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# Competition on Unobserved Attributes: The Case of the Hospital Industry

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# Competition on Unobserved Attributes: The Case of the Hospital Industry

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**Abstract**

To assess strategic interactions in industries where endogenous product characteristics are unobserved to the researcher, we propose an empirical method that brings a competition-in-utility-space framework to the data. We apply the method to the French hospital industry. The utilities offered to patients are inferred from local market shares under AKM exclusion restrictions. The hospitals' objective functions are identified thanks to the gradual introduction of stronger financial incentives over the period of study. Offering more utility to each patient entails incurring higher costs per patient, implying that utilities are mostly strategic complements. Counterfactual simulations show that stronger incentives affect market shares but have little impact on the total number of patient admissions. We quantify the resulting gains for patients and losses for hospitals.

**JEL Codes:** D22; I11; L13.

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

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# 1 Introduction

In many contexts (education, health care, media and cultural industries, tourism, local public goods, etc.), the products and services offered to consumers involve a high number of attributes, the quality of which is difficult to quantify and often unobserved to the researcher. To understand the functioning of markets under such circumstances, we bring the competition-in-utility framework of Armstrong and Vickers (2001) to the data. We subsume all unobserved characteristics into a one-dimensional utility index that serves as a sufficient statistics for perceived quality, reputation, and all the determinants of product attractiveness. Compared to the standard price competition setting, our method involves two main challenges. First, utilities, contrary to prices, are unobserved and must be inferred from the data. Second, not only the level of marginal costs need to be recovered, but also their variation with the utilities provided to consumers. Hence two primitive parameters of marginal costs –intercept and slope– are to be identified, rather than a single one in the price oligopoly framework.

Based on this approach, this article evaluates the causal impact of the activity-based payment system on the French hospital industry. The funding rule, which is similar to the prospective payment system in force in most developed countries, has become the *bête noire* of public hospitals, as *Le Monde* put it in 2018.[1] The newspaper calls the payment system “inflationary”, suggesting that it creates incentives for hospitals to produce as many medical acts as possible. Managers and medical staff complain that the new payment rule promotes a financial logic in the management of nonprofit hospitals, encourages them to admit more patients to avoid budget deficits, and ultimately triggers a “race to activity”.[2] Our methodology allows to assess the validity of these assertions. By simulating a number of counterfactual scenarios, we are able to disentangle the effects of the reform from changes in demand and supply conditions. We can thus evaluate the medium-run impact of the new payment rule on the number of admissions, the market shares, patient surplus and hospital revenues.

We model hospitals as supplying utility directly to patients. First, we infer

[1]See Pommiers (2018), entitled: “What about the activity-based payment system that crystallizes tensions in hospital?”.

[2]A couple of administrative reports commissioned by the government criticize the activity-based funding rule for creating excessive incentives to compete for patients. For 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). In response to these concerns, candidate Emmanuel Macron promised during the 2017 presidential campaign to cap activity-based revenues to 50% of total hospital revenues.

the utilities provided by hospitals from the observation of market shares at a fine geographic level. French hospitals compete to attract patients located in about 37,000 postal code locations, each hospital being connected to others through a high number of patient locations (in the sense that competing hospitals receive patients from the same locations). We can thus apply the estimation procedure developed by Abowd, Kramarz, and Margolis (1999) to recover hospital effects, while controlling from average health status at the postal code level. In practice, we include two-way high-dimensional fixed effects in a discrete-choice setting of Berry (1994), where patients trade off perceived utilities offered by hospitals against travel costs. The hospital effects, which represent the average utility provided by hospitals to patients, are identified from the connectivity of the graph formed by hospitals and patient locations.

Second, we set up a static oligopoly model where hospitals compete for patients by offering them utility. Hospital preferences depend on the number of admitted patients and the average utility provided to them. We consider the simplest possible functional form for the hospitals' objective functions. We assume constant returns to scale, with marginal costs being linear in the utilities provided to patients. The gradual introduction of the activity-based payment system over our period of study provides us with an exogenous change that allows to identify both the intercept and the slope of the marginal cost functions under the assumption of stable preferences. Thus, while the identification of patient choice is based on the geographic dimension, that of hospital costs and preferences crucially exploits the time dimension.

Our main findings are as follows. Regarding the preferences of patients, we find higher travel costs for elders, women and poorer individuals. Richer patients have an intrinsic preference for private for-profit hospitals. The metric we use to measure the average utilities provided to patients is travel time. We find a sizeable dispersion in the utilities offered to patients: the interquartile range of the estimated utilities is equivalent to between 15 and 20 minutes travel time, to be compared with the median travel between patient home and hospital location, namely 22 minutes. We thus document, through a revealed preference approach, a strong heterogeneity in attractiveness among French hospitals.

On the supply side, we uncover a trade-off faced by hospitals in the short-to-medium run, between raising the number of admitted patients and lowering the utility provided to them. We find that hospitals would be better off by admitting more patients and providing them with a lower utility, which of course is not compatible with demand behavior. In equilibrium, the marginal rate of substitution between activity and utility is determined by the sensitivity of demand with respect to utility. The tradeoff is reminiscent of Pope (1989)'s framework, where a hospital can increase its "perceived quality" by spending a *per-admission* amount on services, personnel, and facilities. Under many realistic circumstances, increasing the utility offered to each patient translates into higher costs per patient, which affects negatively the hospital objective function.

Having estimated hospital preferences, we are able to compute by how much a hospital would raise the utility offered to patients in response to stronger financial incentives if all competitors kept their own utilities unchanged ("direct effects of incentives"). We find that among nonprofit hospitals, private hospitals are more responsive to financial incentives than state-owned hospitals. We are also able to compute by how much a hospital would alter the utility it offers to patients in response to competitors changing their utility ("strategic effects"). We find that for almost all ordered pairs of hospitals, the slope of the corresponding reaction function is positive, suggesting that competitive interactions exhibit strategic complementarity. These interactions are strong: 10% (respectively 50%) of the hospitals are exposed to a competitor with respect to which the slope of the reaction function is larger than .17 (resp. .08). The intensity of these interactions decreases with the distance between the two hospitals as the intuition suggests. In practice, when financial incentives are changed for certain hospitals, both direct and strategic effects operate, which, together with changes in demand and supply conditions, gives rise to a new equilibrium in the industry.

Turning to policy evaluation, our main objective is to disentangle the effects of financial incentives from demand and supply shocks. Over our period of study (2005-2008), when financial incentives have been much strengthened for nonprofit hospitals while those of private hospitals remained approximately constant, the number of surgery admissions increased by 8.6% in the nonprofit sector while it stagnated in the for-profit sector. 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) aggregate industry shocks, (iii) hospital-specific demand shocks, (iv) hospital-specific supply shocks. To assess the magnitude of strategic effects, we simulate out-of-equilibrium configurations where each hospital responds to incentives while the other hospitals' strategies are kept fixed.

For the eight clinical departments under consideration, we find that the stronger incentives in the nonprofit sector have caused activity to grow in that sector (by 3% to 12% according to the department), to decline in the for-profit sector (by -1% to -6%), the overall effect being a modest increase (+.2% to +1.2%) at the industry level. When we neutralize strategic effects, the fall in activity of for-profit hospitals is slightly more pronounced (because those hospitals are then prevented from responding to the rise in utility by nonprofit hospitals) and the overall rise in activity is even weaker than indicated above (it is lower than 1% in the eight clinical departments). 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. For instance, in orthopedics, we find that the stronger incentives in the nonprofit sector caused its market share to raise by 1 percentage point while in practice it raised by 1.2 percentage point over the period 2005-2008. By contrast, incentives are found to be responsible for an increase of total activity of .2% to be compared with the much larger increase (4.1%) observed in practice. The difference is mostly explained by industry-wide evolutions and hospital-specific demand shocks. Strategic effects and hospital-specific supply-side shocks play a more modest role.

Altogether, we find little empirical support for the claim that the introduction of the activity-based payment in the nonprofit sector has triggered a race to activity. Rather, we show that the main causal effect of the reform has been to shift market shares away from for-profit hospitals to nonprofit hospitals. This finding is robust to the size of the potential demand. The mechanism underlying the shift in equilibrium due to the introduction of the activity-based payment for nonprofit hospitals can be explained as follows. In response to the stronger incentives placed on them, nonprofit hospitals raise the utility they offer to patients. The for-profit hospitals react by raising their own utility by a substantially lesser amount –about ten times smaller, consistent with the estimated slopes of the reaction functions. Patients benefit from these utility rises, with the benefit corresponding to a 2% to 17% reduction in travel time (depending on the clinical department) for the median hospitalized patients. Hospitals, however, are much worse off at the new equilibrium. The non-revenue part of their objective function, which reflects in particular pecuniary and nonpecuniary costs, diminishes by an amount that is of the same order of magnitude as their activity-based revenues at the beginning of the period.

The paper is organized as follows. Section 2 connects our study to the related literature. Section 3 describes the French hospital industry and presents our data set. Section 4 estimates patient travel costs and the utilities offered by hospitals, explains how to approximate the size of the potential demand, and presents the elasticities of demand with respect to utilities. Section 5 sets up the competition-in-utility framework and estimates the preferences of hospitals. Reaction functions and the nature of strategic interactions are discussed. Section 6 contains counterfactual simulations, in particular the decomposition of the observed evolution of activity into the effects of the policy reform and of changes in demand and supply conditions. Section 7 concludes.

# 2 Related literature

The present article builds and expands on the empirical industrial organization literature. Following Berry, Levinsohn, and Pakes (1995), many studies have estimated oligopoly models under price competition. More recently, a couple of papers have examined competition with endogenous product characteristics (e.g., Draganska, Mazzeo, and Seim, 2009; Fan, 2013; Eizenberg, 2014), addressing the issue of endogenous observed quality. These papers adopt as we do parametric specifications for consumer preferences as well as for fixed and variable production costs.[3] Because we deal here with unobserved quality attributes, that is, with endogenous *unobservables*, we need to further simplify the modelling of the supply side by assuming constant returns to scale. In our framework, fixed costs play no role;[4] only costs that are variable per patient matter, which is plausible given the time frame we consider (short-to-medium run).

The empirical studies that are more closely related to the present work are Hackmann (2019) and Eliason (2017). Our data and method, however, are very different from theirs. Contrary to us, 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.[5] Both papers assume as we do that the variable cost per patient depends on quality, but in their framework firms compete in quality (and potentially price), while in ours they compete directly in utility. Moreover, while Eliason (2017) considers an entry game with capacity choice, we take the structure of the surgery industry as given (there has been very little change in this respect over our period of study).

Our work is also connected to the strand of literature that estimates discrete choice models of hospital demand (e.g., Kessler and McClellan, 2000; Tay, 2003;

[3] Berry and Haile (2014) and Berry and Haile (2016) discuss the nonparametric identification of demand and supply models.

[4] See Brekke, Siciliani, and Straume (2011) and Cellini, Siciliani, and Straume (2018) for theoretical models of quality competition that include both variable and fixed costs.

[5] In 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.

Ho, 2006; Gowrisankaran, Lucarelli, Schmidt-Dengler, and Town, 2011; Ho and Pakes, 2014; Gaynor, Propper, and Seiler, 2016). We depart from the literature in two important dimensions. While most of the existing studies assume a maximum threshold for the distance that patients consider traveling to visit a hospital, we make no a priori assumption on the boundaries of market areas. Taking advantage of the richness of the data in the geographic dimension, we recover the utilities offered to patients by each hospital from the variations of relative market shares across patient locations. The utilities are identified at the hospital-clinical department-year level, controlling for demand variations at the patient location-clinical department-year level. We exploit the connectivity of the bipartite graph formed by hospitals and patient locations: all hospitals compete with others in many patient locations, creating many connections between hospitals in the one-node projected graph. Our method thus combines insights of the economics of network data (Abowd, Kramarz, and Margolis, 1999; Jochmans and Weidner, forthcoming) with demand estimation methods that are now standard in empirical industrial organization (Berry, 1994; Nevo, 2000). In a different vein, Finkelstein, Gentzkow, and Williams (2016) exploit patient mobility across hospital areas to separate demand from supply in the determination of health care utilization.

Next, and related to the earlier point, while most of the existing studies examine hospital choice conditional on hospitalization, we consider the outside option of not undergoing surgery –which potentially includes hospitalization without a surgery intervention. We need to approximate the size of the potential demand to tackle the issue of whether financial incentives have encouraged hospitals to increase the number of surgery admissions.[6] To this aim, we follow Dubois and Lasio (2018) and use the method suggested by Huang, Rojas, et al. (2013) and Huang and Rojas (2014). The method identifies the size of the potential demand as being such that controlling for market fixed effects does not affect the estimation of patient preferences (in particular, utilities and travel costs). We check the robustness of our main findings to the approximated potential demand.

Third, our work is related to the literature on hospital financial incentives. The policy reform we are considering, namely the introduction of an activity-based payment rule, is quite similar to the introduction of the prospective payment

[6] In support of the activity race hypothesis, the above-cited *Le Monde* article, Pommiers (2018), refers its 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 shifts in market shares (business stealing) from an increase in the aggregate number of admissions (market expansion).

system (PPS) for the Medicare program in 1983. There is however a notable difference between the American and French reforms, namely their starting point: a cost-based reimbursement system in the U.S. versus global budgeting in France. The change from cost-plus to price-cap regulation in the American case triggered the fear that hospitals would respond by providing less treatment for patients, with potentially negative effects on quality outcomes (see Cutler, 1995), a different policy concern than the above-mentioned "race to activity".[7] Another 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). We follow the literature by allowing for much heterogeneity in the incentives of each hospital to attract additional patients.

# 3 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.[8] As regards the latter, most of the expenditures are funded by the basic mandatory public health insurance system, see Appendix A.1 for details.

## 3.1 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 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*).[9]

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

[8]The 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.

[9]Private 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.

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 was notoriously inefficient, with the development of expanding hospitals being constrained by scarce resources, while hospitals with less patient admissions earned rents. 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.[10] The effect of the reform on hospital revenues has been approximately neutralized.

Formally, denoting by $r_{Dt}^{\text{FP}}$ and $r_{Dt}^{\text{NP}}$ 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:

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

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

where $\lambda_t$ are the phase-in coefficients:

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

In practice, the rates that have actually been applied by the regulator slightly differed from the above theoretical values, see Appendix B for details.

## 3.2 Scope of the study

Our data set 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, restricting our attention to the eight clinical departments (out of nineteen) that account for the highest number of admissions: orthopedics, ENT-stomatology, ophthalmology, gastroenterology, gynaecology, dermatology, nephrology and circulatory system. These departments have received 21 million admissions over the period.[11] As regards surgery, the structure of the hospital industry has remained constant over the period of study, with no hospital closure or significant merger.

**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.[12]

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 B. Finally,

[11] Together, the nineteen clinical departments have received 23 million surgery admissions over the period of study.

[12] The 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.

we collected demographic variables (education, population, median income, share of elder people, of women) at the postal code level.

**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 clinical departments. 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 2.

**Activity** Figure 1 and Table 2 show the general trend in the number of admissions by legal status. For-profit hospitals hardly increased their total activity in surgery over the years 2005-2008, while the number of admissions at nonprofit hospitals rose by more than 8.6% (.14 million admissions). As a result, the aggregate market shares of nonprofit hospitals for surgery services at the national level rose from 37.4% to 39.5%.

## 3.3 Clinical departments

We consider that demand-side behavior and competition are better described at the level of clinical departments than at the level of DRGs. Indeed, there are hundreds of diagnosis-related groups and the classification is irrelevant for patients and even for family doctors who address them to hospitals. A doctor may trust a particular surgeon, medical team or service within a given hospital, and that trust generally extends beyond a narrow set of DRG codes. Similarly, competitive efforts by hospitals to attract patients in most cases are exerted at the level of clinical departments.

Figure 2 shows that the nonprofit sector has gained market share at the national level over the period of study in each of the eight considered clinical departments. The gains in market shares lie between .7 percentage points in ophtalmology and 5 percentage points in dermatology.

**Hospital revenues and average rates at the clinical department level** Table 3 depicts the evolution of theoretical activity-based revenues in our working 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 €7.8 billion for the eight clinical departments we are considering: €5.1 billion in nonprofit hospitals and €2.8 billion in for-profit hospitals.

We compute reimbursement rates as weighted means at the clinical department level $g$ for every hospital $j$ and year $t$:

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

where the sums are over all DRGs $D$ in the clinical department $g$ and $r_{Djt}$ is defined in (1). Table 4 (top panel) reports the evolution of DRG rates aggregated at the level of the eight clinical departments.[13] 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.[14]

**Reduced-form evidence** Table 5, first column, shows that the trend represented on Figure 1 remains apparent after controlling for hospital-clinical department effects: activity of for-profit hospitals is stable while activity of nonprofit hospitals increases over the years 2005 to 2008. Controlling furthermore for clinical department-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.

Table 6 shows that the number of nurses, surgeons, anesthesiologists and non-medical staff per bed has increased more rapidly in nonprofit hospitals than in for-profit ones.

## 3.4 Patient locations and "demand units"

We use postal codes to represent patient and hospital locations. There are about 37,000 patient postal codes in mainland France. In rural areas, several cities may share the same code. Paris, on the other hand, has 20 postal codes or *arrondissements*, and the second and third largest cities (Marseilles and Lyon) also have many *arrondissements*. Hereafter, patient postal codes are indexed by the letter $z$.

[13] We carried out the exercise for each of the eight clinical departments separately. The eight tables, which are available upon request, exhibit the very same pattern.

[14] Composition effects in (3) due to specialization or to coding strategies (Dafny, 2005) seem to be limited in the data, see Appendix B.

Travel times between patients postal codes (about 37,000) and hospitals postal codes (about 1,000) are available in the data if and only if the hospital has indeed received a patient from the postal code.

We define "demand units" as triples (clinical department, year, patient postal code) or $(g, t, z)$ for which at least one patient admission occurred. As shown in Table 7, our data set contains about .9 million of such demand units. For each demand unit, we observe the number $q_{gjtz}$ of admissions for any hospital $j$ that receives at least one patient from that unit. The total number of admissions in a demand unit is therefore $q_{gtz} = \sum_j q_{gjtz}$. The average unit has roughly 20 admissions in 4 distinct hospitals.

Table 8 reports the distribution of local market shares and travel time per admission, each $(g, j, t, z)$ observation being weighted by the corresponding number of admissions $q_{gjtz}$. If we take the size of the potential demand ("market size") to be the population of the postal code, we find very low market shares $\hat{s}_{gjtz} = q_{gjtz}/\text{pop}_z$, of about .4% on average.[15] For less than 10% of the admissions, a single hospital serves all patients from the demand unit. For more than 75% of admissions, the hospital and patient postal codes are different. The median and mean travel time between patient and hospital for an admission are respectively 22 and 27 minutes. Overall, the dispersion indicators (standard deviation, interquartile range) are relatively high for both local shares and travel times. There is little heterogeneity in the distributions of travel times across clinical departments (see Table 31 in Appendix A.2).

# 4 Demand

In this section, we present our modelling strategy for patient behavior, and explain how we identify and estimate the utilities provided by hospitals. Finally, we show how to approximate the size of the potential demand.

## 4.1 Hospital choice

We represent the process that leads a patient to undergo surgery with a three-stage model, as depicted on Figure 3. First, the patient does or does not undergo surgery (indices $H$ and $\emptyset$). Second, a patient who receives surgery is admitted in either a for-profit hospital or a nonprofit hospital; we accordingly define two nests within group $H$, $n$ = FP and $n$ = NP. Finally, within a nest, the patient

[15] In section 4.4, we provide an approximation of the potential demand, which is much smaller than the population of the postal codes.

chooses her preferred hospital. We carry out the analysis separately for each clinical department and omit the corresponding index $g$ to simplify notations. The indirect utility of patient $i$ living at location $z$, undergoing surgery at date $t$ of hospital $j$ belonging to nest $n$, is given by

$$U_{ijtz} = \delta_{jtz} + \zeta_{iHtz} + (1-\sigma_2)\nu_{intz} + (1-\sigma_1)\varepsilon_{ijtz}, \tag{4}$$

where the mean utility level offered to patients, $\delta_{jtz}$, is specified as

$$\delta_{jtz} = u_{jt} - \mathrm{TC}_t(d_{jz}; X_{tz}) + \gamma\ \mathrm{NP}_j\ X^c_{tz} + \varphi_{tz} + \xi_{jtz}. \tag{5}$$

The patients' outside option is "No surgery". It includes all other medical treatments, with or without hospitalization. Normalizing $\delta_{\emptyset tz} = 0$, the patient's utility from the outside option is

$$U_{\emptyset itz} = \zeta_{i\emptyset tz}. \tag{6}$$

The presence of the outside option –the first stage of the above process– is not usual in the hospital literature. In section 4.4 below, we show how to approximate the size of the potential demand $M_{tz}$, the value of which, however, has no impact on the various coefficients in patient utility or on the residuals $\xi_{jtz}$, because they are absorbed into the parameters $\varphi_{tz}$.[16]

The effects $u_{jt}$ and $\varphi_{tz}$ entering the mean utility $\delta_{jtz}$ in (5) are parameters to be estimated, while the $\xi_{jtz}$'s are statistical disturbances. We discuss in section 4.2 the identification of the two-way fixed-effects $u_{jt}$ and $\varphi_{tz}$, relying on arguments from Abowd, Kramarz, and Margolis (1999). To avoid any confusion for the reader familiar with the empirical industrial organization literature, we stress that in our framework the patient location dimension $z$ plays the role of the market/time dimension $t$ in the decomposition $\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}$ proposed by Nevo (2000). In this setting, time is an extra dimension that is not fundamental for demand identification.[17]

In equation (5), $\mathrm{TC}_t$ stands for the travel costs incurred by patients. These costs are assumed to depend on the distance $d_{jz}$ measured as the travel time between patient home and hospital location and on socio-demographic variables $X_{tz}$ at the postal code level including population, shares of elders (people over 65), of high-school graduates, and of women, as well as median income in the postal

[16]Changing the $M_{tz}$'s only affects the parameters $\varphi_{tz}$ and shifts the utility levels $u_{jt}$ by some constant to accommodate the normalization condition (14). This is unimportant for what follows.

[17]Time, however, is the key dimension for the identification of supply-side behavior (see section 5.2).

code. Travel costs are specified as follows:

$$\text{TC}_t(d_{jz}; X_{tz}) = \alpha_0 \text{Closest}_{jz} + \alpha_1 \, d_{jz} + \alpha_{1X} \, d_{jz} X_{tz} + \alpha_2 d_{jz}^2, \tag{7}$$

where $\text{Closest}_{jz} = \mathbb{1}\{d_{jz} = \min_k d_{kz}\}$ is a dummy variable equal to 1 if hospital $j$ is the hospital closest from postal code $z$.

The vector of parameters $\gamma$ accounts for the variations across patient locations in the taste for nonprofit hospitals; in (5), $\text{NP}_j$ is a dummy variable for nonprofit status. This taste is supposed to depend on age, education, gender, income. The corresponding vector of variables, $X_{tz}^c$, is centered to let $u_{jt}$ represent the average utility (net of travel costs) provided by hospital $j$ at time $t$.

The individual perturbations $\varepsilon_{ijtz}$, $\nu_{intz}$ and $\zeta_{iHtz}$ reflect the nesting structure. We do not introduce a specific patient taste (or nest) for private nonprofit hospitals because these hospitals display the same values as public hospitals and share the same constraints in terms of service.[18] The disturbance $\varepsilon_{ijtz}$ (resp. $\nu_{intz}$) is an idiosyncratic perturbation at the patient (resp. nest) level, while $\zeta_{iHtz}$ is a common disturbance to all hospitals, such that the sum $\zeta_{iHtz} + (1-\sigma_2)\nu_{intz} + (1-\sigma_1)\varepsilon_{ijtz}$ follows an i.i.d. extreme value distribution.

To be consistent with random utility maximization, one must have $0 \leq \sigma_2 \leq \sigma_1 \leq 1$. When $\sigma_1$ approaches 1, preferences are perfectly correlated across hospitals with the same status, so that they become perfect substitutes. Similarly, when $\sigma_2$ approaches 1, preferences are perfectly correlated across the subgroups of for-profit and nonprofit hospitals, so that these nests become perfect substitutes. As Verboven (1996) explains, this setting encompasses three polar cases: (i) when $\sigma_1 = 0$, from which it follows that $\sigma_2$ is also equal to 0, the model boils down to a simple Logit; (ii) when $\sigma_2 = 0$, the model is a one-stage nested Logit with three nests (no hospitalization, hospitalization in the nonprofit or in the for-profit sector); and (iii) when $0 < \sigma_1 = \sigma_2 < 1$, the model is a one-stage nested Logit with two nests (no hospitalization and hospitalization).

The theoretical market share of hospital $j$ is hence equal to:

$$s_{jtz} = s_{jtz|n} s_{ntz|H} s_{Htz} = \frac{e^{\delta_{jtz}/(1-\sigma_1)}}{e^{I_{ntz}/(1-\sigma_1)}} \frac{e^{I_{ntz}/(1-\sigma_2)}}{e^{I_{Htz}/(1-\sigma_2)}} \frac{e^{I_{Htz}}}{1+e^{I_{Htz}}}, \tag{8}$$

[18] Private nonprofit hospitals do not have the same constraints in terms of internal organization and procurement, which might affect their cost efficiency. But patients choose hospitals on the basis of the utility offered to them and travel cost. Conditional on the offered utility, they do internalize efficiency considerations.

where the inclusive values are

$$I_{ntz} = (1-\sigma_1)\log\sum_{k\in n} e^{\delta_{ktz}/(1-\sigma_1)} \tag{9}$$

for $n = \text{FP}, \text{NP}$, and

$$I_{Htz} = (1-\sigma_2)\log\sum_{n=\text{FP,NP}} e^{I_{ntz}/(1-\sigma_2)}. \tag{10}$$

Berry (1994) has shown that preferences encompassed by mean utility levels could be recovered from market shares (inversion of demand) as follows:

$$\log\frac{s_{jtz}}{s_{\emptyset tz}} = \delta_{jtz} + \sigma_1 \log s_{jtz|n} + \sigma_2 \log s_{ntz|H}, \tag{11}$$

which yields our estimating equation for demand:

$$\begin{aligned}\log\frac{s_{jtz}}{s_{\emptyset tz}} = {} & u_{jt} - \alpha_0 \text{Closest}_{jz} - \alpha_1 d_{jz} - \alpha_{1X} d_{jz} X_{tz} - \alpha_2 d_{jz}^2 \\ & + \varphi_{tz} + \gamma \text{NP}_j X_{tz}^c + \sigma_1 \log s_{jtz|n} + \sigma_2 \log s_{ntz|H} + \xi_{jtz}.\end{aligned} \tag{12}$$

The conditional market shares at the right-hand side are $s_{jtz|n} = s_{jtz}/s_{ntz}$ and $s_{ntz|H} = s_{ntz}/s_{Htz}$. We estimate the above equation separately for each clinical department $g$, taking care of the endogeneity of the conditional shares.

## 4.2 Identification

Before getting to the estimation of (12), we address the novel and challenging issue in our modelling approach, namely the identification of the parameters $u_{jt}$ and $\varphi_{tz}$. For each clinical department, there are about 110,000 postal code-year pairs $(t, z)$ and 3,500 hospital-year pairs $(j, t)$. The disturbances $\xi_{jtz}$ reflect deviations from the mean attractiveness of hospital $j$ in patient area $z$ at date $t$. We assume that they are orthogonal to the geographic configuration of the industry:

$$\mathbb{E}\left[\xi_{jtz} \,|\, jt, tz, d_{jz}, d_{jz}X_{tz}, \text{NP}_j X_{tz}^c, Z_{jtz}^D\right] = 0, \tag{13}$$

where the excluded instruments $Z_{jtz}^D$ are presented in the following section.[19] The perception of a hospital's attractiveness may indeed vary across patient locations, due to historical, administrative and economic relationships, or to any other un-

[19] Abowd, Kramarz, and Margolis (1999), p.254, impose the same error structure as (13).

observed 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.

Under these restrictions, demand parameters are identified from the variation in hospitals' market shares. By analogy with the matched employer-employee data framework, our data set takes the form of an undirected bipartite graph, the vertices of which are hospitals and patients' locations (instead of firms and workers). For a given year and clinical department, two hospitals $j$ and $j'$ are connected if they receive patients from a common postal code $z$, and two postal codes $z$ and $z'$ are connected if at least one hospital receives patients from both $z$ and $z'$. Thanks to variations in market shares in the postal code (resp. hospital) dimension, the effects $u_{jt}$ (resp. $\varphi_{tz}$) are identified up to an additive constant for each connected component of the graph, see Abowd, Creecy, and Kramarz (2002).

It turns out that for all of the eight clinical departments and all of the four years 2005 to 2008, all hospitals and all patient locations in the sample are connected.[21] This means for any year $t$, any observation $(j, z)$ and $(j', z')$ can be indirectly connected through a sequence of edges within the bipartite graph. We adopt the following normalization restrictions:

$$\sum_z \text{degree(z)}\, \varphi_{tz} = 0 \tag{14}$$

for all connected components, where degree(z) refers to the number of times a postal code $z$ is involved in some edge with a vertex $j$, i.e., the number of distinct hospitals visited by patients living in $z$.[22] These restrictions are purely conventional. We allow the aggregate demand to vary over time in each clinical department, and therefore the utility levels $u_{jt}$ are identified only up to constants $C_t$ that depend on the year $t$.

As our objects of interest are the utilities provided by hospitals to patients, it is useful to understand the intuition behind their identification. This idea is to get rid of the effect $\varphi_{tz}$ by taking differences of (12) between hospitals $j$ and $k$

[20]For 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. Recall also Footnote 8.

[21]To be precise, this statement is true up to four exceptions, namely four isolated observations $(j, z)$ among the 3.6 million observations. These observations are such that for the year $t$, hospital $j$ receives patients only from postal code $z$, while patients from $z$ visit only hospital $j$. We neglect these four isolated components in what follows.

[22]The connected components of the graph are provided by the `Stata`© procedure `felsdvreg` which uses the above normalization restrictions by default. Equation (14) says that the sum of fixed effects $\varphi_{tz}$ is zero, where $\varphi_{tz}$ is counted as many times as it appears in the data, i.e., as many times as there are distinct hospitals receiving patients from postal code $z$ at year $t$.

that receive patients from $z$ at year $t$. Doing so amounts to consider the one-node projected graph on the hospital dimension, defined by Newman (2010) p. 124 and Jochmans and Weidner (forthcoming). In the projected graph, two hospitals $j$ and $k$ are connected if and only if they have at least one postal code $z$ in common. Newman (2001) page 5 defines the weight of an edge $(j, k)$ in that graph as the sum over common postal codes $z$ of $1/(n_z - 1)$, where $n_z$ is the number of hospitals receiving patients from postal code $z$. Newman then checks that the degree of hospital $j$ in the projected graph weighted in this way is simply the number of postal codes that send patients to $j$ *at the exclusion of those that send patients only to that hospital*. The latter postal codes, indeed, do not contribute to identification. Figure 4 shows the projected graph for orthopedics in 2008, which is rather dense and with no isolated hospital. Table 9 displays for orthopedics in 2008 the distributions of the number of postal codes connected to a hospital and of the Newman-weighted degrees. The two distributions turn out to be very close. We find that 90% of hospitals have a Newman-weighted degree of at least 37, which places us in the favorable case (occupational network) of Jochmans and Weidner (forthcoming).

### 4.3 Estimation

To account for the endogeneity of the conditional shares in (12), we use the instruments proposed by Berry, Levinsohn, and Pakes (1995) based on sums of characteristics of other hospitals. For the share $s_{jtz|n}$, our set of demand instruments $Z^D_{gjtz}$ includes the sum of (squared) distances to other hospitals in the same nest: $\sum_{k \neq j, k \in n} d_{kz}$, $\sum_{k \neq j, k \in n} d^2_{kz}$, 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 $z$ and other hospitals in the same nest $\min_{k \neq j, k \in n} d_{kz}$ interacted with the latter sociodemographics. Altogether, we have 22 instrumental variables. For the share $s_{ntz|H}$, we use the same instruments now based on sums in the other nest: $\sum_{k \notin n} d_{kz}$, $\sum_{k \notin n} d^2_{kz}$, $\min_{k \notin n} d_{kz}$. The estimation of the two first-stage equations consists in regressing $\ln s_{jtz|n}$ and $\ln s_{ntz|H}$ on two-way fixed-effects models and other exogenous variables on top of the above excluded instruments.

The estimation of demand equation (12) consists of a linear IV regression with two endogenous variables, the conditional market shares, in the presence of numerous two-way fixed-effects. This approach has at least two advantages. First, it avoids numerical issues related to nonlinear estimation and provides with a simple, robust framework to recover patients' preferences as well as unobserved attractiveness of hospitals. Second, any estimation error on the fixed-effects $\boldsymbol{u}$ and $\boldsymbol{\varphi}$ viewed as incidental parameters does not contaminate the coefficients $(\boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\sigma})$. In particular, if the postal code-year fixed-effects $\varphi_{tz}$ were to be poorly estimated, this would have no consequence on the supply equation, the welfare analysis,[23] and the assessment of the fit of our model. For all this, we need only $\boldsymbol{\delta}, \boldsymbol{\sigma}$ and $\boldsymbol{u}$ to be consistently estimated, which follows from linearity.

Finally, it is important for our purpose that the utilities $u_{jt}$ provided by hospitals, net of travel costs, are comparable across years, up to the aggregate shifts $C_t$ mentioned in section 4.2. For this reason, we estimate the demand model by pooling the four years together, even though identification is established in cross section. We impose that the relative degrees of substitutability at the different decision stages ($\sigma_1$ and $\sigma_2$) as well as the patient distaste for distance and her preference for nonprofit hospitals (coefficients $\alpha$ and $\gamma$) are constant over the period.

## 4.4 Approximating potential demand

As explained above, the size of potential demand does not affect the coefficients in the patient utility. It does, however, affect the elasticity of demand with respect to the utilities offered to patients. Omitting indices $g$ and $t$, we define own- and cross-semi-elasticities as

$$\eta_{jj} = \frac{1}{q_j}\frac{\partial q_j}{\partial u_j} \quad \text{and} \quad \eta_{jk} = \frac{1}{q_j}\frac{\partial q_j}{\partial u_k}. \tag{15}$$

It follows from (C.1) that the demand own-derivative

$$\frac{\partial q_j}{\partial u_j} = \sum_z q_{jz}\left[\frac{1}{1-\sigma_1} - \left(\frac{1}{1-\sigma_1} - \frac{1}{1-\sigma_2}\right)s_{jz|n} - \frac{\sigma_2}{1-\sigma_2}s_{jz|H} - s_{jz}\right] \tag{16}$$

increases with the potential demand $M_z$ through the unconditional market share $s_{jz} = q_{jz}/M_z$.

It is necessary to approximate the potential demand because the supply side of the model and the counterfactuals depend on the above elasticities. To this aim, 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 demand unit effects $\varphi_{tz}$. We choose the

[23] The effects $\varphi_{tz}$ cancel out in the conditional patient surplus.

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 first that $M_z = \text{pop}_z$:

$$\log \frac{q_{jtz}}{M_z - \sum_j q_{jtz}} = u^0_{jt} - \alpha^0_0 \text{Closest}_{jz} - \alpha^0_1 d_{jz} - \alpha^0_{1X} d_{jz} X_{tz} - \alpha^0_2 d^2_{jz} + \varphi^0_{tz} \\ + \gamma^0 \text{NP}_j X^c_{tz} + \sigma^0_1 \log s_{jtz|n} + \sigma^0_2 \log s_{ntz|H} + \xi^0_{jtz}, \tag{17}$$

which we also estimate without the $\varphi$'s:

$$\log \frac{q_{jtz}}{M_z - \sum_j q_{jtz}} = u_{jt} - \alpha_0 \text{Closest}_{jz} - \alpha_1 d_{jz} - \alpha_{1X} d_{jz} X_{tz} - \alpha_2 d^2_{jz} \\ + \gamma \text{NP}_j X^c_{tz} + \sigma_1 \log s_{jtz|n} + \sigma_2 \log s_{ntz|H} + \xi_{jtz}. \tag{18}$$

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

$$\frac{1}{JT} \sum_{j,t} \left[ (u^0_{jt} - \overline{u^0}) - (u_{jt} - \overline{u}) \right]^2 + \left(\boldsymbol{\alpha}^0 - \boldsymbol{\alpha}\right)^2 + \left(\boldsymbol{\gamma}^0 - \boldsymbol{\gamma}\right)^2 + \left(\boldsymbol{\sigma}^0 - \boldsymbol{\sigma}\right)^2 \tag{19}$$

As Huang, Rojas, et al. (2013) explain, the estimated coefficients in (18) have been found to be empirically monotonic in the market size $M_z$, which guarantees that there is a unique minimizer to the previous criterion. Moreover, none of the above demand coefficients depends on $M_z$, at the exception of $u_{jt}$'s (up to some constant $C_t$) and of $\varphi_{tz}$ which capture precisely the denominator of the left-hand side in (17): our first guess $M_z = \text{pop}_z$ is therefore both natural and innocuous.

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

$$M_z = \theta \ \text{pop}_z + (1 - \theta) q_z, \tag{20}$$

where $q_z = \max_t q_{tz}$ and $\theta \geq 0$ is a parameter to be estimated. Under this specification, the potential demand does not vary over time, which is a reasonable assumption given the short period of time considered. We run our baseline supply-side estimation and counterfactual simulations with the obtained values of the potential demand, and provide robustness checks with respect to $\theta$ in section 6.3.

## 4.5 Results

As explained above, we estimate the demand separately for each clinical department by pooling the four years 2005-2008 together. Tables 10, 11 and 12 report the results for the structural equation and the first stages relative to $\log s_{jtz|n}$ and $\log s_{ntz|H}$ respectively. The estimations are very precise since the data exhibit great variation in both hospital and postal code dimensions. Most of the variance in local market shares is actually captured by our two-way high-dimensional fixed-effects. The tests for excluded instruments have high $F$-stats in all first-stage equations.

For the majority of clinical departments, we reject both the simple Logit and one-stage nested Logit model at usual levels: the null hypotheses of the parameters $\sigma_1$ and $\sigma_2$ being zero or equal to each other are rejected at 5%. Ophtalmology and ENT, stomatology are the two clinical departments where a one-stage nested Logit with three nests (outside option, for-profit hospitals, nonprofit hospitals) is not rejected. By contrast, we cannot reject the two-stage nested Logit choice structure, with the correlation $\sigma_1$ (resp. $\sigma_2$) ranging between .25 (.47) and .71 (.68) in all the other departments. Importantly, these parameters are always such that $0 < \sigma_2 < \sigma_1 < 1$. Patients are more likely to substitute among hospitals than towards the outside option of no surgery, and they are also more likely to substitute within the same legal sector (for-profit or nonprofit).

The signs of estimated parameters remain quite identical from one clinical department 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 clinical departments.

Moreover, tastes for hospitals are not randomly distributed: richer patient locations exhibit a preference in favor of for-profit hospitals, regardless of the clinical department. Except for orthopedics, older patients prefer nonprofit hospitals or are indifferent. Areas with more educated people favor nonprofit hospital for orthopedic and ophthalmologic surgery and have no preference as far as other clinical departments are concerned.

Table 13 and the histograms on Figure 5 show the distributions of the estimated utilities $\hat{u}_{jt}$, for the potential demand determined in section 4.4. Weighting these utilities by activity at the hospital-clinical department-year level shifts the mass of the distribution to the right, which is consistent with bigger hospitals offering higher utilities to patients.

More relevant than the mean is the dispersion of the distribution of utilities. Depending on the clinical department, the range of estimated utilities lies somewhere between 1.5 and 4.5, and the interquartile range as well as the standard deviations are comprised between .2 and .7. To interpret these indicators of dispersion, we express utility differences in terms of travel time to hospitals.[24] To this aim, we increase all the utilities $u_{jt}$ by .1 and compute the reduction in travel times that would generate the same patient surplus gain. We use surpluses conditional on undergoing surgery rather than unconditional surpluses because with the latter the arbitrary convention of zero utility for the outside option affects the computation of compensating variations.

Omitting index $t$, the surplus conditional on undergoing surgery derived from the two-stage nested Logit model writes (up to $1-\sigma_2$ which will disappear in what follows):

$$S_z(\mathbf{u}, \mathbf{d}) \equiv \log\left[\left(\sum_{j\in\text{FP}} e^{\frac{\delta_{jz}(u_j,d_{jz})}{1-\sigma_1}}\right)^{\frac{1-\sigma_1}{1-\sigma_2}} + \left(\sum_{j\in\text{NP}} e^{\frac{\delta_{jz}(u_j,d_{jz})}{1-\sigma_1}}\right)^{\frac{1-\sigma_1}{1-\sigma_2}}\right], \tag{21}$$

where the sums are over hospitals in the nest: for-profit (FP) and nonprofit (NP), and the function $\delta_{jz}(u_j, d_{jz})$ is given by (5). At the level of each patient location $z$, we compute compensating variations by solving for the compression factors $\mathbf{x}$ that satisfy[25]

$$S_z(\tilde{\mathbf{u}}, \mathbf{d}) = S_z(\hat{\mathbf{u}}, \mathbf{d}(\mathbf{1\text{-}x})), \tag{22}$$

with $\tilde{\mathbf{u}} = \hat{\mathbf{u}} + .1$. As shown in Table 14, we find that the median compression factor corresponding to a general utility rise of .1 varies between 12.6% and 35.6% depending on the clinical department. As the median travel time is 22 minutes, this corresponds to hospitals being closer to patients by 3 to almost 8 minutes. Hence, the dispersion indicators reported in Table 13 show a substantial degree of heterogeneity across hospitals in the utilities they provide to patients.

Table 15, the counterpart of Table 5, 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). The differential remains with almost unchanged parameters when we control also for staff, equipment and socio-demographic variables (see the coefficients of nonprofit × 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 16 shows our approximation of potential demand. For the median postal code, the market size represents between .6% and 2.6% of the population, depend-

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

[25]We use a multiplicative compensation rather than an additive one to avoid negative distances.

ing on the clinical department. The potential number of admissions is larger than the maximal number of admissions observed over the years 2005-2008, by between 12% and 39% depending on the department. Table 17 and 18 report the estimated own- and cross-semi-elasticities $\eta_{jj}$ and $\eta_{jk}$ defined in (15), based on these market approximations. Own-semi-elasticities are rather homogeneous along both the hospital and time dimensions and roughly equal to 1.6, but they differ more substantially according to the clinical department: from 1 in ENT, stomatology to 2.6 in gynaecology. Restricting our attention to the strongest interactions between two hospitals $j$ and $k$, i.e., the first percentiles of the distribution (”min” and ”p10” columns of Table 18), the cross semi-elasticities are higher when the two hospitals have the same legal status, which is consistent with intra-sector competition being fiercer than inter-sector competition.

Table 19 shows that state-owned, non-teaching nonprofit hospitals face less elastic demand (in the sense of the own-semi-elasticity), which is consistent with previous findings by Gaynor and Vogt (2003). However, both private nonprofit and teaching hospitals face more elastic demand than for-profit hospitals.

# 5 Supply

In this section, we develop a competition-in-utility framework where hospitals attract patients by offering them utilities. We present our strategy to identify and estimate the hospitals' objective functions.

## 5.1 Competition in utility space

We describe hospital competition within the framework of Armstrong and Vickers (2001). In particular, the patient utility in our demand model (4) and (5) has an additively separable form:

$$U_{gijtz} = u_{gjt} + \psi_{gijtz},$$

where $u_{gjt}$ is the "average" utility offered by hospital $j$ for services in clinical department $g$ at year $t$, and $\psi_{gijtz}$ represents individual patient heterogeneity regarding health status, disutility for travel time to hospital, and other unobserved preferences. Importantly, this framework assumes non-discrimination: hospitals offer the same utility (net of travel costs) irrespective of patient location or of any other individual characteristics. As in the demand part, the analysis is carried out separately for each clinical department and we omit therefore the unnecessary index $g$ in what follows.

The demand addressed to hospital $j$, denoted as $q_{jt}(u_{jt}; u_{-jt}, \phi_t)$, depends on the utility it provides to patients, the utilities offered by the other hospitals, and the set $\phi_t$ of demand shocks $\xi_{jtz}, \varphi_{tz}$, socio-demographic variables $X_{tz}$ driving patient travel costs and preference for nonprofit hospitals. In the rest of this subsection, we simply denote demand functions as $q_j(u_j; u_{-j})$, omitting for clarity the index $t$ as well as the exogenous demand characteristics $\phi_t$.

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

$$V_j(q_j, u_j; r_j) = \overline{T}_j + r_j q_j + \beta_j^q \, q_j + \beta_j^{qu} \, q_j \, u_j. \tag{23}$$

The first two terms in (23) represent the revenue of hospital $j$, made of a lump-sum transfer $\overline{T}_j$ and activity-based revenues, $r_j q_j$. We assume away revenue effects and normalize the marginal utility of revenue to 1.[26]

Hospital costs are accounted for in the last two terms of (23); we assume constant returns to scale (CRS) as in Armstrong and Vickers (2001). Such costs can be pecuniary and non-pecuniary. Our main assumption is that increasing the utility offered to each patient translates into higher costs per patient. 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).[27] Also, in the spirit of Pope (1989), 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 (23) also encompasses non-pecuniary motives such as altruism or managerial empire building. Altruism would be described by a utility term $a\,q\,u$, with $a > 0$, where $q\,u$ is the total utility offered to patients.[28] Empire-building would be described by a term $v\,q$, with $v > 0$.[29] In the absence of cost data, however, we cannot identify the level of marginal costs separately from the importance of non-financial motives.

[26] In practice, as explained in section 3, the payment reform was designed so that the hospitals' budgets remain approximately unchanged during the phase-in period.

[27] The quality of variable inputs, such as food, may also be increased.

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

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

Each hospital chooses the utility it offers to patients so as to maximize

$$\max_{u_j} V_j(q_j(u_j, u_{-j}), u_j; r_j). \tag{24}$$

Figure 6 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, $V_j(q_j, u_j) = \overline{V}$, which are hyperbolas in the $(q_j, u_j)$-space. The hospital maximizes its objective function $V_j$ along the demand curve. At the solution of the problem, its marginal incentive to change its utility is zero:

$$\mu_j(u_j, u_{-j}; r_j) \overset{d}{=} \frac{\mathrm{d}}{\mathrm{d}u_j} V_j(q_j(u_j, u_{-j}), u_j; r_j) = 0. \tag{25}$$

It follows that the derivative of the demand addressed to the hospital is equal to the marginal rate of substitution between $q$ and $u$:

$$\frac{\partial q_j(u_j; u_{-j})}{\partial u_j} = -\frac{\partial V_j/\partial u_j}{\partial V_j/\partial q_j} = -\frac{\beta_j^{qu} q_j}{r_j + \beta_j^q + \beta_j^{qu} u_j}. \tag{26}$$

Introducing the own semi-elasticity $\eta_{jj}$ presented in (15), we can write the first-order condition of the hospitals' maximization problem as

$$r_j + \beta_j^q + \beta_j^{qu} u_j = -\frac{\beta_j^{qu}}{\eta_{jj}}. \tag{27}$$

The second-order condition of the maximization problem, which we empirically verify below, is $\partial \mu_j / \partial u_j < 0$. 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 $\mathrm{D}_u \mu$ with generic entry $\partial \mu^j / \partial u_k$, which we also empirically check.

**Transmission of financial incentives** Figure 7 shows how a hospital responds to a change in financial incentives, the utilities provided by its competitors being fixed. A higher reimbursement rate $r_j$ reduces the marginal rate of substitution between $q$ and $u$ (the right-hand side of (26)), and as a result shifts the solution $(u_j, q_j)$ to the right along the residual demand curve. To see this formally, we differentiate each of the first-order conditions (25) with respect to $r_j$:

$$\frac{\partial \mu^j}{\partial u_j} \mathrm{d}u_j + \frac{\partial \mu^j}{\partial u_{-j}} \mathrm{d}u_{-j} + \frac{\partial \mu^j}{\partial r_j} \mathrm{d}r_j = 0, \tag{28}$$

and we define the transmission rates as

$$\tau_j = \left.\frac{\partial u_j}{\partial r_j}\right|_{u_{-j}} = -\frac{\partial q_j/\partial u_j}{\partial \mu^j/\partial u_j} > 0, \tag{29}$$

where $\partial \mu_j/\partial u_j = \partial^2 V_j/\partial u_j^2$ is given by (D.4) in the Appendix. This latter derivative is negative if the second-order conditions of the hospital's problem hold. Hence, checking that the transmission rates are positive is equivalent to checking that the second-order conditions hold. Using (D.4) and the first-order condition (25), we compute the transmission rates as:

$$\tau_j = -\left(\beta_j^{qu}\left[2 - q_j\frac{\partial^2 q_j/\partial u_j^2}{\partial q_j/\partial u_j}\right]\right)^{-1} \tag{30}$$

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

$$\rho_{jk} = \left.\frac{\partial u_j}{\partial u_k}\right|_{r_j} = -\frac{\partial \mu^j/\partial u_k}{\partial \mu^j/\partial u_j}. \tag{31}$$

The slope $\rho_{jk}$ measures how hospital $j$ changes the utility $u_j$ it provides to patients if competitor $k$ changes $u_k$. An important force that governs the nature of strategic interactions is the costliness of utility, $\beta_j^{qu} < 0$, i.e., the fact that a higher utility implies a higher variable cost. 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.[30] Using (D.3), (D.4) and the first-order condition (25), we compute these slopes as:

$$\rho_{jk} = \frac{q_j(\partial^2 q^j/\partial u_j \partial u_k) - (\partial q^j/\partial u_j)(\partial q^j/\partial u_k)}{2(\partial q^j/\partial u_j)^2 - q_j(\partial^2 q^j/\partial u_j^2)}. \tag{32}$$

**Equilibrium effect of incentives** The transmission rates $\tau_j$ computed in (29) 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

[30]The sign of $\rho_{jk}$ is given by the sign of the numerator of (31) because the denominator is negative from the second-order condition of the hospital's problem. The force described above is embodied in the positive term $\beta_j^{qu}\partial q_j/\partial u_k$ in (D.3), with $\beta_j^{qu} < 0$.

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 $\tau$ whose $(j, j)$-entry is the transmission rate $\tau_j$ defined in (29); the matrix $\rho$ whose generic entry is $\rho_{jk}$, with $\rho_{jj} = 0$ by convention; the Leontief matrix $L = (I - \rho)^{-1}$. We then rearrange (28) as

$$\mathrm{d}u = L\,\tau\,\mathrm{d}r. \tag{33}$$

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 $\tau_k \mathrm{d}r_k$, affects the utility offered by hospital $j$ in equilibrium: $\mathrm{d}u_j = \sum_k l_{jk}\tau_k \mathrm{d}r_k$.

## 5.2 Identification

Bringing the theory to the data requires the utilities offered by hospitals to patients, which we back out from the demand estimation. We plug them into the supply equation to infer hospitals' preferences. Remember that these utilities are only identified up to some constant; as explained below, further assumptions on time-invariant hospitals' preferences lowers the degree of under-identification of those utilities and point identify the evolution of those utilities. Moreover, we have to specify the coefficients $\beta^q$ and $\beta^{qu}$ appearing in the hospital objective (23). To account for unobserved characteristics (technology, organization, patient case-mix, etc.), we place maximal heterogeneity in the parameter that governs the linear dependence in quantity. We specify it as the sum of a hospital-clinical department fixed-effect $\bar{\beta}^q_j$ and of an unobserved supply shock $\omega_{jt}$:

$$\beta^q_{jt} = \bar{\beta}^q_j + \omega_{jt}. \tag{34}$$

We thus allow for unconstrained differences in perceived marginal costs across hospitals.[31] We are not able, however, to allow for much heterogeneity in the second-derivative of the objective function with respect to $q$ and $u$. We assume that, for each clinical department, the coefficient remains constant over the years and is common to all hospitals: $\beta^{qu}_{jt} = \bar{\beta}^{qu}$.[32]

[31] As 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.

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

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 (23), 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 clinical department (see section 4.2).

Our main assumption regarding supply-side behavior is that the objective functions of the hospitals are constant over the four years of the period of study. In particular, marginal costs and managerial preferences do not change during the phase-in of the hospital payment reform. Consistent with our medium-run approach, we assume that hospital managers myopically maximize their short-term objective function, which remains constant (up to supply disturbances). Combining the first-order condition (27) with the above specification, in particular equation (34), adding constants $C_t$ to account for aggregate demand shocks, and rearranging, we obtain

$$u_{jt} + \frac{1}{\eta_{jjt}} = -C_t - \frac{\bar{\beta}_j^q}{\bar{\beta}^{qu}} - \frac{r_{jt}}{\bar{\beta}^{qu}} - \frac{\omega_{jt}}{\bar{\beta}^{qu}}, \tag{35}$$

which yields our estimating supply equation:

$$u_{jt} + \frac{q_{jt}}{\partial q_{jt}/\partial u_{jt}} = a_t + a_j + a_r r_{jt} + \omega'_{jt}, \tag{36}$$

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 $a_t \equiv -C_t$ 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 $\omega_{jt}$. 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 *infra*).

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 (35). As explained in Appendix B, 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 clinical department level, which may give rise to endogenous composition effects, see the discussion in Section 3.3. For these reasons, we instrument the average rates $r_{jt}$ by the phase-in coefficients $\mathrm{NP}_j\lambda_t$ applied to the nonprofit sector, recall (2). Specifically, we rely on the following exclusion restrictions:

$$\mathbb{E}\left[\, \omega_{jt} \mid j,\ t,\ \mathrm{NP}_j\lambda_t \,\right] = 0.$$

The reason why the estimating equation (35) includes constants $C_t$ is that the theoretical utility levels appearing in (27) are identified only up to additive constants that depend on the year and the clinical department. The aggregate demand $C_t$ and the linear coefficients $\bar{\beta}^q_j$ are identified up to additive, clinical department-specific constants $C'$.[33] Hence, the assumption that hospital preferences remain constant over the four years of the period identifies *the evolution of* the aggregate demand for each clinical department. Alternatively, we may allow for aggregate drifts in the linear preference coefficients and interpret $\bar{\beta}^{qu}C_t$ as coming from changes in $\bar{\beta}^q_j$ that are uniform across hospitals. In any case, aggregate shocks affecting demand and supply are not identified separately.

Because $\beta^{qu}_{jt}$ and the semi-elasticities $\eta_{jjt}$ are identified, the sum

$$r_{jt} + \beta^q_j + \beta^{qu}_{jt}(u_{jt} + C_t) = -\frac{\beta^{qu}_{jt}}{\eta_{jjt}} \tag{37}$$

is identified. It follows that the transmission rates $\tau_{jt}$ and the slopes of reaction functions $\rho_{jkt}$ given by (29) and (31), which involve utility levels $u_{jt}$ only through the left-hand side of (37), are identified.

## 5.3 Estimation

The estimation of supply equation (36) proceeds from a linear IV regression for each clinical department with one endogenous variable (the average reimbursement rate at the hospital-year level), time dummies, and hospital fixed effects. This approach avoids numerical issues arising from nonlinear estimation and enables us to recover hospitals' preferences in a robust and transparent fashion. Any estimation error on $u_{jt}$ will be absorbed in the unobserved idiosyncratic shock $\omega_{jt}$ for it appears linearly at the left-hand side of equation (36). The derivative $\partial q_{jt}/\partial u_{jt}$ that appears at the left-hand side is computed from (16) and thus depends only on observables, on the correlations $\hat{\boldsymbol{\sigma}}$ as well as on the approximated parameter $\hat{\theta}$ ruling potential demand, which emphasizes the need for estimating those parameters consistently. We have already seen that there is little concern about the estima-

[33] Increasing $C_t$ by $C'$ and decreasing $\bar{\beta}^q_j$ by $\bar{\beta}^{qu}C'$ leave $-(C_t + \bar{\beta}^q_j/\bar{\beta}^{qu})$ unchanged in (35).

tion of $\boldsymbol{\sigma}$. We provide robustness checks with respect to the approximated market size in Section 6.3, checking that it hardly affects the estimated parameters $\boldsymbol{\beta}$ for hospital preferences.

## 5.4 Results

We estimate hospital preferences from equation (35) separately for each clinical department. The results are reported in Table 20. Recall that the coefficient of the reimbursement rate is $a_r \equiv -1/\bar{\beta}^{qu}$. For all but one of the eight clinical departments, we do not reject $\bar{\beta}^{qu} < 0$ at usual levels, which is consistent with the notion that providing a higher utility to each patient entails a higher marginal cost.[34]

The coefficients $\bar{\beta}^q_j$ increase with hospital size, suggesting that hospitals with larger surgery bed capacity have a stronger preference for increasing their number of patients.

Figure 8 plots the distribution of the estimated transmission rates $\tau_j$, computed from (30) 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 (24) 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 .01 in nephrology, but by up to .06 in dermatology, which is equivalent to reducing the median distance to patients by 4% and 24% respectively (see Table 14 for conversion of utilities into travel times). Table 21 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 $\rho_{jk}$ of hospitals' reaction functions are positive for almost all pairs of hospitals $(j, k)$, all clinical departments and all years in the period of study. This holds for nearly 95% of ordered the pair of hospitals, the pairs $(j, k)$ being weighted by $\sum_z q_{jz}\, q_{kz}$ to reflect how strongly connected the hospitals are. We therefore conclude that strategic complementarity occurs in most interactions. Table 22 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 $\rho_{jkt}$ is higher than .08 at time $t$. The strategic interactions are thus fairly strong, with highest values are close to .2, which compares well to usual results found in

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

the spatial price competition literature (Conley and Topa, 2002; Pinkse, Slade, and Brett, 2002; Conley and Dupor, 2003).

Table 23 show that the slopes of reaction functions $\rho_{jk}$ decrease with the distance $d_{jk}$ between hospital $j$ and $k$. The table reports the result of the estimation of the following two-way fixed-effects model estimated separately for each clinical department $g$:

$$\rho_{jkt} = \alpha_\rho^1 d_{jk} + \alpha_\rho^2 d_{jk}^2 + \alpha_\rho^i \text{Intra}_{jk} + E_{jt} + F_{kt} + \iota_{jkt}. \tag{38}$$

It confirms that distance has a strong, depressing effect on the slopes of reaction functions: $\rho_{jk}$ decreases with time for values of $d_{jk}$ being less than 150. These findings are consistent with the spatial autocorrelation functions estimated in the literature. The coefficient $\alpha_\rho^i$ turns out to be nonnegative in every clinical department (at the exception of gastroenterology), which suggests that intra-sector competition, proxied by $\text{Intra}_{jk} = \text{NP}_j\text{NP}_k + (1 - \text{NP}_j)(1 - \text{NP}_k)$, is generally fiercer than inter-sector competition.

Finally, we check that, for each clinical department and year, the Jacobian matrix $\text{D}_u\mu$, where $\mu = (\mu_j)_j$ is defined in (25), exhibits strict diagonal dominance, which guarantees the stability of the equilibrium as explained above. Moreover, we also check that, for each $g$ and $t$, the matrices $\rho = (\rho_{jk})_{j,k}$ have a spectral radius of roughly .3, which is less than 1 and hence guarantees the invertibility of $I - \rho$ as well as the existence of the Leontief matrix defined in Section 5.1.[35]

# 6 Counterfactual simulations

At this point, we have estimated the demand addressed to each hospital as a function of the utility it provides to patients, the utilities offered by the other hospitals, and a set $\hat{\phi}_t$ of demand shocks and socio-demographic variables $(\hat{\xi}_{jtz}, \hat{\varphi}_{tz}, \hat{X}_{tz})$. We also have estimated hospital preferences in the form of two coefficients $\hat{\beta}_{jt}^q$ and $\hat{\beta}^{qu}$, the former depending on supply shocks $\hat{\omega}_{jt}$. Recovering agents preferences enables us to simulate different policy counterfactuals.

First, we estimate how our structural model performs when predicting the evolution of activity and market shares within our period of study. We compare what our model would have predicted in 2005 (given demand and supply at that time) to what actually happened in 2008. We follow the same route as the literature on the *ex post* evaluation of merger simulation (Peters, 2006; Björnerstedt and

[35]The two invertibility results are in fact equivalent since the Jacobian matrix $\text{D}_u\mu$ is the product $\text{D}_u\mu = \text{diag}(\partial\mu_j/\partial u_j)\,(I - \rho)$, where $\text{diag}(\partial\mu_j/\partial u_j)$ is the diagonal matrix with entries $\partial\mu_j/\partial u_j < 0$.

Verboven, 2016), with the major difference that here hospitals compete in utility rather than in price.

Second, we offer a structural evaluation of the introduction of the activity-based payment system. The model allows to recover the causal effect of reimbursement rates on the number of hospitalized patients and on the aggregate market shares of the two sectors, and thus to disentangle business stealing from market expansion. We also investigate the effect on the patients' surplus (conditional on hospitalization) and on the hospitals' objective functions.

## 6.1 Breaking down the evolution of activity

We examine how our model performs in reproducing the observed changes in activity and market shares. We implement a series of thought experiments that provides us with a decomposition of the observed changes from 2005 to 2008 along different possible channels: financial incentives, demand shocks, supply shocks, strategic effects. For each clinical department $g$, 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 (33);

(b) Same change in rates as above. We compute the response of each hospital separately, keeping fixed the strategy of the competitors, in line with the definition of the transmission rates given in (29);

(c) The industry is hit by the aggregate shock $\hat{C}_{2008} - \hat{C}_{2005}$ identified in section 5.2. 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 $\hat{\phi}_t$ mentioned above (demand shocks and demographic variables) change from their 2005 values to their 2008 values.[37]

(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;

[36] In all the simulations, we take the average reimbursement rate observed in 2008, which is based on the case-mix realized in 2008, see equation (3).

[37] Accordingly weighted, the effects $\hat{\varphi}_{tz}$'s sum up to zero in both 2005 and 2008.

(f) Same as above with the financial change of reimbursement rates, i.e., we combine (a), (c) and (d);

(g) The linear coefficients $\hat{\hat{\beta}}_j^q$ in the hospital objective functions are hit by the supply shocks $\hat{\omega}_{j,2008}$ instead of $\hat{\omega}_{j,2005}$;

(h) All of the above parameters (aggregate and hospital-specific supply and demand shocks as well as reimbursement rates) change to their 2008 values. We simulate the change in the utility provided by each hospital, keeping the competitors' utilities fixed. In other words, we neutralize the effect of strategic interactions in the move from 2005 to 2008.[38]

Table 24 reports the results of simulations (a) to (h) in orthopedics, the largest clinical department. (For the other departments, see Tables 33 to 39 in Appendix E.) Column 1 reports the shift in the aggregate market share of the nonprofit sector in percentage points. The next columns report the evolution of activity in %: 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 first simulation takes the perspective of the researcher in 2005 who aims at predicting the effect of the change in incentives on activity and market shares. The objective function of hospital $j$ under the incentives $\tilde{r}_{jt_1}$ is given by

$$(\tilde{r}_{jt_1} + \hat{\beta}^q_{jt_0})\ \hat{q}_{jt_0}(\tilde{u}_{jt_0}, \tilde{u}_{-jt_0}; \hat{\phi}_{t_0}) + \hat{\beta}^{qu}\ \tilde{u}_{jt_0}\ \hat{q}_{jt_0}(\tilde{u}_{jt_0}, \tilde{u}_{-jt_0}; \hat{\phi}_{t_0}), \tag{39}$$

with $t_0 = 2005$ and $t_1 = 2008$. Hospital $j$ offers utility $\tilde{u}_{jt_0}$ while her rivals offer $\tilde{u}_{-jt_0}$. Demand and supply conditions ($\hat{\phi}_{t_0}$ and $\hat{\beta}^q_{jt_0}$ respectively) are those of year $t_0$. The potential demand is given in Table 16. In this counterfactual environment, hospital $j$ chooses the utility $\tilde{u}_{jt_0}$ it provides to patients to maximize (39), which yields the following first-order condition:

$$\tilde{\mu}_{jt_0}(\tilde{u}_{jt_0}, \tilde{u}_{-jt_0}; \tilde{r}_{jt_1}) = 0, \tag{40}$$

where the function $\mu(.)$ is defined in (25). In simulation (a), we solve the nonlinear system of $J_g \approx 900$ highly nonlinear equations with $J_g$ unknowns, for all $j = 1, \ldots, J_g$, where $J_g$ accounts for the number of hospitals considered in clinical department $g$. To do so, we follow the approach proposed by Bonnet and Dubois

[38] Changing all parameters and allowing for competition in utility yields by construction the situation that prevailed in 2008. We check, but do not show, that this simulation indeed yields a perfect fit of the activity observed in 2008.

(2010), namely we minimize:

$$\text{argmin}_{\tilde{\mathbf{u}}_{t_0}} \sum_{j=1}^{J_g} \left[\tilde{\mu}_{jt_0}(\tilde{\mathbf{u}}_{t_0})\right]^2 . \tag{41}$$

Numerically, this procedure yields a minimum of zero in all the simulations presented below, meaning that we are able to find a Nash equilibrium in all the counterfactual situations we consider. We thus obtain an estimate of optimal $\tilde{\mathbf{u}}_{t_0}$ and are then able to compute counterfactual activity in each hospital given $\tilde{q}_{jt_0} = \hat{q}_{jt_0}(\tilde{u}_{jt_0}, \tilde{u}_{-jt_0}; \hat{\phi}_{t_0})$.

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 +.7 to +5pp depending on the clinical department. The predicted change, under the demand and supply conditions that prevailed in 2005, ranges from +1pp to +4.2pp. In orthopedics, the predicted change in the market share of the nonprofit sector (+1.01pp) accounts for 86% of the observed change (+1.18pp). In general, the predicted change accounts for at least 46% of the observed change (circulatory) and sometimes for more than 100% of the observed change (113% gastroenterology and 142% in ophthalmology).

By contrast, the change in financial incentives does a poor job in replicating the evolution of activity at the industry level (column 2). Depending on the department, the observed change in the total number of surgery admissions ranges from -2.4% to 9.9%, while the predicted change (at the exception of dermatology) ranges from .2% to 1.2%. While financial incentives help predict a reasonable part of the rise in the activity of nonprofit hospitals (between 35% and 100%), they fail to reproduce the evolution of the activity of for-profit hospitals: the model predicts typically a moderate fall (by one or two percent) of the activity of those hospitals in each of the eight clinical departments, while in reality very different evolutions have occurred, ranging from a 10% fall in dermatology to a 8% rise in ophthalmology.

In sum, the results suggest that 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. We believe that this strong result sheds light on both academic and public debates on the impact of activity-based payment: we find here empirical evidence in favor of business stealing rather than market expansion effects.

We now turn to the role of supply and demand shocks. For all clinical departments, the hospital-specific supply shocks $\hat{\omega}_{jt}$ explain almost nothing of the observed variation in hospital activity and in the market share of the nonprofit sector (simulation (g)). Taken 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 much better (simulation (e)). If we also account for the role of the financial incentives (simulation (f)), i.e., we account for all the changes that have occurred between 2005 and 2008 except those relative to supply conditions, we get a very good fit in terms of both activity and market share.

Finally, we can assess strategic effects in two ways. The most informative way is to compare simulations (a) and (b) where only the reimbursement rates change. In response to the stronger incentives, nonprofit hospitals increase the utility they offer to patients. In simulation (a), for-profit hospitals are allowed to respond to this change, and they do so by increasing their own utility, which mitigates the business stealing from nonprofit hospitals. In simulation (b), we do not allow for such a response: we neutralize the strategic responses of rivals by considering hospital $j$'s behavior when the utilities provided by all other rivals are fixed.[39] This explains why the total number of patients and the aggregate market share of for-profit hospitals decline more in case (b) than in case (a). By contrast, strategic effects have an ambiguous impact on the activity of nonprofit hospitals:[40] allowing for-profit (nonprofit) hospitals to respond tends to reduce (increase) nonprofit activity. It is guaranteed, however, that strategic effects push utilities and hence total activity upwards. For instance, activity in gastroenterology would increase by .63% in equilibrium instead of .47% if strategic effects are ignored. In general, we find that the magnitude of the strategic effects is weak.

We may also compare the observed evolution of the industry with the result of simulation (h), where strategic effects are shut down: each hospital responds to changes in incentives and in demand and supply conditions, taking the strategy of the competitors as fixed. Here too many forces are at play to identify qualitative regularities across departments. The main insight is that equilibrium effects, again, appear to be quantitatively modest.

## 6.2 The impact of the reform on hospitals and patients

In what follows, we concentrate on the above-mentioned counterfactual experiment (a), i.e., we change the reimbursement rates from $r_{2005}$ to $r_{2008}$ while keeping

[39]Here, we do not compute a Nash equilibrium, but rather solve $J_g$ single-dimensional optimization problems.

[40]Contrast column 3, lines (a) and (b), of Tables 24 and 35.

the demand and supply conditions that prevailed in 2005 unchanged. This experiment enables us to assess the causal impact of the introduction of activity-based payment in the nonprofit sector[41] on activity, market shares, patients' surplus and hospitals' objectives.

Table 25 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 form .2% to 1.2% depending of the clinical department, which represents a few thousands patients. The aggregate market share of the nonprofit sector would have increased by between 1pp and 4.2pp according to the department. To illustrate, in orthopedics, activity would increase by 2.6% (14,000 patients) in nonprofit hospitals but would decrease by 1.6% (-12,000 patients) in for-profit hospitals: on the whole, only .2% 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 demand unit: in orthopedics, we find that about 13,000 patients would be diverted.

Table 26 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 .019 and .09 depending on the clinical department, which amounts to making hospitals closer to patients by between 1.5 and 7 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 0 to .009 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 .1 (recall Table 22).

To appreciate the impact of the reform on patient welfare, we proceed as for converting utilities into distances (see Section 4.5). Specifically, we compute at the patient 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, i.e., we solve for $x$ in equation (22) with $\hat{u}$ and $\tilde{u}$ being respectively the pre- and post-reform offered utility levels.[42] The simulated reform has the same effect as if the distances to hospitals were compressed for potential patients by the homogeneous

[41] More precisely, we simulate the move from 25% to 100% share of revenues based on activity.

[42] As in Section 4.5, we use the surplus conditional on hospitalization to get results that are independent of any arbitrary normalization.

factor $x_z$ in postal code $z$, the median of which is 10.8% in gastroenterology for instance. This median compression factor is highest in dermatology (17.4%) and lowest in ophthalmology (2.3%), suggesting respectively large and small potential patient gains of activity-based payment in those clinical departments. The distribution of the patient gains shows a strong dispersion across postal codes, with the last decile being about three times higher than the median.

Table 27 shows the effects of the reform on the revenues and objectives of the hospitals. Considering first nonprofit hospitals, column (1) reports the increase in activity-based revenues, which have been roughly multiplied by four. 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 roughly from the non-pecuniary part of the objective function. More importantly, the reform translated in higher pecuniary costs and more managerial pressure exerted on the staff of those hospitals, which is quantified by the evolution of the non-revenue part of their objective function, namely $\beta_j^q \, q_j + \beta_j^{qu} \, q_j \, u_j$, see equation (23). Considering all nonprofit hospitals together, the decrease in that part of the objective represents roughly 70% to 150% of the 2005 revenue of these hospitals (column 3), depending on the clinical department considered. As to for-profit hospitals, they lost activity due to business stealing from the nonprofit sector, and hence their activity-based revenues decreased by 2 to 8%. Because of the more aggressive behavior of the nonprofit sector, they needed to raise the utility offered to patients and suffered a substantial decrease in the non-revenue part of their objective functions. That decrease amounted to 23% to 92% of their 2005 revenues.[43]

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, it made nonprofit hospitals significantly worse off, with a fall in their objective function of the same order of magnitude as their 2005 activity-based revenues. Indirectly, it was also detrimental to for-profit hospitals.

## 6.3 Robustness checks

We stress the point that both demand and supply are estimated thanks to linear IV models, while being embedded in a fully consistent, structural model. This is rather a strength of our approach, avoiding as much as possible numerical issues due to nonlinear estimation for instance. In this section, we wonder whether

[43]Columns 3 and 4 of Table 27 cannot be compared because activity-based revenues have narrower scope in the for-profit sector (reimbursement rates do not include physicians' fees).

our estimates are robust to the approximation of the market size (or potential demand).

Assessing how much our results depend on the market size is crucial since we rely on an approximation of this potential demand, as praised by Dubois and Lasio (2018). Reassuringly, our results vary very little with this parameter. As already explained, $(\boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\sigma}, \boldsymbol{\xi})$ do not depend on the potential demand; neither does the vector $\boldsymbol{u}$, up to some constant. Hence, as far as the demand side is concerned, only the $\varphi$'s are likely to be affected by some estimation error on $\theta$ and therefore on the approximate market size $M_z$. The supply-side vector of parameters $\boldsymbol{\beta}$ turns out to be very robust to the choice of $\theta$ (see Table 28): dividing or multiplying $\hat{\theta}$ by 2, for instance, affects neither $\beta^{qu}$ nor $\beta^{q}$. The fit of our model, especially the quantification of the part in activity change that comes from financial incentives, is also very robust to different choices of market size (see Table 29). In all clinical departments, financial incentives explain little of the evolution of hospitals' activity regardless of $\theta$. Even in the extreme case where the relevant market size would be equal to 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 in most of concerned clinical departments, financial incentives would not push too much to an activity race, at the exception of gastroenterology.

# 7 Concluding remarks

To model strategic interactions in the French hospital industry, we bring the competition-in-utility framework of Armstrong and Vickers (2001) to the data. The gradual introduction of activity-based payment provides an exogenous source of variation in the financial incentives of hospitals, which allows us to identify their objective functions. From the estimated slopes of the reaction functions, we conclude that hospital competition exhibits strategic complementarity. Our model replicates well the evolution of activity over the period. By simulating counterfactual Nash equilibria, we are able to properly disentangle the impact of financial incentives from the effects of aggregate shocks, hospital-specific demand shocks and supply shocks.

We show that nonprofit hospitals have responded to stronger financial incentives by attracting patients who would otherwise have been admitted in for-profit hospitals, rather than by attracting new patients. In other words, we find little empirical support for a market expansion effect. The main causal impact of the payment reform has been to shift market shares away from for-profit hospitals to nonprofit ones, i.e., a business stealing effect. The counterfactual analysis allows to assess welfare effects of the reform. On the one hand, patients have benefited from the reform, and we have quantified their gains in the form of lower travel costs. On the other hand, hospitals have been negatively affected, in particular through increased managerial pressure, which we have quantified in monetary terms. The exercise sheds light on the trade-off faced by the policy maker when designing the financial incentives placed on hospitals.

An important limitation of the study is its relatively short time frame. Because our data set covers the four-year period when the payment reform has been phased in, the horizon we consider is the short-to-medium run (a few years at most). We assume myopic hospital behavior and do not account for long-term strategies such as investment, entry, or specialization. Addressing dynamic issues in our competition-in-utility framework is on our agenda for future research.

Another important extension of the present work is to incorporate observed product attributes in our methodology. In our hospital case study, out-of-pocket expenses incurred by patients are unobserved and clinical quality indicators (such as risk-adjusted complication or mortality rates) are not available. We have therefore subsumed all product attributes 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. A natural avenue for further research is 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 attributes, 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 both the observed and unobserved product attributes.

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# 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.

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.

Berry, S. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, 25(2), 242–262.

Berry, S., and P. Haile (2014): "Identification in differentiated products markets using market level data," *Econometrica*, 82(5), 1749–1797.

——— (2016): "Identification in differentiated products markets," *Annual review of Economics*, 8, 27–52.

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.

Cellini, R., L. Siciliani, and O. R. Straume (2018): "A dynamic model of quality competition with endogenous prices," *Journal of Economic Dynamics and Control*, 94, 190–206.

Choné, P., F. Evain, 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.

Draganska, M., M. Mazzeo, and K. Seim (2009): "Beyond plain vanilla: Modeling joint product assortment and pricing decisions," *Quantitative Marketing and Economics*, 7(2), 105–146.

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.

Eizenberg, A. (2014): "Upstream innovation and product variety in the US home PC market," *The Review of Economic Studies*, 81(3), 1003–1045.

Eliason, P. (2017): "Market Power and Quality: Congestion and Spatial Competition in the Dialysis Industry," Working Paper.

Fan, Y. (2013): "Ownership consolidation and product characteristics: A study of the US daily newspaper market," *The American Economic Review*, 103(5), 1598–1628.

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.

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., 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.

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 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 (forthcoming): "Fixed-effect regressions on network data," *Econometrica*.

Kessler, D. P., and M. B. McClellan (2000): "Is hospital competition socially wasteful?," *The Quarterly Journal of Economics*, 115(2), 577–615.

Lakdawalla, D., and T. Philipson (2006): "The nonprofit sector and industry performance," *Journal of Public Economics*, 90(8-9), 1681–1698.

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. (2001): "Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality," *Physical review E*, 64(1), 016132.

——— (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*, 13 February 2018.

Pope, G. C. (1989): "Hospital nonprice competition and Medicare reimbursement policy," *Journal of Health Economics*, 8, 147–172.

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) |
| $g$ | clinical department |
| $i$ | patient |
| $j$ | hospital |
| $n$ | nest (FP or NP sector) |
| $t$ | 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) |
| $I$ | inclusive values |
| $J$ | # of hospitals |
| $L$ | Leontief matrix depicting strategic interactions among hospitals |
| $M$ | market size (potential demand) |
| $q$ | activity |
| $q_z$ | $\max_t q_{tz}$ |
| $q_{tz}$ | $\sum_j q_{jtz}$ |
| $r$ | reimbursement rate |
| $s$ | market share |
| $S$ | patient surplus (conditional on admission) |
| $T$ | # of years |
| $\overline{T}$ | hospitals' revenues fixed-part (lump-sum transfer) |
| $u$ | utility provided by hospitals to patients (clinical department-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) |
| $Y^c$ | centered $Y$ |
| $Y^0$ | "true" $Y$ |
| $\boldsymbol{Y}$ | vector $Y$ |
| $\tilde{Y}$ | counterfactual $Y$ |
| $\hat{Y}$ | estimated $Y$ |
| $\overline{Y}$ | average $Y$ |
| $Z^D$ | demand-side instruments |
| $Z^S$ | supply-side instruments |

| | |
|---|---|
| $\alpha$ | patients' preferences (travel costs) |
| $\beta$ | hospitals' preferences ($\beta^q$ and $\beta^{qu}$) |
| $\overline{\beta}$ | average hospitals' tastes (net of supply shocks) |
| $\delta$ | mean indirect utility level *à la* Berry (1994) |
| $\Delta$ | $\frac{1}{1-\sigma_1} - \frac{1}{1-\sigma_2}$ |
| $\varepsilon$ | idiosyncratic patient-hospital shock |
| $\eta$ | semi-elasticity of demand wrt utility offered |
| $\gamma$ | taste parameter for nonprofit sector |
| $\lambda$ | phase-in coefficient (NP sector) |
| $\mu$ | hospitals' marginal incentives to change utility offered |
| $\nu$ | idiosyncratic patient-sector shock |
| $\omega$ | unobserved supply shock |
| $\varphi$ | clinical department-year-postal code FE |
| $\phi$ | set of demand characteristics including $(\varphi, \xi, X)$ |
| $\psi$ | unobserved patient heterogeneity |
| $\rho$ | slope of reaction functions |
| $\sigma_1$ | intra-sector correlation |
| $\sigma_2$ | inter-sector correlation |
| $\tau$ | transmission rate |
| $\theta$ | parameter governing approximated size of potential demand |
| $\xi$ | unobserved demand shock at the hospital-postal code level |
| $\zeta$ | idiosyncratic patient shock relative to hospitalization |
| $\emptyset$ | outside option |
| FP | for-profit sector |
| NP | nonprofit sector |
| Closest | postal code's closest hospital |
| (clinical) department | aggregation of DRGs |
| *département* | administrative division of France |
| $\text{pop}_z$ | # of inhabitants in a postal code |
| 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 largest clinical departments 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 clinical department-hospital level

Table 2: 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 clinical department.

Table 3: Estimated hospitals' activity-based revenues (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 4: Hospitals' reimbursement rates (in €)

| | 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 5: Activity: reduced-form evidence

| Dependent variable | # of stays $q_{gjt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| For-profit × 2006 | 11.38*** | | | |
| | (3.23) | | | |
| For-profit × 2007 | 1.27 | | | |
| | (4.17) | | | |
| For-profit × 2008 | -4.69 | | | |
| | (6.26) | | | |
| Nonprofit × 2006 | 15.62*** | 5.01 | | 5.45 |
| | (1.93) | (3.71) | | (3.64) |
| Nonprofit × 2007 | 24.47*** | 24.15*** | | 23.62*** |
| | (2.68) | (4.89) | | (4.65) |
| Nonprofit × 2008 | 45.06*** | 51.15*** | | 51.09*** |
| | (3.69) | (7.18) | | (6.53) |
| Beds | | | 0.91* | 1.12** |
| | | | (0.51) | (0.51) |
| $\text{Beds}^2/1000$ | | | -1.21*** | -1.23*** |
| | | | (0.39) | (0.38) |
| Nurses | | | 0.12* | 0.08 |
| | | | (0.06) | (0.06) |
| Surgeons | | | 2.32*** | 1.68*** |
| | | | (0.72) | (0.60) |
| Anesthesiologists | | | -0.22 | -0.21 |
| | | | (1.46) | (1.21) |
| Staff | | | -0.04 | -0.04 |
| | | | (0.04) | (0.04) |
| MRI | | | -14.95 | -17.99 |
| | | | (13.89) | (13.61) |
| Scanner | | | -2.84 | -2.34 |
| | | | (3.70) | (3.68) |
| Population density | | | 0.01 | 0.02 |
| | | | (0.04) | (0.04) |
| Income | | | -0.00 | 0.00 |
| | | | (0.00) | (0.00) |
| Clinical department-year effects | No | Yes | Yes | Yes |
| Clinical department-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 clinical department × hospital × year level.
Robust standard errors clustered at the hospital level.
Population density and income measured at the *département* level.

Table 6: 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 × 2006 | 0.006** | 0.195*** | 0.002 | 0.031 |
| | (0.003) | (0.056) | (0.002) | (0.065) |
| Nonprofit × 2007 | 0.019*** | 0.556*** | 0.006*** | 0.282** |
| | (0.004) | (0.166) | (0.002) | (0.138) |
| Nonprofit × 2008 | 0.030*** | 0.870*** | 0.010*** | 0.529*** |
| | (0.005) | (0.162) | (0.003) | (0.157) |
| Population density | -0.000** | -0.001* | -0.000 | -0.001** |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| Income | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Clinical department-year effects | Yes | Yes | Yes | Yes |
| Clinical department-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 clinical department × hospital × year level.
Robust standard errors clustered at the hospital level.
Population density and income measured at the *département* level.

Table 7: Summary statistics at the $(g, t, z)$ level

| | mean | s.d. | min | p10 | p25 | median | p75 | p90 | max |
|---|---|---|---|---|---|---|---|---|---|
| # of inhabitants | 2,126 | 8,941 | 7 | 202 | 312 | 605 | 1,370 | 3,492 | 439,374 |
| # of stays | 20.27 | 94.54 | 1 | 1 | 2 | 5 | 13 | 34 | 10,393 |
| # of hospitals | 4.04 | 5.13 | 1 | 1 | 2 | 3 | 5 | 7 | 147 |
| # of observations $(g, t, z)$ | | | | | 885,421 | | | | |

*Source.* French PMSI, individual data, 2005-2008.
*Sample.* 942 hospitals in mainland France.
*Note.* Observations at the clinical department × year × postal code level (17,945,047 discharges).

Table 8: Summary statistics at the $(g, j, t, z)$ level, assuming $M_z = \text{population}_z$

| | mean | s.d. | min | p10 | p25 | median | p75 | p90 | max |
|---|---|---|---|---|---|---|---|---|---|
| Market share (%) | 0.43 | 0.42 | 0.0002 | 0.04 | 0.12 | 0.3 | 0.6 | 0.98 | 8.2 |
| Market share (cond. to hosp.%) | 31.4 | 23.3 | 0.01 | 3.7 | 12.1 | 28.0 | 46.5 | 64.7 | 100 |
| Time (in minutes) | 26.7 | 25.4 | 0 | 0 | 9.5 | 21.5 | 36.5 | 58 | 149.5 |
| # of observations $(g, j, t, z)$ | | | | | 3,576,566 | | | | |

*Source.* French PMSI, individual data, 2005-2008.
*Sample.* 942 hospitals in mainland France.
*Note.* Observations at the clinical department × hospital × year × postal code level (weighted by discharges $q_{gjtz}$).

Table 9: Connectivity of the hospitals' projected graph (Orthopedics, 2008)

| | mean | s.d. | p10 | p20 | p30 | p40 | p50 | p60 | p70 | p80 | p90 | # of obs. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| degree($j$) (unweighted) | 140.3 | 88.5 | 48 | 66 | 80 | 91 | 108 | 130 | 177 | 246 | 281 | 920 |
| degree($j$) (Newman-weighted) | 220 | 211.6 | 37 | 76 | 105 | 139 | 163 | 194 | 236 | 303 | 445 | 920 |
| # of postal codes connected to $j$ | 221.1 | 212.3 | 37 | 77 | 107 | 141 | 164 | 196 | 237 | 307 | 446 | 920 |

Weights: in the one-node projected graph, see Newman (2001).

## Table 10: Demand

| Clinical department $g$ | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
|---|---|---|---|---|---|---|---|---|
| Travel cost ($\alpha$) | | | | | | | | |
| Closest hospital ($\alpha_0$) | -0.058*** | -0.056*** | -0.107*** | -0.052*** | -0.105*** | -0.086*** | -0.134*** | -0.095*** |
| | (0.009) | (0.009) | (0.015) | (0.008) | (0.013) | (0.030) | (0.017) | (0.013) |
| Time ($\alpha_1$) | 0.079*** | 0.084*** | 0.063*** | 0.076*** | 0.162*** | 0.190*** | 0.267*** | 0.219*** |
| | (0.013) | (0.013) | (0.010) | (0.010) | (0.020) | (0.062) | (0.029) | (0.027) |
| Time$^2$ × 100 ($\alpha_2$) | -1.021*** | -0.883*** | -1.071*** | -0.752*** | -1.534*** | -1.441*** | -2.585*** | -1.437*** |
| | (0.108) | (0.131) | (0.146) | (0.096) | (0.188) | (0.494) | (0.296) | (0.186) |
| Time × High school ($\alpha_{1hs}$) | -0.007 | -0.007 | -0.012* | -0.013*** | -0.045*** | -0.045*** | -0.041*** | -0.043*** |
| | (0.009) | (0.007) | (0.007) | (0.005) | (0.010) | (0.017) | (0.015) | (0.009) |
| Time × Elder ($\alpha_{1e}$) | 0.092*** | 0.072*** | 0.091*** | 0.055*** | 0.112*** | 0.129*** | 0.140*** | 0.105*** |
| | (0.014) | (0.012) | (0.013) | (0.008) | (0.015) | (0.049) | (0.022) | (0.015) |
| Time × $10^3$ Income ($\alpha_{1i}$) | -0.003*** | -0.002*** | -0.002*** | -0.001*** | -0.002*** | -0.002* | -0.005*** | -0.002*** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) |
| Time × $10^5$ Population ($\alpha_{1p}$) | 0.040*** | 0.026*** | 0.029*** | 0.026*** | 0.028*** | 0.041*** | 0.058*** | 0.024*** |
| | (0.005) | (0.004) | (0.004) | (0.003) | (0.004) | (0.014) | (0.007) | (0.004) |
| Time × Women ($\alpha_{1w}$) | 0.267*** | 0.198*** | 0.284*** | 0.168*** | 0.280*** | 0.268*** | 0.563*** | 0.200*** |
| | (0.032) | (0.035) | (0.045) | (0.024) | (0.039) | (0.099) | (0.078) | (0.030) |
| Preference for nonprofit hospitals ($\gamma$) | | | | | | | | |
| Nonprofit × High school ($\gamma_{hs}$) | -0.045 | 0.051 | -0.001 | 0.050 | 0.040 | 0.292*** | -0.026 | 0.082** |
| | (0.048) | (0.036) | (0.039) | (0.035) | (0.037) | (0.063) | (0.088) | (0.036) |
| Nonprofit × Elder ($\gamma_e$) | 0.067 | 0.039 | 0.053 | 0.082** | 0.043 | 0.105* | 0.544*** | -0.057* |
| | (0.041) | (0.031) | (0.041) | (0.034) | (0.036) | (0.063) | (0.094) | (0.033) |
| Nonprofit × $10^3$ Income ($\gamma_i$) | -0.007*** | -0.004* | -0.009*** | -0.007*** | -0.008*** | -0.027*** | -0.031*** | -0.008*** |
| | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) | (0.007) | (0.005) | (0.002) |
| Nonprofit × Women ($\gamma_w$) | -0.323*** | 0.119 | 0.108 | 0.186*** | 0.406*** | -0.117 | -0.206 | -0.011 |
| | (0.107) | (0.079) | (0.082) | (0.058) | (0.075) | (0.198) | (0.205) | (0.085) |
| $\sigma_1$ | 0.590*** | 0.698*** | 0.645*** | 0.712*** | 0.593*** | 0.475*** | 0.250*** | 0.578*** |
| | (0.043) | (0.042) | (0.045) | (0.036) | (0.048) | (0.174) | (0.080) | (0.053) |
| $\sigma_2$ | 0.537*** | 0.641*** | 0.574*** | 0.683*** | 0.520*** | 0.374* | 0.133 | 0.470*** |
| | (0.047) | (0.049) | (0.051) | (0.037) | (0.055) | (0.199) | (0.085) | (0.064) |
| # 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 |
| F-test $H_0 : \sigma_1 = \sigma_2$ | 30.76 | 25.87 | 59.49 | 20.45 | 45.69 | 12.36 | 32.31 | 58.57 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Source.* French PMSI, individual data.
Robust standard errors clustered at the hospital level
First stages: see Tables 11 and 12.
*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 11: Demand - First-stage equation #1

| Dependent variable | $\log s_{gjtz\|n}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
| # of hospitals (nest) | -0.211*** | -0.258*** | -0.226*** | -0.250*** | -0.392*** | -0.309*** | -0.222*** | -0.293*** |
| | (-9.96) | (-10.44) | (-12.78) | (-14.58) | (-18.00) | (-11.74) | (-11.67) | (-18.26) |
| # of teaching hosp. (nest) | 0.018 | 0.014 | 0.045** | 0.096*** | 0.206*** | 0.102* | -0.001 | 0.057*** |
| | (0.67) | (0.58) | (2.42) | (4.66) | (10.00) | (1.72) | (-0.04) | (2.98) |
| # of nonprofit hosp. (nest) | -0.156*** | -0.120*** | -0.107*** | -0.136*** | -0.127*** | -0.246*** | -0.139*** | -0.116*** |
| | (-11.78) | (-8.46) | (-8.76) | (-11.04) | (-9.76) | (-11.05) | (-8.80) | (-11.59) |
| # of nonprofit hosp. (nest) × High school | 0.155*** | -0.009 | 0.034 | -0.038* | -0.086*** | -0.003 | 0.016 | 0.012 |
| | (4.20) | (-0.27) | (1.62) | (-1.74) | (-4.37) | (-0.07) | (0.53) | (1.07) |
| # of nonprofit hosp. (nest) × Elder | -0.171*** | -0.209*** | -0.158*** | -0.231*** | 0.032 | -0.263*** | -0.209*** | -0.111*** |
| | (-2.78) | (-3.47) | (-4.11) | (-6.76) | (0.91) | (-3.58) | (-4.24) | (-4.59) |
| # of nonprofit hosp. (nest) × ($10^3$) Income | -0.008*** | -0.002* | -0.004*** | 0.000 | -0.001** | -0.003** | -0.001 | -0.002*** |
| | (-6.80) | (-1.89) | (-5.78) | (0.06) | (-2.21) | (-2.05) | (-1.08) | (-5.42) |
| # of nonprofit hosp. (nest) × Women | 1.072*** | 0.475*** | 0.509*** | 0.411*** | -0.140* | 0.395*** | 0.593*** | 0.091** |
| | (8.47) | (3.46) | (5.65) | (5.58) | (-1.86) | (3.27) | (5.79) | (2.07) |
| $\sum$ size (nest) | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (-7.84) | (-8.46) | (-10.33) | (-6.90) | (-6.70) | (-4.38) | (-8.14) | (-8.69) |
| $\sum$ time (nest) | -0.127*** | -0.042*** | -0.107*** | -0.075*** | -0.041*** | -0.021 | -0.064*** | -0.009 |
| | (-11.63) | (-3.06) | (-11.15) | (-8.60) | (-4.47) | (-1.63) | (-4.97) | (-1.44) |
| $\sum$ time$^2$ (nest) | -0.214*** | -0.357*** | -0.296*** | -0.283*** | -0.539*** | -0.298*** | -0.264*** | -0.334*** |
| | (-7.21) | (-9.75) | (-12.66) | (-13.01) | (-21.24) | (-9.06) | (-9.41) | (-18.25) |
| $\sum$ time to teaching hosp. (nest) | 0.012*** | 0.011*** | 0.008*** | -0.002 | -0.014*** | -0.009 | 0.012*** | 0.003 |
| | (2.72) | (3.16) | (2.83) | (-0.81) | (-4.63) | (-1.16) | (3.76) | (1.31) |
| $\sum$ time to nonprofit hosp. (nest) | 0.013*** | 0.011*** | 0.007*** | 0.013*** | 0.011*** | 0.028*** | 0.012*** | 0.009*** |
| | (6.12) | (4.85) | (3.75) | (7.47) | (6.05) | (6.93) | (5.07) | (7.81) |
| $\sum$ time (nest) × High school | 0.055*** | 0.070*** | 0.037*** | 0.045*** | 0.044*** | 0.034*** | 0.033*** | 0.007** |
| | (7.88) | (8.63) | (6.09) | (7.47) | (7.03) | (4.91) | (4.90) | (2.41) |
| $\sum$ time (nest) × Elder | -0.106*** | -0.108*** | -0.084*** | -0.070*** | -0.068*** | -0.050*** | -0.084*** | -0.041*** |
| | (-12.85) | (-10.52) | (-11.67) | (-10.81) | (-8.54) | (-7.03) | (-12.75) | (-10.94) |
| $\sum$ time (nest) × ($10^3$) Income | -0.001** | -0.001*** | -0.000* | -0.001*** | -0.000 | 0.000 | 0.000 | 0.000*** |
| | (-2.37) | (-4.21) | (-1.72) | (-3.14) | (-0.58) | (0.75) | (0.53) | (2.86) |
| $\sum$ time (nest) × ($10^5$) Population | 0.005*** | 0.002** | -0.000 | 0.003*** | -0.000 | 0.003** | 0.002* | 0.001** |
| | (3.80) | (2.11) | (-0.03) | (3.74) | (-0.19) | (2.41) | (1.90) | (2.22) |
| $\sum$ time (nest) × Women | 0.326*** | 0.211*** | 0.313*** | 0.244*** | 0.256*** | 0.137*** | 0.218*** | 0.143*** |
| | (15.88) | (8.51) | (17.02) | (15.73) | (14.50) | (6.33) | (9.81) | (14.46) |
| Closest (nest) × High school | -0.010*** | -0.010*** | -0.010*** | -0.013*** | -0.008*** | -0.009** | -0.009*** | -0.002 |
| | (-3.22) | (-3.03) | (-3.75) | (-4.78) | (-3.07) | (-2.52) | (-3.22) | (-0.86) |
| Closest (nest) × Elder | -0.002 | 0.002 | -0.002 | -0.003 | -0.007** | -0.009** | -0.001 | -0.006** |
| | (-0.71) | (0.56) | (-0.72) | (-1.04) | (-2.28) | (-2.49) | (-0.18) | (-2.35) |
| Closest (nest) × ($10^3$) Income | 0.000 | 0.000 | 0.001*** | 0.000* | 0.000* | 0.000 | 0.000 | 0.000* |
| | (0.85) | (0.34) | (3.18) | (1.80) | (1.75) | (1.00) | (0.80) | (1.81) |
| Closest (nest) × ($10^5$) Population | 0.007*** | 0.004** | 0.002* | -0.000 | 0.001 | -0.002 | 0.003*** | -0.000 |
| | (4.55) | (2.51) | (1.86) | (-0.24) | (0.80) | (-1.10) | (2.90) | (-0.33) |
| Closest (nest) × Women | -0.027*** | -0.036*** | -0.023*** | -0.037*** | -0.021*** | -0.032*** | -0.027*** | -0.032*** |
| | (-4.13) | (-5.40) | (-3.45) | (-6.02) | (-3.53) | (-5.50) | (-4.56) | (-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 12: Demand - First-stage regression #2

| Dependent variable | $\log s_{gntz\|H}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
| # of hosp. (other nest) | -0.157$^{***}$ | -0.178$^{***}$ | -0.166$^{***}$ | -0.202$^{***}$ | -0.306$^{***}$ | -0.227$^{***}$ | -0.166$^{***}$ | -0.212$^{***}$ |
| | (-9.63) | (-10.83) | (-13.90) | (-16.61) | (-19.15) | (-10.38) | (-11.26) | (-20.07) |
| # of teaching hosp. (other nest) | 0.117$^{***}$ | 0.130$^{***}$ | 0.120$^{***}$ | 0.152$^{***}$ | 0.257$^{***}$ | 0.180$^{***}$ | 0.141$^{***}$ | 0.108$^{***}$ |
| | (8.84) | (9.92) | (13.57) | (14.15) | (16.41) | (7.35) | (9.66) | (14.89) |
| # of nonprofit hosp. (other nest) | -0.167$^{***}$ | -0.172$^{***}$ | -0.137$^{***}$ | -0.165$^{***}$ | -0.162$^{***}$ | -0.275$^{***}$ | -0.209$^{***}$ | -0.123$^{***}$ |
| | (-16.34) | (-14.10) | (-15.28) | (-17.70) | (-15.37) | (-15.29) | (-14.48) | (-19.31) |
| # of nonprofit hosp. (other nest) $\times$ High school | 0.035$^{**}$ | -0.074$^{***}$ | -0.016$^{**}$ | -0.085$^{***}$ | -0.122$^{***}$ | 0.024 | -0.093$^{***}$ | -0.020$^{***}$ |
| | (2.17) | (-5.50) | (-1.96) | (-10.74) | (-16.27) | (1.24) | (-5.59) | (-5.23) |
| # of nonprofit hosp. (other nest) $\times$ Elder | -0.255$^{***}$ | -0.384$^{***}$ | -0.272$^{***}$ | -0.344$^{***}$ | -0.076$^{***}$ | -0.125$^{***}$ | -0.343$^{***}$ | -0.134$^{***}$ |
| | (-8.76) | (-16.05) | (-16.49) | (-24.17) | (-4.98) | (-2.96) | (-16.90) | (-12.96) |
| # of nonprofit hosp. (other nest) $\times$ ($10^3$) Income | -0.005$^{***}$ | -0.001$^{**}$ | -0.002$^{***}$ | 0.002$^{***}$ | 0.000$^{*}$ | -0.004$^{***}$ | 0.002$^{***}$ | -0.001$^{***}$ |
| | (-9.81) | (-2.54) | (-6.09) | (7.36) | (1.70) | (-5.52) | (4.47) | (-4.51) |
| # of nonprofit hosp. (other nest) $\times$ Women | 1.060$^{***}$ | 0.579$^{***}$ | 0.681$^{***}$ | 0.506$^{***}$ | -0.080$^{**}$ | 0.436$^{***}$ | 0.666$^{***}$ | 0.145$^{***}$ |
| | (15.37) | (9.09) | (18.68) | (15.13) | (-2.44) | (7.04) | (11.68) | (9.34) |
| $\sum$ size (other nest) | -0.000$^{***}$ | -0.000$^{***}$ | -0.000$^{***}$ | -0.000$^{***}$ | -0.000$^{***}$ | -0.000$^{***}$ | -0.000$^{***}$ | -0.000$^{***}$ |
| | (-7.05) | (-7.30) | (-10.36) | (-9.36) | (-8.67) | (-3.60) | (-6.97) | (-15.80) |
| $\sum$ time (other nest) | -0.157$^{***}$ | -0.084$^{***}$ | -0.131$^{***}$ | -0.109$^{***}$ | -0.074$^{***}$ | -0.054$^{***}$ | -0.100$^{***}$ | -0.031$^{***}$ |
| | (-22.01) | (-13.04) | (-22.36) | (-22.96) | (-13.60) | (-6.86) | (-13.77) | (-10.96) |
| $\sum$ time$^2$ (other nest) | -0.088$^{***}$ | -0.208$^{***}$ | -0.207$^{***}$ | -0.210$^{***}$ | -0.421$^{***}$ | -0.176$^{***}$ | -0.147$^{***}$ | -0.228$^{***}$ |
| | (-5.13) | (-11.02) | (-16.23) | (-19.88) | (-25.63) | (-7.26) | (-9.05) | (-22.33) |
| $\sum$ time to teaching hosp. (other nest) | -0.010$^{***}$ | -0.009$^{***}$ | -0.007$^{***}$ | -0.014$^{***}$ | -0.024$^{***}$ | -0.020$^{***}$ | -0.011$^{***}$ | -0.006$^{***}$ |
| | (-3.98) | (-5.27) | (-6.03) | (-9.50) | (-14.45) | (-5.41) | (-5.94) | (-7.57) |
| $\sum$ time to nonprofit hosp. (other nest) | 0.016$^{***}$ | 0.018$^{***}$ | 0.011$^{***}$ | 0.016$^{***}$ | 0.015$^{***}$ | 0.032$^{***}$ | 0.022$^{***}$ | 0.010$^{***}$ |
| | (10.59) | (12.93) | (10.95) | (14.19) | (13.76) | (15.24) | (12.44) | (16.31) |
| $\sum$ time (other nest) $\times$ High school | 0.054$^{***}$ | 0.072$^{***}$ | 0.034$^{***}$ | 0.047$^{***}$ | 0.039$^{***}$ | 0.020$^{***}$ | 0.030$^{***}$ | 0.003$^{**}$ |
| | (11.74) | (16.92) | (9.77) | (12.11) | (11.03) | (4.38) | (7.42) | (2.18) |
| $\sum$ time (other nest) $\times$ Elder | -0.082$^{***}$ | -0.083$^{***}$ | -0.070$^{***}$ | -0.057$^{***}$ | -0.056$^{***}$ | -0.047$^{***}$ | -0.068$^{***}$ | -0.030$^{***}$ |
| | (-12.59) | (-14.03) | (-14.82) | (-12.61) | (-9.43) | (-8.58) | (-13.82) | (-12.81) |
| $\sum$ time (other nest) $\times$ ($10^3$) Income | -0.001$^{***}$ | -0.001$^{***}$ | -0.001$^{***}$ | -0.001$^{***}$ | -0.000 | 0.000$^{*}$ | 0.000 | 0.000$^{***}$ |
| | (-4.77) | (-9.04) | (-5.31) | (-5.85) | (-1.39) | (1.90) | (0.47) | (5.51) |
| $\sum$ time (other nest) $\times$ ($10^5$) Population | 0.006$^{***}$ | 0.001 | 0.000 | 0.003$^{***}$ | -0.000 | 0.004$^{***}$ | 0.001$^{***}$ | 0.001$^{***}$ |
| | (9.48) | (1.58) | (1.44) | (8.25) | (-0.96) | (7.67) | (3.85) | (5.62) |
| $\sum$ time (other nest) $\times$ Women | 0.340$^{***}$ | 0.236$^{***}$ | 0.331$^{***}$ | 0.281$^{***}$ | 0.280$^{***}$ | 0.164$^{***}$ | 0.248$^{***}$ | 0.144$^{***}$ |
| | (24.76) | (16.76) | (26.21) | (30.26) | (24.04) | (12.78) | (19.04) | (32.43) |
| Closest (other nest) $\times$ High school | 0.002 | 0.000 | -0.001 | 0.002 | 0.000 | 0.000 | 0.001 | 0.001 |
| | (1.20) | (0.01) | (-0.66) | (1.37) | (0.17) | (0.18) | (0.62) | (0.98) |
| Closest (other nest) $\times$ Elder | -0.007$^{***}$ | -0.003 | -0.003 | -0.002 | -0.006$^{**}$ | 0.002 | -0.003 | -0.004$^{**}$ |
| | (-3.63) | (-1.22) | (-1.39) | (-1.09) | (-2.50) | (0.67) | (-1.42) | (-2.52) |
| Closest (other nest) $\times$ ($10^3$) Income | 0.000 | 0.000 | 0.000$^{*}$ | -0.000 | 0.000$^{**}$ | 0.000 | 0.000 | -0.000 |
| | (1.05) | (0.90) | (1.76) | (-0.38) | (2.28) | (1.30) | (0.43) | (-0.12) |
| Closest (other nest) $\times$ ($10^5$) Population | -0.001 | -0.000 | -0.001$^{***}$ | -0.001 | -0.001$^{***}$ | -0.001$^{**}$ | -0.001$^{**}$ | -0.001$^{***}$ |
| | (-1.21) | (-0.75) | (-2.68) | (-1.59) | (-3.10) | (-2.01) | (-2.32) | (-3.95) |
| Closest (other nest) $\times$ Women | 0.015$^{***}$ | 0.010$^{***}$ | 0.012$^{***}$ | 0.011$^{***}$ | 0.008$^{***}$ | 0.002 | 0.006$^{*}$ | -0.002 |
| | (4.03) | (2.66) | (4.43) | (4.07) | (3.25) | (0.78) | (1.84) | (-0.90) |
| # 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 |
| $R^2$ | 0.698 | 0.615 | 0.620 | 0.584 | 0.500 | 0.754 | 0.723 | 0.462 |
| F-test excluded instruments | 2,202.3 | 1,882 | 2,169.1 | 4,053.4 | 3,372.6 | 3,221.3 | 2,943.6 | 6,404.4 |

*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 (other nest): closest hospital $k$ for hospital $j$ within the complementary nest (either nonprofit or for-profit hospitals).

Table 13: Estimated utilities

| | mean | s.d. | min | p25 | median | p75 | max | # of obs. |
|---|---|---|---|---|---|---|---|---|
| Orthopedics | 1.60 | 0.31 | -1.29 | 1.47 | 1.63 | 1.79 | 2.35 | 3,680 |
| (weighted) | 1.81 | 0.22 | -1.29 | 1.65 | 1.80 | 1.97 | 2.35 | 3,680 |
| ENT, Stomato. | 1.54 | 0.58 | -1.53 | 1.24 | 1.64 | 1.94 | 2.91 | 3,552 |
| (weighted) | 1.96 | 0.37 | -1.53 | 1.73 | 1.98 | 2.21 | 2.91 | 3,552 |
| Ophthalmology | 1.43 | 0.54 | -1.26 | 1.13 | 1.52 | 1.81 | 2.71 | 3,088 |
| (weighted) | 1.85 | 0.34 | -1.26 | 1.62 | 1.86 | 2.08 | 2.71 | 3,088 |
| Gastroenterology | 1.70 | 0.24 | -0.48 | 1.59 | 1.73 | 1.85 | 2.24 | 3,608 |
| (weighted) | 1.83 | 0.17 | -0.48 | 1.72 | 1.84 | 1.95 | 2.24 | 3,608 |
| Gynaecology | 0.92 | 0.17 | -0.16 | 0.82 | 0.92 | 1.03 | 1.36 | 3,560 |
| (weighted) | 1.06 | 0.14 | -0.16 | 0.96 | 1.07 | 1.16 | 1.36 | 3,560 |
| Dermatology | 0.89 | 0.17 | -0.36 | 0.80 | 0.90 | 1.00 | 1.44 | 3,720 |
| (weighted) | 0.99 | 0.15 | -0.36 | 0.89 | 0.99 | 1.10 | 1.44 | 3,720 |
| Nephrology | 0.92 | 0.22 | -0.42 | 0.79 | 0.96 | 1.08 | 1.51 | 3,412 |
| (weighted) | 1.09 | 0.13 | -0.42 | 1.02 | 1.11 | 1.19 | 1.51 | 3,412 |
| Circulatory syst. | 0.62 | 0.27 | -1.28 | 0.46 | 0.64 | 0.82 | 1.23 | 3,516 |
| (weighted) | 0.83 | 0.19 | -1.28 | 0.72 | 0.85 | 0.97 | 1.23 | 3,516 |

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

Table 14: Converting utility levels into travel time compression factors

| | mean | s.d. | min | p25 | median | p75 | max | # of postal codes |
|---|---|---|---|---|---|---|---|---|
| Orthopedics | 23.6 | 13.0 | 89.7 | 27.3 | 19.5 | 15.1 | 6.8 | 30,309 |
| ENT, Stomato. | 17.6 | 13.8 | 94.0 | 18.9 | 12.6 | 9.6 | 4.7 | 28,612 |
| Ophthalmology | 23.3 | 15.2 | 100 | 26.3 | 18.2 | 14.0 | 6.1 | 28,507 |
| Gastroenterology | 28.7 | 16.3 | 100 | 33.7 | 23.2 | 17.4 | 8.1 | 28,914 |
| Gynaecology | 37.6 | 16.3 | 100 | 45.9 | 33.0 | 25.7 | 11.5 | 25,963 |
| Dermatology | 39.7 | 15.5 | 100 | 45.4 | 35.6 | 28.9 | 15.3 | 27,248 |
| Nephrology | 39.7 | 17.2 | 100 | 47.8 | 35.0 | 26.8 | 11.7 | 26,119 |
| Circulatory syst. | 34.4 | 18.0 | 100 | 39.5 | 28.5 | 22.4 | 9.5 | 24,842 |

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

## Table 15: Estimated utilities: reduced-form evidence

| Dependent variable | $\hat{u}_{gjt} \times 10^3$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Nonprofit × 2006 | 14.86*** | | 15.65*** |
| | (3.68) | | (3.69) |
| Nonprofit × 2007 | 27.76*** | | 28.85*** |
| | (4.65) | | (4.66) |
| Nonprofit × 2008 | 38.83*** | | 40.42*** |
| | (5.26) | | (5.21) |
| Beds | | 0.30 | 0.47 |
| | | (0.29) | (0.29) |
| $\text{Beds}^2/1000$ | | -0.28 | -0.30 |
| | | (0.22) | (0.23) |
| Nurses | | 0.06** | 0.03 |
| | | (0.03) | (0.02) |
| Surgeons | | 0.91** | 0.40 |
| | | (0.43) | (0.33) |
| Anesthesiologists | | 0.45 | 0.49 |
| | | (0.67) | (0.53) |
| Staff | | -0.02 | -0.01 |
| | | (0.01) | (0.02) |
| MRI | | -3.14 | -5.57 |
| | | (5.43) | (5.28) |
| Scanner | | -1.22 | -0.60 |
| | | (2.69) | (2.61) |
| Population density | | 0.10*** | 0.11*** |
| | | (0.02) | (0.02) |
| Income | | 0.01* | 0.01** |
| | | (0.00) | (0.00) |
| Clinical department-year effects | Yes | Yes | Yes |
| Clinical department-hospital effects | Yes | Yes | Yes |
| Observations | 28,136 | 28,136 | 28,136 |
| $R^2$ | 0.965 | 0.965 | 0.965 |

Observations at the clinical department × hospital × year level.
Robust standard errors clustered at the hospital level.
Population density and income measured at the *département* level.

## Table 16: Potential demand

| Clinical department | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
|---|---|---|---|---|---|---|---|---|
| $\hat{\theta} \times 10^3$ | 1 | 0.9 | 0.8 | 1.1 | 0.4 | 0.4 | 0.3 | 1 |
| median annual # of stays $q_{tz}$ | 39 | 51 | 49 | 63 | 86 | 88 | 97 | 201 |
| median maximal # of stays $q_z$ | 47 | 61 | 60 | 72 | 97 | 104 | 110 | 219 |
| median potential demand $M_z$ | 57 | 69 | 68 | 82 | 100 | 108 | 113 | 228 |
| median "mark-up" $100\frac{M_z - q_{tz}}{q_{tz}}$ (%) | 39 | 28 | 32 | 29 | 13 | 16 | 13 | 12 |
| median ratio $\frac{M_z}{\text{pop}_z}$ (%) | 0.6 | 0.8 | 0.7 | 0.9 | 1.2 | 1.2 | 1.2 | 2.6 |
| # of observations | 100,696 | 105,431 | 103,643 | 108,983 | 115,949 | 115,190 | 114,286 | 121,243 |

*Source.* French PMSI, individual data, 2005-2008.
*Sample.* 942 hospitals in mainland France.
*Note.* Observations at the postal code × year level (weighted by population).
$\theta$ is the parameter governing market size: $M_z = q_z + \theta(\text{pop}_z - q_z)$.

## Table 17: Own-semi-elasticities

| | mean | s.d. | min | p10 | p25 | median | p75 | p90 | max | # of observations |
|---|---|---|---|---|---|---|---|---|---|---|
| $\eta_{gjt}$ | 1.617 | 0.573 | 0.167 | 0.912 | 1.208 | 1.570 | 1.950 | 2.347 | 3.465 | 28,136 |

Observations $(g, j, t)$ are weighted by $q_{gjt}$. All clinical departments, 2005-2008.
Figures based on the estimated potential demand, see Table 16.

## Table 18: Cross-semi-elasticities

| | mean | s.d. | min | p10 | p25 | median | p75 | p90 | max | # of ordered pairs | $\sum$ weights ($10^9$) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\eta_{gjkt}$ | -0.225 | 0.213 | -2.312 | -0.531 | -0.351 | -0.160 | -0.051 | -0.015 | -0.000 | 2,443,950 | 6.38 |
| nonprofit j - nonprofit k | -0.171 | 0.222 | -2.244 | -0.532 | -0.212 | -0.077 | -0.031 | -0.011 | -0.000 | 422,622 | 0.57 |
| for-profit j - for-profit k | -0.228 | 0.213 | -2.312 | -0.549 | -0.330 | -0.164 | -0.063 | -0.018 | -0.000 | 837,498 | 2.42 |
| nonprofit j - for-profit k | -0.218 | 0.209 | -2.022 | -0.504 | -0.345 | -0.158 | -0.049 | -0.014 | -0.000 | 591,915 | 1.69 |
| for-profit j - nonprofit k | -0.245 | 0.208 | -2.062 | -0.532 | -0.395 | -0.206 | -0.053 | -0.016 | -0.000 | 591,915 | 1.69 |

Observations $(g, j, k, t)$ are weighted by $\sum_z q_{gjtz} q_{gktz}$. All clinical departments, 2005-2008.
Figures based on the estimated potential demand, see Table 16.

## Table 19: Hospital status and demand elasticities

| Dependent variable | Own semi-elasticity $\eta_{gjjt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Nonprofit hospital | -0.193*** | -0.122*** | -0.205*** | -0.135*** |
| | (0.022) | (0.019) | (0.022) | (0.019) |
| Private nonprofit hospital | 0.323*** | 0.313*** | 0.290*** | 0.281*** |
| | (0.043) | (0.037) | (0.041) | (0.035) |
| Teaching hospital | 0.164*** | 0.104*** | 0.157*** | 0.100*** |
| | (0.053) | (0.026) | (0.052) | (0.026) |
| Clinical department-year effects | No | No | Yes | Yes |
| Regional effects | No | Yes | No | Yes |
| Observations | 28,136 | 28,136 | 28,136 | 28,136 |
| $R^2$ | 0.047 | 0.136 | 0.579 | 0.667 |

Observations from nonprofit hospitals at the clinical department × hospital × year level.
Robust standard errors clustered at the hospital level.

## Table 20: Supply

| | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
|---|---|---|---|---|---|---|---|---|
| OLS | | | | | | | | |
| $r_{gjt} \times 10^3$ | -0.006 | 0.022 | -0.042*** | -0.012 | 0.026** | 0.200* | 0.007 | 0.062*** |
| | (0.010) | (0.015) | (0.015) | (0.020) | (0.012) | (0.104) | (0.018) | (0.022) |
| $R^2$ | 0.408 | 0.199 | 0.398 | 0.267 | 0.128 | 0.493 | 0.113 | 0.101 |
| IV | | | | | | | | |
| $r_{gjt} \times 10^3$ | 0.036*** | 0.012** | 0.078*** | 0.018*** | 0.028*** | 0.040 | 0.063*** | 0.014*** |
| | (0.009) | (0.005) | (0.008) | (0.004) | (0.005) | (0.025) | (0.019) | (0.005) |
| 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 × NP
The supply estimation is based on the estimated potential demand, see Table 16.

## Table 21: Transmission rates among nonprofit hospitals

| Dependent variable | Transmission rate $\tau_{gjt} \times 10^6$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Private hospital | 4.397*** | 4.430*** | 3.834*** | 3.862*** |
| | (0.432) | (0.436) | (0.375) | (0.374) |
| Teaching hospital | 3.581*** | 4.983*** | 2.577*** | 3.474*** |
| | (0.425) | (0.510) | (0.242) | (0.343) |
| Size (in 2004) | | -0.004*** | | -0.003*** |
| | | (0.001) | | (0.001) |
| Clinical department-year effects | Yes | Yes | Yes | Yes |
| Regional effects | No | No | Yes | Yes |
| Observations | 12,644 | 12,644 | 12,644 | 12,644 |
| $R^2$ | 0.949 | 0.950 | 0.956 | 0.956 |

Observations from nonprofit hospitals at the clinical department × hospital × year level.
Robust standard errors clustered at the hospital level.

## Table 22: Slopes of reaction functions

| | mean | s.d. | p1 | p10 | p25 | median | p75 | p90 | p99 | # of observations |
|---|---|---|---|---|---|---|---|---|---|---|
| $\bar{\rho}_{gjt} = \max_k \rho_{gjkt}$ | 0.093 | 0.066 | 0.002 | 0.017 | 0.042 | 0.082 | 0.130 | 0.183 | 0.293 | 28,132 |
| nonprofit j - nonprofit k | 0.045 | 0.046 | 0.002 | 0.006 | 0.013 | 0.030 | 0.060 | 0.102 | 0.220 | 12,629 |
| for-profit j - for-profit k | 0.066 | 0.052 | 0.002 | 0.012 | 0.027 | 0.053 | 0.094 | 0.135 | 0.232 | 15,489 |
| nonprofit j - for-profit k | 0.079 | 0.064 | 0.001 | 0.006 | 0.029 | 0.065 | 0.117 | 0.168 | 0.268 | 12,639 |
| for-profit j - nonprofit k | 0.067 | 0.065 | 0.001 | 0.008 | 0.020 | 0.044 | 0.095 | 0.159 | 0.285 | 15,486 |

All observations $(g, j, t)$ but the four isolated connected components. Observations are weighted by $q_{gjt}$.

## Table 23: The effect of distance on slopes of reaction functions

| Dependent variable | Slope of reaction function $\rho_{gjkt}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
| $d_{jk} \times 10^3$ | -0.308*** | -0.343*** | -0.293*** | -0.244*** | -0.357*** | -0.248*** | -0.275*** | -0.181*** |
| | (0.011) | (0.011) | (0.008) | (0.008) | (0.011) | (0.009) | (0.008) | (0.005) |
| $d_{jk}^2 \times 10^6$ | 1.063*** | 1.133*** | 1.002*** | 0.767*** | 1.191*** | 0.687*** | 0.907*** | 0.517*** |
| | (0.045) | (0.046) | (0.033) | (0.029) | (0.041) | (0.035) | (0.031) | (0.016) |
| Intra-sector$_{jk} \times 10^3$ | 0.107 | 0.132 | 0.051 | -0.002 | -0.308*** | 0.727*** | 0.277*** | 0.152*** |
| | (0.091) | (0.103) | (0.071) | (0.071) | (0.089) | (0.102) | (0.070) | (0.046) |
| # 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 |
| $R^2$ | 0.265 | 0.251 | 0.220 | 0.245 | 0.196 | 0.219 | 0.208 | 0.177 |

*Note.* Intra-sector$_{jk}$ is defined as $\text{NP}_k\text{NP}_k + (1 - \text{NP}_j)(1 - \text{NP}_k)$.
Robust standard errors clustered at the hospital level.

## Table 24: Fit: Orthopedics from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\text{NP}}$ | $\Delta q/q$ | $\Delta q/q$ | $\Delta q/q$ | $\Delta q/q$ | $\Delta q/q$ |
| | | | All | NP | FP | NP | FP |
| | | (pp) | (%) | (%) | (%) | (%) | (%) |
| | | | total | total | total | median | median |
| | **observed** | **1.18** | **4.14** | **7.11** | **2.03** | **7.28** | **-1.18** |
| (a) | financial incentives | 1.01 | 0.18 | 2.61 | -1.56 | 2.25 | -1.63 |
| (b) | financial incentives (w/o strategic effects) | 1.01 | 0.14 | 2.58 | -1.59 | 2.16 | -1.61 |
| (c) | aggregate shocks | 0 | -0.57 | -0.58 | -0.57 | -0.58 | -0.57 |
| (d) | hospital-specific demand shocks | 0.23 | 4.4 | 4.99 | 3.98 | 3.5 | 2.62 |
| (e) | aggregate + hospital-specific demand shocks | 0.23 | 3.92 | 4.51 | 3.5 | 3.03 | 2.07 |
| (f) | **all but hospital-specific supply shocks** | **1.25** | **4.07** | **7.2** | **1.84** | **5.88** | **0.72** |
| (g) | hospital-specific supply shocks | 0.29 | 0.03 | 0.73 | -0.47 | 1.72 | -1.21 |
| (h) | neutralizing strategic effects | 1.17 | 4.19 | 7.12 | 2.1 | 7.58 | -0.99 |

These figures are based on the potential demand shown in Table 16.

## Table 25: Impact of the reform on volumes and market shares

| Clinical department | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
|---|---|---|---|---|---|---|---|---|
| # of competing hospitals | 879 | 853 | 930 | 890 | 902 | 772 | 888 | 920 |
| Activity-based revenues in 2008 (€m) | 418 | 691 | 375 | 668 | 1,690 | 761 | 531 | 2,713 |
| # of admissions - observed in 2005 ($10^3$) | 239 | 322 | 317 | 419 | 574 | 593 | 632 | 1,315 |
| # of admissions - counterfactual ($10^3$) | 241 | 323 | 321 | 420 | 578 | 594 | 634 | 1,317 |
| # of admissions - observed in 2008 ($10^3$) | 248 | 354 | 300 | 410 | 585 | 646 | 624 | 1,369 |
| Change in # of admissions (%) | 0.7 | 0.3 | 1.2 | 0.3 | 0.6 | 0.2 | 0.3 | 0.2 |
| Change in # of admissions (nonprofit, %) | 7.1 | 3.3 | 12.3 | 3.9 | 6.5 | 4.4 | 5.2 | 2.6 |
| Change in # of admissions (for-profit, %) | -2.3 | -1.6 | -5.8 | -2.7 | -4.9 | -1.2 | -1.4 | -1.6 |
| 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 | 39.4 | 43.2 | 46.9 | 51.1 | 26 | 27.5 | 42.6 |
| Change in nonprofit market share (points) | 2 | 1.1 | 4.2 | 1.6 | 2.8 | 1 | 1.3 | 1 |
| Nonprofit market share - observed in 2008 (%) | 36.1 | 39.8 | 45.6 | 48.3 | 50.8 | 25.7 | 28.6 | 42.8 |
| Change in # of admissions - nonprofit hospitals ($10^3$) | 5 | 4 | 15 | 7 | 18 | 6 | 9 | 14 |
| Change in # of admissions - for-profit hospitals ($10^3$) | -4 | -3 | -11 | -6 | -15 | -5 | -7 | -12 |
| Admissions switching to nonprofit hospitals ($10^3$) | 5 | 4 | 13 | 7 | 16 | 6 | 8 | 13 |

*Note.* Counterfactual experiment: see line (a) from Table 24.

## Table 26: 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) | (7) |
| Orthopedics | 0.025 | 0.002 | 417 | 503 | 2.6 | 7.5 | 30,309 |
| ENT, Stomato. | 0.052 | 0.002 | 400 | 488 | 2.9 | 10.4 | 28,612 |
| Ophthalmology | 0.039 | 0 | 303 | 469 | 2.3 | 7.9 | 28,507 |
| Gastroenterology | 0.067 | 0.009 | 415 | 487 | 10.8 | 31.8 | 28,914 |
| Gynaecology | 0.026 | 0.001 | 404 | 486 | 5.8 | 16.6 | 27,248 |
| Dermatology | 0.09 | 0.009 | 421 | 509 | 17.4 | 42.5 | 25,963 |
| Nephrology | 0.019 | 0.001 | 395 | 458 | 4.2 | 15.5 | 26,119 |
| Circulatory syst. | 0.03 | 0.005 | 406 | 473 | 6.8 | 23.2 | 24,842 |

*Note.* Counterfactual experiment: see line (a) from Table 39.
Column (5) and (6): (in %).

## Table 27: Impact of the reform on hospitals

| | Change in activity-based revenues | | Change in nonpecuniary objective | | # of hospitals | |
|---|---|---|---|---|---|---|
| | All NP hospitals | All FP hospitals | All NP hospitals | All FP hospitals | NP | FP |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Orthopedics | 2.86 | -0.02 | -1.02 | -0.67 | 417 | 503 |
| ENT, Stomato. | 2.83 | -0.08 | -0.88 | -0.56 | 400 | 488 |
| Ophthalmology | 2.52 | -0.07 | -0.7 | -0.23 | 303 | 469 |
| Gastroenterology | 2.96 | -0.02 | -1.38 | -0.92 | 415 | 487 |
| Gynaecology | 2.85 | -0.06 | -1.19 | -0.68 | 404 | 486 |
| Dermatology | 3.4 | 0.02 | -1.46 | -0.87 | 421 | 509 |
| Nephrology | 2.71 | -0.07 | -0.95 | -0.67 | 395 | 458 |
| Circulatory syst. | 2.6 | -0.02 | -0.85 | -0.47 | 406 | 473 |

*Note.* Counterfactual experiment: see line (a) from Table 24.
Figures in columns (1) to (4) are expressed in terms of 2005 activity-based revenues.
Activity-based revenues are lower in the FP sector: reimbursement rates do not cover physicians' fees.

## Table 28: Supply estimation: Robustness to market size

| | Circulatory syst. | Nephrology | Dermatology | Gynaecology | Gastroenterology | Ophthalmology | ENT, Stomato. | Orthopedics |
|---|---|---|---|---|---|---|---|---|
| IV - market size: $M_z = q_z + 0.5\hat{\theta}_(\text{pop}_z - q_z)$ | | | | | | | | |
| $r_{gjt}$ | 0.037*** | 0.012** | 0.079*** | 0.018*** | 0.029*** | 0.040 | 0.063*** | 0.014*** |
| | (0.009) | (0.005) | (0.008) | (0.004) | (0.005) | (0.025) | (0.019) | (0.005) |
| IV - market size: $M_z = q_z + \hat{\theta}_(\text{pop}_z - q_z)$ | | | | | | | | |
| $r_{gjt}$ | 0.036*** | 0.012** | 0.078*** | 0.018*** | 0.028*** | 0.040 | 0.063*** | 0.014*** |
| | (0.009) | (0.005) | (0.008) | (0.004) | (0.005) | (0.025) | (0.019) | (0.005) |
| IV - market size: $M_z = q_z + 2\hat{\theta}_(\text{pop}_z - q_z)$ | | | | | | | | |
| $r_{gjt}$ | 0.035*** | 0.011** | 0.075*** | 0.018*** | 0.027*** | 0.040 | 0.062*** | 0.013*** |
| | (0.008) | (0.005) | (0.007) | (0.003) | (0.004) | (0.025) | (0.019) | (0.005) |
| IV - market size: $M_z = \text{pop}_z$ | | | | | | | | |
| $r_{gjt}$ | 0.029*** | 0.009** | 0.059*** | 0.015*** | 0.017*** | 0.030 | 0.042*** | 0.009** |
| | (0.008) | (0.004) | (0.006) | (0.003) | (0.003) | (0.022) | (0.015) | (0.004) |
| 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 × NP.
The second panel is a reminder of Table 20.

Table 29: How much do financial incentives explain of the change in activity? Robustness wrt market size

| | observed change | change due to financial incentives | | | |
|---|---|---|---|---|---|
| $\theta$ | | $0.5\hat{\theta}$ | $\hat{\theta}$ | $2\hat{\theta}$ | 1 |
| | (1) | (2) | (3) | (4) | (5) |
| Orthopedics | 4.14 | 0.16 | 0.18 | 0.21 | 0.86 |
| ENT, Stomato. | -1.38 | 0.28 | 0.3 | 0.33 | 1.25 |
| Ophthalmology | 9.04 | 0.2 | 0.22 | 0.24 | 0.81 |
| Gastroenterology | 1.86 | 0.58 | 0.63 | 0.72 | 2.64 |
| Gynaecology | -2.07 | 0.24 | 0.3 | 0.4 | 1.18 |
| Dermatology | -2.42 | 1.05 | 1.23 | 1.53 | 3.8 |
| Nephrology | 9.85 | 0.23 | 0.27 | 0.34 | 0.81 |
| Circulatory syst. | 3.57 | 0.53 | 0.66 | 0.84 | 1.84 |

Figures:relative change in activity from 2005 to 2008 (in %).

$\theta$ is the parameter governing market size: $M_z = q_z + \theta(\text{pop}_z - q_z)$.

Column (1) is a reminder of line "observed", column (2) of Table 24 and Tables 33 to 39.

Column (3) is a reminder of line (a), column (2) of Table 24 and Tables 33 to 39.

# Figures

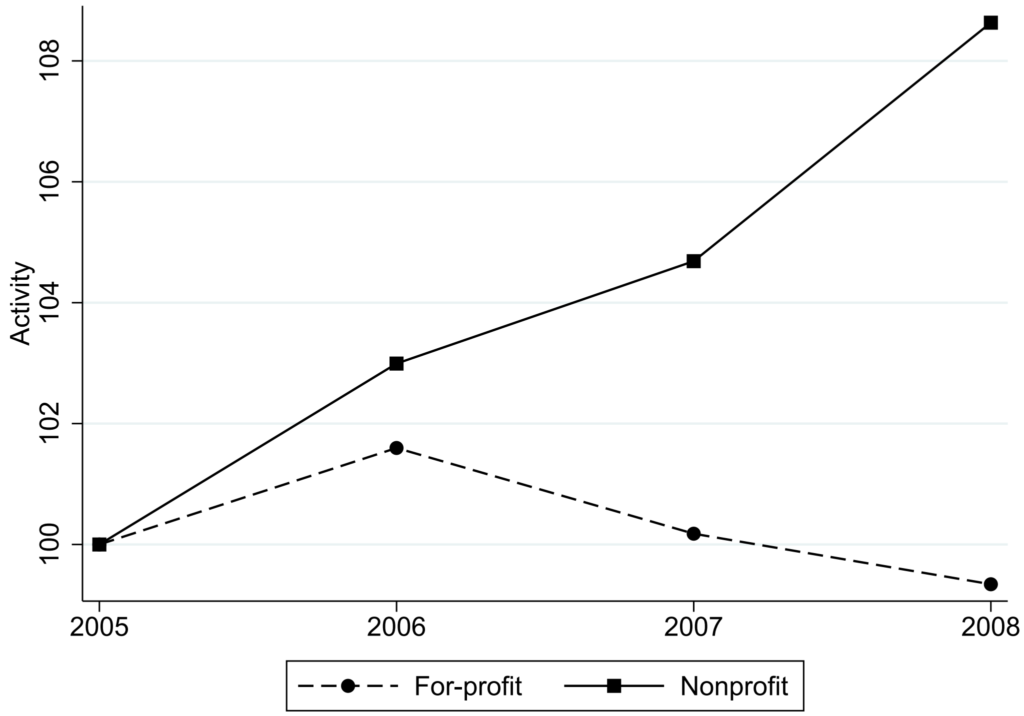
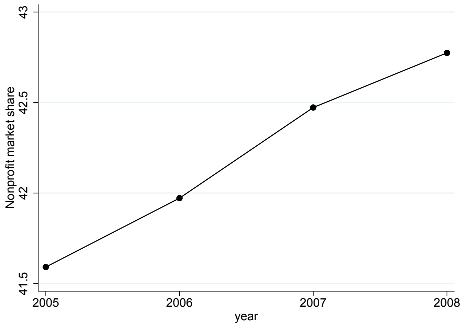
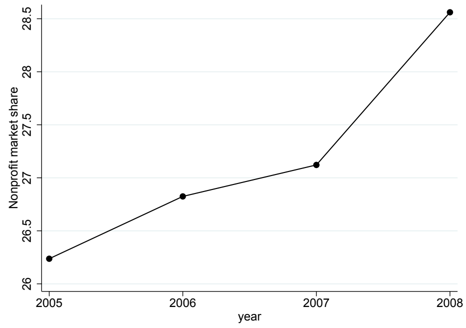


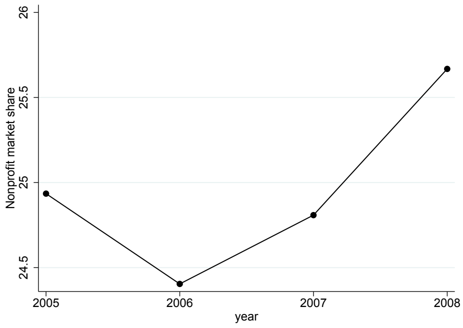

Figure 1: Evolution of the number of surgery admissions in mainland France (by legal status)



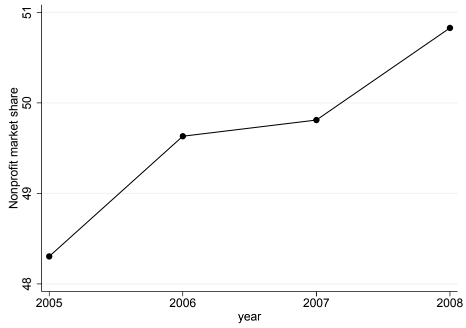

(a) Orthopedics



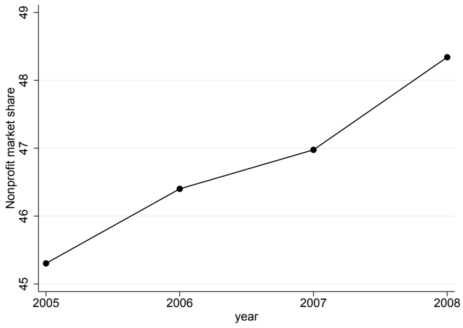

(b) ENT, Stomatology



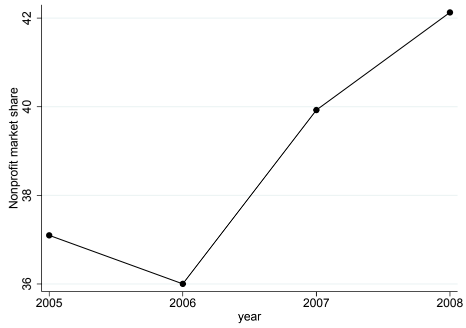

(c) Ophtalmology



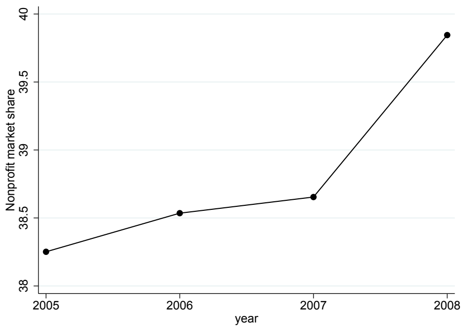

(d) Gastroentrology



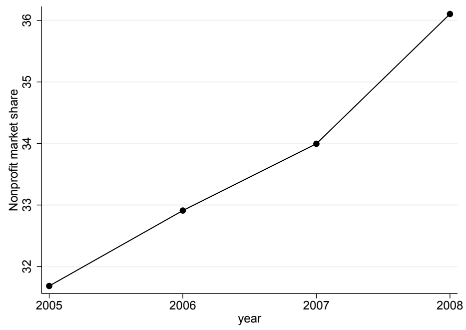

(e) Gynaecology




(f) Dermatology




(g) Nephrology




(h) Circulatory system

Figure 2: Market share of the nonprofit sector (by clinical department)

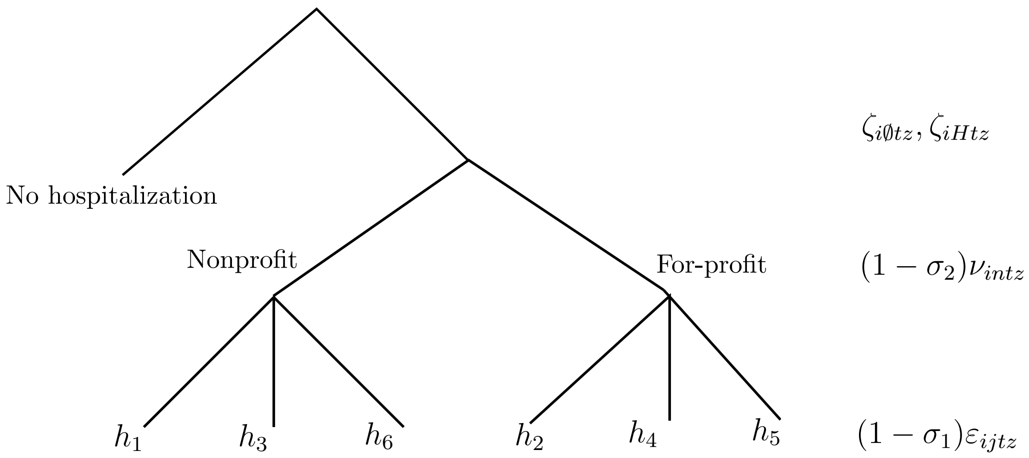



Figure 3: Two-level nested Logit: $0 < \sigma_2 < \sigma_1 < 1$

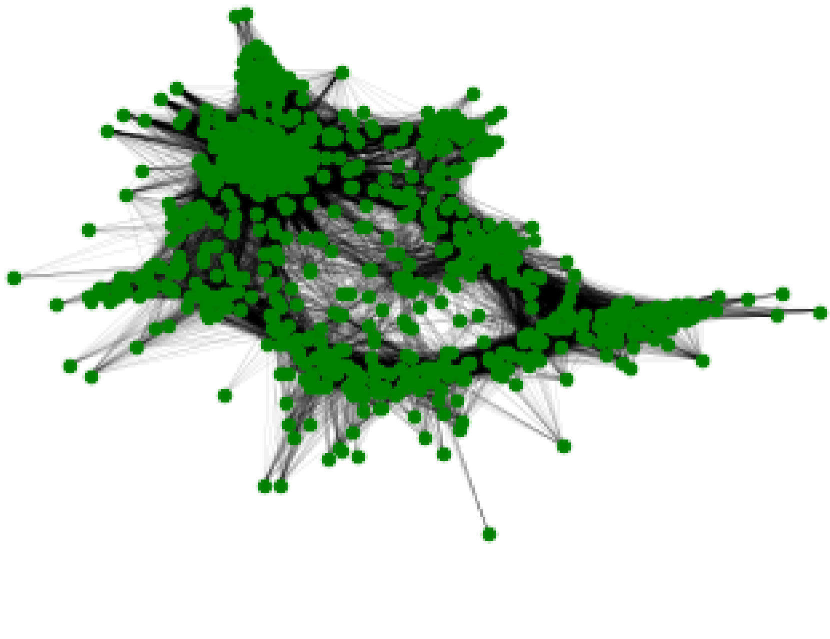
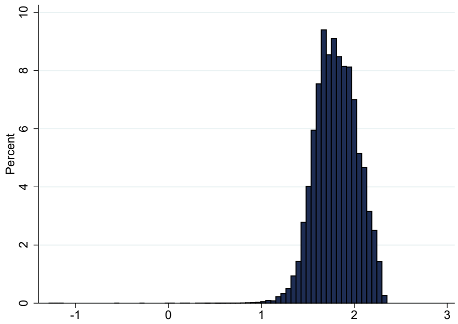
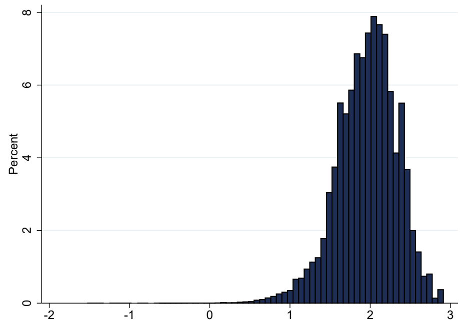


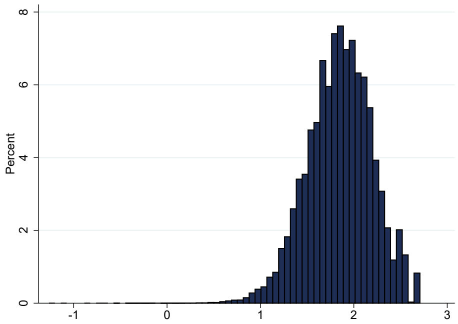
Figure 4: Newman-weighted hospital projected graph (Orthopedics, 2008)



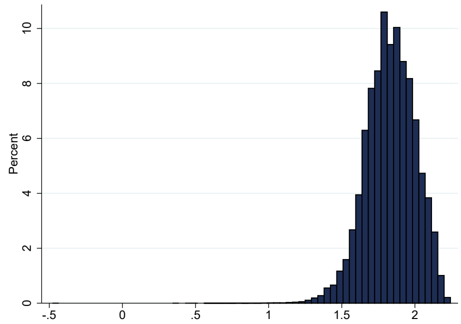

(a) Orthopedics



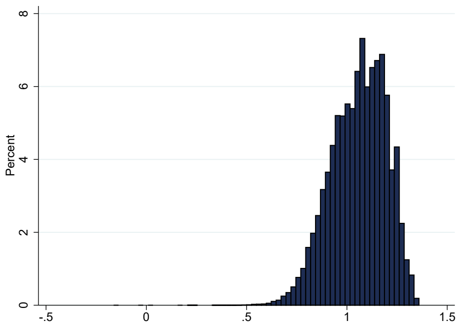

(b) ENT, Stomatology



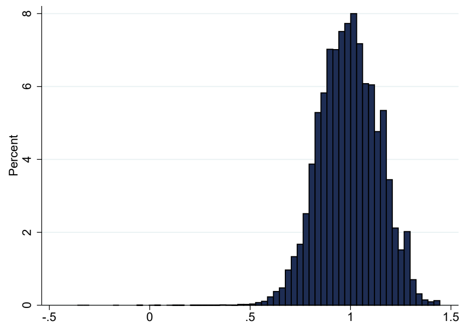

(c) Ophtalmology



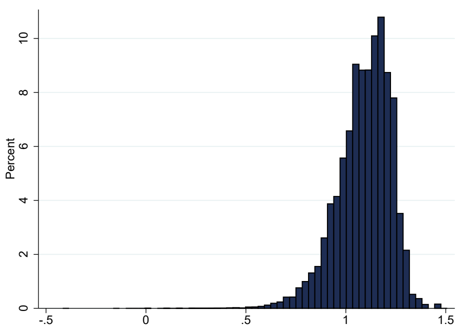

(d) Gastroentrology



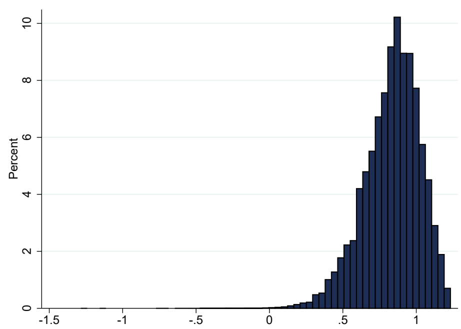

(e) Gynaecology




(f) Dermatology




(g) Nephrology




(h) Circulatory system

Figure 5: Estimated utilities provided to patients (by clinical department, weighted by admissions, 2005-2008)

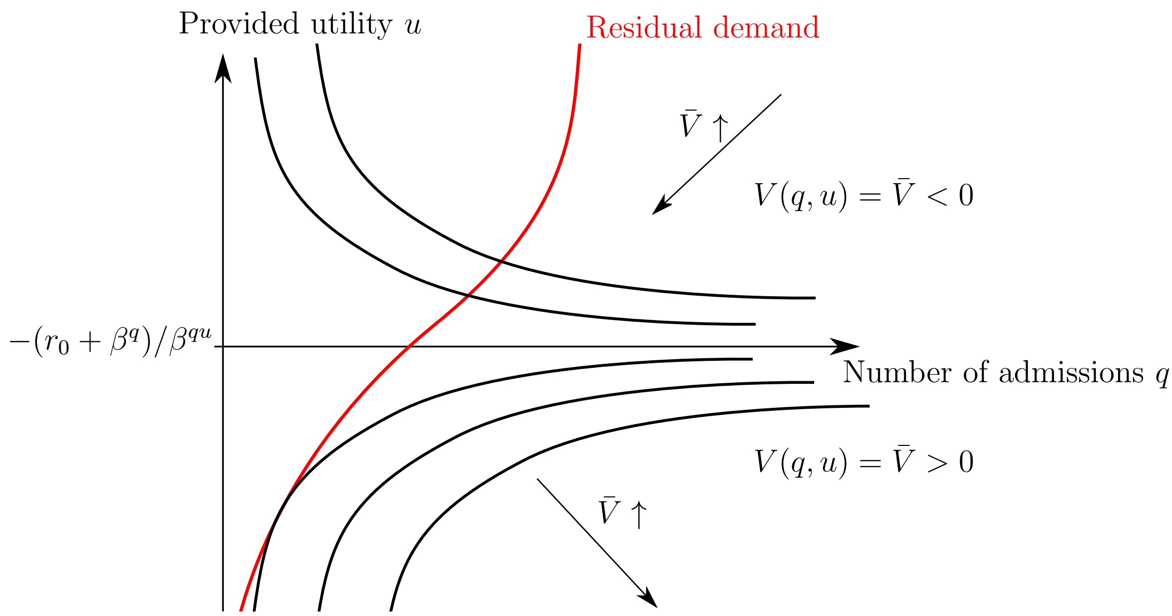



Figure 6: Hospital problem (given utilities provided by competitors), with $\beta^{qu} < 0$

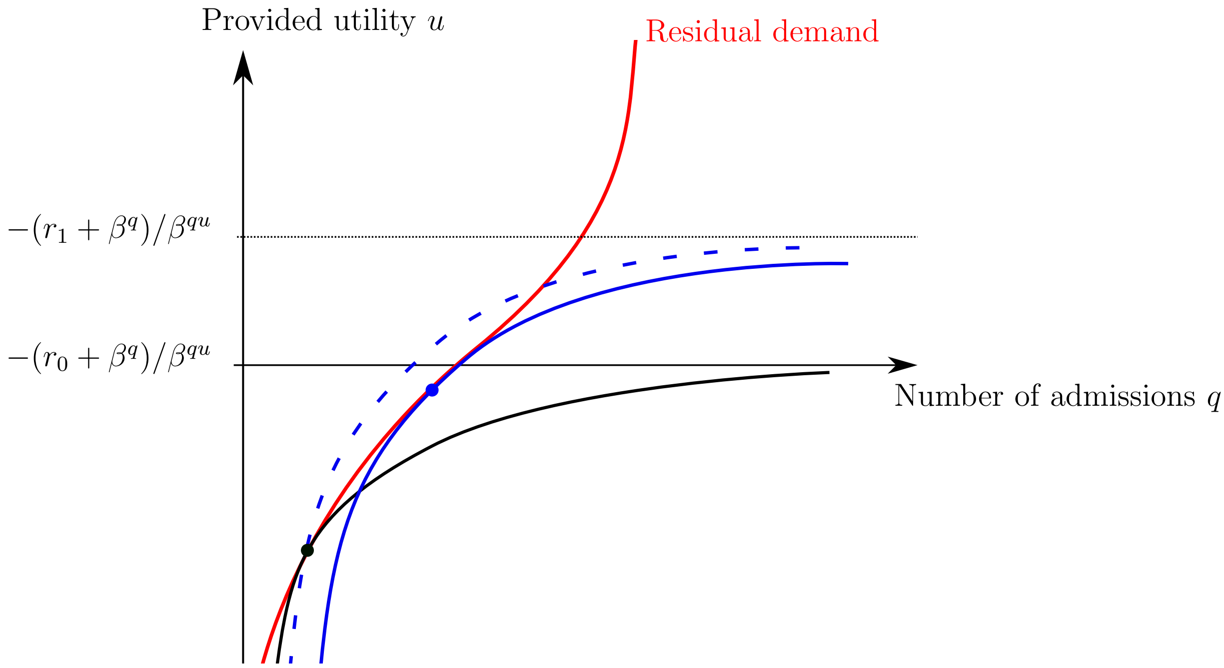



Figure 7: Increasing $r$ from $r_0$ to $r_1 > r_0$ makes iso-$V$ curves steeper: $q$ and $u$ increase from black point to blue point

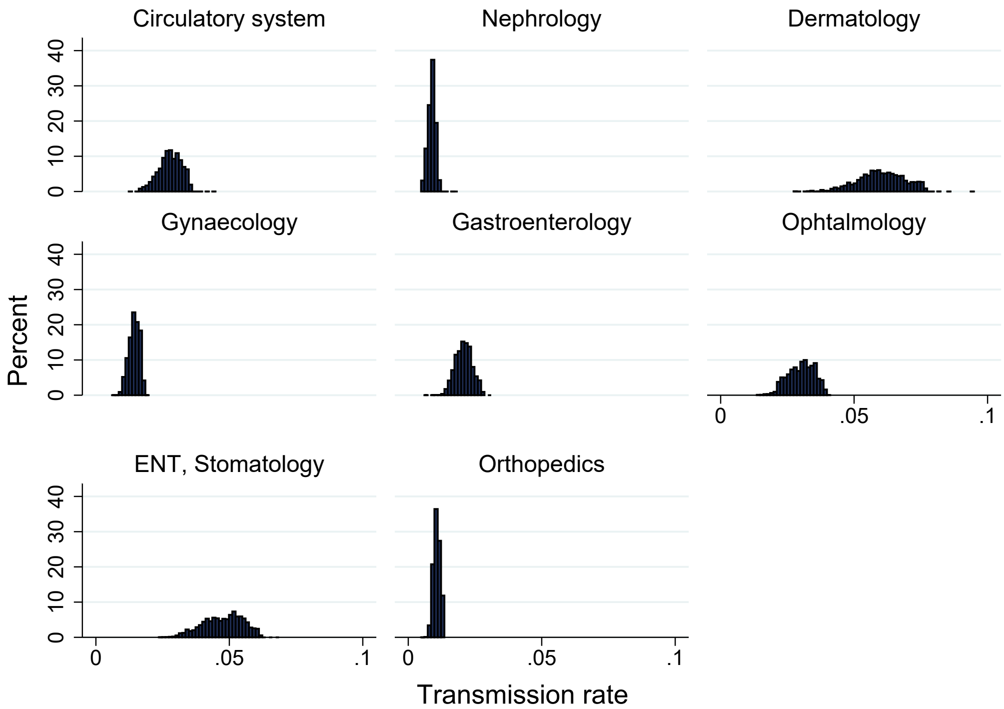



Figure 8: Transmission rates: Distribution of the rise in utility following a €1,000 shock on reimbursement rates

# Appendix

## 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 insurers[44], 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 (clinical department-hospital) level in such a way that an observation is present only if the hospital has admitted at least one

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

patient (regardless of her home location) in the clinical department each year from 2005 to 2008.

**Activity** Table 30 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 30: Summary statistics at the hospital level

| | | Nonprofit hospitals | | | | | | For-profit hospitals | | All hospitals | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | State-owned | | Private | | Total | | | | | |
| # of hospitals | | 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) |

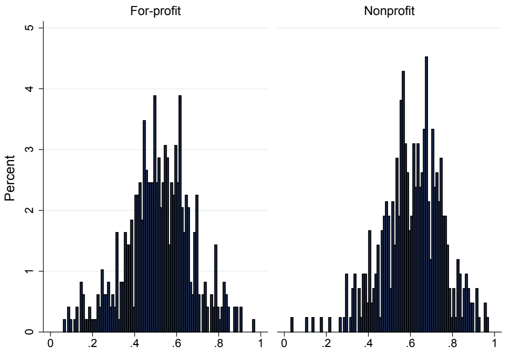
*Source.* French PMSI, individual data, 2005-2008.
*Sample.* 942 hospitals in mainland France.
*Note.* Size is measured as the number of surgical beds in 2004.

**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.

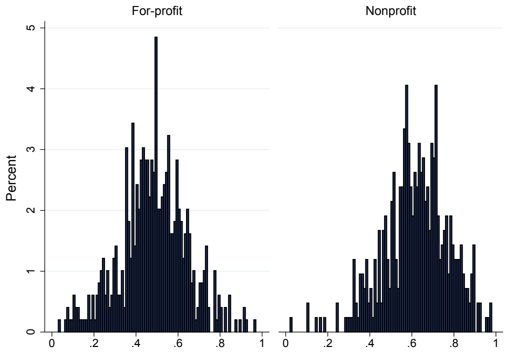
The distributions of annual occupancy rates at the hospital level (ratio of total length of surgery stays over number of available nights) are shown on Figure 9. The mode of the occupancy rates lies somewhere between 60% and 70%. Occupancy is slightly higher in nonprofit hospitals (between 65% and 80%) 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.

**Patient locations and "demand units"** All distances in the paper are based on the center of the corresponding postal codes, and are computed with INRA's

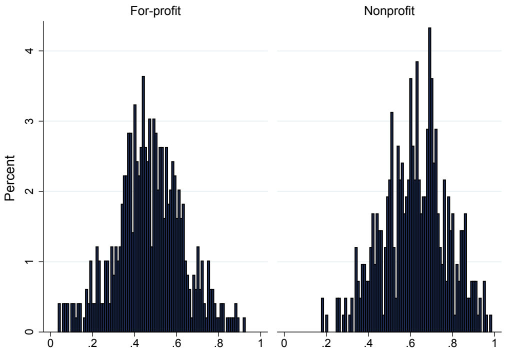
Odomatrix software.



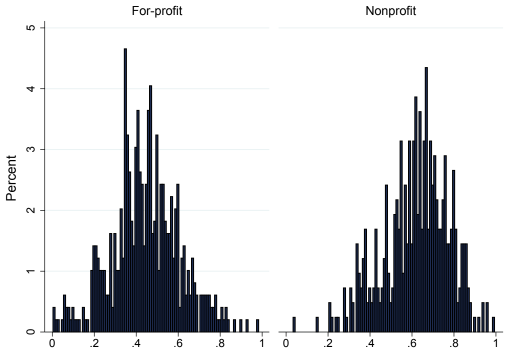

(a) 2005




(b) 2006




(c) 2007




(d) 2008

Figure 9: Hospitals' occupancy rates

## Travel time (by clinical department)

Table 31: Travel time

| | mean | s.d. | min | p10 | p25 | median | p75 | p90 | max | # of obs. |
|---|---|---|---|---|---|---|---|---|---|---|
| All clinical departments 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 clinical department × hospital × year × postal code level.
Weights: discharges $q_{gjtz}$.
Travel time: in minutes.

# B 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.[45] 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

[45] The 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 0.7% 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 32 displays the most frequent price change occurring between two consecutive periods:

Table 32: 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 32, 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[46] 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)) or specialization of activity within clinical departments into particular DRGs. Such strategies make the composition of activity (share of the DRGs within clinical departments) 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 4 shows that the weights used (contemporaneous or lagged admissions) have little effect on the level of the average rates. The impact of composition effects on average DRG rates are of second order compared to the dramatic rise caused by the policy reform in the nonprofit sector.

[46]Hospital endowments prior to the reform were more or less generous for historical reasons.

# C Two-stage nested Logit model: Demand derivatives

**Market share of hospital $j$ in nest $n$ for each demand unit $(g, t, z)$**

$$s_j = s_{j|n} s_{n|H} s_H = \frac{e^{\delta_j/(1-\sigma_1)}}{e^{I_n/(1-\sigma_1)}} \frac{e^{I_n/(1-\sigma_2)}}{e^{I_H/(1-\sigma_2)}} \frac{e^{I_H}}{1+e^{I_H}}$$

with

$$e^{I_n/(1-\sigma_1)} = \sum_{k\in n} e^{\delta_k/(1-\sigma_1)} \Longleftrightarrow I_n = (1-\sigma_1)\ln \sum_{k\in n} e^{\delta_k/(1-\sigma_1)} \qquad n = \text{FP}, \text{NP}$$

$$e^{I_H/(1-\sigma_2)} = \sum_{n=\text{FP,NP}} e^{I_n/(1-\sigma_2)} \Longleftrightarrow I_H = (1-\sigma_2)\ln \sum_{n=\text{FP,NP}} e^{I_n/(1-\sigma_2)}$$

$$\frac{\partial I_n}{\partial \delta_j} = s_{j|n}\mathbb{1}_{j\in n} \qquad \frac{\partial I_H}{\partial \delta_j} = s_{j|H}$$

$$\frac{\partial s_{j|n}}{\partial \delta_k} = \frac{1}{1-\sigma_1} s_{j|n}(\mathbb{1}_{k=j} - s_{k|n})\mathbb{1}_{k\in n}$$

$$\frac{\partial s_{n|H}}{\partial \delta_k} = \frac{1}{1-\sigma_2} s_{k|H}(\mathbb{1}_{k\in n} - s_{n|H})$$

$$\frac{\partial s_{j|H}}{\partial \delta_k} = \left(\left[\frac{1}{1-\sigma_1} s_{j|H}\right]\mathbb{1}_{k=j} - \Delta s_{j|n} s_{k|H}\right)\mathbb{1}_{k\in n} - \frac{1}{1-\sigma_2} s_{j|H} s_{k|H}$$

$$\frac{\partial s_H}{\partial \delta_j} = s_j(1-s_H)$$

**First-order own derivative**

$$\frac{\partial s_j}{\partial \delta_j} = s_j\left[\frac{1}{1-\sigma_1} - \Delta s_{j|n} - \frac{\sigma_2}{1-\sigma_2} s_{j|H} - s_j\right] \tag{C.1}$$

**First-order cross-derivative, with $j$ and $k$ in the same nest**

$$\frac{\partial s_j}{\partial \delta_k} = -s_j\left[\Delta s_{k|n} + \frac{\sigma_2}{1-\sigma_2} s_{k|H} + s_k\right]$$

**First-order cross-derivative, with $j$ and $k$ in different nests**

$$\frac{\partial s_j}{\partial \delta_k} = -\frac{1}{1-\sigma_2} s_j\left[\sigma_2 s_{k|H} + (1-\sigma_2)s_k\right]$$

To solve the system (40), we resort to the `fsolve` routine provided by `Matlab`©

and feed up this routine with the analytic Jacobian $D_u\mu$, which requires to compute second-order derivatives (also needed for checking the stability of the equilibrium).

**Second-order own derivatives**

$$\frac{\partial^2 s_j}{\partial \delta_j^2} = s_j \left[\frac{1}{1-\sigma_1} - \Delta s_{j|n} - \frac{\sigma_2}{1-\sigma_2} s_{j|H} - s_j\right] \left[\frac{1}{1-\sigma_1} - \Delta s_{j|n} - \frac{\sigma_2}{1-\sigma_2} s_{j|H} - 2s_j\right] - s_j \left[\frac{1}{1-\sigma_1} \Delta s_{j|n}(1-s_{j|n}) + \frac{\sigma_2}{1-\sigma_2} s_{j|H} \left(\frac{1}{1-\sigma_1} - \Delta s_{j|n} - \frac{1}{1-\sigma_2} s_{j|H}\right)\right]$$

**Second-order cross-derivative, with $j$ and $k$ in the same nest**

$$\frac{\partial^2 s_j}{\partial \delta_j \partial \delta_k} = s_j \left(\frac{1}{1-\sigma_1} \Delta s_{j|n} s_{k|n} + \frac{\sigma_2}{1-\sigma_2} s_{j|H} [\Delta s_{k|n} + \frac{1}{1-\sigma_2} s_{k|H}] - [\Delta s_{k|n} + \frac{\sigma_2}{1-\sigma_2} s_{k|H} + s_k][\frac{1}{1-\sigma_1} - \Delta s_{j|n} - \frac{\sigma_2}{1-\sigma_2} s_{j|H} - 2s_j]\right)$$

**Second-order cross-derivative, with $j$ and $k$ in different nests**

$$\frac{\partial^2 s_j}{\partial \delta_j \partial \delta_k} = \frac{1}{1-\sigma_2} s_j \left(\frac{\sigma_2}{1-\sigma_2} s_{j|H} s_{k|H} - [\sigma_2 s_{k|H} + (1-\sigma_2) s_k] \left[\frac{1}{1-\sigma_1} - \Delta s_{j|n} - \frac{\sigma_2}{1-\sigma_2} s_{j|H} - 2s_j\right]\right)$$

# D Slopes of reaction functions

The first-order condition of the hospital problem, equation (26), can be rewritten as $\mu^j(u_j, u_{-j}) = 0$, where

$$\mu^j(u_j, u_{-j}) = (r_j + \beta_j^q) \frac{\partial q_j}{\partial u_j} + \beta_j^{qu} \left(q_j + u_j \frac{\partial q_j}{\partial u_j}\right). \tag{D.1}$$

The slope of the reaction function, i.e., hospital $j$'s response to a change in hospital $k$'s utility, is given by

$$\rho_{jk} = \frac{\partial u_j}{\partial u_k} = -\frac{\partial \mu^j / \partial u_k}{\partial \mu^j / \partial u_j} \tag{D.2}$$

with

$$\frac{\partial \mu^j}{\partial u_k} = (\beta_j^q + r_j) \frac{\partial^2 q_j}{\partial u_j \partial u_k} + \beta_j^{qu} \left[\frac{\partial q_j}{\partial u_k} + u_j \frac{\partial^2 q_j}{\partial u_j \partial u_k}\right] \tag{D.3}$$

and

$$\frac{\partial \mu^j}{\partial u_j} = (\beta_j^q + r_j) \frac{\partial^2 q_j}{\partial u_j^2} + \beta_j^{qu} \left[2 \frac{\partial q_j}{\partial u_j} + u_j \frac{\partial^2 q_j}{\partial u_j^2}\right]. \tag{D.4}$$

# E Counterfactual simulations by clinical departments

Table 33: Fit: ENT, Stomatology from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\text{NP}}$ (pp) | $\Delta q/q$ All (%) total | $\Delta q/q$ NP (%) total | $\Delta q/q$ FP (%) total | $\Delta q/q$ NP (%) median | $\Delta q/q$ FP (%) median |
| | **observed** | **2.32** | **-1.38** | **7.35** | **-4.49** | **3.38** | **-5.87** |
| (a) | financial incentives | 1.28 | 0.3 | 5.18 | -1.44 | 3.47 | -1.53 |
| (b) | financial incentives (w/o strategic effects) | 1.32 | 0.22 | 5.25 | -1.57 | 3.69 | -1.58 |
| (c) | aggregate shocks | 0.05 | 1.4 | 1.6 | 1.33 | 1.77 | 1.39 |
| (d) | hospital-specific demand shocks | 0.77 | -3.51 | -0.68 | -4.51 | -2.92 | -3.41 |
| (e) | aggregate + hospital-specific demand shocks | 0.96 | -2.12 | 1.45 | -3.39 | -1.24 | -2 |
| (f) | **all but hospital-specific supply shocks** | **2.28** | **-1.79** | **6.73** | **-4.82** | **3.44** | **-3.55** |
| (g) | hospital-specific supply shocks | 0.39 | 0.23 | 1.74 | -0.31 | -0.28 | -0.74 |
| (h) | neutralizing strategic effects | 2.49 | -1.87 | 7.44 | -5.18 | 3.4 | -6.14 |

These figures are based on the potential demand shown in Table 16.

Table 34: Fit: Ophtalmology from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\text{NP}}$ (pp) | $\Delta q/q$ All (%) total | $\Delta q/q$ NP (%) total | $\Delta q/q$ FP (%) total | $\Delta q/q$ NP (%) median | $\Delta q/q$ FP (%) median |
| | **observed** | **0.73** | **9.04** | **12.24** | **7.97** | **8.5** | **3.96** |
| (a) | financial incentives | 1.04 | 0.22 | 4.39 | -1.17 | 4.13 | -1.16 |
| (b) | financial incentives (w/o strategic effects) | 1.06 | 0.16 | 4.42 | -1.25 | 4.23 | -1.19 |
| (c) | aggregate shocks | 0.13 | 6.85 | 7.39 | 6.66 | 8.36 | 6.95 |
| (d) | hospital-specific demand shocks | 0.26 | 2.27 | 3.33 | 1.91 | 0.82 | 0.72 |
| (e) | aggregate + hospital-specific demand shocks | 0.37 | 8.61 | 10.2 | 8.08 | 7.68 | 6.53 |
| (f) | **all but hospital-specific supply shocks** | **1.38** | **8.78** | **14.79** | **6.79** | **12.13** | **5.4** |
| (g) | hospital-specific supply shocks | -0.44 | -0.02 | -1.8 | 0.57 | -2.36 | -0.37 |
| (h) | neutralizing strategic effects | 1.48 | 7.44 | 13.8 | 5.32 | 11.34 | 0.91 |

These figures are based on the potential demand shown in Table 16.

Table 35: Fit: Gastroenterology from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\text{NP}}$ (pp) | $\Delta q/q$ All (%) total | $\Delta q/q$ NP (%) total | $\Delta q/q$ FP (%) total | $\Delta q/q$ NP (%) median | $\Delta q/q$ FP (%) median |
| | **observed** | **2.52** | **1.86** | **7.19** | **-3.11** | **6.6** | **-4.24** |
| (a) | financial incentives | 2.84 | 0.63 | 6.54 | -4.9 | 4.64 | -5.2 |
| (b) | financial incentives (w/o strategic effects) | 2.93 | 0.47 | 6.56 | -5.22 | 4.53 | -5.17 |
| (c) | aggregate shocks | -0.01 | -0.83 | -0.84 | -0.82 | -0.87 | -0.83 |
| (d) | hospital-specific demand shocks | 0.96 | 2.03 | 4.07 | 0.12 | 3.26 | 0.11 |
| (e) | aggregate + hospital-specific demand shocks | 0.96 | 1.25 | 3.26 | -0.62 | 2.35 | -0.56 |
| (f) | **all but hospital-specific supply shocks** | **3.73** | **1.87** | **9.74** | **-5.48** | **7.78** | **-5.88** |
| (g) | hospital-specific supply shocks | -0.76 | -0.04 | -1.6 | 1.42 | -0.74 | 0.76 |
| (h) | neutralizing strategic effects | 2.64 | 2.01 | 7.59 | -3.21 | 7.37 | -4.6 |

These figures are based on the potential demand shown in Table 16.

Table 36: Fit: Gynaecology from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\text{NP}}$ (pp) | $\Delta q/q$ All (%) total | $\Delta q/q$ NP (%) total | $\Delta q/q$ FP (%) total | $\Delta q/q$ NP (%) median | $\Delta q/q$ FP (%) median |
| | **observed** | **3.04** | **-2.07** | **4.49** | **-7.51** | **4.6** | **-12.47** |
| (a) | financial incentives | 1.63 | 0.3 | 3.9 | -2.68 | 3.44 | -2.99 |
| (b) | financial incentives (w/o strategic effects) | 1.66 | 0.24 | 3.91 | -2.8 | 3.48 | -2.93 |
| (c) | aggregate shocks | 0.02 | 1.34 | 1.38 | 1.3 | 1.45 | 1.39 |
| (d) | hospital-specific demand shocks | 1.56 | -4.15 | -0.84 | -6.89 | -1.63 | -8.99 |
| (e) | aggregate + hospital-specific demand shocks | 1.57 | -2.66 | 0.71 | -5.44 | -0.05 | -7.5 |
| (f) | **all but hospital-specific supply shocks** | **3.22** | **-2.33** | **4.61** | **-8.08** | **3.65** | **-10.28** |
| (g) | hospital-specific supply shocks | 0.26 | 0.09 | 0.66 | -0.39 | 1.5 | 0.12 |
| (h) | neutralizing strategic effects | 3.05 | -2.55 | 4.01 | -7.99 | 3.9 | -12.55 |

These figures are based on the potential demand shown in Table 16.

Table 37: Fit: Dermatology from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\text{NP}}$ (pp) | $\Delta q/q$ All (%) total | $\Delta q/q$ NP (%) total | $\Delta q/q$ FP (%) total | $\Delta q/q$ NP (%) median | $\Delta q/q$ FP (%) median |
| | **observed** | **5.03** | **-2.42** | **10.81** | **-10.23** | **9.28** | **-9.32** |
| (a) | financial incentives | 4.24 | 1.23 | 12.26 | -5.8 | 8.5 | -6.65 |
| (b) | financial incentives (w/o strategic effects) | 4.3 | 0.97 | 12.11 | -6.13 | 8.23 | -6.73 |
| (c) | aggregate shocks | -0.01 | -0.79 | -0.82 | -0.77 | -0.81 | -0.8 |
| (d) | hospital-specific demand shocks | 3.29 | -6.06 | 1.88 | -11.11 | 1.4 | -8.14 |
| (e) | aggregate + hospital-specific demand shocks | 3.35 | -6.94 | 1.07 | -12.04 | 0.61 | -8.82 |
| (f) | **all but hospital-specific supply shocks** | **7.73** | **-5.56** | **13.2** | **-17.51** | **10.77** | **-14.8** |
| (g) | hospital-specific supply shocks | -0.05 | -0.03 | -0.15 | 0.05 | -0.4 | 3.44 |
| (h) | neutralizing strategic effects | 6.79 | -5.61 | 10.86 | -16.1 | 9.58 | -14.95 |

These figures are based on the potential demand shown in Table 16.

Table 38: Fit: Nephrology from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\mathrm{NP}}$ (pp) | $\Delta q/q$ All (%) total | $\Delta q/q$ NP (%) total | $\Delta q/q$ FP (%) total | $\Delta q/q$ NP (%) median | $\Delta q/q$ FP (%) median |
| | **observed** | **1.59** | **9.85** | **14.43** | **7.02** | **10.45** | **1.93** |
| (a) | financial incentives | 1.14 | 0.27 | 3.26 | -1.58 | 1.97 | -1.71 |
| (b) | financial incentives (w/o strategic effects) | 1.19 | 0.2 | 3.33 | -1.74 | 2.01 | -1.74 |
| (c) | aggregate shocks | -0.01 | -0.82 | -0.86 | -0.8 | -0.92 | -0.83 |
| (d) | hospital-specific demand shocks | 0.94 | 10.08 | 12.79 | 8.39 | 10.89 | 5.88 |
| (e) | aggregate + hospital-specific demand shocks | 0.93 | 9.37 | 12.04 | 7.72 | 9.97 | 5.35 |
| (f) | **all but hospital-specific supply shocks** | **2.09** | **9.62** | **15.62** | **5.9** | **12.41** | **3.57** |
| (g) | hospital-specific supply shocks | 0.47 | 10.3 | 11.65 | 9.47 | 8.47 | 4.41 |
| (h) | neutralizing strategic effects | 1.66 | 9.88 | 14.64 | 6.94 | 10.58 | 1.33 |

These figures are based on the potential demand shown in Table 16.

Table 39: Fit: Circulatory system from 2005 to 2008

| | | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|---|
| | | $\Delta s^{\mathrm{NP}}$ (pp) | $\Delta q/q$ All (%) total | $\Delta q/q$ NP (%) total | $\Delta q/q$ FP (%) total | $\Delta q/q$ NP (%) median | $\Delta q/q$ FP (%) median |
| | **observed** | **4.42** | **3.57** | **18.01** | **-3.12** | **12** | **-3.73** |
| (a) | financial incentives | 2.02 | 0.66 | 7.08 | -2.32 | 1.9 | -2.48 |
| (b) | financial incentives (w/o strategic effects) | 2.13 | 0.5 | 7.26 | -2.63 | 2.09 | -2.49 |
| (c) | aggregate shocks | -0.07 | -5.3 | -5.52 | -5.2 | -5.9 | -5.48 |
| (d) | hospital-specific demand shocks | 2.66 | 7.59 | 16.63 | 3.4 | 15.15 | 4.28 |
| (e) | aggregate + hospital-specific demand shocks | 2.56 | 2.58 | 10.89 | -1.27 | 9.98 | -0.74 |
| (f) | **all but hospital-specific supply shocks** | **4.67** | **3.3** | **18.53** | **-3.76** | **13.98** | **-2.82** |
| (g) | hospital-specific supply shocks | -0.04 | 0.02 | -0.09 | 0.08 | 0.08 | 0.19 |
| (h) | neutralizing strategic effects | 4.21 | 4.33 | 18.18 | -2.1 | 11.2 | -3.08 |

These figures are based on the potential demand shown in Table 16.