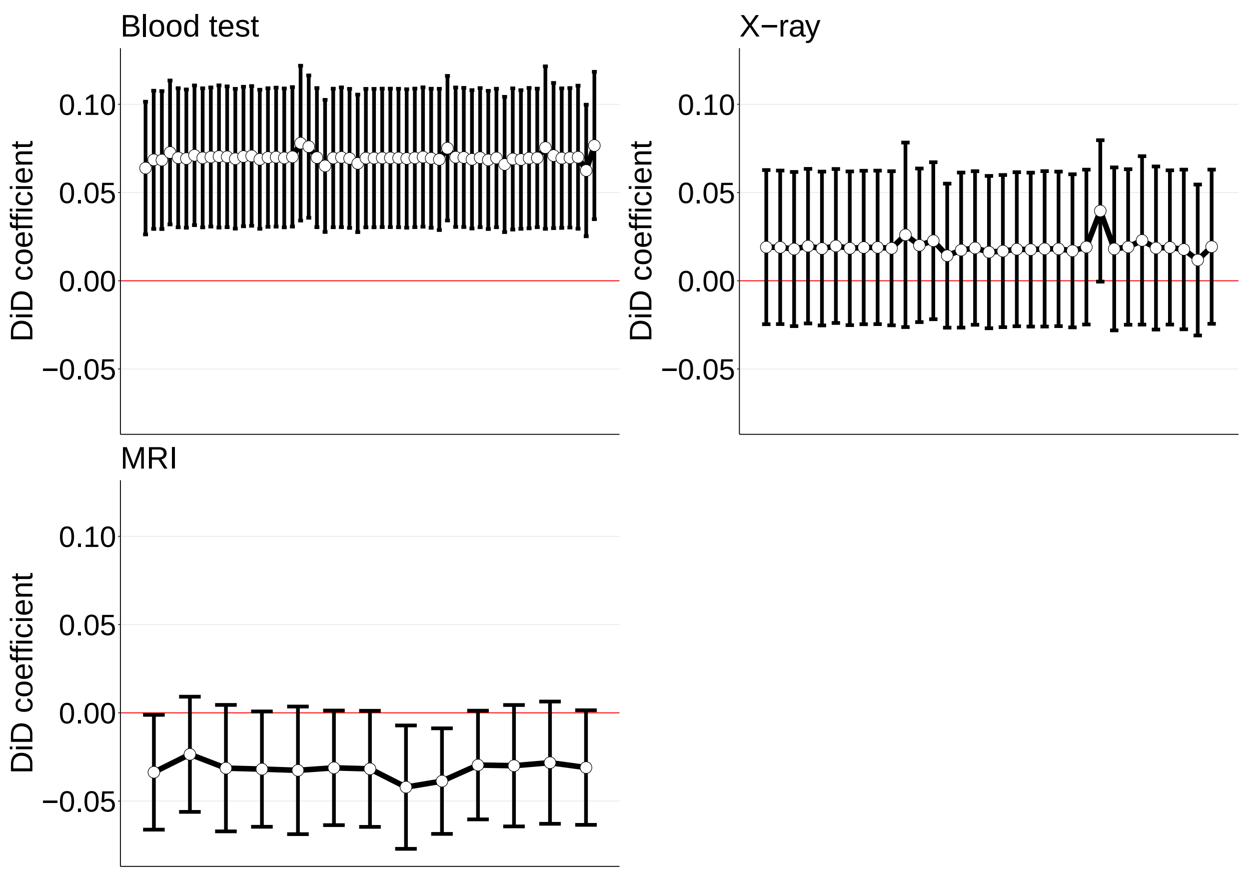

Figure A4: DiD coefficients: Treated Units Dropped One-By-One

Notes: The figure plots the difference-in-differences point estimates and confidence intervals based on specification in column 1 of Table 2. Each estimate on the x-axis is based on sample where each target unit is dropped from the sample in turn and then replaced back to the sample.

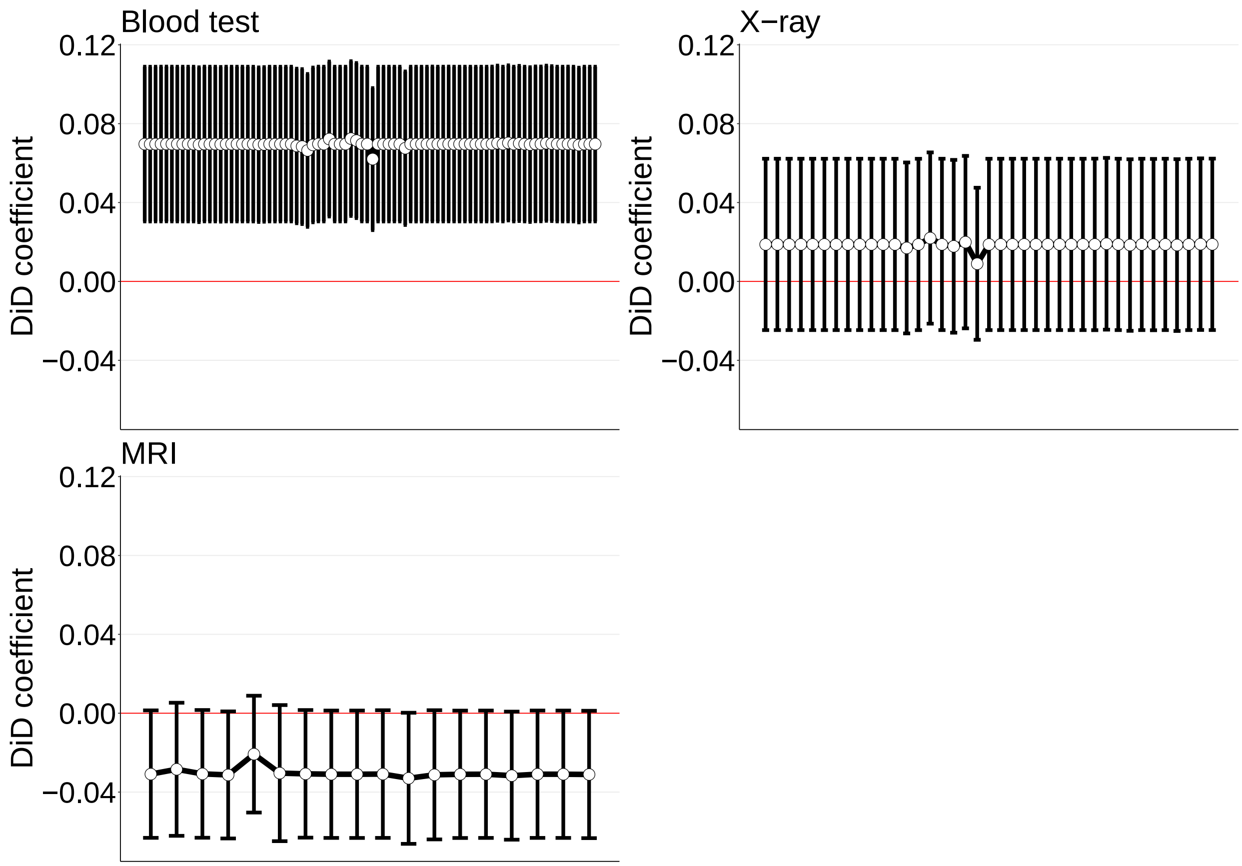

Figure A5: DiD coefficients: Control Units Dropped One-By-One

Notes: The figure plots the difference-in-differences point estimates and confidence intervals based on specification in column 1 of Table 2. Each estimate on the x-axis is based on a sample where each control unit is dropped from the sample in turn and then replaced back to the sample.

A.3 Robustness for 20km and 70km Market Radii

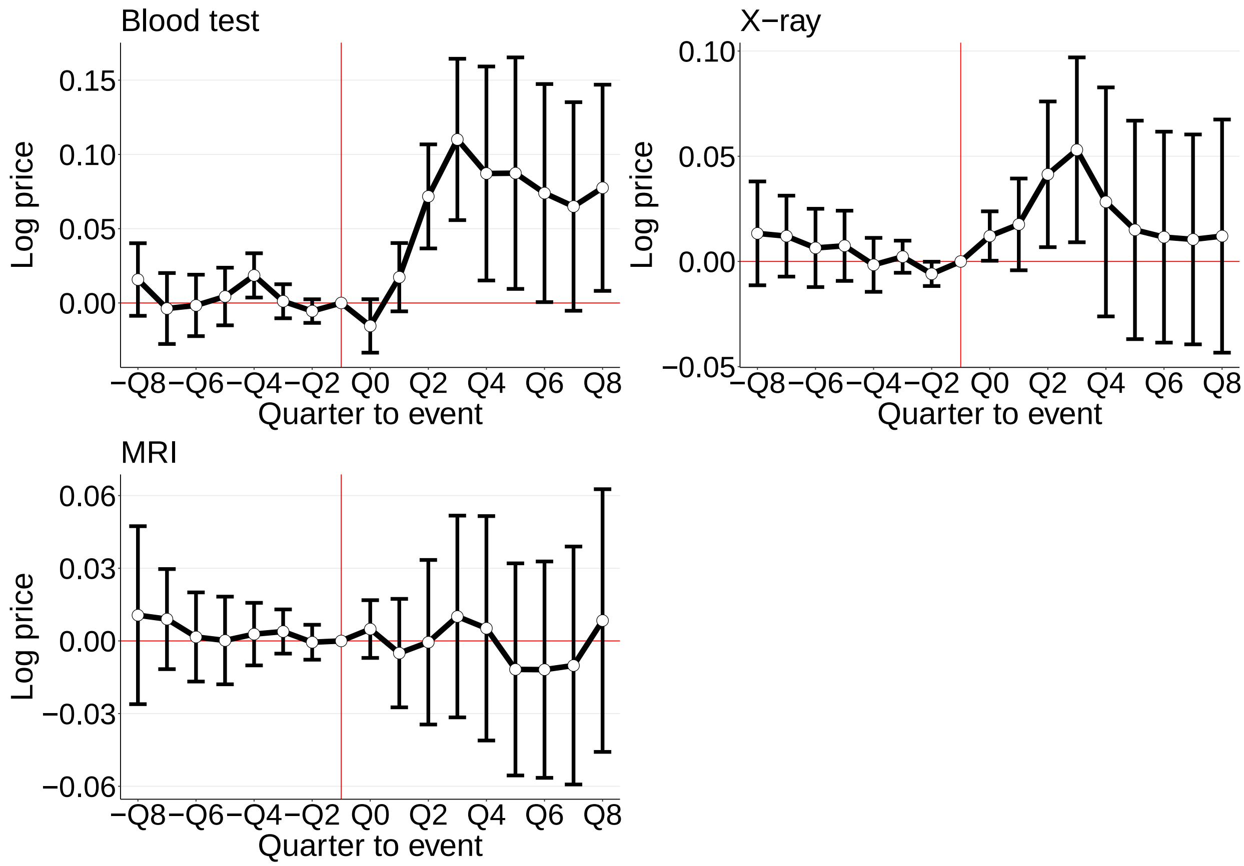

Figure A6: Event Study for Prices in Target Units, 20km Market Radius

Notes: The figure plots the point estimates and confidence intervals from the event study regression. $-Q1$ is the omitted period. Controls include fixed effects for health care units, finer procedure type, and common time trend.

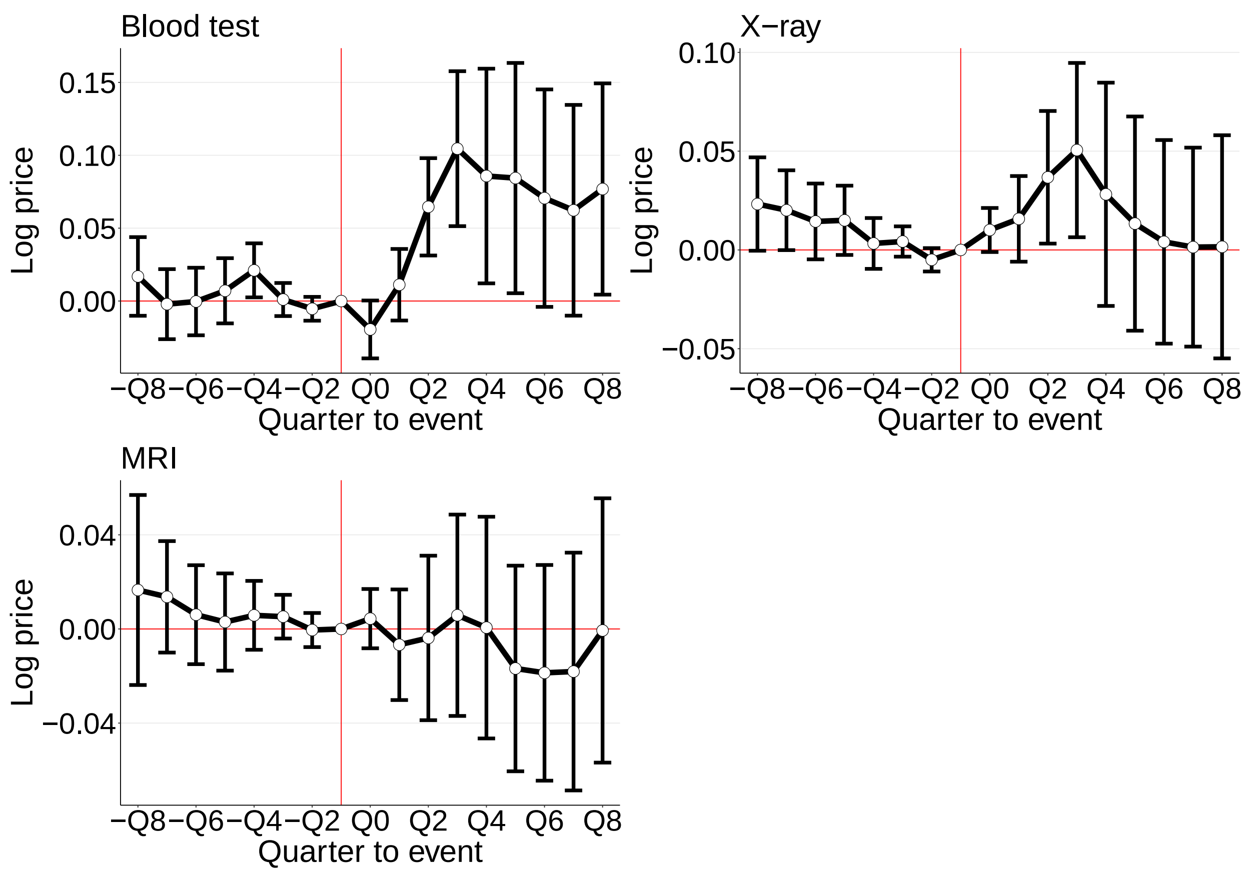

FIGURE A7: Event Study for Prices in Target Units, 70km Market Radius

Notes: The figure plots the point estimates and confidence intervals from the event study regression. $-Q1$ is the omitted period. Controls include fixed effects for health care units, finer procedure type, and common time trend.

Table A5: Effect of Acquisition on Prices in Target Units, 20km Market Radius

	(1)	(2)	(3)	(4)	(5)
Blood test					
DiD	0.066***	0.065***	0.063***	0.079***	0.083***
	(0.020)	(0.018)	(0.020)	(0.025)	(0.021)
Observations	1,338,626	1,338,626	1,338,626	1,338,626	1,338,626
X-ray					
DiD	0.020	0.023	0.021	0.015	0.018
	(0.022)	(0.022)	(0.020)	(0.031)	(0.031)
Observations	360,072	360,072	360,072	360,072	360,072
MRI					
DiD	−0.030*	−0.033**	−0.029*	−0.036***	−0.038***
	(0.015)	(0.016)	(0.016)	(0.010)	(0.011)
Observations	55,356	55,356	55,356	55,356	55,356
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. "Add. controls" includes controls for shares of patients with diabetes, heart condition, cancer, ulcer, lung disease, and mental health disorder, based on diagnoses in sickness allowance register and special drug reimbursement register, purchasing a diagnostic procedure from a health care unit in a given quarter, and the market HHI. See Table A2 for the list of used codes in the diagnoses.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A6: Effect of Acquisition on Prices in Target Units, 70km Market Radius

	(1)	(2)	(3)	(4)	(5)
Blood test					
DiD	0.055***	0.054***	0.054***	0.074***	0.075***
	(0.017)	(0.016)	(0.017)	(0.022)	(0.020)
Observations	1,061,810	1,061,810	1,061,810	1,061,810	1,061,810
X-ray					
DiD	0.007	0.003	0.008	−0.008	−0.008
	(0.018)	(0.018)	(0.017)	(0.028)	(0.025)
Observations	309,318	309,318	309,318	309,318	309,318
MRI					
DiD	−0.028	−0.034*	−0.027	−0.037***	−0.036***
	(0.018)	(0.018)	(0.019)	(0.010)	(0.010)
Observations	49,559	49,559	49,559	49,559	49,559
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. "Add. controls" includes controls for shares of patients with diabetes, heart condition, cancer, ulcer, lung disease, and mental health disorder, based on diagnoses in sickness allowance register and special drug reimbursement register, purchasing a diagnostic procedure from a health care unit in a given quarter, and the market HHI. See Table A2 for the list of used codes in the diagnoses.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A7: Effect of Acquisition on Prices in Target, Acquiring, and Rival Units, 20km Market Radius

	(1)	(2)	(3)	(4)	(5)
Blood test					
DiD×Target	0.062***	0.061***	0.061***	0.063***	0.065***
	(0.022)	(0.021)	(0.023)	(0.021)	(0.020)
DiD×Acquirer	0.053***	0.050***	0.053***	0.050***	0.043**
	(0.013)	(0.013)	(0.012)	(0.016)	(0.017)
DiD×Rival	−0.003	−0.006	−0.002	0.004	0.002
	(0.018)	(0.016)	(0.018)	(0.021)	(0.020)
Observations	2,374,239	2,374,239	2,374,239	2,374,239	2,374,239
X-ray					
DiD×Target	0.013	0.010	0.013	0.008	0.008
	(0.023)	(0.023)	(0.021)	(0.027)	(0.026)
DiD×Acquirer	−0.019*	−0.020*	−0.015	−0.023*	−0.022*
	(0.011)	(0.011)	(0.010)	(0.012)	(0.011)
DiD×Rival	0.004	0.005	0.003	0.009	0.009
	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
Observations	690,071	690,071	690,071	690,071	690,071
MRI					
DiD×Target	−0.008	−0.006	−0.008	0.019	0.018
	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)
DiD×Acquirer	−0.042*	−0.035*	−0.042*	−0.018	−0.017
	(0.024)	(0.020)	(0.024)	(0.015)	(0.016)
DiD×Rival	−0.030	−0.028	−0.030	−0.008	−0.008
	(0.021)	(0.020)	(0.021)	(0.015)	(0.016)
Observations	147,313	147,313	147,313	147,313	147,313
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. "Target" stands the acquired units, "Acquirer" stands for the units that are in the market area of the target units and belong to the acquiring firm, and "Rival" stands for the target unit's rivaling units in the same market area. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A8: Effect of Acquisition on Prices in Target, Acquiring, and Rival Units, 70km Market Radius

	(1)	(2)	(3)	(4)	(5)
Blood test					
DiD×Target	0.043**	0.043**	0.043**	0.041**	0.042**
	(0.021)	(0.020)	(0.022)	(0.018)	(0.017)
DiD×Acquirer	0.026**	0.022*	0.026**	0.026**	0.020
	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)
DiD×Rival	−0.040**	−0.039**	−0.036*	−0.044**	−0.042**
	(0.019)	(0.017)	(0.019)	(0.020)	(0.019)
Observations	2,382,814	2,382,814	2,382,814	2,382,814	2,382,814
X-ray					
DiD×Target	0.007	0.003	0.009	−0.001	−0.001
	(0.020)	(0.020)	(0.019)	(0.023)	(0.023)
DiD×Acquirer	−0.013	−0.013	−0.009	−0.013	−0.013
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
DiD×Rival	−0.003	−0.003	−0.003	−0.006	−0.006
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	702,859	702,859	702,859	702,859	702,859
MRI					
DiD×Target	−0.010	−0.010	−0.010	0.018	0.016
	(0.020)	(0.019)	(0.020)	(0.018)	(0.017)
DiD×Acquirer	−0.041*	−0.042**	−0.041*	−0.017	−0.019
	(0.023)	(0.019)	(0.023)	(0.015)	(0.016)
DiD×Rival	−0.033	−0.032	−0.032	−0.008	−0.008
	(0.021)	(0.022)	(0.022)	(0.015)	(0.016)
Observations	148,974	148,974	148,974	148,974	148,974
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. “Target” stands the acquired units, “Acquirer” stands for the units that are in the market area of the target units and belong to the acquiring firm, and “Rival” stands for the target unit’s rivaling units in the same market area. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A9: Effect of In-market and Out-Of-Market Acquisition on Blood Testing Prices in Target Units, 20km Market Radius

	(1)	(2)	(3)	(4)	(5)
DiD×In-market	0.068***	0.068***	0.064***	0.079***	0.084***
	(0.020)	(0.019)	(0.021)	(0.025)	(0.021)
DiD×Out-of-market	0.026	0.018	0.028	0.036	0.028
	(0.057)	(0.054)	(0.058)	(0.081)	(0.075)
Observations	1,338,626	1,338,626	1,338,626	1,338,626	1,338,626
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. In-market acquisitions are acquisitions where the acquiring firm already has at least one unit in the market area. Out-of-market acquisitions are acquisitions where the acquiring firm does not have existing units in the target units market area. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A10: Effect of In-market and Out-Of-Market Acquisition on Blood Testing Prices in Target Units, 70km Market Radius

	(1)	(2)	(3)	(4)	(5)
DiD×In-market	0.065***	0.065***	0.064***	0.090***	0.089***
	(0.018)	(0.018)	(0.018)	(0.027)	(0.024)
DiD×Out-of-market	−0.062	−0.073*	−0.060	−0.082	−0.118**
	(0.041)	(0.038)	(0.043)	(0.059)	(0.051)
Observations	1,061,810	1,061,810	1,061,810	1,061,810	1,061,810
Time FE	X	X	X	X	X
Unit FE	X	X	X	X	X
Add. controls		X			X
Time×Procedure type FE			X		
Time×Hospital district FE				X	X

Notes: The outcome is the log price. Each column is estimated from a separate regression. In-market acquisitions are acquisitions where the acquiring firm already has at least one unit in the market area. Out-of-market acquisitions are acquisitions where the acquiring firm does not have existing units in the target units market area. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A11: Effect of Acquisition on Volume in Target Units, 20km Market Radius

	(1)	(2)	(3)	(4)
Blood test				
DiD	0.032	0.134	0.021	0.154
	(0.116)	(0.097)	(0.129)	(0.111)
Observations	4,193	4,193	4,193	4,193
X-ray				
DiD	-0.058	0.037	-0.027	0.051
	(0.155)	(0.042)	(0.175)	(0.047)
Observations	2,085	2,085	2,085	2,085
MRI				
DiD	-0.292^{*}	-0.054	-0.136	-0.012
	(0.164)	(0.080)	(0.164)	(0.067)
Observations	643	643	643	643
Time FE	X	X	X	X
Unit FE	X	X	X	X
Add. controls		X		X
Time×Hospital district FE			X	X

Notes: The unit of observation is health care unit×quarter. The outcome is the log number of procedures. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table A12: Effect of Acquisition on Volume in Target Units, 70km Market Radius

	(1)	(2)	(3)	(4)
Blood test				
DiD	0.009	0.116	0.007	0.143
	(0.103)	(0.093)	(0.123)	(0.108)
Observations	2,330	2,330	2,330	2,330
X-ray				
DiD	−0.062	0.032	−0.025	0.049
	(0.138)	(0.031)	(0.177)	(0.033)
Observations	1,438	1,438	1,438	1,438
MRI				
DiD	−0.172	0.048	−0.019	0.059*
	(0.137)	(0.063)	(0.125)	(0.033)
Observations	414	414	414	414
Time FE	X	X	X	X
Unit FE	X	X	X	X
Add. controls		X		X
Time×Hospital district FE			X	X

Notes: The unit of observation is health care unit×quarter. The outcome is the log number of procedures. See Table 2 for more information.
***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

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