

DISCUSSION PAPER SERIES

DP14328
(v. 2)

FINANCIAL INCENTIVES AND COMPETITIVE PRESSURE: THE CASE OF THE HOSPITAL INDUSTRY

Philippe Choné and Lionel Wilner

INDUSTRIAL ORGANIZATION



FINANCIAL INCENTIVES AND COMPETITIVE PRESSURE: THE CASE OF THE HOSPITAL INDUSTRY

Philippe Choné and Lionel Wilner

Discussion Paper DP14328
First Published N/A
This Revision 30 October 2020

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

This Discussion Paper is issued under the auspices of the Centre's research programmes:

- Industrial Organization

Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

Copyright: Philippe Choné and Lionel Wilner

FINANCIAL INCENTIVES AND COMPETITIVE PRESSURE: THE CASE OF THE HOSPITAL INDUSTRY

Abstract

In the late 2000s, a regulatory reform dramatically strengthened the incentives of French nonprofit hospitals to attract patients. Exploiting exhaustive data for surgery treatments and modeling hospitals as supplying utility to patients, we show that increased competitive pressure on nonprofit hospitals caused them to perform more procedures but did not inflate overall activity. Although they have gained market shares, nonprofit hospitals have been significantly worse off after the reform. To adjust to stronger financial incentives, they incurred an additional effort (pecuniary and non-pecuniary costs) equivalent to about a quarter of their annual revenue.

JEL Classification: D22, I11, L13

Keywords: Competition in utility space, financial incentives, payment reform, hospital choice

Philippe Choné - philippe.chone@ensae.fr
CREST (Paris) and CEPR

Lionel Wilner - lionel.wilner@ensae.fr
INSEE (Paris)

Financial incentives and competitive pressure: The case of the hospital industry

Philippe Choné* Lionel Wilner†

October 30, 2020

Abstract

In the late 2000s, a regulatory reform dramatically strengthened the incentives of French nonprofit hospitals to attract patients. Exploiting exhaustive data for surgery treatments and modeling hospitals as supplying utility to patients, we show that increased competitive pressure on nonprofit hospitals caused them to perform more procedures but did not inflate overall activity. Although they have gained market shares, nonprofit hospitals have been significantly worse off after the reform. To adjust to stronger financial incentives, they incurred an additional effort (pecuniary and non-pecuniary costs) equivalent to about a quarter of their annual revenue.

JEL Codes: D22; I11; L13.

Keywords: Competition in utility space; financial incentives; payment reform; hospital choice.

*Center for Research in Economics and Statistics (CREST), 5 avenue Henry Le Chatelier, 91764 Palaiseau Cedex, France. Please address correspondence to chone@ensae.fr. We are grateful to Steve Berry, Kurt Brekke, Xavier d'Haultfœuille, Jan De Loecker, Pierre Dubois, Liran Einav, Pierre-Yves Geoffard, Gautam Gowrisankaran, Daniel Herrera, Nicolas Jacquemet, Laurent Lamy, Albert Ma, Martin Peitz, Carol Propper, Devesh Raval, Ted Rosenbaum, Luigi Siciliani, Michelle Sovinsky, Frank Verboven and Engin Yilmaz for insightful comments. We also thank seminar participants at Bergen University, Boston University, Cergy University, Crest, Ensai Rennes, Insee, KU Leuven, Mannheim University, Marseilles University, Paris Dauphine University, Toulouse School of Economics, UC Santa Barbara, York University as well as attendees of various workshops and conferences. This research has benefited from the support of *Labex ECODEC* –a joint-venture of HEC, ENSAE and Ecole Polytechnique– and of *Health Chair* –a joint initiative by PSL, Université Paris-Dauphine, ENSAE, MGEN and ISTYA under the aegis of the Fondation du Risque (FDR).

†INSEE-CREST, 88 avenue Verdier, 92120 Montrouge, France. Email: lionel.wilner@ensae.fr.

1 Introduction

“*The only thing that matters today is to perform even more procedures, to have more patients, to make more money.*”¹ This complaint by medical and non-medical personnel has been recurring since the introduction of the “*Tarifification à l’activité*” (colloquially known as T2A) in French public hospitals. This funding rule is an activity-based payment similar to the prospective payment system now in force in most developed countries. As *Le Monde* put it in 2018, the T2A has become the *bête noire* of public hospitals (Pommiers, 2018).

In the public debate, the critic of the T2A is strongly associated with that of hospital competition. A key feature of the industry (at least in the market segment we are considering in this paper, surgery care) is the strength of the private sector in France. Prior to the reform, public hospitals had little incentives to compete with private hospitals. After the reform, the need to secure funding may have pushed hospital managers to compete more fiercely and to require more effort from their staff.² Furthermore, competitive forces do not affect only the interactions between public and private hospitals, but also the interactions between public hospitals. Administrative reports have criticized the activity-based funding rule for creating excessive incentives to compete for patients.³

It is important to contrast the introduction of the T2A system in France with the 1983 Medicare reform in the United States. In the American case, the *pre-reform* payment rule was a cost-plus mechanism. The move to price-cap regulation, which was designed to curb rising expenditures and encourage efficient cost reduction (Shleifer, 1985; Laffont and Tirole, 1993), triggered the fear that hospitals would respond by cutting back on treatment intensity, with potentially negative effects on quality outcomes.⁴

In France, on the contrary, public hospitals prior to the reform were funded through “global budgeting”. They received an annual lump-sum transfer that did not depend on reported costs and was not subject to negotiations with the

¹Quotation by Pr. Stéphane Dauger, head of the pediatric critical care unit at Hôpital Robert-Debré in Paris, taken from “*The only thing that matters today is to have more patients’: Hospital and race to funding*” (*Le Monde*, June 2020).

²In French public hospitals, physicians and nurses are employees and as such placed under the managers’s hierarchical authority.

³For instance, Boissier (2012) states that “in case of direct competition between two hospitals for the same activity in a given local area, the funding instrument does not encourage the hospitals to cooperate or to share services. Indeed, each hospital has an incentive to increase activity to earn more revenue.” See also Hubert and Martineau (2015), Veran (2017).

⁴See Cutler (1995). See also Acemoglu and Finkelstein (2008) for an assessment of the impact of the U.S. reform on technological processes (capital-labor ratios).

regulator. Because prior to the reform the transfer did not respond to the evolution of their activity, global budgeting insulated nonprofit hospitals from competition. After the reform was fully implemented, revenues became a linear function of the number of procedures performed. This dramatic change may have encouraged hospitals to perform more procedures than under global budgeting, explaining why President Hollande called the T2A “inflationary”.⁵ President Macron promised during the 2017 presidential campaign to cap activity-based revenues to 50% of total hospital revenues.

In this paper, we estimate the causal effects of the T2A on hospitals and patients at the level of mainland France for eight major diagnosis categories. Our purpose is to quantify the implicit “effort” that came with increased competitive pressure. By effort, we mean all pecuniary and non-pecuniary costs required from nonprofit hospitals to adjust to the stronger financial incentives. We also ask whether the T2A caused the overall number of surgery procedures to rise relative to global budgeting.

To this aim, we build an empirical framework that features competition between hospitals and allows for heterogeneity in their objective functions. We model hospitals as supplying utility directly to patients. Hospital preferences depend on the number of admitted patients and on the average utility provided to them. We allow the marginal costs to depend on the utilities provided to patients. We expect that raising the utility offered to each patient translates into higher costs per patient. Under the assumption of stable costs and preferences, the introduction of the activity-based payment system provides us with an exogenous change that identifies both the hospital-specific intercept and the slope of the marginal cost functions.

Equipped with the hospitals’ objective functions, we are able to assess the causal impact of the payment reform on patients and hospitals. In the spirit of the literature on *ex post* evaluation of merger simulation (Peters, 2006; Björnerstedt and Verboven, 2016), we compute counterfactual Nash equilibria to break down the observed effects of the policy reform into a number of separate components: (i) the response to stronger financial incentives, (ii) hospital-specific demand shocks, (iii) hospital-specific supply shocks, and (iv) aggregate industry-wide shocks.

Our main findings are as follows. The interquartile range of the estimated utilities is equivalent to between 15 and 20 minutes travel time (depending on the considered diagnosis), to be compared with the median travel between patient

⁵ “François Hollande opposes the “hospital as a firm” ideology, Le Monde, February 2, 2012.

home and hospital location, namely 22 minutes. We thus document, through a revealed preference approach, a strong heterogeneity in attractiveness across French hospitals. Regarding incentives in equilibrium, we find that in the nonprofit sector, the primary motivation of nonprofit hospitals is not to pocket reimbursement rates. Financial incentives account for less than 10% of their total marginal incentives to attract patients. Among nonprofit hospitals, private hospitals are more responsive to financial incentives than state-owned hospitals.

For almost all ordered pairs of hospitals, competitive interactions exhibit strategic complementarity. To get a sense of the magnitude of strategic interactions, we compute by how much hospitals alter the utility they offer to patients in response to competitors changing their utility. We find that 10% (respectively 50%) of the hospitals are exposed to a competitor with respect to which the slope of the reaction function is larger than .15 (resp. .07). The slopes of reaction functions decrease with the distance between the two hospitals as intuition suggests.

Turning to policy evaluation, we disentangle the effects of T2A from demand and supply shocks. In response to the stronger incentives placed on them, nonprofit hospitals have raised the utility they offer to patients. The for-profit hospitals have reacted by raising their own utility by a substantially lesser amount—more than ten times smaller, consistent with the estimated slopes of the reaction function. For the eight major diagnosis categories under consideration, the regulatory change has caused activity to grow in the nonprofit sector by 3% to 14% and to decline in the for-profit sector by -1% to -5%, the overall effect being a modest increase (+.3% to +2.4%) at the industry level. Comparing to the observed outcomes, we find that the change in incentives accounts well for the aggregate shift in market shares from the for-profit sector to the nonprofit sector, but poorly for changes in total activity. The evolution of total activity is mostly explained by industry-wide and hospital-specific demand shocks; strategic effects and hospital-specific supply-side shocks play a more modest role. Altogether, there is little empirical support for the claim that the introduction of T2A in the nonprofit sector has inflated overall hospital activity.

Finally, and importantly, we find that nonprofit hospitals, even though they have increased activity and market share, have been much worse off under T2A than under the previous global budgeting system. The non-revenue part of their objective function, which accounts for all pecuniary and nonpecuniary costs as well as for intrinsic motivation, has fallen over the years 2005 to 2008 when the reform was phased in. We estimate that, compared to the 2005 equilibrium, the additional “effort” incurred by public hospitals in 2008 is equivalent to about one quarter of

a full-year activity-based revenue. Although our data does not allow to pinpoint the induced costs within nonprofit hospitals (operational costs, managerial costs, tiredness and discontentment among hospital personnel, etc.), our quantification exercise shows that the effort required from hospitals to adjust to the new funding regime has been substantial. The T2A reform was not designed to compensate any additional effort caused by increased financial pressure.

Related literature This article is primarily related to the literature on hospital competition. Regarding consumer demand in general, the industrial organization literature pioneered by [Berry \(1994\)](#) and [Berry, Levinsohn, and Pakes \(1995\)](#) allows for flexible substitution patterns by using random coefficient models.⁶ In the context of hospital choice, a rapidly growing literature (e.g., [Ho, 2006](#); [Gowrisankaran, Nevo, and Town, 2015](#); [Gaynor, Propper, and Seiler, 2016](#); [Ho and Lee, 2017](#); [Garmon, 2017](#); [Raval, Rosenbaum, and Tenn, 2017](#); [Barrette, Gowrisankaran, and Town, 2020](#); [Raval and Rosenbaum, forthcoming](#)) places most of the emphasis on observed patient heterogeneity, and relies on tractable demand structures such as logit or nested logit to avoid incidental parameters problems in the presence of a high number of dummy variables.⁷ We follow this route, and check that our findings are robust to various nesting structures. The above studies generally proceed by grouping patient admissions together based on observed characteristics, the most important of which being diagnosis, patient location, and age. A strand of literature initiated by [Raval, Rosenbaum, and Tenn \(2017\)](#) has refined the grouping methodology, using more patient characteristics when this is compatible with a reasonable group size. Recent papers adopt group sizes of between 10 and 50 individuals. The sizes of our patient groups are at the low end of this range because France has more postal codes than the United States, with five times less residents on average. We check that our results are robust to the size of the patient groups.

Two aspects of demand estimation require special attention in our context: the treatment of the outside good and the estimation of the hospital indicators. Regarding the outside good, [Gaynor, Propper, and Seiler \(2016\)](#) observe that a large part of the healthcare literature does not consider any outside good. Some

⁶[Tay \(2003\)](#) estimates a random-coefficient discrete-choice model for inpatient hospital care services related to the treatment of heart attacks.

⁷[Ho and Pakes \(2014\)](#) noticed the incidental parameters issue. In the context of health plan choice, [Miller, Petrin, Town, and Chernew \(2019\)](#) and [Starc and Town \(2020\)](#) adopt random utility demand systems with logit or nested logit structures as the above-cited paper do for hospital choice.

papers, (e.g., [Gowrisankaran, Lucarelli, Schmidt-Dengler, and Town, 2011, 2018](#)) define the outside option as the set of hospitals outside a certain distance range. Guided by our research question, we follow a different approach. To estimate the number of individuals that a hospital might possibly convince to undergo surgery, we rely on the protocol proposed by [Huang, Rojas, et al. \(2013\)](#) and [Huang and Rojas \(2014\)](#), and implemented by [Dubois and Lasio \(2018\)](#).

To estimate and identify the utilities offered to patients (hospital indicators), we exploit the variations of market shares across patient groups. Our method builds upon a standard empirical industrial organization model ([Berry, 1994; Nevo, 2000](#)), to which we add a new ingredient, namely patient group indicators to control for local potential demand. We are thus led to consider a *two-way* fixed-effect model, with both hospital and patient group indicators. The identification of the hospital and patient group effects is based on the same idea as that of firm and worker effects in statistical models for matched employer-employee data, see [Abowd, Kramarz, and Margolis \(1999\)](#).⁸ Here, we exploit the strong local connectivity of the bipartite graph formed by hospitals and patient groups. Intuitively, precise estimation requires many patient groups per hospital, which is the case empirically. [Jochmans and Weidner \(2019\)](#) relate the precision of the estimation to the connectivity of the graph formed by hospitals and patient groups.

It is important to relate the present study to the literature on hospital non-price competition, in particular to the recent studies of [Eliason \(2017\)](#) and [Hackmann \(2019\)](#). We stress that the research question, data and method of these two studies are very different from ours. These two articles rely on sufficient statistics for quality: [Hackmann \(2019\)](#) uses the nurse-to-resident staffing ratios in the nursing home industry while [Eliason \(2017\)](#) uses five indicators of clinical quality and patient outcomes for outpatient dialysis.⁹ Both papers assume that the variable cost per patient depends on quality, and in their framework firms compete in quality (and potentially price).¹⁰ By contrast, we use exhaustive data to study the impact of a massive, across-the-board rise in financial incentives on the surgery industry at the level of France (five million admissions par year). No quality data (indicators

⁸In a related vein, [Finkelstein, Gentzkow, and Williams \(2016\)](#) exploit patient mobility across hospital areas to separate demand from supply in the determination of health care utilization.

⁹In the U.S. nursing home case studied by [Hackmann \(2019\)](#), 24% of residents pay the private rate set by the nursing home, which is an important difference with the French surgery industry. The U.S. market for outpatient dialysis studied by [Eliason \(2017\)](#), where there is little price competition due to the dominance of Medicare, is closer to the French environment.

¹⁰Moreover, while [Eliason \(2017\)](#) considers an entry game with capacity choice, we take the structure of the surgery industry as given. Over our period of study, there has been virtually no change in market structure for the segment we consider (surgery care).

of clinical or perceived quality) is available at this level of aggregation. Assuming that hospitals compete in utility rather than in quality, we are able to estimate the effort required from nonprofit hospitals to adjust to the new incentives.

Our work is also related to the literature on hospital financial incentives. A series of work investigate how the responsiveness to financial incentives depends on the legal or ownership status of a hospital (Duggan, 2000, 2002; Gaynor and Vogt, 2003; Lakdawalla and Philipson, 2006). As these papers have observed, the differences in objective functions of for-profit and nonprofit hospitals can be represented by different perceived marginal costs. We follow the literature by allowing for much heterogeneity in the incentives of each hospital.

The paper is organized as follows. Section 2 describes the French hospital industry and presents our dataset. Section 3 estimates demand, including patient travel costs and the utilities offered by hospitals. Section 4 sets up the competition-in-utility framework and estimates the preferences and reaction functions of hospitals. Section 5 presents the results and contains counterfactual simulations as well as a number of robustness checks (patient grouping, specification of hospital choice, size and specification of potential demand, alternative ways to account for case-mix variations within diagnosis categories). Section 6 concludes. A glossary of notations is available in the appendix.

2 Institutional context and data

In France, hospital choice is and has always been unrestricted. The choice may result from a joint decision of the patient, her family and the general practitioner, but the latter has no financial interest in the decision. There is a complete disconnection between the funding systems of ambulatory care and hospital care.¹¹ As regards the latter, most of the expenditures are funded by the basic mandatory public health insurance system, see Appendix A.1 for details.

2.1 The hospital industry and the payment reform

The industry has historically been divided into two “sectors” according to the legal status of hospitals, either for-profit or nonprofit. For-profit hospitals are numerous

¹¹The GPs contracting system contains no regulatory feature that could systematically interfere with referral decisions, contrary for instance to what happened in England prior to the 2006 NHS reform studied by Gaynor, Propper, and Seiler (2016). No capitation scheme, such as the one designed by U.S. insurers and described by Ho and Pakes (2014), has ever existed in France.

in France, with about 500 hospitals in surgical care. Nonprofit hospitals can be either state-owned (public hospitals, including teaching hospitals) or private. All nonprofit hospitals share the same obligations in terms of public service (e.g., no restriction in access to care; 24/7 operating time). Private nonprofit hospitals are owned by private institutions such as associations, religious institutions, or nonprofit supplementary health insurers (*mutuelles*).¹²

Both sectors have now moved to a fixed-price activity-based payment. The change was completed as early as 2005 in the for-profit sector, and financial incentives have not dramatically evolved thereafter in that sector. Before 2005, for-profit hospitals were already submitted to a prospective payment based on DRG prices. The reimbursement rates, however, included a *per diem* fee: as a result, they depended on the length of stay. Moreover, these rates were negotiated annually and bilaterally between the local regulator and each hospital, and were consequently history- and geography-dependent. Starting 2005, all for-profit hospitals have been reimbursed the same rate for a given DRG and those rates no longer depend on the length of stay.

By contrast, for nonprofit hospitals, the payment reform has represented a fundamental change in the funding principles. Indeed, over the years 1984 to 2004, those hospitals have been funded through an annual lump-sum transfer from the government known as “global endowment” (“*dotation globale*”), which depended very loosely on the nature or evolution of their activity. The funding rule potentially hindered the development of expanding hospitals due to scarce resources. It was therefore replaced in 2005 with an activity-based payment system, whereby each patient stay is assigned to a diagnosis-related group (DRG) and paid a fixed price accordingly, as is the case in most developed countries. The shift from global budgeting to the activity-based payment rule, however, has been implemented gradually. For the concerned hospitals, activity-based revenues accounted for 10% of the resources in 2004, the remaining part being funded by a residual endowment. The share of the budget funded by activity-based revenues has been increased to 25% in 2005, to 35% in 2006, to 50% in 2007, and eventually to 100% in 2008. The residual endowment has been accordingly reduced in the process, and eventually suppressed in 2008.¹³ The effect of the reform on hospital revenues

¹²Private nonprofit hospitals claim to share the same ethic values as public hospitals. Their profit is fully employed to innovate, invest in new equipments or develop new services for patients. Although they have the same obligations in terms of service, they are not subject to the same constraints in terms of internal organization or procurement.

¹³A series of lump-sum transfers have subsisted, some of which are linked to particular activities such as research and teaching.

has been approximately neutralized.

Formally, denoting by r_{Dt}^{FP} and r_{Dt}^{NP} the DRG rate administratively set at year t for DRG D in the for-profit and in the nonprofit sector at the national level, the reimbursement rates that applies to a particular hospital j are given during the phase-in of the reform as follows:

$$r_{Djt} = \begin{cases} r_{Dt}^{\text{FP}} & \text{if } j \in \text{FP} \\ \lambda_t r_{Dt}^{\text{NP}} & \text{if } j \in \text{NP}, \end{cases} \quad (1)$$

where λ_t are the phase-in coefficients:

$$(\lambda_{2005}, \lambda_{2006}, \lambda_{2007}, \lambda_{2008}) = (.25, .35, .5, 1). \quad (2)$$

In practice, the rates that have actually been applied by the regulator slightly differed from the above theoretical values, see Appendix [A.3](#) for details.

2.2 Scope of the study

Our dataset covers the four-year phase-in period of the payment reform, namely the years 2005 to 2008. The geographic area under consideration is mainland France, i.e., metropolitan France at the exclusion of Corsica.

We concentrate on surgery services, a segment in which the structure of the hospital industry has remained constant over the period of study, with no entry, hospital closure or significant merger.

We restrict our attention to the eight major diagnosis categories (out of nineteen) that account for the highest number of admissions: orthopedics, ENT-stomatology, ophthalmology, gastroenterology, gynaecology, dermatology, nephrology and circulatory system. These categories account for 21 million surgery admissions out of 23 million over the period of study.

Data The empirical analysis primarily relies on two administrative sources based on mandatory reporting by each and any hospital in France: *Programme de Médicalisation des Systèmes d'Information* (PMSI) and *Statistique Annuelle des établissements de santé* (SAE). Both sources cover exhaustively the universe of French hospitals. The former contains all hospital admissions, providing in particular the patient postal code and the DRG to which the patient stay has been assigned. The latter provides information about equipment, staff and bed capacity. Available data sources in France do not contain the information whether a

procedure has been scheduled in advance, and therefore do not allow to distinguish elective surgery from urgent surgery.¹⁴

We observe the list of DRG rates set by the regulator at the national level in each of the two legal sectors. Further details are provided in Appendix A.3. To allow for observed heterogeneity in hospital preferences, we collect demographic variables (education, structure of the population by age and gender, median income) at the postal code level.

All distances in the paper are based on the center of the corresponding postal codes, and are computed with INRA’s Odomatrix[©] software. The distances are defined as travel times by road.

Sample selection Table 1 depicts the successive selection steps from the original PMSI database to the working sample (see Appendix A.2 for details). The selection process leaves us with 85% of the whole 5.3 million surgery admissions per year in the eight main diagnosis categories. Our working sample contains finally 17,945,047 stays from 2005 to 2008. It includes 942 hospitals, among which 423 nonprofit hospitals (353 state-owned, 70 private nonprofit hospitals) and 519 private, for-profit hospitals, see Table 3.

Activity Figure 1 and Table 3 show the general trend in the number of admissions by legal status over our period of study (2005-2008), when financial incentives have been much strengthened for nonprofit hospitals. The number of surgery admissions increased by 8.6% in the nonprofit sector (.14 million more admissions) while it stagnated in the for-profit sector. As a result, the aggregate market share of nonprofit hospitals for surgery services at the national level rose from 37.4% to 39.5%.

The nonprofit sector has gained market share at the national level over the period of study in each of the eight considered diagnosis categories. The gains in market shares lie between .7 pp in ophthalmology and 5 pp in dermatology.

Hospital revenues and average rates at the diagnosis category level Table 4 depicts the evolution of theoretical activity-based revenues in our working

¹⁴The question of whether the patient arrived through the hospital emergency department has been introduced in the administrative questionnaire in 2004. Because the variable did not enter the DRG classification algorithm and did not matter for reimbursement purposes, the quality of the response was initially very poor and improved gradually over time. As hospitals started to correctly fill in the information, the apparent “emergency rate” nearly doubled over the period 2005-2008, which makes it unusable for our longitudinal analysis.

sample, based on the DRG rates r_{Djt} set nationally and on current activity q_{Djt} . In 2008, after the reform has been fully implemented in nonprofit hospitals, those revenues are €7.8bn for the eight diagnosis categories we are considering: €5.1bn in nonprofit hospitals and €2.8bn in for-profit hospitals.

We compute reimbursement rates as weighted means at the diagnosis category level g for every hospital j and year t :

$$r_{gjt} = \frac{\sum_{D \in g_t} r_{Djt} q_{Djt}}{\sum_{D \in g_t} q_{Djt}}, \quad (3)$$

where the sums are over all DRGs D in the diagnosis category g and r_{Djt} is defined in (1). Table 5 (top panel) reports the evolution of DRG rates aggregated at the level of the eight diagnosis categories.¹⁵ The introduction of activity-based payment is best described by the dramatic rise in the theoretical DRG-rates in the nonprofit sector. By contrast, DRG rates in the for-profit sector vary little during the period. Composition effects in (3) due to specialization or to coding strategies (e.g., Dafny, 2005; Gowrisankaran, Joiner, and Lin, 2019) are of limited importance in our context.¹⁶

Reduced-form evidence Table 6, first column, shows that the trend represented on Table 3 remains apparent after controlling for hospital-diagnosis effects: the activity of for-profit hospitals is stable while the activity of nonprofit hospitals increases over the years 2005 to 2008. Controlling furthermore for diagnosis category-year effects confirms that activity has increased more rapidly in the nonprofit sector (column 2). The differential remains with almost unchanged parameters when we control also for staff, equipment and socio-demographic variables (see the coefficients of nonprofit \times year in column 4). The last two columns, however, are to be interpreted with caution as the explanatory variables related to staff and equipment may be endogenous.

¹⁵We carried out the exercise for each of the eight diagnosis categories separately. The eight tables, which are available upon request, exhibit the very same pattern.

¹⁶In Appendix A.3, we check the impact of composition effects on average DRG rates is of second order compared to the dramatic rise caused by the policy reform in the nonprofit sector. In Section 5.5, we check that accounting or not for observed case-mix variations affects very little our counterfactual exercises.

3 Demand

3.1 Hospital choice

Following a set of recent papers (e.g., Garmon, 2017; Raval, Rosenbaum, and Tenn, 2017; Barrette, Gowrisankaran, and Town, 2020; Raval and Rosenbaum, forthcoming), we assume that patients with similar characteristics have the same choice probabilities for each hospital, which we derive from a nested logit model. Our baseline specification has three nests: nonprofit hospitals (NP), for-profit hospital (FP), and the outside good. We group patient admissions together based on such characteristics. In our baseline model, patient grouping is based on major diagnosis categories and patient locations (postal codes). The utility of patients in group i undergoing surgery in hospital j belonging to nest n at date t is given by

$$U_{ijt} = \delta_{ijt} + \zeta_{int} + (1 - \sigma)\varepsilon_{ijt}, \quad (4)$$

where ε_{ijt} is an identically and independently extreme value. The variable ζ_{int} is common to all hospitals in nest n and has a distribution function that depends on σ , with $0 \leq \sigma < 1$.¹⁷ The mean utility level offered to patients in group i is specified as

$$\delta_{ijt} = u_{jt} - \text{TC}(d_{ij}; X_{it}) + \gamma \text{NP}_j X_{it} + \varphi_{it} + \xi_{ijt}. \quad (5)$$

The coefficients of the hospital and patient group indicators, u_{jt} and φ_{it} , are parameters to be estimated, while the ξ_{ijt} 's are statistical disturbances. The outside option, "No surgery", includes all other medical treatments, with or without hospitalization, and the corresponding mean utility is normalized to zero. The travel costs incurred by patients, denoted by TC, are assumed to depend quadratically on the travel time d_{ij} and on the characteristics of patients.¹⁸ The vector of parameters γ accounts for the variations in the taste for nonprofit hospitals; NP_j is a dummy variable for nonprofit status. This taste is supposed to depend on age, education, gender, income.

Following Berry (1994), we estimate

$$\begin{aligned} \log \frac{s_{ijt}}{s_{i\emptyset t}} &= u_{jt} + \alpha_0 \text{Closest}_{ij} - \alpha_1 d_{ij} - \alpha_2 d_{ij}^2 - \alpha_{1X} d_{ij} X_{it} \\ &+ \varphi_{it} + \gamma \text{NP}_j X_{it} + \sigma \log s_{ijt|n} + \xi_{ijt}, \end{aligned} \quad (6)$$

¹⁷See Berry (1994) or Verboven (1996) for details.

¹⁸As we do not observe income or education at the patient level, we use the share of high-school graduates and median income in the postal code.

where $\text{Closest}_{ij} = \mathbb{1}\{d_{ij} = \min_k d_{ik}\}$ is a dummy variable equal to 1 if hospital j is the closest hospital from patient i 's postal code.

The empirical counterparts of the unconditional and conditional market shares are $s_{ijt} = q_{ijt}/M_{it}$ and $s_{ijt|n} = q_{ijt}/\sum_{j \in n} q_{ijt}$. We approximate the size of the potential demand M_{it} for patient group i using the method of [Huang, Rojas, et al. \(2013\)](#) and [Huang and Rojas \(2014\)](#). The intuition is as follows. The nested logit specification includes patient group indicators that “absorb” the size of the potential of demand. If that size is correct, it should be the case that removing the patient group indicators from the model does not affect the estimation results. The value that minimizes the distance between the models with and without patient group indicators is therefore our preferred estimate of the potential demand.¹⁹ We make sure that our results are robust to alternative sizes and specifications of the potential demand.

The disturbances ξ_{ijt} reflect deviations from the mean attractiveness of hospital j in patient group i at date t . We assume that they are orthogonal to the geographic configuration of the industry:

$$\mathbb{E} [\xi_{ijt} \mid it, jt, d_{ij}, d_{ij}X_{it}, \text{NP}_j, Z_{ijt}^D] = 0, \quad (7)$$

where the excluded instruments Z_{ijt}^D are presented below. The perception of a hospital's attractiveness may indeed vary across patient locations, due to historical, administrative and economic relationships, or to any other unobserved link between patient and hospital locations.²⁰ Hospitals' locations were decided several decades before the period of study and remain extremely stable over time in surgical care, hence we take the industry geography as exogenous.

To account for the endogeneity of the conditional shares $s_{ijt|n}$ in (6), we use the instruments proposed by [Berry, Levinsohn, and Pakes \(1995\)](#) based on sums of characteristics of other hospitals. Our set of demand instruments Z_{ijt}^D includes the sum of (squared) distances to other hospitals in the same nest: $\sum_{k \neq j, k \in n} d_{ik}$, $\sum_{k \neq j, k \in n} d_{ik}^2$, as well as interactions with time-varying sociodemographic variables at the postal code level: population, income, shares of women, of elder and of high-school graduates. Excluded instruments also include the minimum distance between patient location and other hospitals in the same nest, $\min_{k \neq j, k \in n} d_{ik}$, in-

¹⁹We approximate potential demand in all the variants of the model considered for robustness. See online appendix [B.2](#) for details.

²⁰For instance, general practitioners practicing in a given area may have connections to a particular hospital and therefore have (positive or negative) information about that hospital. In this regard, recall Footnote [11](#).

teracted with the latter socio-demographics. Altogether, we have 22 instrumental variables.

3.2 Identification and estimation

We now discuss the identification of the two-way fixed-effects u_{jt} and φ_{it} in Equation (6), relying on arguments from [Abowd, Kramarz, and Margolis \(1999\)](#). We impose the same error structure as they do. Under these restrictions, demand parameters are identified from the variation in hospitals' market shares across patient groups. By analogy with the matched employer-employee data framework, our dataset takes the form of an undirected bipartite graph, the vertices of which are hospitals and patients (instead of firms and workers). For a given year, two hospitals j and j' are connected if they receive patients from the same group i , and two patient groups i and i' are connected if at least one hospital receives patients from both i and i' . Thanks to variations in market shares in the patient (resp. hospital) dimension, the patient and hospital indicators u_{jt} (resp. φ_{it}) are identified up to an additive constant for each connected component of the graph, see [Abowd, Creecy, and Kramarz \(2002\)](#). We adopt the following normalization restrictions:

$$\sum_i \text{degree}(i) \varphi_{it} = 0 \tag{8}$$

for all connected components, where $\text{degree}(i)$ refers to the number of distinct hospitals visited by patients of group i . Equation (8) says that the sum of fixed effects φ_{it} is zero, where φ_{it} is counted as many times as it appears in the data, i.e., as many times as there are distinct hospitals receiving patients from patient group i at year t . As these restrictions are conventional, the utilities u_{jt} are identified only up to year-specific constants C_t in each diagnosis category.

It turns out that for the four years 2005 to 2008 and the eight diagnosis categories under consideration, all hospitals and all patient groups in the sample are connected.²¹ This means for any year t , any observation (i, j) and (i', j') can be indirectly connected through a sequence of edges within the bipartite graph. [Jochmans and Weidner \(2019\)](#) relate the statistical precision of the estimator of the u_{jt} to the connectivity structure of the graph. In online appendix [B.1](#), we

²¹To be precise, this statement is true up to four exceptions, namely four isolated observations among the 3.6 million observations. These observations are such that at a given year a hospital receives patients from a single postal code, while patients from that location visit only the considered hospital. We neglect these four isolated components in what follows. The connected components of the graph are provided by the `Stata`® procedure `felsdvreg` which uses the above normalization restrictions by default.

show that the graph is strongly locally connected. For instance, in orthopedics, 90% of hospitals are connected to more than 37 patient groups.

4 Supply

In this section, we present a static competition-in-utility framework à la [Armstrong and Vickers \(2001\)](#), and we explain how to bring it to the data.

4.1 Competition in utility space

We assume that the objective functions of the hospitals depend on their revenue, their number of admissions and the utility they offer to patients:

$$V_j(q_j, u_j; r_j) = \bar{T}_j + r_j q_j + \beta_j^q q_j + \beta_j^{qu} q_j u_j. \quad (9)$$

The first two terms in (9) represent the revenue of hospital j , made of a lump-sum transfer \bar{T}_j and activity-based revenues, $r_j q_j$.²² Hospital costs are accounted for in the last two terms of (9); we assume constant returns to scale (CRS) as in [Armstrong and Vickers \(2001\)](#). Such costs can be pecuniary and non-pecuniary. As [Pope \(1989\)](#) noticed, hospitals may increase their “perceived quality” by spending a *per-admission* amount on services, personnel, and facilities. To provide a higher utility to each patient, a hospital must devote more resource per patient, e.g., increase the ratio of staff per patient ([Hackmann, 2019](#); [Eliason, 2017](#)).²³ Also, it may be possible to raise the utility per patient while keeping the staff constant, by having the existing staff exert more effort per patient. Extra effort from staff can require to pay overtime hours and/or translate into non-pecuniary costs for the hospital management. In any case, total effort, defined as effort per patient multiplied by the number of patients, should enter the objective of the hospital manager. The objective (9) also encompasses non-pecuniary motives such as altruism or managerial empire building. Altruism would be described by a utility term $a q_j u_j$, with $a > 0$, where $q_j u_j$ is the total utility offered to patients.²⁴ Empire-building would be described by a term $v q_j$, with $v > 0$.²⁵ In the absence

²²We assume away revenue effects and normalize the marginal utility of revenue to 1. In practice, as explained in section 2, the payment reform was designed so that the hospitals’ budgets remain approximately unchanged during the phase-in period.

²³The quality of variable inputs, such as food, may also be increased.

²⁴This specification expresses that hospitals value patients’ surplus net of transportation costs as in [Brekke, Siciliani, and Straume \(2011\)](#).

²⁵Non-financial motives are necessary to rationalize positive numbers of admissions in the absence of activity-based reimbursement, i.e., at periods when $r_j = 0$.

of cost data, however, we cannot identify the level of marginal costs separately from the importance of non-financial motives.

Hospital j chooses the utility it offers to patients so as to maximize

$$\max_{u_j} V_j(q_j(u_j, u_{-j}), u_j; r_j), \quad (10)$$

where $q_j(u_j, u_{-j})$ denotes its demand function. We show in the online appendix C that at the solution of the problem, the derivative of the demand addressed to the hospital is equal to the marginal rate of substitution between q and u :

$$\frac{\partial q_j(u_j; u_{-j})}{\partial u_j} = -\frac{\partial V_j / \partial u_j}{\partial V_j / \partial q_j} = -\frac{\beta_j^{qu} q_j}{r_j + \beta_j^q + \beta_j^{qu} u_j}. \quad (11)$$

Introducing the own semi-elasticity $\eta_{jj} = \partial \ln q_j / \partial u_j$, we can write the first-order condition of the hospitals' maximization problem as

$$r_j + \beta_j^q + \beta_j^{qu} u_j = -\frac{\beta_j^{qu}}{\eta_{jj}}. \quad (12)$$

Below, we empirically check that the second-order condition of the maximization problem holds. In a general study on comparative statics under imperfect competition, Dixit (1986) provides sufficient conditions for the stability of an equilibrium. The simplest set of sufficient conditions is obtained by requiring strict diagonal dominance for the Jacobian matrix of the maximization problem (see details in the online appendix C), which we also check empirically.

Transmission of financial incentives A higher reimbursement rate r_j reduces the marginal rate of substitution between q_j and u_j (the right-hand side of (11)) and hence increases the offered utility u_j —the competitors' utilities being fixed. To express the pass-through of reimbursement rate into the utility provided to patients, we introduce the transmission rates

$$\tau_j = \left. \frac{\partial u_j}{\partial r_j} \right|_{u_{-j}} = - \left(\beta_j^{qu} \left[2 - \frac{q_j \partial^2 q_j / \partial u_j^2}{(\partial q_j / \partial u_j)^2} \right] \right)^{-1}. \quad (13)$$

In the online appendix C, we show that the transmission rates are positive if and only if the second-order conditions hold (both properties hold empirically).

Reaction functions The above first-order conditions define hospital j 's best response to its competitors' utilities u_{-j} . In the online appendix C, we derive the expression for the slopes of the reaction functions:

$$\rho_{jk} = \left. \frac{\partial u_j}{\partial u_k} \right|_{r_j} = \frac{q_j(\partial^2 q^j / \partial u_j \partial u_k) - (\partial q^j / \partial u_j)(\partial q^j / \partial u_k)}{2(\partial q^j / \partial u_j)^2 - q_j(\partial^2 q^j / \partial u_j^2)}. \quad (14)$$

The slope ρ_{jk} measures how hospital j changes the utility u_j it provides to patients if competitor k changes u_k . Many forces govern the nature of strategic interactions. Of particular importance is the fact that a higher utility implies a higher variable cost, $\beta_j^{qu} < 0$. If hospital k offers more utility, then hospital j 's activity decreases due to business stealing, and as a result producing utility becomes less costly for hospital j , which therefore reacts by raising its own utility. This force thus pushes toward strategic complementarity. Our specification, however, does not impose complementarity as other forces are at play, see the online appendix for details.

Equilibrium effect of incentives The transmission rates τ_j computed in (13) express the hypothetical responses of each hospital to a change in financial incentives if all its competitors kept their strategy fixed. Yet following a change of incentives, strategic interactions lead all hospitals to change their strategies, and accordingly the whole equilibrium configuration is modified.

To derive how the utilities provided by the hospitals are shifted in equilibrium, we introduce the following matrices: the diagonal matrix τ whose (j, j) -entry is the transmission rate τ_j defined in (13); the matrix ρ whose generic entry is ρ_{jk} , with $\rho_{jj} = 0$ by convention; the Leontief matrix $L = (I - \rho)^{-1}$. We then rearrange (C.2) as

$$du = L \tau dr. \quad (15)$$

The Leontief matrix L summarizes how the direct effects of incentives propagate through the whole set of strategic interactions to yield a new equilibrium outcome. The generic element of L , l_{jk} , expresses the extent to which the direct effect of a change in hospital k 's incentives, namely $\tau_k dr_k$, affects the utility offered by hospital j in equilibrium: $du_j = \sum_k l_{jk} \tau_k dr_k$.

4.2 Identification and estimation

We assume that the preferences of the hospitals are stable (up to industry-wide trends for each major diagnosis category) over our four-year period of interest. To account for unobserved characteristics (technology, organization, patient case-mix,

etc.), we place maximal heterogeneity in the parameter β^q that governs the linear dependence of preference with the number of admissions. We specify it as the sum of a hospital-diagnosis fixed-effect $\bar{\beta}_j^q$ and of an unobserved supply shock ω_{jt} :

$$\beta_{jt}^q = \bar{\beta}_j^q + \omega_{jt}. \quad (16)$$

We thus allow for unconstrained differences in perceived marginal costs across hospitals.²⁶ We are not able, however, to allow for heterogeneity in the second-derivative of the objective function with respect to q_j and u_j , the parameter β_j^{qu} . We assume that, for each diagnosis category, β^{qu} remains constant over the four-year period and is common to all hospitals: $\beta_{jt}^{qu} = \bar{\beta}^{qu}$.²⁷

Identification in our setup is demanding for two reasons. First, while only a single supply-side parameter for each firm (its marginal cost) is unknown in most price competition models, we need here to identify two coefficients of the objective functions, namely the coefficients of q_j and $q_j u_j$ in (9), which can be thought of as the intercept and the slope of the hospital's marginal cost. Second, contrary to the recent literature about quality competition (e.g., [Hackmann, 2019](#); [Eliason, 2017](#)), we do not rely on observable quality indicators. We identify the utilities provided by hospitals only up to constants C_t that depend on the year and the diagnosis category (see section 3.2).

For any year and diagnosis category, hospitals maximize their objective, knowing the demand addressed to them. Taking the first-order condition (12) at year t and using it with the above specification, in particular equation (16), adding constants C_t to account for aggregate shocks, and rearranging, we obtain

$$u_{jt} + \frac{1}{\eta_{jjt}} = -C_t - \frac{\bar{\beta}_j^q}{\bar{\beta}^{qu}} - \frac{r_{jt}}{\bar{\beta}^{qu}} - \frac{\omega_{jt}}{\bar{\beta}^{qu}}, \quad (17)$$

which yields our estimating supply equation:

$$u_{jt} + \frac{q_{jt}}{\partial q_{jt} / \partial u_{jt}} = a_t + a_j + a_r r_{jt} + \omega'_{jt}, \quad (18)$$

where the coefficient $a_r \equiv -1/\bar{\beta}^{qu}$ permits to recover $\bar{\beta}^{qu}$, $a_j \equiv -\bar{\beta}_j^q/\bar{\beta}^{qu}$ and

²⁶As observed by [Gaynor and Vogt \(2003\)](#), [Lakdawalla and Philipson \(2006\)](#), [Gowrisankaran, Nevo, and Town \(2015\)](#), the differences in objective functions of for-profit and nonprofit hospitals may be represented by different perceived marginal costs.

²⁷We investigated alternative specifications in which the coefficient $\bar{\beta}^{qu}$ depends on hospital characteristics (private status, size and teaching activity), but this observed heterogeneity turns out to be significant in only two diagnosis categories.

$a_t \equiv -C_t$ are hospital- and year- fixed-effects that provide us with estimates of $\bar{\beta}_j^q$ and C_t , while $\omega'_{jt} \equiv -\omega_{jt}/\bar{\beta}^{qu}$ is an error term related to the unobserved supply shock ω_{jt} . This equation relies on the utilities estimated previously, making hence a link between demand and supply. Interestingly, it further reduces, in turn, the degree of underidentification of these utilities (see below).

The identification of the coefficient $\bar{\beta}^{qu}$ proceeds from the policy reform, namely the variation in the reimbursement rates of nonprofit hospitals at the right-hand side of (17). As explained in Appendix A.3, we do not observe all the corrections applied by the regulator to the theoretical formulae (1) and (2), so we observe the hospital reimbursement rates with error. Moreover, these rates have been aggregated at the diagnosis category level, which may give rise to endogenous composition effects, recall Footnote 16. For these reasons, we instrument the average rates r_{jt} by the phase-in coefficients $\text{NP}_j \lambda_t$ applied to the nonprofit sector, recall (2).

The constants C_t in equation (17), which are specific to each diagnosis category, may represent either aggregate demand shocks or aggregate supply shocks. The theoretical utility levels appearing in (12) are identified only up to additive constants that depend on the year and the diagnosis. The constants C_t and the linear coefficients $\bar{\beta}_j^q$ are identified up to additive, diagnosis category-specific constants C' .²⁸ We allow for the presence of demand-side and supply-side aggregate shocks, which we cannot identify separately.

Because β_{jt}^{qu} and the semi-elasticities η_{jjt} are identified, the sum

$$r_{jt} + \beta_j^q + \beta_{jt}^{qu}(u_{jt} + C_t) = -\frac{\beta_{jt}^{qu}}{\eta_{jjt}} \quad (19)$$

is identified. It follows that the transmission rates τ_{jt} and the slopes of reaction functions ρ_{jkt} given by (13) and (14), which involve utility levels u_{jt} only through the left-hand side of (19), are identified.

Because the utilities u_{jt} appear linearly at the left-hand side of equation (18), any estimation error is absorbed into the unobserved idiosyncratic shock ω_{jt} . The computation of the derivatives $\partial q_{jt}/\partial u_{jt}$ that appear at the left-hand side does not use the estimated utilities but only observed market shares, the estimated correlation $\hat{\sigma}$ and the approximated parameter $\hat{\theta}$ ruling potential demand. The estimation of the supply equation (18) proceeds from a linear IV regression with a single endogenous variable, time dummies, and hospital fixed effects. This

²⁸Increasing C_t by C' and decreasing $\bar{\beta}_j^q$ by $\bar{\beta}^{qu} C'$ leave $-(C_t + \bar{\beta}_j^q/\bar{\beta}^{qu})$ unchanged in (17).

approach avoids numerical issues arising from nonlinear estimation and enables us to recover hospitals’ preferences in a robust and transparent manner. In particular, we check in Section 5.5 that the coefficient of interest $a_r = -1/\bar{\beta}^{qu}$ in the supply equation is robust to alternative models of hospital choice, patient grouping strategies, sizes of potential demand, and ways to account for case-mix variations over the period.

5 Results

5.1 Demand

Tables 8 and 9 show the estimation results for our baseline specification. For all diagnosis categories, the parameters are very precisely estimated. Most of the variance in local market shares is captured by our two-way high-dimensional fixed-effects. The tests for excluded instruments have high F -stats in the first-stage equation.

For all diagnoses but ophthalmology, we reject the simple logit model at usual levels.²⁹ The signs of estimated parameters remain quite identical from one diagnosis category to another, though there is significant heterogeneity in magnitudes. We find empirical evidence of preference for being admitted to the closest hospital as well as diminishing marginal travel costs. Besides, travel costs decrease with income and are higher in more crowded areas as well as for women and elders, for all considered diagnosis categories. Richer patient locations exhibit a preference in favor of for-profit hospitals, regardless of the diagnosis category. Except for orthopedics, older patients prefer nonprofit hospitals or are indifferent. Areas with more educated people favor nonprofit hospitals for orthopedic and ophthalmologic surgery and have no preference as far as other diagnosis categories are concerned.

Table 10 shows the distributions of the estimated utilities \hat{u}_{jt} , for the potential demand determined in section B.2. Depending on the diagnosis category, the range of estimated utilities lies somewhere between -3.6 and 3.4, the standard deviations are comprised between .3 and .9, and the interquartile ranges vary from .5 to 1.1. To get a sense of the dispersion of utilities, we express utility differences in terms of travel time to hospitals.³⁰ To this aim, we increase all the utilities u_{jt} by .1 and

²⁹The null hypotheses of the parameter σ being zero is rejected at 5%, with the correlation σ ranging between .1 and .2 for all other diagnosis categories.

³⁰Monetary conversions would require heroic assumptions as most hospital expenditures are covered by basic and supplementary health insurance.

compute the reduction in travel times that would generate the same patient surplus gain.³¹ As shown in Table 11, a general utility rise of .1 corresponds to a reduction in travel time of between 10.8% and 15.3% depending on the diagnosis. As the median travel time is 22 minutes, this corresponds to hospitals being virtually closer to patients by 2 to 3 minutes. Hence, the dispersion indicators reported in Table 10 show a substantial degree of heterogeneity across hospitals in the utilities they provide to patients.

Table 12 shows that the estimated utilities evolve in a similar manner as the observed number of admissions. Utilities increase more rapidly in nonprofit hospitals than in for-profit ones (column 1).³² The differential remains with almost unchanged parameters when we control also for staff, equipment and socio-demographic variables (see the coefficients of nonprofit \times year in column 3). The last two columns, however, are to be taken with caution as the explanatory variables related to staff and equipment may be endogenous.

Table 13 shows our approximation of potential demand. For the median postal code, the market size represents between .6% and 2.5% of the population, depending on the diagnosis category. The potential number of admissions is not much larger than the maximal number of admissions observed over the years 2005-2008, by between .7% and 12.4% depending on the diagnosis category.

5.2 Supply

Table 14 shows the estimation results associated with equation (17). For all but one of the eight diagnosis categories, we do not reject $\bar{\beta}^{qu} = -1/a_r < 0$ at usual levels, which is consistent with the notion that providing a higher utility to each patient entails a higher marginal cost.³³

The incentives of hospital j to attract an additional patient, $\partial V_j / \partial q_j = r_j + \beta_j^q + \beta_j^{qu} u_j$, consist of a part due to activity-based revenues (increasing earnings by r_j euros) and a remaining part $\beta_j^q + \beta_j^{qu} u_j$ that incorporates costs and non-pecuniary motives. Table 15 shows the share of activity-based incentives in marginal incentives, $r_j / (r_j + \beta_j^q + \beta_j^{qu} u_j)$, for the median non-profit and for-profit hospitals in 2008. Our results suggest that this share does not exceed 10% in the non-profit sector for most diagnosis categories. That the primary motivation of nonprofit

³¹Details are available upon request.

³²Table 7 shows that the number of nurses, surgeons, anesthesiologists and nonmedical staff per bed has increased more rapidly in nonprofit hospitals than in for-profit ones.

³³The exception is ophthalmology. We use the Delta method to test the statistical significance of $\bar{\beta}^{qu}$.

hospitals to treat patients is not to pocket the corresponding reimbursement rate may not surprise health care practitioners.³⁴

Figure 2 plots the distribution of the estimated transmission rates τ_j , computed from (13) and multiplied by 1,000 for readability. All these rates are positive. Recall that a transmission rate is positive if and only if the corresponding second-order condition of the hospital program (10) holds true. Our model, therefore, is not rejected by the data. Following a positive shock of €1,000 on reimbursement rates r_{jt} , the median hospital raises its utility by .02 in nephrology or in orthopedics, but by up to .12 in dermatology, which is equivalent to reducing the median distance to patients by 3-4%, and 24% respectively (recall Table 11 on how to convert utilities into travel times). Table 16 shows that, among nonprofit hospitals, private hospitals are more responsive to financial incentives than state-owned hospitals, which is consistent with Duggan (2000).

The estimated slopes ρ_{jk} of hospitals' reaction functions are positive for almost all pairs of hospitals (j, k) , all diagnosis categories and all years in the period of study. This holds for nearly 95% of ordered pairs of hospitals, the pairs (j, k) being weighted by $\sum_i q_{ij} q_{ik}$ to reflect how strongly connected the hospitals are. We therefore conclude that strategic complementarity occurs in most interactions. Table 17 reports the distribution of $\bar{\rho}_j = \max_k \rho_{jk}$, the highest slope of the reaction functions for each hospital j with respect to all of its competitors k . For roughly half of the observations (j, t) , hospital j faces at least one competitor k for which ρ_{jkt} is higher than .07 at time t . The strategic interactions are thus fairly strong, with highest values being close to .2, which compares well to usual results found in the spatial price competition literature (Conley and Topa, 2002; Pinkse, Slade, and Brett, 2002; Conley and Dupor, 2003).

Table 18 shows that the slopes of reaction functions ρ_{jk} decrease with the distance d_{jk} between hospital j and k . It confirms that distance has a strong, depressing effect on the slopes of reaction functions: ρ_{jk} decreases with time for values of d_{jk} being less than 150. At the exception of gastroenterology, the slope of the reaction function tends to be higher when the two hospitals are both for-profit or both nonprofit, suggesting that intra-sector competition is generally fiercer than inter-sector competition.

Finally, we check that, for each diagnosis category and year, the Jacobian matrix defined in the online appendix exhibits strict diagonal dominance, which

³⁴We find significant heterogeneity in the linear coefficients β_j^q of the hospital objectives. Details are available upon request.

guarantees the stability of the equilibrium as explained above.³⁵

5.3 Breaking down the evolution of activity

We implement a series of thought experiments that allow to break down the observed changes from 2005 to 2008 along different channels: financial incentives, demand shocks, supply shocks, strategic effects. For each diagnosis category, we start with the environment that prevailed in 2005 (demand and supply conditions and reimbursement rates) and successively replace certain parameters with their values in 2008. Specifically, we simulate the following counterfactual situations:

- (a) The reimbursement rates change from r_{2005} to r_{2008} .³⁶ We compute the Nash equilibrium that prevails after the change, thus assessing the total effect of incentives as in equation (15);
- (b) We implement the same change in rates as above, shutting down strategic effects. The response of each hospital separately, given the strategy of the competitors, yields the transmission rate (13);
- (c) The industry is hit by the (demand- or supply-side) aggregate shock $\hat{C}_{2008} - \hat{C}_{2005}$ mentioned in section 4.2. We compute the Nash equilibrium that would prevail, otherwise keeping the environment of 2005 unchanged;
- (d) All the components of the patient choice problem, namely the choice set and the variables $\hat{\phi}_t$ (demand shocks and demographic variables) change from their 2005 values to their 2008 values;
- (e) The patient choice problem changes as above and additionally the aggregate shock $\hat{C}_{2008} - \hat{C}_{2005}$ hits the industry, i.e., (c) and (d) are combined;
- (f) We account for all changes but hospital-specific shocks, i.e., we combine (a), (c) and (d);
- (g) The linear coefficients $\hat{\beta}_j^g$ in the hospital objective functions are hit by the supply shocks $\hat{\omega}_{j,2008}$ instead of $\hat{\omega}_{j,2005}$;

³⁵We also check that, for each g and t , the matrices $\rho = (\rho_{jk})_{j,k}$ have a spectral radius that is less than 1, which guarantees the invertibility of $I - \rho$, hence the existence of the Leontief matrix defined in Section 4.1.

³⁶In this section, we take the average reimbursement rate observed in 2008, r_{2008} , which is based on the observed case-mix in 2008, see equation (3).

Numerically, we follow the approach proposed by [Bonnet and Dubois \(2010\)](#): we minimize the sum of squares of the (adequately modified) first-order conditions. The procedure yields a minimum value of zero in all the simulations presented below. In all the variants we run, we obtain excellent numerical results, with rapid convergence to observed and counterfactual equilibria.

Table 19 reports the results of simulations (a) to (g) in orthopedics, the largest diagnosis category. (For the other diagnoses, see Tables D.1 to D.7 in Appendix D.) Column 1 reports the shift, in pp, in the aggregate market share of the nonprofit sector. The next columns report the percentage variation of activity: total activity at the industry level (column 2), in the nonprofit and for-profit sectors separately (columns 3 and 4); median increase in activity at the hospital level for nonprofit and for-profit hospitals (columns 5 and 6).

The change in financial incentives (line (a)) explains a fairly large part of the observed shift in activity from the for-profit sector to the nonprofit sector (column 1). Remember that the observed change in the aggregate market share of nonprofit hospitals ranges from +.7pp to +5pp depending on the diagnosis category. The predicted change, under the demand and supply conditions that prevailed in 2005, ranges from +.9pp to +4pp. In orthopedics, the predicted change in the market share of the nonprofit sector (+1.05pp) accounts for 89% of the observed change (+1.18pp). In general, the predicted change accounts for at least 45% of the observed change (circulatory), and sometimes for more than 100% of the observed change (107% in gastroenterology and 125% in ophthalmology).

By contrast, the change in financial incentives does not explain much of the observed evolution of activity at the industry level (column 2). Depending on the diagnosis category, the observed change in the total number of surgery admissions ranges from -2.4% to +9.9%, while the change due to pure financial incentives (at the exception of dermatology) ranges from +.2% to +1%. While financial incentives predict a reasonable part of the rise in the activity of nonprofit hospitals (between 22% and 120%), they account for a limited part of activity variations in the for-profit sector. In sum, the stronger financial incentives in the nonprofit sector have caused activity to shift away from the for-profit sector to the nonprofit sector, but had only a modest effect on the total number of surgery admissions.

For all diagnosis categories, the hospital-specific supply shocks $\hat{\omega}_{jt}$ explain almost nothing of the observed variations in hospital activity (simulation (g)). Those variations are very well explained by the changes in financial incentives, the hospital-specific demand shocks $\hat{\phi}_t$ and the aggregate shocks \hat{C}_t , as simula-

tion (f) shows.³⁷

Finally, to assess the magnitude of strategic effects, we compare simulations (a) and (b). In simulation (b), we neutralize the strategic responses of rivals by considering hospital j 's behavior when the utilities provided by all other rivals are fixed.³⁸ We find that the total number of patients and the aggregate market share of for-profit hospitals decline more in case (b) than in case (a). While strategic effects have an ambiguous impact on the activity of for-profit hospitals,³⁹ they always push utilities and hence total activity upwards. For instance, activity in gastroenterology would increase by 1.02% in equilibrium instead of .81% if strategic effects are ignored. In general, we find that strategic effects are of modest magnitude.

5.4 The impact of the reform on hospitals and patients

We now evaluate how the policy reform has affected the industry. We use the structural model to determine the causal effect of the increased financial incentives. The counterfactual experiment (a) changes the reimbursement rates from r_{2005} to $4r_{2005}$ in the nonprofit sector while maintaining the rates in the for-profit sector as well as the demand and supply conditions that prevailed in 2005.⁴⁰

Table 20 documents the impact of the reform on volumes and market shares. Consistent with the above findings, the effect on the total number of surgery admissions would have been modest, ranging from .3% to 2.4% depending of the diagnosis category, which represents a few thousands patients. The aggregate market share of the nonprofit sector would have increased by between 1.1pp and 4.3pp according to the diagnosis category. To illustrate, in orthopedics, activity would increase by 3% (17,000 patients) in nonprofit hospitals but would decrease by 1.7% (13,000 patients) in for-profit hospitals: on the whole, only .3% patients more would undergo surgery. To measure the extent of business stealing, we compute the number of patients who would switch from nonprofit to for-profit hospitals if the number of admissions was maintained constant in each patient group: we find that about 15,000 patients would be diverted in orthopedics.

³⁷Taken separately, the aggregate shocks \hat{C}_t and the local demand shocks $\hat{\phi}_t$ do not explain much of the variation in activity (simulations (c) and (d)), but taken together they do better (simulation (e)).

³⁸Here, we do not compute a Nash equilibrium, but rather solve J single-dimensional optimization problems.

³⁹Contrast column 3, lines (a) and (b), of Tables 19 and D.3.

⁴⁰We check in Section 5.5 that accounting or not for case-mix variations in the computation of the counterfactual rate does not change the estimated effect on activity, market shares, patients' surplus and hospitals' objectives.

Table 21 depicts how the utilities provided by the hospitals and the expected surplus of the patients are affected by the reform. At the counterfactual equilibrium, all nonprofit hospitals raise the offered utility in response to the stronger financial incentives. The median increase in utility response lies between .052 and .141 depending on the diagnosis category, which amounts to making hospitals closer to patients by between 1 and 4 minutes. For-profit hospitals face unchanged reimbursement rates. Yet they react in equilibrium to the change in their competitors' strategy; specifically, they respond by raising the utility offered to patients. The median utility increase ranges from .003 to .012 in the for-profit sector. The difference in the order of magnitude of the response with the nonprofit sector is consistent with the slopes of the reaction functions being positive and of the order of .07-.08 (recall Table 17).

To appreciate the impact of the reform on patient welfare, we compute at the postal code level the percentage variation in the distances to hospitals that would have the same effect as the reform on the expected patient surplus. The simulated reform has the same effect as if the distances to hospitals were reduced by some factor in every postal code, the median of which is 10.6% in gastroenterology for instance. This median equivalent reduction is highest in dermatology (15%) and lowest in ophthalmology (2.7%), suggesting respectively large and small gains for patients with these diagnoses. The patient gains are highly dispersed across postal codes, with the last decile being about three times higher than the median.

Importantly, we now quantify the supplementary effort incurred by hospitals. Table 22 presents the effects of the reform on their revenues and objective functions. Activity-based revenues have been multiplied by slightly more than four, which is due to the slight increase in volumes caused by the stronger incentives. Recall, however, that at the same time the government lowered lump-sum transfers so as to make the reform approximately budget-neutral for nonprofit hospitals. As a result, the net effect of the reform for these hospitals stems from the non-revenue part of the objective function, namely $\beta_j^q q_j + \beta_j^{qu} q_j u_j$ (recall equation (9)), which encompasses all pecuniary and non-pecuniary costs incurred by hospitals. Considering all nonprofit hospitals together, this part of their objective has fallen by between -9.3% and -1.9% depending on the considered diagnosis category (column 7). Since that non-revenue part is several times larger than the revenue part (Table 15), the change is actually very substantial, with a magnitude roughly equal to 25% of annual activity-based revenues in the post-reform regime, i.e., all of 2005 activity-based revenues (recall equation (2)). For instance, in the ENT-stomatology department, it represents €98m, hence slightly more than

2005 activity-based revenues (€79m). Put differently, the order of magnitude of the effort is a quarter of the annual activity-based revenues after the reform has been phased in. This result is remarkably stable across the eight major diagnosis categories.

In sum, the reform induced a slight increase in the number of hospitalizations and an increase in the expected surplus of hospitalized patients. On the other hand, nonprofit hospitals have been placed under strong competitive pressure, and had to incur an additional effort equivalent to the quarter of their (post-reform) activity-based revenues.

5.5 Robustness checks

Below we run a number of variants of the model. We obtain excellent numerical results, with rapid convergence to counterfactual equilibria. The estimated effort incurred by nonprofit hospitals hardly varies across variants.

Grouping patients by age brackets In Appendix E.1, we check that refining patient groups by separating patients below and above 65 affects neither estimation nor simulation results. As far as orthopedics is concerned, the coefficient of the financial incentives in the supply equation, a_r , is .030(0.008), to be compared with .026 (.009) in the baseline model (see Table 14). The non-revenue part of the objective of nonprofit hospitals decreases by 2.1%, very similar to the 1.9% fall in the baseline specification. The respective roles of incentives, demand and supply shocks reported in Table E.1 are similar to those reported in Table 19.

Size of patient groups In Appendix E.2, we redo the whole exercise for orthopedics by keeping large groups only, specifically groups with more than the median number of patient admissions (17 admissions). This selection leads to exclude less than 10% of the admissions, as Table E.2 shows. As these groups are associated with urban areas, this selection limits measurement errors on travel time. Comparing Tables 14 and E.3 shows that the estimation of the supply equation is very robust. In this variant, the non-revenue part of the objective of nonprofit hospitals decreases by 2.5%.

Alternative nesting structures Our baseline demand specification features three nests based on the legal status of the hospitals. In Appendix E.3, we consider two alternative nested logit models that differ in the treatment of private

nonprofit hospitals (recall Footnote 12). We consider three nests based on ownership status (state-owned hospitals, private hospitals, outside good) and four nests (nonprofit private hospitals, for-profit private hospitals, state-owned hospitals and the outside option). These two demand models are not rejected by the data, and the corresponding supply-side estimation results (Tables E.5 and E.7), as well as the counterfactual simulations (Tables E.6 and E.8) are close to those obtained in the baseline model. In terms of both fit and counterfactuals, the simulated Nash equilibria lead to very similar policy conclusions as our baseline model. For instance, in the three nests specification, the non-revenue part of the objective of nonprofit hospitals decreases by 1.8%.

Size and specification of potential demand Our preferred results rely on the approximation method exposed in Section B.2. The results vary very little with the parameter θ that governs the market size in (B.4). Table E.9 in Appendix E.4 shows that the supply-side results are very robust: halving or doubling $\hat{\theta}$ affects neither β^{qu} nor β^q . The fit of our model, especially the activity change caused by financial incentives, is also very robust to different choices of market size (see Table E.10); the variation in the non-revenue part of the objective of nonprofit hospitals remains almost unchanged at -1.9%. Even in the extreme case where the potential demand would consist of the whole population in the postal code (while our estimates suggest its order of magnitude is only 1% of that population), we would still find that financial incentives do not increase admissions by much, at the exception of gastroenterology, and that the non-revenue part of the objective of nonprofit hospitals decreases, though by only -0.5%.

Tables E.11 and E.12 show further that the results are not affected when the size of potential demand is specified as the arithmetic mean $M_i = \theta \text{pop}_i + (1 - \theta)q_i$ instead of the geometric mean $\log(M_i) = \theta \log(\text{pop}_i) + (1 - \theta) \log(q_i)$. In this variant, the non-revenue part of the objective of nonprofit hospitals decreases by 1.8%.

Case-mix variations with major diagnosis categories In Appendix E.5, we examine the role played by case-mix variations (i.e., changes in the composition of hospitals' activity) in assessing the effect of stronger incentives. We concentrate on the counterfactual experiment (a) of section 5.3 in which we change financial incentives, and maintain the demand and supply conditions that prevailed in 2005. In section 5.3, the reimbursement rates are computed on the basis of the observed case-mix in 2008 while in section 5.4, the computation is based on the observed

case-mix in 2005. We check by comparing Tables 20 and E.13, Tables 21 and E.14 as well as Tables 22 and E.15 that the definition of counterfactual reimbursement rates does not change results by much. In this variant, the non-revenue part of the objective of nonprofit hospitals decreases by 1.7%.

6 Concluding remarks

Within only a couple of years, the *tarification à l'activité* (T2A) has deeply transformed the funding mechanism of French nonprofit hospitals, forcing them to earn revenue from their realized activity and making the whole industry more competitive. Anecdotal evidence, a never-ending public debate, and recurrent complaints from health care professionals suggest increased managerial pressure, fatigue among hospital staff at all levels, and poor social acceptability of the reform.⁴¹

The structural econometric approach developed in this article allows to quantify the extra effort that nonprofit hospitals incurred to adjust to the new regulatory environment. For surgical treatments, our estimates suggest that these extra costs are equivalent to about a quarter of a full-year activity-based revenue. This order of magnitude is remarkably stable across the eight major diagnosis categories considered in this study. Although our data does not allow to pinpoint the induced costs within nonprofit hospitals, the quantification exercise shows that nonprofit hospitals had to incur a substantial amount of additional costs, be they pecuniary or not. The funding reform was expected to maintain the revenues of nonprofit hospitals constant and was not supposed to cover these extra costs. More research and policy discussion is needed to determine whether and how extra effort caused by increased financial pressure should be compensated.

Our analysis also sheds lights on the supposedly “inflationary” impact of T2A. In support of the “activity race” scenario, Pommiers (2018) refers *Le Monde* readers to the Ministry of Health documenting that the number of surgery admissions has increased in the nonprofit sector *more rapidly than* in the for-profit sector after the former has been exposed to the new payment rule (Choné, Evain, Wilner, and Yilmaz, 2014). A difference-in-differences analysis, however, is not enough to distinguish business stealing from market expansion. Our counterfactual simulations show that nonprofit hospitals have responded to the stronger financial incentives by attracting patients who otherwise would have been admitted in for-profit hos-

⁴¹The public health crisis caused by the coronavirus disease has only exacerbated complaints and critics against hospital competition and T2A.

pitals. In other words, we find no empirical support for a market expansion effect caused by T2A.

Finally, we mention a couple of avenues for further research. First, on the methodological front, a natural extension would be to account for observed and endogenous product characteristics. Due to data limitations, we cannot observe out-of-pocket expenses incurred by patients, waiting times, or clinical quality indicators such as risk-adjusted complication or mortality rates. We have therefore subsumed all product characteristics into a one-dimensional utility index, and specified the providers' objectives as functions of that index and of an output variable, namely the number of patient admissions. It would be interesting to extend the method to environments where the researcher does observe certain attributes such as prices or quality indicators, while other important characteristics chosen by the providers remain unobserved. The extended method would require estimating a set of first-order conditions for the observed and unobserved characteristics, rather than a single one as we have done here. Provided that enough exogenous instruments are available, the method should allow to identify consumer and provider preferences for observed and unobserved product characteristics.

Second, given the relatively short time frame of the study, we have assumed myopic hospital behavior and have not modeled long-term strategies such as investment, entry, product repositioning, specialization.⁴² In particular, we have assumed that the marginal preferences of hospitals for attracting patients are stable over the four-year period. With longer observation periods, it would be interesting to explore whether the effect of the stronger financial incentives can be identified separately from changes in the objectives of the hospitals.

References

ABOWD, J. M., R. H. CREECY, AND F. KRAMARZ (2002): "Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data," Cornell University Working Paper.

ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): "High wage workers and high wage firms," *Econometrica*, 67(2), 251–333.

⁴²Dafny (2005), who studied the effect of changes in diagnosis-specific prices, found no convincing evidence that hospitals increased admissions differentially, suggesting a "relative lack of specialization in the hospital industry". Over our four-year period of interest, we have checked that case-mix variations are of a second order of magnitude compared to the massive, across-the-board rise in the financial incentives caused by the T2A.

- ACEMOGLU, D., AND A. FINKELSTEIN (2008): “Input and technology choices in regulated industries: Evidence from the health care sector,” *The Journal of Political Economy*, 116(5), 837–880.
- ARMSTRONG, M., AND J. VICKERS (2001): “Competitive Price Discrimination,” *The RAND Journal of Economics*, 32(4), 579–605.
- BARRETTE, E., G. GOWRISANKARAN, AND R. TOWN (2020): “Countervailing Market Power and Hospital Competition,” Discussion paper, National Bureau of Economic Research.
- BERRY, S. (1994): “Estimating Discrete-Choice Models of Product Differentiation,” *The RAND Journal of Economics*, 25(2), 242–262.
- BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): “Automobile Prices in Market Equilibrium,” *Econometrica*, 63(4), 841–890.
- BJÖRNERSTEDT, J., AND F. VERBOVEN (2016): “Does merger simulation work? Evidence from the Swedish analgesics market,” *American Economic Journal: Applied Economics*, 8(3), 125–64.
- BOISSIER, P. (2012): “[L’Hôpital](#),” Inspection générale des affaires sociales, Rapport remis au Président de la République, au Parlement et au Gouvernement.
- BONNET, C., AND P. DUBOIS (2010): “Inference on Vertical Contracts between Manufacturers and Retailers Allowing for Non Linear Pricing and Resale Price Maintenance,” *The RAND Journal of Economics*, 41(1), 139–164.
- BREKKE, K. R., L. SICILIANI, AND O. R. STRAUME (2011): “Hospital Competition and Quality with Regulated Prices,” *Scandinavian Journal of Economics*, 113(2), 444–469.
- CHONÉ, P., F. EVAÏN, L. WILNER, AND E. YILMAZ (2014): “[Réforme du financement des hôpitaux publics : quel impact sur leur niveau d’activité?](#),” Insee Analyses 15.
- CONLEY, T. G., AND B. DUPOR (2003): “A Spatial Analysis of Sectoral Complementarity,” *The Journal of Political Economy*, 111(2), 311–352.
- CONLEY, T. G., AND G. TOPA (2002): “Socio-Economic Distance and Spatial Patterns in Unemployment,” *Journal of Applied Econometrics*, 17(4), 303–327.

- COUR DES COMPTES (2009): “Chapitre VII.- La mise en oeuvre de la T2A : bilan à mi-parcours,” in *Rapport sur la Sécurité Sociale*.
- CUTLER, D. M. (1995): “The Incidence of Adverse Medical Outcomes under Prospective Payment,” *Econometrica*, 63(1), 29–50.
- DAFNY, L. S. (2005): “How Do Hospitals Respond to Price Changes?,” *The American Economic Review*, 95(5), 1525–1547.
- DIXIT, A. (1986): “Comparative Statics for Oligopoly,” *International Economic Review*, 27(1), 107–122.
- DUBOIS, P., AND L. LASIO (2018): “Identifying Industry Margins with Unobserved Price Constraints: Structural Estimation on Pharmaceuticals,” *The American Economic Review*, 108(12), 3685–3724.
- DUGGAN, M. (2002): “Hospital market structure and the behavior of not-for-profit hospitals,” *The RAND Journal of Economics*, 33(3), 433–446.
- DUGGAN, M. G. (2000): “Hospital ownership and public medical spending,” *The Quarterly Journal of Economics*, 115(4), 1343–1373.
- ELIASON, P. (2017): “Market Power and Quality: Congestion and Spatial Competition in the Dialysis Industry,” Working Paper.
- FINKELSTEIN, A., M. GENTZKOW, AND H. WILLIAMS (2016): “Sources of geographic variation in health care: Evidence from patient migration,” *The Quarterly Journal of Economics*, 131(4), 1681–1726.
- GARMON, C. (2017): “The accuracy of hospital merger screening methods,” *The RAND Journal of Economics*, 48(4), 1068–1102.
- GAYNOR, M., C. PROPPER, AND S. SEILER (2016): “Free to choose? Reform, choice, and consideration sets in the English National Health Service,” *The American Economic Review*, 106(11), 3521–57.
- GAYNOR, M., AND W. VOGT (2003): “Competition among hospitals,” *The RAND Journal of Economics*, 34(4), 764.
- GOWRISANKARAN, G., K. A. JOINER, AND J. LIN (2019): “How Do Hospitals Respond to Payment Incentives?,” Discussion paper, National Bureau of Economic Research.

- GOWRISANKARAN, G., C. LUCARELLI, P. SCHMIDT-DENGLER, AND R. TOWN (2011): “The Impact of the Medicare Rural Hospital Flexibility Program on Patient Choice,” *International Journal of Industrial Organization*, 29(3), 342–344.
- (2018): “Can amputation save the hospital? The impact of the Medicare Rural Flexibility Program on demand and welfare,” *Journal of Health Economics*, 58, 110–122.
- GOWRISANKARAN, G., A. NEVO, AND R. TOWN (2015): “Mergers when prices are negotiated: Evidence from the hospital industry,” *The American Economic Review*, 105(1), 172–203.
- HACKMANN, M. B. (2019): “Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home Industry,” *The American Economic Review*, 109(5), 1684–1716.
- HO, K. (2006): “The Welfare Effects of Restricted Hospital Choice in the US Medical Care Market,” *Journal of Applied Econometrics*, 21(7), 1039–1079.
- HO, K., AND R. S. LEE (2017): “Insurer competition in health care markets,” *Econometrica*, 85(2), 379–417.
- HO, K., AND A. PAKES (2014): “Hospital Choices, Hospital Prices, and Financial Incentives to Physicians,” *The American Economic Review*, 104(12), 3841–3884.
- HUANG, D., AND C. ROJAS (2014): “Eliminating the outside good bias in logit models of demand with aggregate data,” *Review of Marketing Science*, 12(1), 1–36.
- HUANG, D., C. ROJAS, ET AL. (2013): “The Outside Good Bias in Logit Models of Demand with Aggregate Data,” *Economics Bulletin*, 33(1), 198–206.
- HUBERT, J., AND F. MARTINEAU (2015): “[Mission Groupements Hospitaliers de Territoire: Rapport intermédiaire](#),” Ministère des affaires sociales, de la santé et des droits des femmes.
- JOCHMANS, K., AND M. WEIDNER (2019): “Fixed-Effect Regressions on Network Data,” *Econometrica*, 87(5), 1543–1560.
- LAFFONT, J.-J., AND J. TIROLE (1993): *A theory of incentives in procurement and regulation*. MIT press.

- LAKDAWALLA, D., AND T. PHILIPSON (2006): “The nonprofit sector and industry performance,” *Journal of Public Economics*, 90(8-9), 1681–1698.
- MILLER, K. S., A. PETRIN, R. TOWN, AND M. CHERNEW (2019): “Optimal Managed Competition Subsidies,” Discussion paper, National Bureau of Economic Research.
- NEVO, A. (2000): “Mergers with Differentiated Products: The Case of the Ready-to-Eat Cereal Industry,” *The RAND Journal of Economics*, 31(3), 395–421.
- NEWMAN, M. E. (2010): *Networks: An introduction*. Oxford University Press.
- PETERS, C. (2006): “Evaluating the performance of merger simulation: Evidence from the US airline industry,” *The Journal of Law and Economics*, 49(2), 627–649.
- PINKSE, J., M. E. SLADE, AND C. BRETT (2002): “Spatial price competition: A semiparametric approach,” *Econometrica*, 70(3), 1111–1153.
- POMMIERS, E. (2018): “[Qu’est-ce que la T2A, qui cristallise les tensions à l’hôpital ?](#),” *Le Monde*, [English title: “What is the activity-based payment system that crystallizes tensions in hospitals?”].
- POPE, G. C. (1989): “Hospital nonprice competition and Medicare reimbursement policy,” *Journal of Health Economics*, 8, 147–172.
- RAVAL, D., AND T. ROSENBAUM (forthcoming): “Why is Distance Important for Hospital Choice? Separating Home Bias from Transport Costs,” *Journal of Industrial Economics*.
- RAVAL, D., T. ROSENBAUM, AND S. A. TENN (2017): “A semiparametric discrete choice model: An application to hospital mergers,” *Economic Inquiry*, 55(4), 1919–1944.
- SHLEIFER, A. (1985): “A theory of yardstick competition,” *The RAND journal of Economics*, pp. 319–327.
- STARC, A., AND R. J. TOWN (2020): “Externalities and benefit design in health insurance,” *The Review of Economic Studies*.
- TAY, A. (2003): “Assessing Competition in Hospital Care Markets: The Importance of Accounting for Quality Differentiation,” *The RAND Journal of Economics*, 34(4), 786–814.

VERAN, O. (2017): “L'évolution des modes de financement des établissements de santé: Une nouvelle échelle de valeur,” Report for the Minister of Health.

VERBOVEN, F. (1996): “International price discrimination in the European car market,” *The RAND Journal of Economics*, 27(2), 240–268.

Glossary of notations

D	diagnosis-related group (DRG)
g	major diagnosis category
i	patient group
j	hospital
n	nest
t	year
z	postal code
a	coefficients of the supply equation
C, C'	degrees of underidentification of u
d	travel time
H	hospitalization (full set of hospitals)
J	# of hospitals
L	Leontief matrix depicting strategic interactions among hospitals
M	market size (potential demand)
q	activity
q_i	$\max_t q_{it}$
q_{it}	$\sum_j q_{ijt}$
r	reimbursement rate
s	market share
T	# of years
\bar{T}	hospitals' revenues fixed-part (lump-sum transfer)
u	utility provided by hospitals to patients (diagnosis category-hospital-year FE)
u_{-j}	$J - 1$ vector of utilities provided by hospital j 's competitors
U	patients' indirect utility
V	hospitals' objective function
X	socio-demographic covariates (demand equation)
Y^0	"true" Y
\mathbf{Y}	vector Y
\tilde{Y}	counterfactual Y
\hat{Y}	estimated Y
\bar{Y}	average Y
Z^D	demand-side instruments
Z^S	supply-side instruments

α	patients' preferences (travel costs)
β	hospitals' preferences (β^q and β^{qu})
$\bar{\beta}$	average hospitals' tastes (net of supply shocks)
δ	mean indirect utility level <i>à la</i> Berry (1994)
Δ	$\frac{\sigma}{1-\sigma}$
ε	idiosyncratic patient-hospital shock
η	semi-elasticity of demand wrt utility offered
γ	taste parameter for nonprofit sector
λ	phase-in coefficient (NP sector)
ζ	idiosyncratic patient-nest shock
ω	unobserved supply shock
φ	diagnosis category-year-patient group FE
ϕ	set of demand characteristics including (φ, ξ, X)
ψ	unobserved patient heterogeneity
ρ	slope of reaction functions
σ	intra-group correlation
τ	transmission rate
θ	parameter governing approximated size of potential demand
ξ	unobserved demand shock at the hospital-patient group level
\emptyset	outside option
FP	for-profit sector
NP	nonprofit sector
Closest	patient group's closest hospital
major diagnosis category	aggregation of DRGs
<i>département</i>	administrative division of France
pop_i	# of inhabitants of patient group i 's area of residence
TC	travel cost

Tables

Table 1: Sample selection

	Initial sample	Local hospitals	Coming from home	Non-missing covariates
# of admissions in surgery	21,153,485	21,145,692	20,919,275	20,268,637
# of hospitals	1,565	1,374	1,365	1,324
	Travel time < 150 minutes	Hospital size	Postal code sociodemographics	Balanced panel (final sample)
# of admissions in surgery	19,858,335	19,253,024	18,604,353	17,945,047
# of hospitals	1,313	1,050	1,050	942

Source. French PMSI, 2005-2008, individual data, surgery inpatient and outpatient admissions.

Note. Initial sample: raw data, 8 major diagnosis categories only

Local hospitals: focusing on non-local hospitals only

Coming from home: admissions of patients coming from home only

Non-missing covariates: postal code and travel time to hospital available in the data

Travel time < 150 minutes: focusing on travel time lower than 150 minutes

Hospital size: positive # of surgical beds from 2004 to 2008

Postal code sociodemographics: positive # of inhabitants, median income, share of elder, of high-school graduates and of women from 2005 to 2008

Balanced panel: at least one patient every year from 2005 to 2008 at the diagnosis category-hospital level

Table 2: Travel time

	mean	s.d.	min	p10	p25	median	p75	p90	max	# of obs.
All diagnosis categories and years	26.7	25.4	0	0	9.5	21.5	36.5	58	149.5	3,576,566
Orthopedics	28	26.3	0	0	10	22.5	38	61.5	149.5	795,638
ENT, Stomato.	29.2	27.4	0	0	9	20.5	34	51	149.5	466,121
Ophthalmology	29.2	27.4	0	0	10	23.5	40.5	60.5	149.5	440,989
Gastroenterology	22.9	22.6	0	0	7.5	18.5	31.5	48.5	149.5	447,437
Gynaecology	28.9	26.9	0	0	10.5	23	40	64	149.5	430,943
Dermatology	24.2	24.1	0	0	8	19	33	53	149.5	354,033
Nephrology	25.9	24.7	0	0	9	21	36	56.5	149.5	332,805
Circulatory syst.	28.9	26.9	0	0	11	23.5	40	62	149.5	308,600

Source. French PMSI, individual data, 2005-2008.

Sample. 942 hospitals in mainland France.

Note. Observations at the diagnosis category \times hospital \times year \times postal code level.

Weights: discharges q_{gijt} .

Travel time: in minutes.

Table 3: Surgery services in France: Summary statistics at the sector level

		Nonprofit hospitals			For-profit hospitals	All hospitals
		State-owned	Private	Total		
# of hospitals		353	70	423	519	942
admissions (millions)	2005	1.46	0.189	1.65	2.76	4.41
	2006	1.51	0.193	1.70	2.81	4.5
	2007	1.53	0.196	1.73	2.77	4.49
	2008	1.59	0.204	1.79	2.74	4.54
market share (%)	2005	33.1	4.3	37.4	62.6	100
	2006	33.4	4.3	37.7	62.3	100
	2007	34.1	4.4	38.4	61.6	100
	2008	35.0	4.5	39.5	60.5	100

Source. French PMSI, individual data, 2005-2008.

Sample. 942 hospitals in mainland France with at least one admission every year in a diagnosis category.

Table 4: Estimated hospitals' activity-based revenues (in 2005 €bn)

	2005	2006	2007	2008
Nonprofit hospitals	1.27	1.79	2.59	5.05
For-profit hospitals	2.85	2.86	2.86	2.79

Source. French PMSI, individual data.

Sample. 942 hospitals of the final sample shown on Table 1.

The revenues take the geographic adjustment for the Paris region into account.

Surgery inpatient and outpatient admissions.

Table 5: Hospitals' reimbursement rates (in 2005 €)

	2005	2006	2007	2008
Nonprofit hospitals	770	1,053	1,501	2,817
For-profit hospitals	1,032	1,021	1,033	1,018
Nonprofit hospitals ($t - 1$)	.	1,045	1,479	2,786
For-profit hospitals ($t - 1$)	.	1,010	1,015	1,012

Note. Average reimbursement rates r_{gjt} .

Source. French PMSI, individual data.

Sample. 942 hospitals in mainland France.

Bottom panel computed with $t - 1$ case-mix.

Table 6: Activity: reduced-form evidence

Dependent variable	# of stays q_{gjt}			
	(1)	(2)	(3)	(4)
For-profit \times 2006	11.38*** (3.23)			
For-profit \times 2007	1.27 (4.17)			
For-profit \times 2008	-4.69 (6.26)			
Nonprofit \times 2006	15.62*** (1.93)	5.01 (3.71)		5.45 (3.64)
Nonprofit \times 2007	24.47*** (2.68)	24.15*** (4.89)		23.62*** (4.65)
Nonprofit \times 2008	45.06*** (3.69)	51.15*** (7.18)		51.09*** (6.53)
Beds			0.91* (0.51)	1.12** (0.51)
Beds ² /1000			-1.21*** (0.39)	-1.23*** (0.38)
Nurses			0.12* (0.06)	0.08 (0.06)
Surgeons			2.32*** (0.72)	1.68*** (0.60)
Anesthesiologists			-0.22 (1.46)	-0.21 (1.21)
Staff			-0.04 (0.04)	-0.04 (0.04)
MRI			-14.95 (13.89)	-17.99 (13.61)
Scanner			-2.84 (3.70)	-2.34 (3.68)
Population density			0.01 (0.04)	0.02 (0.04)
Income			-0.00 (0.00)	0.00 (0.00)
Diagnosis category-year effects	No	Yes	Yes	Yes
Diagnosis category-hospital effects	Yes	Yes	Yes	Yes
Observations	28,136	28,136	28,136	28,136
R^2	0.942	0.965	0.965	0.965

Observations at the diagnosis category \times hospital \times year level.

Robust standard errors clustered at the hospital level.

Population density and income measured at the *département* level.

Table 7: Medical and non-medical staff per bed: reduced-form evidence

Dependent variable	Nurses per bed	Surgeons per bed	Anesthesiologists per bed	Adm. staff per bed
Nonprofit \times 2006	0.006** (0.003)	0.195*** (0.056)	0.002 (0.002)	0.031 (0.065)
Nonprofit \times 2007	0.019*** (0.004)	0.556*** (0.166)	0.006*** (0.002)	0.282** (0.138)
Nonprofit \times 2008	0.030*** (0.005)	0.870*** (0.162)	0.010*** (0.003)	0.529*** (0.157)
Population density	-0.000** (0.000)	-0.001* (0.001)	-0.000 (0.000)	-0.001** (0.000)
Income	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Diagnosis category-year effects	Yes	Yes	Yes	Yes
Diagnosis category-hospital effects	Yes	Yes	Yes	Yes
Observations	28,136	28,136	28,136	28,136
R^2	0.927	0.933	0.928	0.876

Observations at the diagnosis category \times hospital \times year level.

Robust standard errors clustered at the hospital level.

Population density and income measured at the *département* level.

Table 8: Demand

Major diagnosis category g	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
Travel cost (α)								
Closest hospital (α_0)	0.124*** (0.014)	0.155*** (0.014)	0.250*** (0.014)	0.161*** (0.012)	0.217*** (0.013)	0.137*** (0.013)	0.154*** (0.013)	0.178*** (0.011)
Time (α_1)	0.168*** (0.021)	0.231*** (0.022)	0.146*** (0.018)	0.236*** (0.016)	0.336*** (0.018)	0.304*** (0.022)	0.307*** (0.019)	0.411*** (0.013)
Time ² × 100 (α_2)	-2.171*** (0.080)	-2.428*** (0.098)	-2.486*** (0.083)	-2.331*** (0.076)	-3.187*** (0.089)	-2.306*** (0.091)	-2.973*** (0.104)	-2.703*** (0.070)
Time × High school (α_{1hs})	-0.015 (0.019)	-0.019 (0.019)	-0.029* (0.015)	-0.042*** (0.014)	-0.093*** (0.016)	-0.072*** (0.016)	-0.047*** (0.016)	-0.081*** (0.013)
Time × Elder (α_{1e})	0.197*** (0.021)	0.199*** (0.020)	0.211*** (0.018)	0.171*** (0.016)	0.233*** (0.018)	0.206*** (0.022)	0.161*** (0.020)	0.198*** (0.013)
Time × 10 ³ Income (α_{1i})	-0.006*** (0.001)	-0.006*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.005*** (0.001)	-0.003*** (0.001)
Time × 10 ⁵ Population (α_{1p})	0.085*** (0.006)	0.072*** (0.005)	0.068*** (0.004)	0.081*** (0.005)	0.057*** (0.004)	0.066*** (0.005)	0.066*** (0.005)	0.046*** (0.004)
Time × Women (α_{1w})	0.566*** (0.039)	0.543*** (0.044)	0.660*** (0.043)	0.519*** (0.032)	0.583*** (0.035)	0.429*** (0.041)	0.648*** (0.043)	0.377*** (0.023)
Preference for nonprofit hospitals (γ)								
Nonprofit × High school (γ_{hs})	-0.098 (0.100)	0.140 (0.104)	-0.005 (0.091)	0.152 (0.117)	0.082 (0.080)	0.466** (0.212)	-0.030 (0.101)	0.154** (0.071)
Nonprofit × Elder (γ_e)	0.149* (0.088)	0.113 (0.088)	0.134 (0.091)	0.269*** (0.104)	0.091 (0.075)	0.169* (0.097)	0.629*** (0.094)	-0.105* (0.060)
Nonprofit × 10 ³ Income (γ_i)	-0.015*** (0.005)	-0.011** (0.005)	-0.022*** (0.004)	-0.021*** (0.004)	-0.017*** (0.004)	-0.044*** (0.006)	-0.035*** (0.005)	-0.016*** (0.003)
Nonprofit × Women (γ_w)	-0.714*** (0.203)	0.314 (0.235)	0.251 (0.203)	0.569*** (0.204)	0.844*** (0.156)	-0.182 (0.275)	-0.241 (0.220)	-0.021 (0.158)
σ	0.131*** (0.018)	0.171*** (0.022)	0.176*** (0.018)	0.108*** (0.019)	0.154*** (0.016)	0.159*** (0.022)	0.137*** (0.023)	0.206*** (0.016)
# of hospital-year effects	3,516	3,412	3,720	3,560	3,608	3,088	3,552	3,680
# of postal code-year effects	100,696	105,431	103,643	108,983	115,949	115,190	114,286	121,243
# of connected components (mobility groups)	5	5	4	4	4	5	5	4
Observations	308,600	332,805	354,033	430,943	447,437	440,989	466,121	795,638

Source: French PMSI, individual data.

Robust standard errors clustered at the hospital level

First stage: see Table 9

Note. Covariates interacted with Nonprofit (second panel) are centered.

For the sake of readability, "time" is divided by 10.

Legend. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (in all subsequent estimation tables as well).

Table 9: Demand - First-stage equation

Dependent variable	$\log s_{ijt/n}$							
	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
# of hospitals (nest)	-0.211*** (-9.96)	-0.258*** (-10.44)	-0.226*** (-12.78)	-0.250*** (-14.58)	-0.392*** (-18.00)	-0.309*** (-11.74)	-0.222*** (-11.67)	-0.293*** (-18.26)
# of teaching hosp. (nest)	0.018 (0.67)	0.014 (0.58)	0.045** (2.42)	0.096*** (4.66)	0.206*** (10.00)	0.102* (1.72)	-0.001 (-0.04)	0.057*** (2.98)
# of nonprofit hosp. (nest)	-0.156*** (-11.78)	-0.120*** (-8.46)	-0.107*** (-8.76)	-0.136*** (-11.04)	-0.127*** (-9.76)	-0.246*** (-11.05)	-0.139*** (-8.80)	-0.116*** (-11.59)
# of nonprofit hosp. (nest) × High school	0.155*** (4.20)	-0.009 (-0.27)	0.034 (1.62)	-0.038* (-1.74)	-0.086*** (-4.37)	-0.003 (-0.07)	0.016 (0.53)	0.012 (1.07)
# of nonprofit hosp. (nest) × Elder	-0.171*** (-2.78)	-0.209*** (-3.47)	-0.158*** (-4.11)	-0.231*** (-6.76)	0.032 (0.91)	-0.263*** (-3.58)	-0.209*** (-4.24)	-0.111*** (-4.59)
# of nonprofit hosp. (nest) × (10 ³) Income	-0.008*** (-6.80)	-0.002* (-1.89)	-0.004*** (-5.78)	0.000 (0.06)	-0.001** (-2.21)	-0.003** (-2.05)	-0.001 (-1.08)	-0.002*** (-5.42)
# of nonprofit hosp. (nest) × Women	1.072*** (8.47)	0.475*** (3.46)	0.509*** (5.65)	0.411*** (5.58)	-0.140* (-1.86)	0.395*** (3.27)	0.593*** (5.79)	0.091** (2.07)
∑ size (nest)	-0.000*** (-7.84)	-0.000*** (-8.46)	-0.000*** (-10.33)	-0.000*** (-6.90)	-0.000*** (-6.70)	-0.000*** (-4.38)	-0.000*** (-8.14)	-0.000*** (-8.69)
∑ time (nest)	-0.127*** (-11.63)	-0.042*** (-3.06)	-0.107*** (-11.15)	-0.075*** (-8.60)	-0.041*** (-4.47)	-0.021 (-1.63)	-0.064*** (-4.97)	-0.009 (-1.44)
∑ time ² (nest)	-0.214*** (-7.21)	-0.357*** (-9.75)	-0.296*** (-12.66)	-0.283*** (-13.01)	-0.539*** (-21.24)	-0.298*** (-9.06)	-0.264*** (-9.41)	-0.334*** (-18.25)
∑ time to teaching hosp. (nest)	0.012*** (2.72)	0.011*** (3.16)	0.008*** (2.83)	-0.002 (-0.81)	-0.014*** (-4.63)	-0.009 (-1.16)	0.012*** (3.76)	0.003 (1.31)
∑ time to nonprofit hosp. (nest)	0.013*** (6.12)	0.011*** (4.85)	0.007*** (3.75)	0.013*** (7.47)	0.011*** (6.05)	0.028*** (6.93)	0.012*** (5.07)	0.009*** (7.81)
∑ time (nest) × High school	0.055*** (7.88)	0.070*** (8.63)	0.037*** (6.09)	0.045*** (7.47)	0.044*** (7.03)	0.034*** (4.91)	0.033*** (4.90)	0.007** (2.41)
∑ time (nest) × Elder	-0.106*** (-12.85)	-0.108*** (-10.52)	-0.084*** (-11.67)	-0.070*** (-10.81)	-0.068*** (-8.54)	-0.050*** (-7.03)	-0.084*** (-12.75)	-0.041*** (-10.94)
∑ time (nest) × (10 ³) Income	-0.001** (-2.37)	-0.001*** (-4.21)	-0.000* (-1.72)	-0.001*** (-3.14)	-0.000 (-0.58)	0.000 (0.75)	0.000 (0.53)	0.000*** (2.86)
∑ time (nest) × (10 ⁵) Population	0.005*** (3.80)	0.002** (2.11)	-0.000 (-0.03)	0.003*** (3.74)	-0.000 (-0.19)	0.003** (2.41)	0.002* (1.90)	0.001** (2.22)
∑ time (nest) × Women	0.326*** (15.88)	0.211*** (8.51)	0.313*** (17.02)	0.244*** (15.73)	0.256*** (14.50)	0.137*** (6.33)	0.218*** (9.81)	0.143*** (14.46)
Closest (nest) × High school	-0.010*** (-3.22)	-0.010*** (-3.03)	-0.010*** (-3.75)	-0.013*** (-4.78)	-0.008*** (-3.07)	-0.009** (-2.52)	-0.009*** (-3.22)	-0.002 (-0.86)
Closest (nest) × Elder	-0.002 (-0.71)	0.002 (0.56)	-0.002 (-0.72)	-0.003 (-1.04)	-0.007** (-2.28)	-0.009** (-2.49)	-0.001 (-0.18)	-0.006** (-2.35)
Closest (nest) × (10 ³) Income	0.000 (0.85)	0.000 (0.34)	0.001*** (3.18)	0.000* (1.80)	0.000* (1.75)	0.000 (1.00)	0.000 (0.80)	0.000* (1.81)
Closest (nest) × (10 ⁵) Population	0.007*** (4.55)	0.004** (2.51)	0.002* (1.86)	-0.000 (-0.24)	0.001 (0.80)	-0.002 (-1.10)	0.003*** (2.90)	-0.000 (-0.33)
Closest (nest) × Women	-0.027*** (-4.13)	-0.036*** (-5.40)	-0.023*** (-3.45)	-0.037*** (-6.02)	-0.021*** (-3.53)	-0.032*** (-5.50)	-0.027*** (-4.56)	-0.032*** (-6.75)
# of hospital-year effects	3,516	3,412	3,720	3,560	3,608	3,088	3,552	3,680
# of postal code-year effects	100,696	105,431	103,643	108,983	115,949	115,190	114,286	121,243
# of connected components (mobility groups)	5	5	4	4	4	5	5	4
Observations	308,600	332,805	354,033	430,943	447,437	440,989	466,121	795,638
R ²	0.852	0.856	0.872	0.851	0.845	0.814	0.843	0.829
F-test excluded instruments	998.6	895.2	1,016	1,493.9	1,524.4	1,158.2	1,094.8	2,176.1

Source. French PMSI, individual data.

Note. Estimates of excluded instruments only are reported here (other estimates are available upon request).

t-statistics issued from robust standard errors clustered at the hospital level.

For the sake of readability, "time" is divided by 10.

Closest (nest): closest hospital k for hospital j within a nest of either for-profit or nonprofit hospitals.

Table 10: Estimated utilities

	mean	s.d.	min	p25	median	p75	max	# of obs.
Circulatory syst.	0.50	0.58	-3.56	0.15	0.54	0.92	1.80	3,516
(weighted)	0.95	0.40	-3.56	0.71	0.99	1.24	1.80	3,516
Nephrology	0.98	0.60	-2.70	0.62	1.07	1.41	2.59	3,412
(weighted)	1.44	0.36	-2.70	1.23	1.49	1.71	2.59	3,412
Dermatology	0.51	0.39	-2.40	0.29	0.52	0.76	1.79	3,720
(weighted)	0.74	0.34	-2.40	0.50	0.74	0.98	1.79	3,720
Gynaecology	0.65	0.52	-2.71	0.33	0.66	1.01	2.01	3,560
(weighted)	1.08	0.42	-2.71	0.78	1.12	1.41	2.01	3,560
Gastroenterology	1.77	0.50	-2.75	1.55	1.84	2.09	2.90	3,608
(weighted)	2.05	0.35	-2.75	1.82	2.06	2.30	2.90	3,608
Ophthalmology	1.27	0.87	-3.04	0.78	1.42	1.87	3.31	3,088
(weighted)	1.94	0.55	-3.04	1.58	1.96	2.31	3.31	3,088
ENT, Stomato.	1.28	0.67	-2.25	0.94	1.40	1.74	2.86	3,552
(weighted)	1.76	0.43	-2.25	1.49	1.79	2.05	2.86	3,552
Orthopedics	1.95	0.58	-3.49	1.71	2.01	2.30	3.36	3,680
(weighted)	2.33	0.42	-3.49	2.04	2.32	2.63	3.36	3,680

Note. Figures correspond to estimated utilities \hat{u}_{gjt} .
Weights: admissions q_{gjt} .

Table 11: Percentage reduction in travel times equivalent to increasing utility levels by .1

	mean	s.d.	min	p25	median	p75	max	# of postal codes
Circulatory syst.	19.8	15.9	4.6	11.1	14.3	20.4	100.0	24,842
Nephrology	18.9	14.1	4.4	10.4	13.9	20.8	92.6	26,119
Dermatology	20.1	13.4	5.1	11.7	15.3	23.0	100.0	27,248
Gynaecology	17.0	12.6	5.2	10.1	12.7	17.5	100.0	25,963
Gastroenterology	16.9	13.8	4.0	8.6	11.7	18.2	81.3	28,914
Ophthalmology	16.4	13.6	3.8	8.9	11.8	17.4	100.0	28,507
ENT, Stomato.	15.9	13.3	4.1	8.4	11.0	16.7	91.5	28,612
Orthopedics	14.4	10.7	3.7	8.3	10.8	15.9	79.1	30,309

Note. Time compression factors (in %) obtained in 2005 counterfactuals where all hospitals offer $u+0.1$ instead of u .

Table 12: Estimated utilities: reduced-form evidence

Dependent variable	$\hat{u}_{gjt} \times 10^3$		
	(1)	(2)	(3)
Nonprofit \times 2006	28.58*** (6.57)		29.53*** (6.59)
Nonprofit \times 2007	54.21*** (8.22)		55.37*** (8.23)
Nonprofit \times 2008	79.39*** (9.41)		81.07*** (9.32)
Beds		0.41 (0.57)	0.75 (0.58)
Beds ² /1000		-0.45 (0.43)	-0.50 (0.44)
Nurses		0.13*** (0.05)	0.08* (0.04)
Surgeons		1.79** (0.76)	0.78 (0.57)
Anesthesiologists		0.76 (1.25)	0.85 (0.97)
Staff		-0.04 (0.02)	-0.03 (0.03)
MRI		-5.30 (9.76)	-10.15 (9.39)
Scanner		-3.58 (4.96)	-2.38 (4.77)
Population density		0.15*** (0.04)	0.17*** (0.04)
Income		0.01** (0.01)	0.02** (0.01)
Diagnosis category-year effects	Yes	Yes	Yes
Diagnosis category-hospital effects	Yes	Yes	Yes
Observations	28,136	28,136	28,136
R^2	0.955	0.955	0.955

Observations at the diagnosis category \times hospital \times year level.
 Robust standard errors clustered at the hospital level.
 Population density and income measured at the *département* level.

Table 13: Potential demand

Major diagnosis category	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
$\hat{\theta} \times 10^3$	22	11	23	17	4	6	8	2
median maximal # of stays q_i	44	57	56	70	95	102	108	218
median potential demand M_i	49	61	63	76	97	105	112	220
median "mark-up" $100 \frac{M_i - q_i}{q_i}$ (%)	12.4	5.6	12.3	8.5	1.8	2.7	3.6	0.7
median ratio $\frac{M_i}{\text{pop}_i}$ (%)	0.6	0.7	0.7	0.9	1.1	1.2	1.3	2.5
# of observations	29,996	30,186	30,146	30,321	30,430	30,423	30,403	30,464

Source: French PMSI, individual data, 2005-2008.
 Sample: 942 hospitals in mainland France.
 Note: Observations at the postal code level (weighted by population).
 θ is the parameter governing market size: $\log(M_i) = \theta \log(\text{pop}_i) + (1 - \theta) \log(q_i)$.

Table 14: Supply

	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
OLS								
$\tau_{gjt} \times 10^3$	-0.005 (0.016)	0.056 (0.038)	-0.083** (0.032)	-0.046 (0.060)	0.055** (0.024)	0.316* (0.165)	0.007 (0.020)	0.114*** (0.040)
R^2	0.424	0.202	0.454	0.291	0.143	0.509	0.117	0.101
IV								
$\tau_{gjt} \times 10^3$	0.072*** (0.018)	0.028** (0.013)	0.160*** (0.017)	0.058*** (0.011)	0.053*** (0.009)	0.054 (0.039)	0.071*** (0.022)	0.026*** (0.009)
F-test	621.7	1,679.7	1,890.5	8,487.2	3,922.4	3,265.5	709.8	6,999.5
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,516	3,412	3,720	3,560	3,608	3,088	3,552	3,680

Robust standard errors clustered at the hospital level
 Excluded instrument: phase-in step function \times NP
 The supply estimation is based on the estimated potential demand, see Table 13.

Table 15: The share of marginal incentives due to activity-based revenues

	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
NP hospitals	8.2	5.5	23.3	10.8	14.4	7.5	8.1	6.2
# of NP hospitals	406	395	421	404	415	303	400	417

Median ratio $r_j/(r_j + \beta_j^i + \beta_j^i a_j)$ in 2008 (in %).

Lecture. In orthopedics, financial incentives account for 6% of non-profit hospitals' marginal incentives to attract patients.

Note. These shares cannot be compared across legal statuses because activity-based revenues have narrower scope in the FP sector.

Table 16: Transmission rates among nonprofit hospitals

Dependent variable	Transmission rate $\tau_{gjt} \times 10^6$			
	(1)	(2)	(3)	(4)
Private hospital	7.985*** (0.741)	8.044*** (0.749)	6.962*** (0.643)	7.009*** (0.640)
Teaching hospital	6.434*** (0.752)	8.890*** (0.898)	4.596*** (0.424)	6.126*** (0.596)
Size (in 2004)		-0.008*** (0.002)		-0.004*** (0.001)
Diagnosis category-year effects		Yes	Yes	Yes
Regional effects		No	No	Yes
Observations		12,644	12,644	12,644
R^2		0.952	0.953	0.959

Observations from nonprofit hospitals at the diagnosis category \times hospital \times year level.

Robust standard errors clustered at the hospital level.

Table 17: Slopes of reaction functions

	mean	s.d.	p1	p10	p25	median	p75	p90	p99	# of observations
$\hat{\rho}_{gjt} = \max_k \rho_{gjkt}$	0.078	0.054	0.002	0.015	0.036	0.069	0.108	0.149	0.237	28,132
nonprofit j - nonprofit k	0.039	0.038	0.002	0.006	0.012	0.028	0.054	0.086	0.181	12,629
for-profit j - for-profit k	0.058	0.045	0.002	0.011	0.024	0.047	0.083	0.119	0.210	15,489
nonprofit j - for-profit k	0.064	0.053	0.001	0.005	0.022	0.052	0.095	0.138	0.219	12,639
for-profit j - nonprofit k	0.054	0.052	0.001	0.007	0.017	0.036	0.075	0.125	0.230	15,486

All (g, j, t) observations weighted by q_{gjt} , at the exclusion of the four isolated connected components.

Table 18: The effect of distance on slopes of reaction functions

Dependent variable	Slope of reaction function ρ_{gjkt}							
	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
$d_{jk} \times 10^3$	-0.221*** (0.007)	-0.263*** (0.008)	-0.197*** (0.005)	-0.173*** (0.005)	-0.300*** (0.009)	-0.215*** (0.008)	-0.253*** (0.008)	-0.164*** (0.004)
$d_{jk}^2 \times 10^6$	0.758*** (0.030)	0.872*** (0.033)	0.673*** (0.021)	0.542*** (0.020)	1.009*** (0.033)	0.602*** (0.029)	0.836*** (0.028)	0.470*** (0.015)
Intra-sector $_{jk} \times 10^3$	0.475*** (0.063)	0.462*** (0.077)	0.365*** (0.046)	0.272*** (0.049)	-0.139* (0.072)	0.752*** (0.086)	0.335*** (0.064)	0.218*** (0.042)
# of year-hosp. j effects	3,515	3,411	3,720	3,560	3,608	3,087	3,551	3,680
# of year-hosp. k effects	3,515	3,411	3,720	3,560	3,608	3,087	3,551	3,680
Observations	210,118	237,222	332,238	286,348	340,968	212,930	307,602	516,524
R^2	0.276	0.259	0.226	0.250	0.200	0.219	0.209	0.178

Note. Intra-sector $_{jk}$ is defined as $NP_k NP_j + (1 - NP_j)(1 - NP_k)$.

Robust standard errors clustered at the hospital level.

Table 19: Breaking down activity variations: Orthopedics from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	1.18	4.14	7.11	2.03	7.28	-1.24
(a) financial incentives	1.05	0.27	2.80	-1.53	2.44	-1.60
(b) financial incentives (w/o strategic effects)	1.05	0.22	2.74	-1.57	2.35	-1.58
(c) aggregate shocks	0	-0.82	-0.83	-0.81	-0.85	-0.80
(d) hospital-specific demand shocks	0.22	4.49	5.03	4.10	3.53	2.64
(e) aggregate + hospital-specific demand shocks	0.18	3.88	4.32	3.56	2.72	2.01
(f) all but hospital-specific supply shocks	1.23	4.09	7.17	1.90	5.73	0.37
(g) hospital-specific supply shocks	0.29	0.09	0.78	-0.40	1.64	-1.30

These figures are based on the potential demand shown in Table 13.

Table 20: Impact of the reform on volumes and market shares

Diagnosis category	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
# of competing hospitals	879	853	930	890	902	772	888	920
# of admissions - observed (10^3)	239	322	317	419	574	593	632	1,315
# of admissions - counterfactual (10^3)	243	324	325	422	581	595	635	1,319
Change in # of admissions (%)	1.4	0.6	2.4	0.9	1.1	0.4	0.4	0.3
Change in # of admissions (nonprofit, %)	10.1	3.7	13.7	5.1	7.5	4.8	6	3
Change in # of admissions (for-profit, %)	-2.7	-1.4	-4.8	-2.6	-4.8	-1.1	-1.5	-1.7
Nonprofit market share - observed (%)	31.7	38.3	38.9	45.3	48.3	24.9	26.2	41.6
Nonprofit market share - counterfactual (%)	34.4	39.4	43.2	47.2	51.4	26	27.7	42.7
Change in nonprofit market share (points)	2.7	1.2	4.3	1.9	3.1	1.1	1.5	1.1
Change in # of admissions - nonprofit hospitals (10^3)	8	5	17	10	21	7	10	17
Change in # of admissions - for-profit hospitals (10^3)	-4	-3	-9	-6	-14	-5	-7	-13
Admissions switching to nonprofit hospitals (10^3)	6	4	13	8	17	6	9	15

Note. Counterfactual experiment: r_{2005} is multiplied by 4 in the non-profit sector.

Table 21: Impact of the reform on patients

	Median $\tilde{u} - \hat{u}$		# of hospitals		Travel time compression factor		# of postal codes
	NP	FP	NP	FP	median	p90	
	(1)	(2)	(3)	(4)	(5)	(6)	
Circulatory syst.	0.088	0.005	406	473	8.2	25.8	24,842
Nephrology	0.053	0.003	395	458	4.1	14.4	26,119
Dermatology	0.194	0.008	421	509	15.0	39.0	25,963
Gynaecology	0.094	0.004	404	486	6.5	19.1	27,248
Gastroenterology	0.141	0.012	415	487	10.6	31.6	28,914
Ophthalmology	0.066	0.003	303	469	2.7	9.7	28,507
ENT, Stomato.	0.073	0.004	400	488	3.5	12.5	28,612
Orthopedics	0.052	0.003	417	503	2.9	8.2	30,309

Note. Counterfactual experiment: r_{2005} is multiplied by 4 in the non-profit sector.

Columns (5) and (6): in %.

Table 22: Impact of the reform on nonprofit hospitals

	Activity-based revenues	Activity-based revenues	Revenue part	Non-revenue part	# of hospitals
	Observed (€m)	Counterfactual (€m)	Change (%)	Change (%)	
	(1)	(2)	(3)	(4)	
Circulatory syst.	62	284	358	-5.2	406
Nephrology	109	454	316	-1.9	395
Dermatology	64	294	362	-9.3	421
Gynaecology	120	505	322	-3.5	404
Gastroenterology	317	1,379	335	-6.8	415
Ophthalmology	76	318	320	-2.1	303
ENT, Stomato.	79	342	333	-3.0	400
Orthopedics	445	1,836	313	-1.9	417

Note. Counterfactual experiment: r_{2005} is multiplied by 4 in the non-profit sector.

Lecture. In orthopedics, the reform increased by 313% the total activity-based revenues in the non-profit sector.

Lecture. In orthopedics, the reform decreased by 1.9% the non-revenue part $\beta^a q + \beta^{a^u} q_u$ of all non-profit hospitals.

Figures

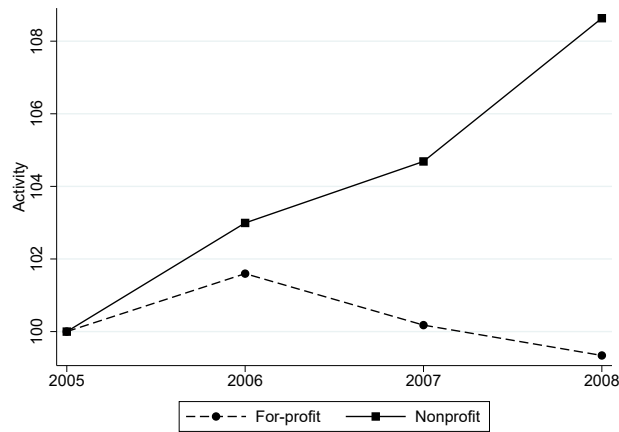


Figure 1: Evolution of the number of surgery admissions in mainland France (by legal status)

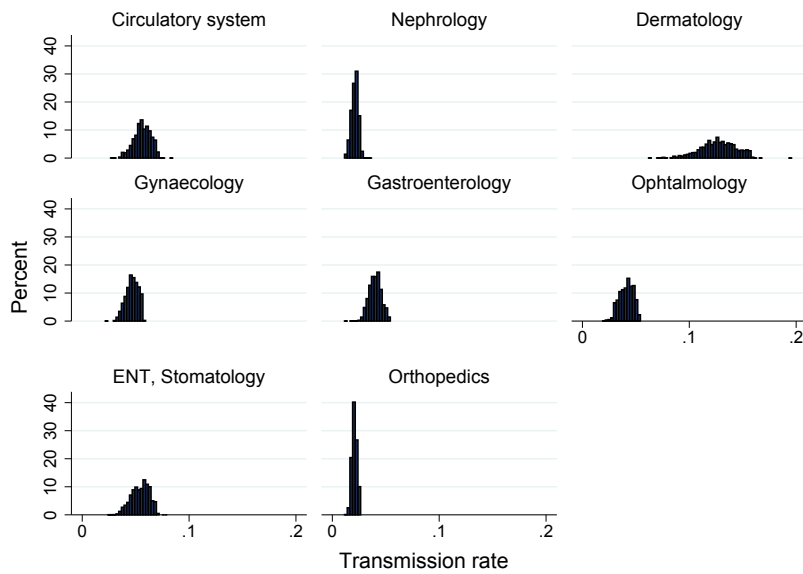


Figure 2: Transmission rates: Distribution of the rise in utility following a €1,000 shock on reimbursement rates

For online publication

A Industry and data details

A.1 Institutional background

According to the French National Health Accounts, 92% of hospital expenditures are funded by the public and mandatory health insurance scheme, 5% by supplementary insurers⁴³, and 3% by patients. These shares have remained stable since 2005. Hospital expenditures in the Health Accounts include physician fees, but do not include extra services such as single room or bed/meal for accompanying person.

Supplementary insurers generally cover the fixed daily fee that hospitals charge for accommodation and meals. However, they may not fully cover extra services (e.g., individual room with television) or extra-billings that doctors may charge. Out-of-pocket expenses have remained stable during our period of study (the years 2005 to 2008), accounting for 3% of total hospital expenditures.

A.2 Data

Hospital status One nonprofit hospital switched from private to state-owned status in 2007.

Sample selection We drop the so-called “local hospitals”, whose surgery activity is very modest. We select patients coming from home because we use the patients’ home postal codes. We remove missing values (travel time or postal codes) and outliers from the data. We discard observations with travel time above 150 minutes because they may correspond to patients who need surgery while on vacation far from their home. We drop hospitals that report no capacity, i.e., no bed, in surgical care when answering to the mandatory SAE survey. We rule out admissions which stem from patients coming from postal codes where some information on population, income, share of elder, high-school graduate or women is missing. We balance our panel at the (diagnosis category-hospital) level in such

⁴³This includes the state-funded supplementary insurance for the poor. Overall, 96% of French households were covered by supplementary health insurance.

a way that an observation is present only if the hospital has admitted at least one patient (regardless of her home location) in the diagnosis category each year from 2005 to 2008.

Activity Table A.1 shows activity at the hospital level. For-profit hospitals have generally more patient admissions per year than nonprofit hospitals (5,285 versus 4,237 in 2008). It is confirmed that the average number of admissions at for-profit hospitals has been fairly stable while it rose at nonprofit hospitals over the phase-in period of the reform (2005-2008).

Table A.1: Summary statistics at the hospital level

# of hospitals	Nonprofit hospitals						For-profit hospitals		All hospitals		
	State-owned		Private		Total						
	353		70		423			519		942	
	year	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
# of stays	2005	4,140	(4,160)	2,695	(1,884)	3,901	(3,912)	5,320	(3,250)	4,683	(3,630)
	2006	4,268	(4,315)	2,752	(1,957)	4,017	(4,059)	5,405	(3,276)	4,782	(3,712)
	2007	4,325	(4,363)	2,844	(2,015)	4,084	(4,108)	5,330	(3,271)	4,770	(3,721)
	2008	4,487	(4,561)	2,956	(2,092)	4,237	(4,292)	5,285	(3,298)	4,815	(3,811)
Size (in 2004)	2005	122	(160)	82	(55)	115	(149)	84	(43)	98	(106)

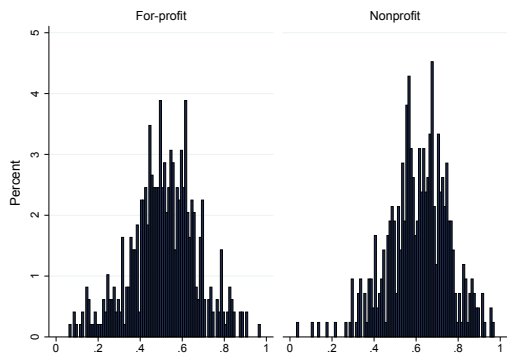
Source. French PMSI, individual data, 2005-2008.

Sample. 942 hospitals in mainland France.

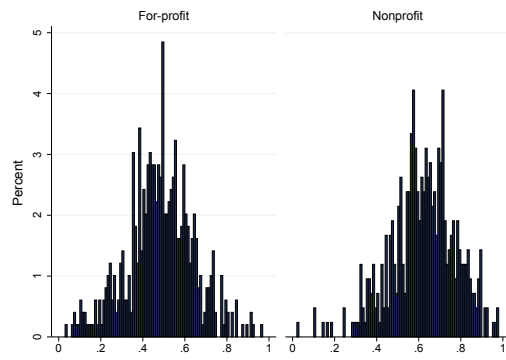
Note. Size is measured as the number of surgical beds in 2004.

Capacity and occupancy rate State-owned hospitals have on average slightly larger bed capacity than for-profit hospitals (115 beds versus 84). The shares of these two categories of hospitals in the total surgery bed capacity are roughly equal at the national level (47% each). The 70 private nonprofit hospitals are on average smaller and account for the remaining 6% of the aggregate bed capacity. There has been little evolution of the number of surgery beds within the period.

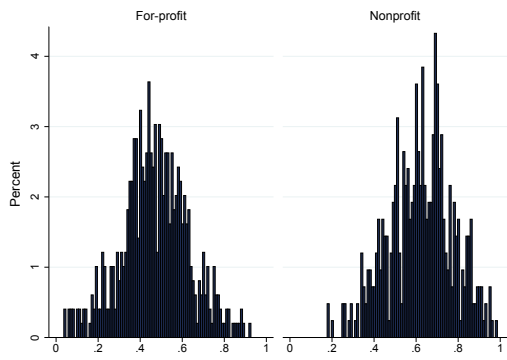
The distributions of annual occupancy rates at the hospital level (ratio of total length of surgery stays over number of available nights) are shown on Figure A.1. The mode of the occupancy rates lies somewhere between 60% and 70%. Occupancy is slightly higher in nonprofit hospitals (between 65% and 80%) than in for-profit hospitals (between 50% and 70%). This result may seem to be at odds with the larger bed capacity and the lower activity of nonprofit hospitals. The apparent paradox is explained by the longer length of stay in those hospitals.



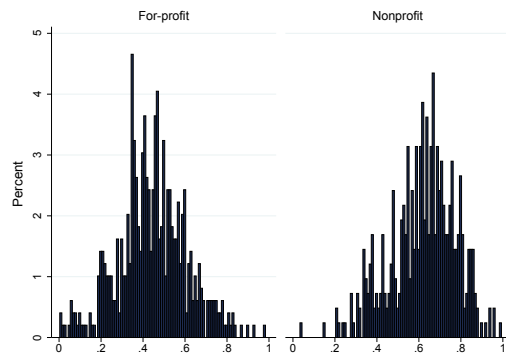
(a) 2005



(b) 2006



(c) 2007



(d) 2008

Figure A.1: Hospitals' occupancy rates

A.3 DRG rates

The DRG-based reimbursement schemes differ in scope across legal statuses. In the nonprofit sector, patient admissions are entirely funded through the prospective system. By contrast, in the for-profit sector, DRG rates do not include physician fees, which are covered separately by the basic and supplementary health insurance systems (with possibly a share incurred by patients).

Source The classification algorithm (v10c version) of DRGs has remained constant over the period of study. We collected rates from the government decrees (*Arrêtés*) published in the *Journal Officiel* and available online at <https://www.atih.sante.fr/prestations-tarifs-et-autres-textes-officiels>. We converted them into delimited format.⁴⁴ Seven different periods are to be considered: as far as nonprofit hospitals are concerned,

1. from 03-01-2005 to 06-30-2005: Circulaire DHOS/F3/F1 no 2005-103 du 23 février 2005
2. from 07-01-2005 to 02-28-2006: Arrêté du 30 juin 2005
3. from 03-01-2006 to 08-31-2006: Arrêté du 5 mars 2006
4. from 09-01-2006 to 02-28-2007: Arrêté du 25 août 2006
5. from 03-01-2007 to 12-31-2007: Arrêté du 27 février 2007
6. from 01-01-2008 to 02-29-2008: Arrêté du 26 décembre 2007
7. from 03-01-2008 to 12-31-2008: Arrêté du 27 février 2008

while in the case of for-profit hospitals:

1. from 03-01-2005 to 06-30-2005: Circulaire DHOS/F3/F1 no 2005-103 du 23 février 2005
2. from 07-01-2005 to 02-28-2006: Arrêté du 30 juin 2005
3. from 03-01-2006 to 08-31-2006: Arrêté du 5 mars 2006
4. from 09-01-2006 to 09-30-2006: Arrêté du 25 août 2006
5. from 10-01-2006 to 02-28-2007: Arrêté du 27 septembre 2006

⁴⁴The Excel data available at <https://www.atih.sante.fr/tarifs-mco-et-had> contain minor typos, some of which are discussed hereafter.

6. from 03-01-2007 to 02-29-2008: Arrêté du 27 février 2007

7. from 03-01-2008 to 12-31-2008: Arrêté du 27 février 2008

Data cleaning We paid attention to typos appearing in the original decrees: for instance, DRG 15Z06C is reimbursed €1,545.66 in all periods but €154.66 in the first period. Also, for the very few DRGs having several rates within the same period, we impute a unique value that corresponds to the average, minimal or maximal rate depending on the trend observed over the seven periods mentioned above. Overall, these corrections apply to a tiny amount of the raw data (less than .7% of DRG-year observations).

Empirically, we observe that the distribution of price changes across DRGs is extremely concentrated; the only exception concerns the move from period 1 to period 2 for which we do not observe any modal price change (the median price change being roughly zero). Table A.2 displays the most frequent price change occurring between two consecutive periods:

Table A.2: Mode of the distribution of price changes at the DRG level

sector	FP	NP
period		
1-2	.	.
2-3	0	0
3-4	-3.1	0
4-5	4.23	0.6
5-6	0	-3.7
6-7	0.5	0.5

Figures: in %.

In the PMSI, we dispose of the year of admission only, hence we have to assume that the admission dates are uniformly distributed over the year.

At the end of this process, we are left with 816 (842) DRGs in the for-profit (nonprofit) sector. Price changes either follow the general evolution shown in Table A.2, or correspond to the one observed in the decrees.

Corrections applied by the regulator As explained in [Cour des Comptes \(2009\)](#), the regulator applied a number of corrections to the theoretical formulae (1) and (2). First, “geographic coefficients”, which have remained fixed during the phase-in period, were applied for the Paris region as well as for Corsica and

overseas regions to compensate for hospital extra costs. Second, in both legal sectors, hospital-specific “transition coefficients” have been applied to account for past differences in funding and limit the impact of the reform on the hospital revenue. As a result of these adjustments, the rates varied across hospitals within each sector during the phase-in period of the reform. However, for nonprofit hospitals, most of the variation in reimbursement rates is driven by the phase-in of the reform.

In our empirical analysis, we apply the geographic adjustment for the Paris region, and correct the rates for inflation. We do not observe, however, the hospital-specific adjustments (transition coefficients).

Composition effects The stronger financial incentives in the nonprofit sector may have triggered upcoding strategies (optimization or manipulation of the classification algorithm, see [Dafny \(2005\)](#) and [Gowrisankaran, Joiner, and Lin \(2019\)](#)) or specialization of activity within diagnosis categories into particular DRGs. Such strategies make the composition of activity (share of the DRGs within diagnosis categories) endogenous.

To assess the empirical importance of composition effects, we compute average rates each year between 2006 and 2008 using the DRG structure of the previous year $\left(\sum_{D \in g_{t-1}} r_{Djt} q_{Dj,t-1}\right) / \left(\sum_{D \in g_{t-1}} q_{Dj,t-1}\right)$. Comparing the top and bottom panels of [Table 5](#) shows that the weights used (contemporaneous or lagged admissions) have little effect on the level of the average rates.

B Demand estimation

B.1 Graph connectivity

[Jochmans and Weidner \(2019\)](#) show that precise estimation of the utilities u_{jt} requires a high degree of each hospital in the one-node projected graph to be high for consistency. In the projected graph, two hospitals j and j' are connected if and only if they have at least one group i in common, see [Newman \(2010\)](#).⁴⁵ [Figure B.1](#) shows the projected graph for orthopedics in 2008. Though the graph is weakly globally connected ($\lambda_2 = .01$), it is strongly locally connected, as the inverse of the

⁴⁵The adjacency matrix of the projected graph has entry $A'_{jj'} = \sum_{i \in [j] \cap [j']} 1/|[i]|$, where $|[i]|$ is the number of hospitals connected to patient group i , if hospitals j and j' are connected, and zero otherwise, see [Jochmans and Weidner \(2019\)](#). Degrees in the connected graph, $d'_j = \sum_{j'} A'_{jj'} = \sum_{i \in [j]} (|[i]| - 1) / |[i]|$ is slightly lower than $|[j]|$, the number of patient groups connected to hospital j .

Table B.1: Connectivity of the hospitals' projected graph (Orthopedics, 2008)

	mean	s.d.	p10	p20	p30	p40	p50	p60	p70	p80	p90	# of obs.
degree d_j^l	220	211.6	37	76	105	139	163	194	236	303	445	920
h_j	163.3	539.2	5.4	12.5	17.4	22.2	28.2	36.8	49.5	75.8	120.9	920
H_j	549.7	825.5	0.1	11.6	37.4	92.2	150.3	238.8	359	553.6	799	920
Postal codes connected to j	221.1	212.3	37	77	107	141	164	196	237	307	446	920

The local connectivity indicators h_j and H_j are computed from Jochmans and Weidner (2019).
 The last line is related to the bipartite graph. See Footnote 45 for the comparison with first line.

harmonic mean of the degree in the projected graph, $h^{-1} = .021$, which compares favorably to $h^{-1} = .06$ in the occupational network example of Jochmans and Weidner (2019).⁴⁶ Table B.1 reports the distributions of the number of patient groups connected to a hospital and two measures of local connectivity h_j and H_j , suggesting stronger local connectivity than in their occupational network example.

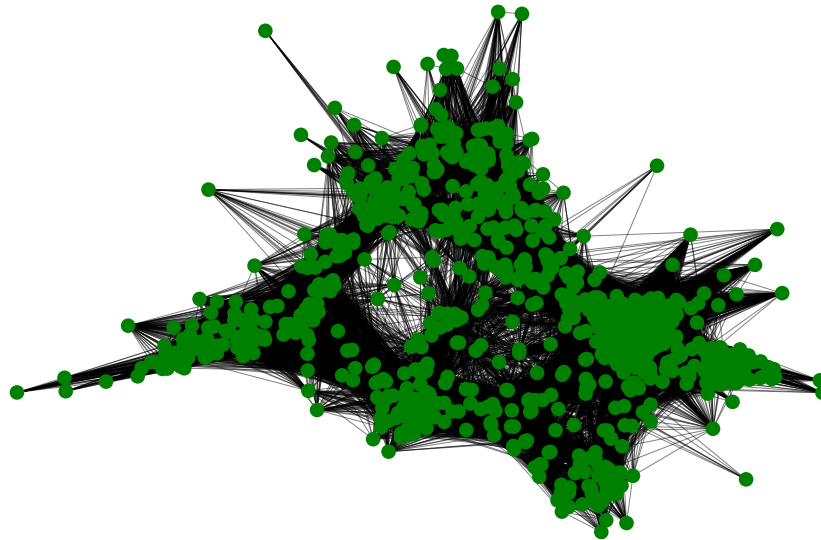


Figure B.1: Weighted hospital projected graph (Orthopedics, 2008)

⁴⁶For better precision, the degrees should be large, and h^{-1} should be small.

B.2 Approximating potential demand

The market sizes M_{it} have no impact on the various coefficients in patient utility or the residuals ξ_{ijt} , because they are absorbed into the patient group indicators φ_{it} .⁴⁷ Yet they affect the elasticity of demand that enter the left-hand side of the supply equation (17).

To approximate the size of potential demand, we follow the approach developed by Huang, Rojas, et al. (2013), Huang and Rojas (2014) and Dubois and Lasio (2018), based on the comparison of two demand models, with and without the patient group effects φ_{it} . We choose the potential demand (or “market size”) to make the main demand parameters as close as possible from one specification to the other: the relevant market size is such that controlling for market fixed-effects does not affect the estimated coefficients. We implement this procedure assuming that the potential demand does not vary over time: $M_{it} = M_i$, which is a reasonable assumption given the short period of time considered, and first that $M_i = \text{pop}_i$:

$$\log \frac{q_{ijt}}{M_i - \sum_j q_{ijt}} = u_{jt}^0 + \alpha_0^0 \text{Closest}_{ij} - \alpha_1^0 d_{ij} - \alpha_2^0 d_{ij}^2 - \alpha_{1X}^0 d_{ij} X_{it} \quad (\text{B.1})$$

$$+ \varphi_{it}^0 + \gamma^0 \text{NP}_j X_{it} + \sigma^0 \log s_{ijt|n} + \xi_{ijt}^0,$$

which we also estimate without the φ 's:

$$\log \frac{q_{ijt}}{M_i - \sum_j q_{ijt}} = u_{jt} + \alpha_0 \text{Closest}_{ij} - \alpha_1 d_{ij} - \alpha_2 d_{ij}^2 \quad (\text{B.2})$$

$$- \alpha_{1X} d_{ij} X_{it} + \gamma \text{NP}_j X_{it} + \sigma \log s_{ijt|n} + \xi_{ijt}.$$

We then minimize the goodness-of-fit criterion based on the differences in the estimated parameters estimates $(\alpha^0, \gamma^0, \sigma^0, \mathbf{u}^0)$ and $(\alpha, \gamma, \sigma, \mathbf{u})$:

$$\frac{1}{JT} \sum_{j,t} \left[(u_{jt}^0 - \bar{u}^0) - (u_{jt} - \bar{u}) \right]^2 + (\alpha^0 - \alpha)^2 + (\gamma^0 - \gamma)^2 + (\sigma^0 - \sigma)^2 \quad (\text{B.3})$$

To avoid estimating a very high number of distinct potential demands (one in each of the 37,000 postal codes), we consider the following specification:

$$\log(M_i) = \theta \log(\text{pop}_i) + (1 - \theta) \log(q_i), \quad (\text{B.4})$$

⁴⁷Changing the M_{it} 's only affects the parameters φ_{it} and shifts the utility levels u_{jt} by constants to accommodate the normalization condition (8). The constants are absorbed in the aggregate shocks C_t in the supply equations.

where $q_i = \max_t q_{it}$ and $\theta \geq 0$ is a parameter to be estimated.

For all diagnosis categories and all the variants that we run to check robustness (see section 5.5), we find that there exists a unique value of the demand size parameter that minimizes the fit criterion, as shown on Figure B.2.

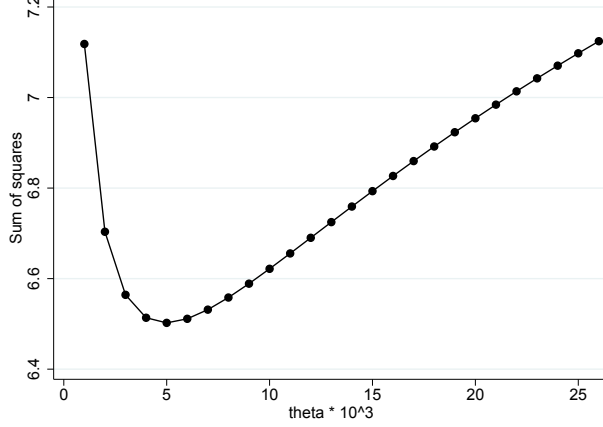


Figure B.2: A statistical criterion for potential demand (orthopedics, large patient groups only)

C Theory

The marginal incentives of hospital j to change the utility it provides to patients are given by

$$\mu_j(u_j, u_{-j}; r_j) \stackrel{d}{=} \frac{d}{du_j} V_j(q_j(u_j, u_{-j}), u_j; r_j). \quad (\text{C.1})$$

In equilibrium, these incentives are zero. Figure C.1 depicts, for given values of the competitors' utilities u_{-j} , the residual demand curve, $q_j = q_j(u_j; u_{-j})$, as well as the hospital iso-objective curves, $V_j(q_j, u_j) = \bar{V}$, which are hyperbolas in the (q_j, u_j) -space. The hospital maximizes its objective function V_j along the demand curve. The Jacobian matrix of the maximization problem, which is mentioned in the text, is $D_u \mu$ and has with generic entry $\partial \mu_j / \partial u_k$, where $\mu = (\mu_j)_j$ is defined in (C.1).

Differentiating each of the first-order conditions (C.1) with respect to r_j , we get

$$\frac{\partial \mu_j}{\partial u_j} du_j + \frac{\partial \mu_j}{\partial u_{-j}} du_{-j} + \frac{\partial \mu_j}{\partial r_j} dr_j = 0. \quad (\text{C.2})$$

It follows that the transmission rates are given by $\tau_j = -(\partial q_j / \partial u_j) / (\partial \mu_j / \partial u_j)$ and are positive if and only if the second-order conditions of the hospital's problem

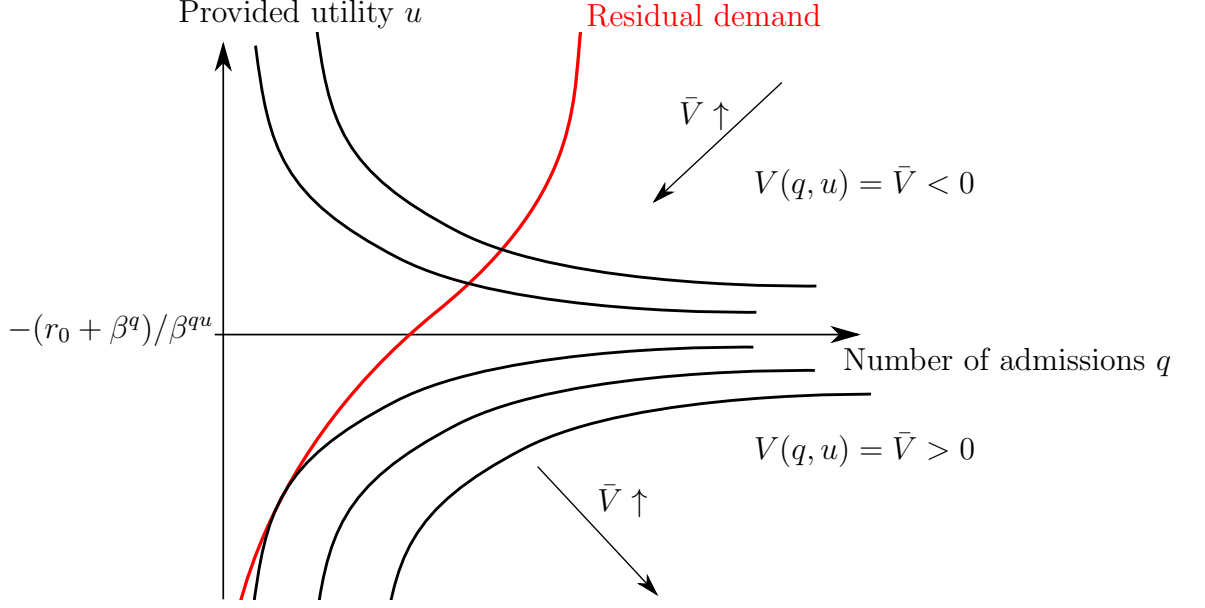


Figure C.1: Hospital problem (given utilities provided by competitors), with $\beta^{qu} < 0$

hold. Combining

$$\frac{\partial \mu_j}{\partial u_j} = (\beta_j^q + r_j + 2u_j) \frac{\partial^2 q_j}{\partial u_j^2} + 2\beta_j^{qu} \frac{\partial q_j}{\partial u_j}. \quad (\text{C.3})$$

with the first-order condition (11) yields (13). Figure C.2 shows how a hospital responds to a change in financial incentives, the utilities provided by its competitors being fixed.

The slope of the reaction function

$$\rho_{jk} = \left. \frac{\partial u_j}{\partial u_k} \right|_{r_j} = - \frac{\partial \mu_j / \partial u_k}{\partial \mu_j / \partial u_j}. \quad (\text{C.4})$$

Using the first-order condition (C.1), the equations (C.3), (C.4), and

$$\frac{\partial \mu_j}{\partial u_k} = (\beta_j^q + r_j) \frac{\partial^2 q_j}{\partial u_j \partial u_k} + \beta_j^{qu} \left[\frac{\partial q_j}{\partial u_k} + u_j \frac{\partial^2 q_j}{\partial u_j \partial u_k} \right] \quad (\text{C.5})$$

yields (14). The sign of ρ_{jk} is given by the sign of the numerator of (14) because the denominator is negative from the second-order condition of the hospital's problem. As explained in the text, costliness of quality, $\beta_j^{qu} < 0$, and business stealing $\partial q_j / \partial u_k < 0$, together push towards strategic complementarity (recall that $\partial \mu_j / \partial u_j$ is negative).

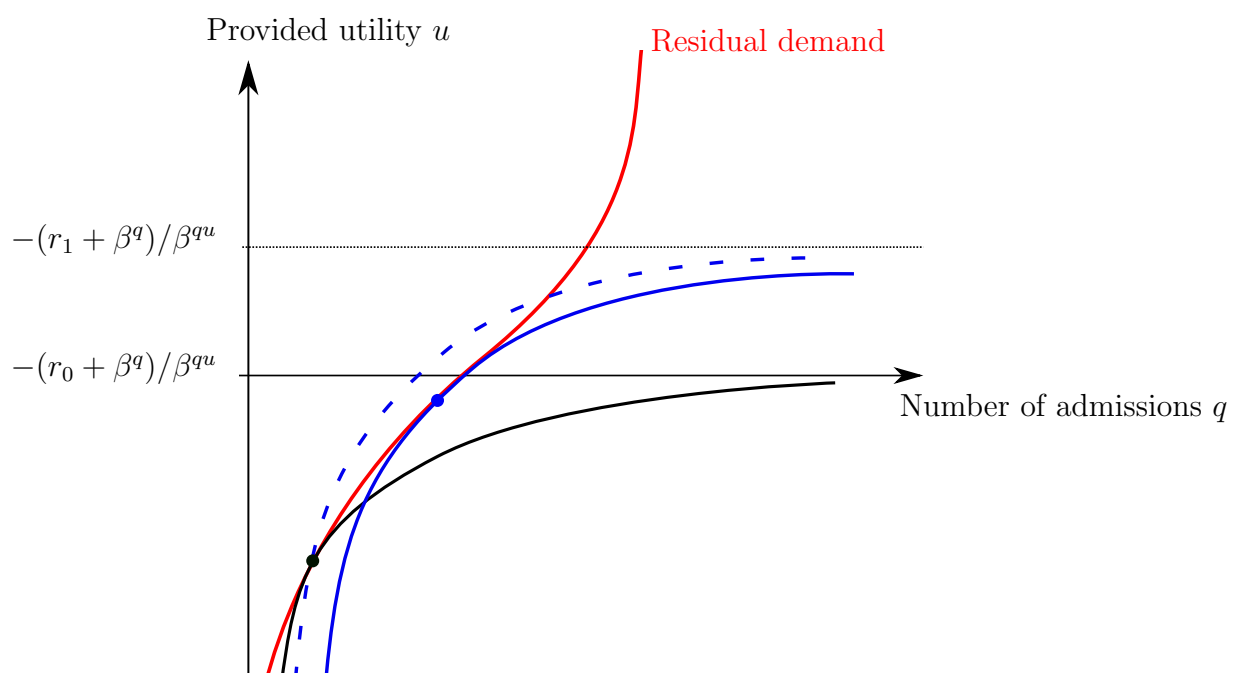


Figure C.2: Increasing r from r_0 to $r_1 > r_0$ makes iso- V curves steeper: q and u increase from black point to blue point

D Counterfactual simulations by diagnosis categories

Table D.1: Breaking down activity variations: ENT, Stomatology from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	2.32	-1.38	7.35	-4.48	3.38	-5.91
(a) financial incentives	1.28	0.35	5.22	-1.39	3.58	-1.46
(b) financial incentives (w/o strategic effects)	1.31	0.26	5.25	-1.51	3.73	-1.52
(c) aggregate shocks	0.06	1.7	1.94	1.62	2.15	1.7
(d) hospital-specific demand shocks	0.72	-3.95	-1.31	-4.89	-3.29	-3.79
(e) aggregate + hospital-specific demand shocks	0.8	-2.01	0.97	-3.07	-1.14	-1.98
(f) all but hospital-specific supply shocks	2.12	-1.63	6.3	-4.45	3.48	-3.47
(g) hospital-specific supply shocks	0.45	0.1	1.83	-0.51	-0.53	-0.78

These figures are based on the potential demand shown in Table 13.

Table D.2: Breaking down activity variations: Ophtalmology from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	0.73	9.04	12.25	7.97	8.51	3.96
(a) financial incentives	0.91	0.27	3.92	-0.95	3.74	-0.92
(b) financial incentives (w/o strategic effects)	0.92	0.21	3.9	-1.02	3.72	-0.95
(c) aggregate shocks	0.24	10.05	11.1	9.7	13.06	10.17
(d) hospital-specific demand shocks	0.17	-1.76	-1.08	-1.98	-3.88	-3.42
(e) aggregate + hospital-specific demand shocks	0.41	8.43	10.2	7.84	7.23	5.95
(f) all but hospital-specific supply shocks	1.29	8.65	14.26	6.79	11.27	4.78
(g) hospital-specific supply shocks	-0.4	0.06	-1.54	0.59	-1.92	-0.71

These figures are based on the potential demand shown in Table 13.

Table D.3: Breaking down activity variations: Gastroenterology from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	2.52	1.86	7.19	-3.11	6.6	-4.23
(a) financial incentives	2.69	1.02	6.65	-4.23	5.02	-4.45
(b) financial incentives (w/o strategic effects)	2.74	0.81	6.54	-4.54	4.86	-4.51
(c) aggregate shocks	-0.01	-1.58	-1.61	-1.56	-1.65	-1.59
(d) hospital-specific demand shocks	0.89	2.28	4.17	0.51	3.95	0.09
(e) aggregate + hospital-specific demand shocks	0.87	0.83	2.66	-0.87	2.34	-1.29
(f) all but hospital-specific supply shocks	3.51	1.84	9.24	-5.07	7.6	-5.58
(g) hospital-specific supply shocks	-0.58	0.13	-1.07	1.26	-0.66	0.64

These figures are based on the potential demand shown in Table 13.

Table D.4: Breaking down activity variations: Gynaecology from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	3.04	-2.07	4.49	-7.51	4.6	-12.47
(a) financial incentives	1.76	0.77	4.68	-2.47	4.38	-2.64
(b) financial incentives (w/o strategic effects)	1.76	0.65	4.57	-2.59	4.21	-2.65
(c) aggregate shocks	0.05	3.33	3.45	3.23	3.77	3.62
(d) hospital-specific demand shocks	1.41	-7.46	-4.59	-9.84	-5.41	-12.15
(e) aggregate + hospital-specific demand shocks	1.42	-3.42	-0.41	-5.93	-0.99	-8.08
(f) all but hospital-specific supply shocks	3.2	-2.55	4.33	-8.25	3.73	-10.68
(g) hospital-specific supply shocks	0.25	0.2	0.76	-0.27	1.65	0.32

These figures are based on the potential demand shown in Table 13.

Table D.5: Breaking down activity variations: Dermatology from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	6.73	-5.49	10.85	-15.9	9.31	-14.25
(a) financial incentives	3.99	2.36	12.86	-4.33	9.46	-4.90
(b) financial incentives (w/o strategic effects)	3.96	2.02	12.40	-4.60	9.09	-5.01
(c) aggregate shocks	-0.02	-1.70	-1.76	-1.66	-1.76	-1.77
(d) hospital-specific demand shocks	3.41	-6.70	1.48	-11.90	-0.05	-8.09
(e) aggregate + hospital-specific demand shocks	3.41	-8.50	-0.48	-13.62	-2	-10
(f) all but hospital-specific supply shocks	7.56	-5.81	12.48	-17.47	9.95	-14.75
(g) hospital-specific supply shocks	0.12	-0.09	0.21	-0.28	0.13	3.32

These figures are based on the potential demand shown in Table 13.

Table D.6: Breaking down activity variations: Nephrology from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	1.59	9.85	14.43	7.02	10.45	1.93
(a) financial incentives	1.05	0.47	3.22	-1.23	2.14	-1.27
(b) financial incentives (w/o strategic effects)	1.07	0.38	3.18	-1.35	2.06	-1.34
(c) aggregate shocks	-0.03	-1.18	-1.26	-1.13	-1.4	-1.23
(d) hospital-specific demand shocks	0.99	9.97	12.82	8.21	11.12	5.84
(e) aggregate + hospital-specific demand shocks	0.96	9.04	11.79	7.33	9.93	5.12
(f) all but hospital-specific supply shocks	2.01	9.43	15.19	5.86	12.52	3.73
(g) hospital-specific supply shocks	0.08	0.42	0.63	0.28	-0.23	-1.61

These figures are based on the potential demand shown in Table 13.

Table D.7: Breaking down activity variations: Circulatory system from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	4.42	3.57	18.01	-3.12	12	-3.73
(a) financial incentives	2	1.01	7.39	-1.95	2.43	-1.96
(b) financial incentives (w/o strategic effects)	2.05	0.84	7.36	-2.19	2.37	-2.03
(c) aggregate shocks	-0.21	-8.71	-9.3	-8.44	-10.03	-9.09
(d) hospital-specific demand shocks	2.82	10.01	19.81	5.47	18.8	6.07
(e) aggregate + hospital-specific demand shocks	2.61	2.16	10.59	-1.75	9.11	-1.44
(f) all but hospital-specific supply shocks	4.71	3.27	18.64	-3.85	13.98	-3.43
(g) hospital-specific supply shocks	-0.1	-0.03	-0.34	0.12	0.27	0.39

These figures are based on the potential demand shown in Table 13.

E Robustness checks

E.1 Grouping patients according to age bracket

Table E.1: Breaking down activity variations: Orthopedics from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	1.18	4.14	7.11	2.03	7.28	-1.24
(a) financial incentives	1.18	0.36	3.21	-1.67	2.81	-1.73
(b) financial incentives (w/o strategic effects)	1.18	0.30	3.14	-1.72	2.69	-1.74
(c) aggregate shocks	-0.01	-2.68	-2.71	-2.66	-2.78	-2.69
(d) hospital-specific demand shocks	-0.01	5.92	5.9	5.94	4.41	4.24
(e) aggregate + hospital-specific demand shocks	0	3.76	3.75	3.77	2.17	2.04
(f) all but hospital-specific supply shocks	1.17	4.07	7.01	1.98	5.06	-0.11
(g) hospital-specific supply shocks	0.34	0.04	0.85	-0.53	1.22	-0.96

E.2 Large patient groups only

Table E.2: Sample selection with large groups (orthopedics, 2008)

	Working sample	$q_{ij} > 17$
# of observations (i, j)	795,638	568,363
# of hospitals j	920	920
# of postal codes	30,273	15,074
# of admissions $\sum_{i,j} q_{ij}$	1,369,191	1,253,239

Note. 17 is the median number of admissions in orthopedics.

Table E.3: Supply

	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
IV								
$r_{ijt} \times 10^3$ (baseline)	0.072*** (0.018)	0.028** (0.013)	0.160*** (0.017)	0.058*** (0.011)	0.053*** (0.009)	0.054 (0.039)	0.071*** (0.022)	0.026*** (0.009)
Observations	3,516	3,412	3,720	3,560	3,608	3,088	3,552	3,680
$r_{ijt} \times 10^3$	0.079*** (0.019)	0.020 (0.013)	0.180*** (0.018)	0.057*** (0.012)	0.059*** (0.009)	0.043 (0.043)	0.070*** (0.025)	0.030*** (0.009)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,506	3,400	3,719	3,554	3,604	3,069	3,538	3,677

Robust standard errors clustered at the hospital level.

Excluded instrument: phase-in step function \times NP.

The top panel is a reminder of Table 14.

Table E.4: Breaking down activity variations: Orthopedics from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	1.2	3.92	6.94	1.8	6.92	-1.21
(a) financial incentives	1.22	0.28	3.24	-1.8	2.78	-1.87
(b) financial incentives (w/o strategic effects)	1.2	0.23	3.14	-1.82	2.62	-1.82
(c) aggregate shocks	0	-0.89	-0.89	-0.88	-0.88	-0.88
(d) hospital-specific demand shocks	0.12	4.33	4.64	4.11	2.6	2.81
(e) aggregate + hospital-specific demand shocks	0.13	3.66	3.97	3.44	1.73	2.11
(f) all but hospital-specific supply shocks	1.35	3.88	7.26	1.49	5.26	0.41
(g) hospital-specific supply shocks	0.19	0.14	0.6	-0.17	1.75	-1.48

These figures are based on the subsample of unit demands with more than 17 patients.

E.3 Alternative demand structures

E.3.1 Grouping private nonprofit with for-profit (rather than state-owned) hospitals

Table E.5: Supply

	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
IV								
$r_{ijt} \times 10^3$ (baseline)	0.072*** (0.018)	0.028** (0.013)	0.160*** (0.017)	0.058*** (0.011)	0.053*** (0.009)	0.054 (0.039)	0.071*** (0.022)	0.026*** (0.009)
$r_{ijt} \times 10^3$	0.069*** (0.018)	0.027** (0.012)	0.156*** (0.016)	0.054*** (0.010)	0.053*** (0.009)	0.053 (0.040)	0.068*** (0.021)	0.025*** (0.009)
F-test	621.7	1,679.7	1,890.5	8,487.2	3,922.4	3,265.5	709.8	6,999.5
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,516	3,412	3,720	3,560	3,608	3,088	3,552	3,680

Robust standard errors clustered at the hospital level.
 Excluded instrument: phase-in step function \times NP.
 The top panel is a reminder of Table 14.

Table E.6: Breaking down activity variations: Orthopedics from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	1.18	4.14	7.11	2.03	7.28	-1.24
(a) financial incentives	1.03	0.26	2.75	-1.52	2.39	-1.58
(b) financial incentives (w/o strategic effects)	1.04	0.21	2.71	-1.57	2.33	-1.55
(c) aggregate shocks	0	-0.77	-0.78	-0.76	-0.79	-0.76
(d) hospital-specific demand shocks	0.17	4.48	4.91	4.18	4.1	2.6
(e) aggregate + hospital-specific demand shocks	0.17	3.88	4.3	3.58	3.38	2.08
(f) all but hospital-specific supply shocks	1.2	4.09	7.1	1.94	5.96	0.57
(g) hospital-specific supply shocks	0.31	0.1	0.85	-0.43	1.36	-1.13

E.3.2 Four nests

Table E.7: Supply

	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
IV								
$r_{ijt} \times 10^3$ (baseline)	0.072*** (0.018)	0.028** (0.013)	0.160*** (0.017)	0.058*** (0.011)	0.053*** (0.009)	0.054 (0.039)	0.071*** (0.022)	0.026*** (0.009)
$r_{ijt} \times 10^3$	0.075*** (0.019)	0.027* (0.014)	0.172*** (0.019)	0.060*** (0.011)	0.055*** (0.009)	0.054 (0.041)	0.070*** (0.023)	0.024*** (0.009)
F-test	621.7	1,679.7	1,890.5	8,487.2	3,922.4	3,265.5	709.8	6,999.5
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,516	3,412	3,720	3,560	3,608	3,088	3,552	3,680

Robust standard errors clustered at the hospital level.
 Excluded instrument: phase-in step function \times NP.
 The top panel is a reminder of Table 14.

Table E.8: Breaking down activity variations: Orthopedics from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	1.18	4.14	7.11	2.03	7.28	-1.24
(b) financial incentives (w/o strategic effects)	1.03	0.18	2.66	-1.58	2.28	-1.41

NB No convergence obtained for the channel "financial incentives only".

E.4 Size and specification of potential demand

Table E.9: Supply estimation: Robustness to the size of potential demand

	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
IV - market size: $\log(M_i) = .5\hat{\theta}\log(\text{pop}_i) + (1 - .5\hat{\theta})\log(q_i)$								
r_{ijt}	0.074*** (0.018)	0.028** (0.013)	0.166*** (0.018)	0.059*** (0.011)	0.054*** (0.009)	0.054 (0.040)	0.072*** (0.022)	0.026*** (0.009)
IV - market size: $\log(M_i) = \hat{\theta}\log(\text{pop}_i) + (1 - \hat{\theta})\log(q_i)$								
r_{ijt}	0.072** (0.018)	0.028** (0.013)	0.160*** (0.017)	0.058*** (0.011)	0.053*** (0.009)	0.054 (0.039)	0.071*** (0.022)	0.026*** (0.009)
IV - market size: $\log(M_i) = 2\hat{\theta}\log(\text{pop}_i) + (1 - 2\hat{\theta})\log(q_i)$								
r_{ijt}	0.068*** (0.017)	0.027** (0.012)	0.150*** (0.015)	0.055*** (0.010)	0.052*** (0.008)	0.054 (0.039)	0.069*** (0.021)	0.026*** (0.009)
IV - market size: $M_i = \text{pop}_i$								
r_{ijt}	0.052*** (0.015)	0.020* (0.010)	0.110*** (0.011)	0.041*** (0.008)	0.029*** (0.006)	0.042 (0.034)	0.047*** (0.017)	0.014* (0.008)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,516	3,412	3,720	3,560	3,608	3,088	3,552	3,680

Robust standard errors clustered at the hospital level.
 Excluded instrument: phase-in step function \times NP.
 The second panel is a reminder of Table 14.

Table E.10: How much do financial incentives explain the change in activity?
 Robustness wrt the size of potential demand

θ	observed change		change due to financial incentives		
	(1)	$0.5\hat{\theta}$ (2)	$\hat{\theta}$ (3)	$2\hat{\theta}$ (4)	1 (5)
Circulatory syst.	3.57	0.86	1.01	1.37	3.25
Nephrology	9.85	0.43	0.47	0.56	1.69
Dermatology	-5.49	2.05	2.36	3.21	7.12
Gynaecology	-2.07	0.66	0.77	1.05	3.2
Gastroenterology	1.86	0.98	1.02	1.15	4.47
Ophthalmology	9.04	0.25	0.27	0.3	1.1
ENT, Stomato.	-1.38	0.32	0.35	0.42	1.42
Orthopedics	4.14	0.26	0.27	0.28	1.32

Figures: relative change in activity from 2005 to 2008 (in %).
 θ is the parameter governing potential demand: $\log(M_i) = \theta\log(\text{pop}_i) + (1 - \theta)\log(q_i)$.
 Column (1) is a reminder of line "observed", column (2) of Table 19 and Tables D.1 to D.7.
 Column (3) is a reminder of line (a), column (2) of Table 19 and Tables D.1 to D.7.

Table E.11: Supply with linear specification of potential demand

	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
IV								
$r_{ijt} \times 10^3$ (baseline)	0.072*** (0.018)	0.028** (0.013)	0.160*** (0.017)	0.058*** (0.011)	0.053*** (0.009)	0.054 (0.039)	0.071*** (0.022)	0.026*** (0.009)
$r_{ijt} \times 10^3$	0.055*** (0.015)	0.022** (0.011)	0.119*** (0.012)	0.044*** (0.009)	0.041*** (0.007)	0.050 (0.037)	0.058*** (0.019)	0.025*** (0.009)
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,516	3,412	3,720	3,500	3,608	3,088	3,552	3,680

Assuming $M_t = \theta \text{pop}_t + (1 - \theta) q_t$ instead of $\log(M_t) = \theta \log(\text{pop}_t) + (1 - \theta) \log(q_t)$.
 Robust standard errors clustered at the hospital level.
 Excluded instrument: phase-in step function \times NP.
 The top panel is a reminder of Table 14.

Table E.12: Breaking down activity variations: Orthopedics from 2005 to 2008

	(1)	(2)	(3)	(4)	(5)	(6)
	Δs^{NP}	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$	$\Delta q/q$
	(pp)	All	NP	FP	NP	FP
		(%)	(%)	(%)	(%)	(%)
		total	total	total	median	median
observed	1.18	4.14	7.11	2.03	7.28	-1.24
(a) financial incentives	1.02	0.38	2.84	-1.38	2.51	-1.43
(b) financial incentives (w/o strategic effects)	1.01	0.32	2.76	-1.42	2.38	-1.43
(c) aggregate shocks	0	-1.18	-1.18	-1.18	-1.19	-1.21
(d) hospital-specific demand shocks	0.21	4.65	5.18	4.27	4.12	2.85
(e) aggregate + hospital-specific demand shocks	0.22	3.61	4.16	3.22	3.18	1.79
(f) all but hospital-specific supply shocks	1.24	3.96	7.06	1.74	5.7	0.35
(g) hospital-specific supply shocks	0.28	0.09	0.76	-0.39	1.56	-1

E.5 Counterfactual rates based on observed case-mix

Table E.13: Impact of the reform on volumes and market shares (based on 2008 reimbursement rates)

Major diagnosis category	Circulatory syst.	Nephrology	Dermatology	Gynaecology	Gastroenterology	Ophthalmology	ENT, Stomato.	Orthopedics
# of competing hospitals	879	853	930	890	902	772	888	920
# of admissions - observed (10^3)	239	322	317	419	574	593	632	1,315
# of admissions - counterfactual (10^3)	242	324	325	422	580	594	635	1,318
Change in # of admissions (%)	1	0.5	2.4	0.8	1	0.3	0.3	0.3
Change in # of admissions (nonprofit, %)	7.4	3.2	12.9	4.7	6.6	3.9	5.2	2.8
Change in # of admissions (for-profit, %)	-1.9	-1.2	-4.3	-2.5	-4.2	-0.9	-1.4	-1.5
Nonprofit market share - observed in 2005 (%)	31.7	38.3	38.9	45.3	48.3	24.9	26.2	41.6
Nonprofit market share - counterfactual (%)	33.7	39.3	42.9	47.1	51	25.8	27.5	42.6
Change in nonprofit market share (points)	2	1	4	1.8	2.7	0.9	1.3	1
Change in # of admissions - nonprofit hospitals (10^3)	6	4	16	9	18	6	9	15
Change in # of admissions - for-profit hospitals (10^3)	-3	-2	-8	-6	-13	-4	-6	-12
Admissions switching to nonprofit hospitals (10^3)	4	3	12	7	15	5	8	14

Note. Counterfactual experiment: see line (a) from Table 19.
Counterfactual reimbursement rates are r_{2008} rather than $4r_{2005}$.

Table E.14: Impact of the reform on patients (based on 2008 reimbursement rates)

	Median $\tilde{u} - \hat{u}$		# of hospitals		Travel time compression factor	p90	# of postal codes
	NP	FP	NP	FP	median		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Circulatory syst.	0.058	0.006	406	473	6.0	20.7	24,842
Nephrology	0.044	0.002	395	458	3.4	12.2	26,119
Dermatology	0.181	0.011	421	509	14.8	37.4	25,963
Gynaecology	0.083	0.003	404	486	5.7	16.1	27,248
Gastroenterology	0.125	0.014	415	487	9.6	29.7	28,914
Ophthalmology	0.053	0	303	469	1.8	6.5	28,507
ENT, Stomato.	0.059	0.002	400	488	2.8	9.9	28,612
Orthopedics	0.048	0.003	417	503	2.6	7.6	30,309

Note. Counterfactual experiment: see line (a) from Table D.7.
Counterfactual reimbursement rates are r_{2008} rather than $4r_{2005}$.
Columns (5) and (6): in %.

Table E.15: Impact of the reform on nonprofit hospitals (based on 2008 reimbursement rates)

	Activity-based revenues	Activity-based revenues	Revenue part	Non-revenue part	# of hospitals
	Observed (€m)	Counterfactual (€m)	Change (%)	Change (%)	
	(1)	(2)	(3)	(4)	(5)
Circulatory syst.	62	223	260	-3.7	406
Nephrology	109	404	270	-1.6	395
Dermatology	64	281	342	-8.9	421
Gynaecology	120	465	288	-3.1	404
Gastroenterology	317	1,254	296	-6.0	415
Ophthalmology	76	266	250	-1.5	303
ENT, Stomato.	79	303	283	-2.4	400
Orthopedics	445	1,721	287	-1.7	417

Note. Counterfactual experiment: see line (a) from Table 19.
Counterfactual reimbursement rates are r_{2008} rather than $4r_{2005}$.

Lecture. In orthopedics, the reform increased by 287% the total activity-based revenues in the non-profit sector.
Lecture. In orthopedics, the reform decreased by 1.7% the nonpecuniary objective of all non-profit hospitals.