# Are Public Hospitals Inefficient? An Empirical Study on French Data**

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**Abstract**

Using an almost exhaustive panel of French hospitals during the pre-Covid period, 2015-2019, we studied the comparative efficiency of ordinary public hospitals, teaching public, for-profit and not-for-profit private hospitals. Our comparison is based on the estimation of conditional labor-demand functions, explaining the employment levels of several categories of personnel, including doctors and nurses, as a function of a list of hospital outputs. We show that there exist large, significant and robust differences in the employment levels of various categories of personnel between the four groups of hospitals, conditional on the same vector of outputs. The public hospitals employ on average much more nurses, assistant-nurses and administrative workers than the for-profit hospitals, conditional on the same list of outputs. The public teaching hospitals, *i.e.*, the largest hospitals in France, are the least efficient, from this point of view. These results are obtained while controlling for the average severity of cases (*i.e.*, the casemix index), the average age of patients, the research activity and training (*i.e.*, higher education) activities. For instance, we find that the teaching hospitals employ 60% more registered nurses than the for-profit hospitals, conditional on the same output vector.

Key Words : Public Hospitals; France; Teaching Hospitals; Clinics; Private Non-Profit Hospitals; Outpatient Medicine and Surgery; Severity of Cases; Medical Doctors; Nurses; Econometrics; Multiple Outputs; Multiple Inputs; Conditional Labor-Demand Estimation; Productivity; Economic Efficiency.

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# 1 Introduction

The present article proposes an empirical study of productivity in French hospitals, based on a rich public database disclosed by the French government. An interesting feature of the French health-care system is that it rests on public hospitals working alongside and competing with a sizable private sector. The public teaching hospitals are the largest institutions and the most visible, in addition to a network of regional institutions. But France also has a fringe of private clinics and a variety of private non-profit institutions, forming an important group. This allows us to compare the efficiency of ordinary public, teaching public, private non-profit and private for-profit institutions. Using an official database covering almost all hospitals in France during the pre-Covid years 2015-2019, we find striking differences between the sub-samples of institutions sorted by legal status (*i.e.*, type of ownership).

We find that the public sector and particularly the public teaching hospitals make an inefficient use of several categories of personnel, including mainly the registered nurses; the assistant nurses and the non-medical administrative workers, and also, to a lesser extent, the physicians and surgeons. Teaching public hospitals employ on average much more of each of the 4 personnel categories listed above than private hospitals, to produce the same array of outputs. The results are both significant and robust. The gaps are wide: for instance, the French for-profit hospitals employ around 50% less registered nurses than the public teaching hospitals for the same output vector. It is important to emphasize that these results are obtained while controlling for the selection of patients, using a severity index, for the average age of patients, and for the resources used by research and training activities. It seems that we observe an instance of public-sector inefficiency.

We reach these conclusions with a simple parametric approach that is compatible with a multi-output, multi-input setting. Our comparative assessments of productive efficiency essentially rest on a standard tool from Microeconomics, the *conditional input-demand functions*, explaining a vector of labor inputs (employment levels of several categories of personnel) as functions of a list of 11 outputs, the most important of these being: inpatient and outpatient short-term acute care stays (including surgery, medicine and obstetrics); emergency department stays; treatment sessions; long-term stays. In brief, we propose a parametric, input-based study of productivity. The approach has several advantages, and does not require observations of the complete list of inputs. The conditional input-demand can be derived from cost minimization subject to a generalized, multi-output production function, leading to an input-demand function depending on the various log-output levels. Our main results are obtained when the input-demand functions are estimated in sub-samples of hospitals, determined by observable characteristics, such as the legal status. Based on the estimates, we can compute various efficiency indices. In particular, we can compare the current inputs of a given public hospital with the counterfactual input vector that a "privatized" version of the same hospital would use.

Our estimation methods are simple and standard. The input-demand functions can be viewed as reduced forms. If true, outputs are exogenous in input-demand regressions. This is only one of several possible assumptions, that may be reasonable under some conditions. A certain degree of skepticism on the latter point nevertheless led us to use some standard instrumental-variable estimators based on lagged-outputs. In essence, we show that our results are not sensitive to this type of instrumentation. In addition, we find that output levels are very persistent and that the model is mainly estimated thanks to substantial between-hospital variability.

There are some advantages of an input-based approach, as compared to a production-function approach, when it comes to treating potential endogeneity problems. Indeed, it is easy to show that, even if outputs are exogenous in the input-demand equation, in contrast, the inputs are endogenous in the production equation, using inputs to explain output. In essence, our strategy is to divide the sample in a number of cells (*i.e.*, subsamples) and estimate a different input-demand model for each cell. The cell-based models are then used to construct counterfactuals. For instance, we can predict the labor demand of a public hospital, if this hospital was a private for-profit institution. We provide a more complete justification for this simple approach below.

There exists an important international literature on hospital efficiency analyses, using data envelopment analysis (*i.e.*, DEA), stochastic frontier models (*i.e.*, SFA), Malmquist index techniques and standard Microeconometrics, like cost-function estimation.[1] A review paper by Hollingsworth (2003) comments on the results of more than 150 studies applying various methods to health-care. It is to be noted that his list does not include a single study of French hospitals. This is due to the fact that the quality and the availability of French public data has increased substantially in the past ten years. There is no consensus on the most appropriate method for the study of health-care organizations.[2] Some recent contributions, based on cost function estimation and other related tools, shed light on the delicate question of economies of scale and scope in hospitals.[3],[4] Our sub-sample approach rests on the idea that observable characteristics, like legal status, may determine different production frontiers and that the resulting efficiency differences can be studied with the help of factor-demand functions, since the latter

[1] An overview of standard methods is presented in Greene (2008). The pioneering work of Charnes, Cooper and Rhodes (1978) applied Linear Programming results to develop DEA. The seminal papers on the Stochastic Frontier Model are due to Aigner *et al.* (1977) and Meeusen and van den Broek (1977).

[2] On the lack of consensus, see *e.g.*, Hollingsworth and Street (2006). See also Castelli *et al.* (2015) who propose to "go back to basics"; these authors study productivity in the English NHS with the help of a multi-output, multi-input approach and show the existence of a substantial cross-hospital variability. Stochastic frontier models assume that the production function is only observed up to a random error, and rest on a parametric specification of the production function. In contrast, the statistical approaches descending from DEA aim at non-parametric estimation of a "deterministic" maximal production frontier. The up-to-date non-parametric estimation methods develop subtle ways of avoiding excessive sensitivity to outliers, while retaining the idea of consistently estimating maximal production for each vector of inputs (see, *e.g.*, Daouia, Simar and Florens (2021).

[3] See *e.g.*, Crémieux and Ouellette (2001), Wilson and Carey (2004), Preyra and Pink (2006), Gaynor *et al.* (2015), Carey and Mitchell (2018).

[4] The Malmquist index for efficiency comparisons is another methodological tradition based on standard Microeconomics. Our approach of efficiency comparisons is in the spirit — if not an exact application — of the theory of index numbers for the measurement of productivity, as exposed in Caves *et al.* (1982). See also Caves and Christensen (1980). These ideas go back at least to Malmquist (1953).

are well-adapted to the study of multi-dimensional outputs.

There exists an equally important literature on the comparative performances of hospitals according to forms of ownership. Sloan (2000) surveys the literature on not-for-profit hospitals. Kornai's *soft-budget-constraint* theory[5] provides an important analytical tool for the interpretation of our results; this is demonstrated by Duggan's (2000) classic article on Californian hospitals. See also Horwitz and Nichols (2009). Recent work on this topic has studied non-profit to for-profit conversions of nursing homes.[6]. On hospitals in Europe, recent results are often mixed and sometimes find that the performance of public hospitals is better than that of the private sector.[7]

We did not study the quality of health care. It is difficult to study the quality of a given hospital in general. We know that the variance of quality used to be large in France, thanks to Gobillon and Milcent (2013), but their article focuses on AMI and uses data from the 1998-2003 period, before the introduction of the prospective payments system in the country. The links between technology and quality are probably important: underinvestment in ambulatory surgery and medicine is likely to be a cause of the relative inefficiency of French public hospitals and at the same time, may also explain the between-hospital variance of quality.[8] In France, nowadays, the average citizen's perceptions about quality do not clearly rank public hospitals above the private ones. To substantiate this claim, we provide descriptive statistics for two important quality scores below. The patients have a relatively favorable perception of the quality of clinics and nonprofit hospitals.[9]

A small number of articles has been published on the productivity of French hospitals. France changed its hospital funding system in 2004 to adopt a version of prospective payments based on Diagnostic Related Groups — 20 years after the equivalent reform in the United States. This reform caused a state of permanent tension and social crisis in public hospitals. Dormont and Milcent (2019), Choné and Wilner (2022), using data collected earlier than the period covered by the present study, focus on the possible impact of increased competition among hospitals. For instance, Choné and Wilner (2022) show that the implementation of the French prospective payments system between 2004 and 2008 had substantial effects, increasing the intensity of competition between the public and private sectors. The contributions of Clark and Milcent (2011, 2018) provide an important clue as to whether the inefficient number of nurses that we observe in public hospitals can be explained by Political Economy considerations. Clark and Milcent showed that in the recent past, French public hospitals have been used as policy tools to

[5] See Kornai, Maskin et Roland (2003).

[6] See *e.g.*, Bos *et al.* (2017), Lu and Lu (2023)

[7] See, *e.g.*, the review articles of Kruse *et al.* (2018) and Tynkkynen and Vrangbaek (2018).

[8] On the interaction of quality and specialization, see, *e.g.*, Clark and Huckman (2012).

[9] On the quality of hospitals in the US, see Kunz *et al.* (2024). These authors show that for-profit ownership is negatively correlated with quality: the situation seems different in France. Kunz *et al.* (2024) also show that the not-for-profit status tends to be associated with higher quality; and it happens that the French nonprofits have better satisfaction scores, as shown below, in Section 2.

fight local unemployment. Hospitals hired significantly more nurses and assistant-nurses when the local unemployment rate was higher and when the city council was leaning towards the left. This is a very likely consequence of the fact that, before a major reform of public hospital governance rules[10], enacted in 2009, mayors were the chairmen of public hospital boards. Given that the degree of employment protection is very high among public employees, 20 years later, we observe the persistent impact of past hiring policies. These facts provide a rather credible interpretation of our results.

To sum up, a likely explanation for the productivity differences that we uncover is that they result from of a combination of a few important factors: underinvestment in new technologies, and particularly in ambulatory surgery, possibly due to a shortage of public funds; personnel and trade-union resistance to change; the influence of local politicians in a recent past, and finally, the government's credibility problem. The latter factor probably plays a catalyzing role: the French public teaching hospitals being "too big to fail", the government cannot easily impose rationalization by threatening to reduce grants — this is Kornai's soft-budget constraint problem. The excess-employment bias of public firms is a well-known stylized fact.[11] Further work is needed to confirm these intuitions.

In the following, in Section 2, we describe the data and present some descriptive statistics. Section 3 presents the labor-demand functions and discusses our method. Section 4 presents estimation results obtained with the complete sample, mixing public and private hospitals, using lagged outputs as instruments. In addition we present some robustness tests. Section 5 use sub-sample estimates of the input-demand functions to build counterfactuals and compare the efficiency public and private hospitals. We present specific statistics measuring efficiency differences. Section 6 presents further robustness checks and Section 7 gathers concluding remarks. Additional results are presented in three appendices, including an appendix devoted to a structural interpretation of our conditional factor-demand model, based on a multi-output Cobb-Douglas specification.

# 2 Data and Some Descriptive Statistics

## 2.1 Data. The Panel

As indicated above, the data set that we used is the official, publicly disclosed, yearly report of the French public health administration on all registered hospitals and clinics of the country, produced thanks to the joint efforts of the hospitals, who report the data, the public health

[10] The act called *loi HPST*.

[11] Again, see Kornai *et al.* (2003), Duggan (2000). More generally, there exists a large literature on the effects of ownership and privatization; see the survey of Meggisson and Netter (2001); on excess employment and political interference, see the classics, *e.g.*, Mueller (1989), Donahue (1989), Shleifer and Vishny (1994); see also Bartel and Harrison (2005), Brown *et al.* (2006).

insurance system (*i.e., Assurance-Maladie*) and the Ministry of Health (*i.e., Ministère de la Santé*). In the recent years, the French Government has made substantial efforts to disclose data on hospitals and hospital patients. A public agency, the ATIH[12] produces and discloses several surveys. A publicly accessible web-site, called *Hospidiag*, discloses various indicators and measures of performance computed by another public agency called ANAP.[13] We exploited the most easily accessible data sets, called SAE (*i.e., Statistique annuelle des établissements*), reporting a list of outputs and inputs each year and for each hospital. Stacking several years of the SAE data, we obtain a panel. We used a few years, immediately before the Covid 19 pandemic, that is, the years 2015-2019. We ignored 2020 and 2021 because of many missing-data problems due to the pandemic. It follows that our data set is a short panel, but this panel is almost balanced, since the list of hospitals doesn't vary much from year to year, and we have a rich cross-section every year, with an almost exhaustive set of institutions established on the French territory. In addition to these data, we exploited the PMSI files[14], gathering all patient discharge files (and not publicly disclosed, but available to researchers under some conditions), to compute additional indicators, in particular, refined severity, *i.e., casemix* indices, a specialization index and an average patient age, for each hospital. These variables are crucial to control for patient selection, as we will see below.

There are around 1400 hospitals and clinics in the panel. We distinguish four categories of institutions: *(i)* the *public teaching hospitals* (in French *CHU* for *Centres Hospitaliers Universitaires*), typically the biggest urban hospitals of the country; *(ii)* the *ordinary public hospitals* (*i.e.*, all the public hospitals that are not CHUs); *(iii)* the *private not-for-profit hospitals* (typically with a non-profit legal status, that do not distribute dividends); *(iv)* the *private for-profit hospitals* (including *clinics*).

We observe many input measures for each institution in the panel. We will mainly focus on 4 personnel aggregates, the number of doctors, including surgeons[15], the number of full-time equivalent registered nurses (*i.e.*, *infirmiers*); the number of full-time equivalent assistant-nurses (*i.e.*, *aides-soignants*); and the administrative (non-medical) staff. We aggregate several categories of registered nurses, some being chief nurses, or nurses with special qualifications. We also aggregate several categories of administration employees.

The problem is now to measure hospital outputs. Our elementary measure of production is the hospital stay (*i.e., séjour* in French). A stay is not the same thing as a patient; not a number of days, not a disease, not a treatment and not a bed. By definition, a stay is a person admitted on some day, with one or several pathologies, receiving one or several treatments, who may use or not use a bed, who may use a bed during a day or more, and leaving the hospital at some point. If the patient returns after some time, this is another stay. We have an outpatient (or

[12] *i.e., Agence technique de l'information sur l'hospitalisation*; see https://www.atih.sante.fr)

[13] ANAP is an acronym for *Agence Nationale d'Appui à la Performance des Etablissements de Santé.*

[14] PMSI means *Programme de Médicalisation des Systèmes d'Information.*

[15] See Appendix A for details on the count of MDs.

ambulatory) stay if the patient does not spend at least one night in the hospital. In such a case, the length of stay, measured in days, is conventionally set equal to zero.[16] The number of beds[17] is a measure of hospital capacity for inpatient stays, used by the regulator. The unit of measurement for the outpatient capacity is the *slot*.[18]

Counting the number of patients receiving treatment when they need it, independently of the severity of their case, is justified by reasonable welfare criteria. The number of stays corresponds to an *ex ante* point of view of the public regulator who wants to provide insurance to citizens and therefore also ensure that they will be treated, whatever the severity of their illness. It is implicit that each case is a drawing in a distribution of severity, implying a distribution of the cost of treatment.

The severity of cases is measured by reference to the cost of treatment itself and this cost can reflect inefficiencies. To measure hospital outputs, we could recompute weighted aggregate numbers of stays of various types, with weights reflecting the costs incurred by the hospital. The weights would be proportional to the prices used to value the Diagnosis Related Groups in the prospective payment system. We have doubts about the sample of hospitals used by the regulator to estimate these prices, and about the fact that these valuations are unbiased. Inefficiencies in the production of care could in fact be interpreted as differences in severity. Adding up all stays in a certain category of hospital activity is completely exempt of this type of ambiguity. We therefore use the number of stays as a measure of output, and we control for the percentage of severe cases and the average age of patients, to take patient selection into account. As we will see, our casemix index has significant and non-negligible effects on employment levels.

Next, hospitals are multi-output producers, and we observe a number of aggregates for each hospital and each year. The first and most important type of stay can be called *Short-term acute care* or *STAC stay*.[19] We crucially distinguish the *inpatient* and the *outpatient* STAC stays. We can disaggregate the inpatient (resp. outpatient) STAC stays in inpatient (resp. outpatient) surgery (hereafter *STAC-Surg*) and inpatient (resp. outpatient) Medicine and Obstetrics (hereafter *STAC-MO*). The next most important aggregate is the *Emergency Department* or *ED stay*.[20] Next, we find the number of *sessions*.[21] Sessions are typically devoted to chemotherapy, radiotherapy, dialysis, etc. In addition, we have the following other output measures: *Psychiatry department stays*, that can be inpatient or outpatient stays; *follow-up care and rehabilitation*[22];

[16] There are other specific units of measure of production. For psychiatric departments: the *venue*; for emergency rooms: the *passage*; etc.

[17] *i.e., lits* in French.

[18] *i.e.*, our translation of the French word *place*.

[19] This is our translation of the French *Médecine-Chirurgie-Obstétrique*, or MCO, that could also be translated as Medicine-Surgery-Obstetrics.

[20] *i.e.*, in French, *passage aux urgences*. Note that the number of Emergency department stays is net of the number of stays in STAC.

[21] Our translation of the French *séances*.

[22] *i.e.*, translation of the equivalent French *Soins de suite et réadaptation* or SSR. This corresponds roughly to the notion of post-acute care.

the *Long-term care unit* or *LTAC stays*;[23]; *Home Hospitalization*[24]; and finally the *Outpatient Consultations*[25].

To sum up, we have up to 11 kinds of medical output. Some are of course more heterogeneous than others, but a reasonable statistical model should neither aggregate all hospital stays nor rely on an arbitrarily long list of finely distinguished products. STAC stays amount to 36% of all stays in ordinary public hospitals; 44% in the teaching public hospitals; 37% in the private nonprofit hospitals and 64% in private for-profit hospitals. Emergency department stays amount to 35% of all stays in ordinary public hospitals; 26% in the public teaching hospitals; 7.5% in the private nonprofit hospitals and 11% in the private for-profit sector. Finally, sessions amount to only 11% in public hospitals; 17.5% in the private for profit hospitals, but 40% in the private nonprofit sector. These figures indicate a relative specialization of hospital categories: the nonprofits are strong on sessions (particularly on cancer treatment), the clinics are strong on STAC and public hospitals run important EDs. The sum of the three most important categories, *i.e.*, STAC, ED stays and sessions, always represents more than 80% of the total number of stays in a given institution. To these we should in principle add two other outputs: research and training (*i.e.*, higher education).

With the help of the *PMSI* files, we computed crucial indicators and performance measures. The most important of these indices is a severity index, hereafter called *Casemix*, which measures the percentage of high severity cases treated by the hospital in a given year.[26] Our casemix index is refined, by type of stay and by hospital branch, using PMSI files. Controlling for *Casemix* will, as usual, correct for the impact of the selection of patients on productivity. To control for patient selection, it is also crucial to compute the average patient age, hereafter *Average Age*. Another important variable measures the research activity of the institution, based on publications in medical journals[27], hereafter called *Research*. We also use a teaching intensity indicator[28], hereafter called *Training*. These variables permit us, although imperfectly, to capture the impact of research and teaching on the use of inputs. [29] Finally, using PMSI files, we constructed a specialization index, hereafter *Specialization*, which is an entropy measure of the dispersion of an hospital's activity types.[30]

[23] Our translation from the French *Unités de soins de longue durée* or USLD.

[24] In French, *hospitalisation à domicile*.

[25] *I.e., Actes et consultations externes*. Outpatient consultations pose a problem because they are reported in the public sector, whereas in the private sector, most outpatient consultations are part of the doctor's private practice, and therefore not recorded. In spite of this, outpatient consultations are an output of public hospitals and should be taken into consideration.

[26] There are four severity grades, ranging from 1 to 4, and *Casemix* is the percentage of patients with severity 3 or 4.

[27] This is variable A11 in *Hospidiag*.

[28] Variable A10 in *Hospidiag*.

[29] For details on these variables, see https://hospidiag.atih.sante.fr/sihnat/hospidiag/pdf/fiche_technique.pdf.

[30] See Appendix A for details.

## 2.2 Descriptive Statistics

The first striking indications are provided by elementary descriptive statistics, showing very significant differences between the types of hospital ownership, all pointing in the same direction. Marked differences exist not only between public and private institutions, but also between teaching and ordinary hospitals, within the public sector itself. The substantial variance of variables, driven by a high degree of heterogeneity is also striking.

### 2.2.1 Average Productivity of Hospital Personnel

If we compare hospitals with a different legal status, we observe very substantial and very striking average productivity differences for each category of personnel, in the years 2015-2019. Table 1 gives measures of average productivity in 4 categories of hospitals (Teaching Public, Ordinary Public, Private For-Profit and Private Non-profit). The productivity measure is simply the total number of stays divided by the number of employees in each of 3 categories: MDs (including surgeons), registered nurses, assistant nurses. The top rows of the table give the average severity index (*i.e.*, casemix, between 0 and 1) and the average patient age (in years). The first striking observation is the fact that the private sector selects patients with a much smaller severity. The last line of Table 1 also shows that the average length of stay (hereafter ALOS), based on inpatient stays only, is longer in public hospitals. Next, the productivity of nurses and assistant nurses is much smaller in the public sector. For instance we find 274 stays per nurse in the private for-profit sector while the corresponding figure is only 109 stays per nurse in the teaching public hospitals. The difference is even bigger in the case of assistant-nurses. The way assistant-nurses are employed in clinics seems very different from the rest of the institutions, including the non-profits.[31] In the case of doctors, the interpretation is more delicate, because doctors are more productive in the ordinary public hospitals, and the least productive in the teaching hospitals.

Table 1: Casemix Index, Average Patient Age and Number of Stays per Employee and per Year, 2015-2019.

| | Teaching | For-Profit | Non-Profit | Public |
|---|---|---|---|---|
| Casemix | 0.18 | 0.02 | 0.03 | 0.15 |
| Av. Patient Age | 57.61 | 57.72 | 62.13 | 63.33 |
| Av. Length of Stay (in Days) | 7.37 | 4.21 | 7.72 | 8.98 |
| Av. Productivity MDs | 298.8 | 377.0 | 341.8 | 393.8 |
| Av. Productivity Nurses | 109.2 | 274.0 | 154.6 | 144.9 |
| Av. Productivity Assistant-Nurses | 142.4 | 502.6 | 243.8 | 159.1 |

[31] The average productivity measures of the administrative personnel range from 1 to 4.

We will come back to the interpretation of these facts below. Further examination of these simple statistics show that they are very robust. The median values, the quantiles, the values weighted by the number of beds give the same indications. In essence, the econometric work will also confirm these observations.

### 2.2.2 Hospital Quality

We now try to substantiate the claim that the quality of French hospitals is not clearly better in the public sector. We have two sources of information: grades given by official inspectors from the *High Health Authority* (*i.e.*, *Haute Autorité de Santé*), visiting the institutions, and the result of surveys conducted among former patients. There are four grades A, B, C, D. Table 2 gives the percentage of A grades in the population of hospitals; the percentage of As for 5 out the 20 items of the certification procedure, and the percentage for the overall grade. The coverage amounts to 90% of the hospitals. The private hospitals have clearly better grades on average. Next, a patient satisfaction survey, called *E-Satis*, is also available.[32] Patients are

Table 2: Results of Certification Process; 2014-2019. Percentage of A grades

| | Teaching | For-Profit | Non-Profit | Public |
|---|---|---|---|---|
| Management of Patient File | 0.49 | 0.85 | 0.85 | 0.70 |
| Infection Risk | 0.63 | 0.88 | 0.92 | 0.74 |
| Management of Medication | 0.39 | 0.76 | 0.78 | 0.57 |
| Management of Quality and Risks | 0.67 | 0.84 | 0.81 | 0.69 |
| Patient Pathway | 0.86 | 0.86 | 0.89 | 0.70 |
| Overall Certification Grade | 0.08 | 0.52 | 0.54 | 0.21 |

contacted when they return home, and fill a questionnaire. Scores are given for stays longer than 48 hours and for outpatient surgery stays. Table 3 reports some results. At the end, they report if they would recommend the hospital to a friend. In addition there are scores for the handling or management of patients. The grades are between 0 and 100. The contrast between public and private hospitals is not very strong. Yet, the grades are better for the private non-profit institutions.

### 2.2.3 Rate of Use of Equipment

Finally, our data set includes various measures of the medical equipment in each hospital, but with many missing observations. So we can have a glance at some ratios. A first measure is the number of *appliances*. By definition, the number of appliances is the sum of the number of

[32] E-satis is administered by the *Haute Autorité de Santé i.e.*. See, for instance, https://www.has-sante.fr/jcms/c_2030354/fr/iqss-e-satis-mesure-de-la-satisfaction-et-de-l-experience-des-patients-hospitalises.

Table 3: E-Satis, Patient-Satisfaction Scores, 2019

| | Teaching | For-Profit | Non-Profit | Public |
|---|---|---|---|---|
| % Recommend (Inpatient) | 55.08 *(10.55)* | 59.59 *(10.84)* | 68.16 *(11.09)* | 49.75 *(11.39)* |
| % Recommend (Outpatient) | 64.32 *(8.26)* | 63.41 *(8.74)* | 75.51 *(9.86)* | 64.25 *(10.08)* |
| Medical handling score | 79.36 *(2.45)* | 81.84 *(2.62)* | 82.52 *(2.76)* | 78.29 *(3.16)* |
| Overall score | 75.78 *(3.20)* | 75.86 *(2.76)* | 78.91 *(3.13)* | 77.75 *(2.85)* |

Note: Average Scores *(standard deviations)*. % Recommend is the percentage of patients who recommend the hospital.

scanners, MRI Machines, positron emission tomography instruments and scintillation cameras. If we count the number of appliances and divide it by the number of STAC stays, and multiply by $10^3$, we obtain the ratios of Table 4. The figures of Table 4 do not suggest that the public sector lacks equipment. We see that the non-profit sector has higher ratios, probably because many of them are specialized in cancerology.

Table 4: Number of Appliances per thousand STAC stays; 2016-2019

| | Public | For Profit | Non-Profit | Teaching |
|---|---|---|---|---|
| Mean | 0.24 | 0.21 | 0.37 | 0.16 |
| Median | 0.17 | 0.15 | 0.24 | 0.15 |
| *Number of observations* | 1,838 | 853 | 363 | 482 |

We can also mesure the number of operating rooms.[33] We were able to compute a ratio of the number of operating rooms per thousand stays in surgery departments (including outpatient surgery) in a number of hospitals. These ratios are displayed in Table 5, and this time, we see a striking difference between the public and private sectors (including teaching hospitals). In Table 5, the median ratio row seems more reliable, due to heterogeneity, but the median number of operating rooms per stay in the public sector is roughly twice the value of the same median ratio in private for-profit hospitals, the non-profits occupying an intermediary position.

Table 5: Number of Operating Rooms per thousand STAC stays; 2016-2019

| | Public | For Profit | Non-Profit | Teaching |
|---|---|---|---|---|
| Mean | 2.61 | 1.38 | 1.83 | 10.62 |
| Median | 1.76 | 0.975 | 1.43 | 2.04 |
| *Number of observations* | 1,606 | 2170 | 457 | 481 |

[33] *I.e.*, in French *salles d'intervention* or *salles d'opération*.

Based on these figures, it is not obvious that the French public hospitals lack capital. On the contrary, they give the impression that at least some of them under-utilize their production capacity. This question would clearly deserve further research.

# 3 Estimation of Conditional Input-Demand Functions

Our goal is now to estimate the productivity differences between hospitals. It happens that, with our data, a standard microeconomic labor-demand model yields significant and robust results. In any empirical study of hospitals, a well-known difficulty is the multi-output nature of hospital production. On the one hand, some aggregation is imposed for the sake of tractability, but on the other hand, precision and credibility impose a multi-input, multi-output model taking the diversity of hospital stays into account in a flexible way. The ideal situation would be one in which we would be able to put each stay in one of several severity classes. Then, we would estimate the demand for personnel for a long list of activity measures. To be more precise, with $K$ measures of output and $L$ levels of severity, we would estimate a model with at least $KL$ variables. With, say, three or four categories of severity and 10 types of stay, we would reach the limits of what can be obtained with the data. We will therefore control for severity and show that our casemix index is a significant variable, showing that more personnel is indeed needed to take care of severe cases.

## 3.1 The Model

Let $x_{kit}$ denote the log-employment of personnel category $k$ in hospital $i$ during year $t$; let $y_{it}$ denote a vector of log-output levels; let $z_{it}$ denote a vector of controls, including a constant. Assume in addition that the set of hospitals can be partitioned in a finite number of cells, or subsamples, indexed by $s$ with $s = 1, \ldots, S$. Each cell is defined by certain observable characteristics, for instance, a cell may contain all the private non-profit hospitals with more than 200 beds. We assume that the inputs $x_{it}$ can be expressed as a linear function of outputs $y_{it}$ and controls, with a variable coefficient regression function of the form

$$x_{it} = a^s + b^s y_{it} + c^s z_{it} + \epsilon_{sit}, \tag{1}$$

where $a^s$ and $b^s$ and $c^s$ are parameters that may freely vary with cell $s$. We assume that there is a key omitted variable called *managerial ability*, denoted $\theta_i$. This variable represents various factors, including unobservable cost minimization efforts. A higher managerial ability presumably reduces the regression constant and also diminishes the elasticity terms. Suppose now that the model underlying the above regressions can be written,

$$x_{it} = \alpha - \theta_i + (\beta - \gamma\theta_i) y_{it} + c^s z_{it} + u_{it}, \tag{2}$$

where $u_{it}$ is an independent term with a zero mean, $\alpha$, $\beta$, and $\gamma > 0$ are parameters. Assume in addition that managerial talent is strongly related to cell $s$: more precisely, we have $\theta_i = \bar{\theta}^s + \xi_{si}$,

where $i$ belongs to cell $s$ and $\xi_{si}$ is a random term with a zero mean, independent from $y_{it}$. Then, the underlying model can easily be rewritten,

$$x_{it} = \alpha - \bar{\theta}^s + (\beta - \gamma\bar{\theta}^s)y_{it} + c^s z_{it} + u_{it} - \xi_{si}(1 + \gamma y_{it}). \tag{3}$$

This is clearly our cell-based regression model (1) with $a^s = \alpha - \bar{\theta}^s$, $b^s = \beta - \gamma\bar{\theta}^s$ and $\epsilon_{sit} = u_{it} - \xi_{si}(1 + \gamma y_{it})$.

It is now easy to check that $(a^s, b^s, c^s)$ can be consistently estimated by OLS in each sub-sample $s$. This is because $Cov(y_{it}, \epsilon_{sit}) = 0$ for all $s$ under our assumptions.[34] Note that we are *not* identifying $\alpha$, $\beta$ and $\gamma$, but crucially, we do not need these parameters for efficiency comparisons. Yet, the model is completely identified at the cost of one additional normalization, namely, the assumption that some weighted average of the $\theta^s$, with known weights, is equal to zero.[35] We could still have doubts about the independence of $u_{it}$ and $y_{it}$ at time $t$. We would then have $Cov(y_{it}, \epsilon_{sit}) = Cov(y_{it}, u_{it}) \neq 0$. If $y_{it}$ is uncorrelated with future shocks $u_{i,t+k}$, $k > 0$, and $Cov(u_{it}, u_{ir}) = 0$ for all $t \neq r$, we can then use $y_{i,t-1}$ as an instrument for $y_{it}$ in the cell-based model. More generally, if $y_{it}$ is uncorrelated with future shocks $u_{i,t+r}$, $r \geq k$, we can use $y_{i,t-k}$ as an instrument for $y_{it}$.

To sum up, the underlying idea is that a small managerial ability pushes a hospital above the efficient demand for inputs, given a vector of outputs; we are not assuming that all hospital managers have the same degree of managerial ability and therefore the same efficiency.

As a consequence, we will estimate the input-demand equations in 4 different sub-samples of hospitals (*i.e.*, Private for-profit; Non-profit; Ordinary public; Teaching). We could refine the analysis by considering subdivisions of sub-samples, for instance, a refined partition distinguishing the large public hospitals and the small public hospitals, etc.[36] But we also need a sufficient number of observations in each cell.

Given this, we can predict employment levels $\hat{x}^s$ in each sub-sample $s$, and we can compute counterfactual employment levels, that is, we can "privatize" a public hospital, or "nationalize" a private hospital, and compare the results in terms of predicted employment. When we "privatize" a public hospital, we predict what the input demands of the public hospital would be if it was private, using the estimated equation for a private hospital. The above discussion shows that, doing this, we will implicitly assume that managerial talent is equal to its average value in the private sector. This is a reasonable way of predicting the effects of privatization.

[34] To prove this point, we first compute $Cov(y_{it}, \epsilon_{sit}) = Cov(y_{it}, u_{it}) - Cov(y_{it}, \xi_{si}) - \gamma Cov(y_{it}, y_{it}\xi_{si})$. Since $\mathbb{E}(\xi_{si}|y_{it}) = 0$, using the law of iterated expectations, we find that $\mathbb{E}(y_{it}\xi_{si}) = \mathbb{E}[y_{it}\mathbb{E}(\xi_{si}|y_{it})] = 0$ and similarly, $\mathbb{E}(y_{it}^2\xi_{si}) = 0$. Since we assumed that $u_{it}$ is independent from $y$, we have $Cov(u_{it}, y_{it}) = 0$ and it follows that $Cov(y_{it}, \epsilon_{sit}) = 0$.

[35] To prove this, assume that $\sum_s q_s\bar{\theta}^s = 0$ for some weights $q_s > 0$ such that $\sum_s q_s = 1$. Then, we have $\sum_s q_s\hat{a}^s = \alpha - \sum_s q_s\bar{\theta}^s = \alpha$. This gives an estimate $\hat{\alpha}$ and we immediately derive $\hat{\theta}^s = \hat{\alpha} - \hat{a}^s$. To obtain $\hat{\beta}$ we simply compute $\sum_s q_s\hat{b}^s = \hat{\beta} - \gamma\sum q_s\hat{\theta}^s = \hat{\beta}$. Finally we obtain $\hat{\gamma} = (\hat{\beta} - \hat{b}_s)/\hat{\theta}^s$ ($\gamma$ is overidentified).

[36] We will explore the impact of hospital size in some robustness checks.

### 3.2 Further Discussion of the Estimation Method

**Conditional Input-Demand vs. Production Function.** Our approach is to estimate conditional input-demand functions. For instance, estimate the number of full-time equivalent registered nurses needed to treat a given array of stays of various types. This approach is firmly grounded in standard microeconomics. An alternative approach would have been to use a standard production function model, but our input-demand approach has several advantages that we discuss below, in Appendix B.

**Input Prices.** We do not observe input prices, but conditional input-demand functions can be estimated without information on input prices, when it is known that the time-variability of relative prices is limited. Indeed, prices (*i.e.*, wage rates) are very sluggish in the short period under study.[37] The relative wages of the different personnel categories did not vary much in this short observation period and if we added input-price observations, the variability of the latter would be too small to warrant estimation of price or log-price coefficients. We therefore focus on quantities and provide a form of input-output analysis.

**Discussion of the Estimation Method.** We estimate the conditional demand functions for 4 categories of personnel: doctors (and surgeons); registered nurses; assistant nurses and administrative staff. We first estimate "average" input-demand functions, pooling all hospitals, but adding dummies to distinguish the 4 hospital categories. This is tantamount to assuming that $b^s$ and $c^s$ are constant (but that $a^s$ varies with $s$). In this latter form, which is the simplest, input-demand differences are captured by differences in the regression constant. We find that regression constants differ significantly from one category of hospitals to the next.

Then, we consider sub-samples of hospitals with the same legal status and we estimate the $4 \times 4 = 16$ equations, *i.e.*, 4 subsamples and 4 inputs. These equations are finally used to compute counterfactuals.

In view of our results, we do not suspect a severe endogeneity problem (*i.e.*, $\epsilon_{it}$ correlated with explanatory variable $y_{is}$, conditional on controls $z$). The hospital labor demand adjusts in response to demand for treatment and stays by patients.[38] There are random demand shocks affecting the various activity measures on the right-hand side of the equations. For instance, an epidemic of bronchiolitis among infants in a given region, in year $t$. The quantity of labor $x_{it}$ will respond to these shocks.

Yet, an endogeneity bias affecting the coefficients of output variables is still possible, due to the

[37] In addition, wage rates do not differ too much from one hospital to the next. We know, for instance, that the wages of nurses are not higher, on average, in the private sector. See the figures disclosed by the government, DREES, "Les salaires dans les établissements de santé", 2019 and later; https://drees.solidarites-sante.gouv.fr/. Yet, doctors may earn more in the private sector. These differences can in any case be captured by differences in the regression constants.

[38] The personnel may vary quickly as a response to short-run shocks, because each hospital director can adjust the workforce, even in the public sector, by means of short-term contracts.

contemporaneous correlation of $\epsilon_{it}$ with $y_{it}$. Using the two-year lagged value of each log-output variable as an instrument for the corresponding log-output appearing on the right-hand side of the equation can take care of this kind of correlation, and also correct for a correlation of $y_{it}$ and $\epsilon_{i,t-1}$.[39] We present estimates obtained with a two-year lag, but the OLS estimates, also presented, are very close. Our main results are in fact very robust, and instrumentation does not change our conclusions, in essence.[40]

Next, we show that each coordinate of the output vector $y_{it}$ is well-approximated by a simple AR1 model with a value of the autocorrelation coefficient ranging between .4 and .93, when we consider the most important stay types.[41] It follows that each coordinate of $y_{it}$ is strongly correlated with the corresponding coordinate of $y_{i,t-1}$.

Our approach is completely valid only if the instruments are independent of possible hospital fixed effects *conditional on controls*.[42] The latter assumption is reasonable because we have a sufficiently rich list of control variables.

First, we find labor-demand equations explaining a big share of employment variability, with $R^2$ values above .85, showing that we probably did not omit the most important variables. Secondly, we have a long list of controls that do characterize well the hospital types: a list of dummies indicating if an activity is present or not; a number of measures of equipment, etc., and the legal-status indicators. If they were unobserved or omitted, these variables would combine to form hospital fixed-effects, possibly correlated to outputs.

**Further Discussion of Panel Structure and Instrumental Variables.** An alternative, and in principle more convincing identification strategy would have been to use some instruments for the number of stays (*i.e.*, the output measures), for instance, exogenous shocks on demand for healthcare due to epidemics. Our attempts typically led to the conclusion that available instruments are weak and(or) lead to a lack of precision. Next, the panel structure allows for the use of a within-hospital, fixed-effects estimator. We also tried this approach, but the within-hospital time variation is not sufficient to obtain estimates that are more credible than OLS estimates. Because the panel is short, we reach the limit of what the data can support with the use of standard within-hospital, fixed effects or first-difference estimators. Now, instrumenting the *within* estimators with lagged outputs, using the Arellano-Bond estimator or even the *system GMM* estimator *à la* Blundell-Bond, for the same reason, is not yielding more convincing results (see, *e.g.*, Arellano and Bond (1991), Blundell and Bond (1998)). Our system GMM estimates

[39] We also tried instrumenting all outputs with their one-year lagged value and with their 2015 values, eliminating the year 2015 from the dataset: the results are very similar.

[40] Part of the explanation is that innovations $\epsilon_{it}$ are the result of "political" decisions of the public regulator that are nearly orthogonal to output, because they do not respond to short-term shocks on the demand for health-care.

[41] The cross first-order autocorrelations of $y_{it}$ are all close to zero: in other words, the first-order autocorrelation matrix of $y_{it}$ is nearly diagonal. These results are presented in the Appendix D, Tables 19 and 20.

[42] In this context, this is tantamount to assuming that these fixed effects are negligible or independent of output levels. In other words, fixed effects are simply "random effects"; see *e.g.*, Wooldridge (2010, chap. 11.2))

are presented in Appendix C.2, Table 18. None of these methods being fully satisfactory or feasible given the data, we present below our results based on sub-sample estimation.

### 3.3 Can we Detect Inefficiencies?

**Use of Counterfactuals** Can we detect inefficient hospitals or groups of hospitals with our method? The answer is yes, with some qualifications. Suppose that we find two hospitals, labeled 1 and 2 with the same output vector, $y_1 = y_2$, hospital 1 being public and hospital 2 being private for-profit. If we observe in addition that $x_2 < x_1$, meaning that the for-profit hospital, as compared to the public one, does not require more of any input, and uses strictly less of at least one input, then, the public hospital is less efficient. But there are two difficulties: *(a)*, we do not observe all the inputs, and *(b)*, we need at least a counterfactual, for private hospitals cannot be exactly matched with public hospitals. To solve *(b)*, as already mentioned, we consider subsets of hospitals, the subsample $P$ of ordinary public hospitals, the subsample denoted $FP$ of for-profit hospitals, and we estimate our input-demand model in each subsample. The estimated models are then used to predict $\hat{x}_1^{fp} = \hat{a}^{fp} + \hat{b}^{fp} y_1 + \hat{c}^{fp} z_1$, that is, the input requirement of hospital 1 if it was private for-profit with the same output vector $y_1$, using the parameter estimates obtained in the private for-profit subset $FP$, namely, $\hat{a}^{fp}$, $\hat{b}^{fp}$ and $\hat{c}^{fp}$.

Next, we can consider $P$, the subsample of public hospitals, and compute the differences between the counterfactuals $\hat{x}_i^{fp}$ and the predicted input $\hat{x}_i^{p} = \hat{a}^{p} + \hat{b}^{p} y_i + \hat{c}^{p} z_i$, using the parameters $(\hat{a}^p, \hat{b}^p, \hat{c}^p)$ of the public-hospitals model, for the same $i$ in $P$. An average (or a median) of these differences over all $i$ in $P$ indicates a possible inefficient combination of inputs among public hospitals.

Because of difficulty *(a)*, in principle, there is a doubt about the extent of inefficiency if we observe physical capital imperfectly. The public hospital, for instance, could have chosen a different capital/labor ratio: in other words, we might observe the components of a short-term cost function, or the capital/labor ratio might not be optimal. But the hospitals have access to the same technologies and the industry structure is stable over time. As a consequence, it is reasonable to assume that we observe long-run labor-demand functions in the private sector. Now, if input prices are the same for all hospitals, and if we assume that for-profit hospitals are cost minimizers, in principle, any difference between $\hat{x}_1^{fp}$ and $\hat{x}_1^{p}$ suggests the presence of inefficiencies in the public hospital. For the argument to be valid, it is in fact sufficient that the for-profit hospitals be on average closer to cost minimization (or just better managers) than the public hospitals. If the differences are large and the input prices are not very different in the public sector, the argument remains valid.[43] Wage rate differences may be substantial for doctors though — it is well-known that doctors typically earn more in the private sector — but then we should find that the private sector tends to employ less doctors for a given output,

[43] In practice, the wage rates can vary with the legal status but we already mentioned that these differences are not very large in the case of nurses.

which is not always true empirically, as we will see. Higher wages in the private sector could also reflect the fact that physicians work longer in the latter sector. It is unclear if, say, a surgeon's compensation *per hour of operation* is very different in the public and the private institutions. Finally, the fact that we find large differences between categories of hospitals is reassuring: they cannot entirely be the result of input-price differences.

**Suboptimal Capital or X-inefficiency?** In practice, as shown below, we observe that public hospitals employ much more registered nurses, assistant nurses and administrative staff than their for-profit counterparts, for given output vector and casemix. A reason for this could be that public hospitals lack equipment or are undercapitalized. In Section 2 above, we provided indications suggesting that public hospitals are not undercapitalized.[44] It follows that other sources of inefficiency must be present. Some of these sources are reflected in the fact that public and private hospitals appear to have different production functions. This is why we suspect that mismanagement, insufficient effort incentives, adverse selection in recruitment processes and political interference are important explanations for the observed differences. Finally, if there exists increasing returns in hospital production, these returns may not be apparent because large hospitals suffer from organizational problems or are simply not well managed. If a public hospital is large like 4 clinics, with the same activity mix, it should in principle be able to produce *at least* as many stays as four clinics, *i.e.*, the returns should be weakly increasing. This is not what the data show.

# 4 Empirical Results on Productivity Differences

## 4.1 Main regressions on pooled data

We now present the estimation results for the input-demand functions in log-linear form defined above. The input-demand functions have the following right-hand side variables (in logs): 1°) STAC inpatient stays; 2°) STAC outpatient stays; 3°) emergency department stays; 4°) stays in the psychiatric department; 5°) sessions; 6°) follow-up care and rehabilitation; 7°) Long-term care unit stays; 8°) home hospitalization; 9°) Outpatient consultations. To these outputs we add measures of Research and Teaching activities, the Casemix index, average patient age and the interaction of average patient age with casemix. In addition, a list of dummies indicate if each type of activity is present or not in the hospital.[45] We also include an index measuring the degree of specialization of the hospital (denoted *Spec*). Finally, we control for the legal status by means of 3 dummies indicating, for-profit, non-profit and ordinary public hospitals, the teaching hospitals being the reference group.

[44] Our descriptive statistics indeed suggest that the existing equipment is under-utilized in the public sector. Sirven and Lescher-Cluzel (2023) provide elements confirming that French public hospitals are not under-equipped.

[45] To be precise, if a number of stays is zero, we conventionally set the log-stays also equal to zero. This is very close to using $\ln(1+y)$ instead of $\ln(y)$.

Comparisons show that the differences between IV and OLS estimates are small. In essence, the conclusions are the same with OLS and IV. We suspect that the difference between the two estimators is mainly due to sample size, because lagging output by two years forces us to drop the first two years of the panel, which include about 40% of the observations.

Tables 6-7 give the estimated values of conditional input-demand coefficients for 4 different personnel aggregates: assistant-nurses (column (1)); MDs (column (2)), registered nurses (column (3)) and administrative staff (column (4)). Table 6 displays the results when lagged log-output variables are used as instruments, with a 2-year lag, while Table 7 gives the OLS version of the same coefficients. Table 6-7 give the estimated coefficients of an average input-demand function estimated on all the hospitals in the sample, but we distinguish hospital sub-samples by means of dummies indicating the legal status (*i.e.*, ownership type), the teaching public hospitals being the reference. It is easy to check that the coefficients of the latter dummies are significant and very large — we return to this point below. We see that most coefficients of log-output variables (*i.e.*, $b$ coefficients) are estimated with good precision.[46] The coefficient of the Casemix index is very significant, with a positive sign. Casemix has a nonnegligible impact: given that it is ranging from 0 to 1, a coefficient of 2 means that a 10 points increase in average severity leads to a 20% increase in the demand for personnel. This means that we are successfully controlling for casemix differences, and that severity empirically matters. The interaction of severity with the average patient age also matters: this interaction variable has a significant negative sign, meaning that severity is less costly when average patient age is higher.[47] The specialization index has a negative and significant impact on the demand for doctors and nurses, showing that more specialized institutions are also more efficient. The latter result is remarkably robust.

## 4.2 Common Coefficients on Output Measures but Different Constants for Different Legal Categories of Hospitals

To analyze further the meaning of the results of Tables 6-7, we compute the exact percentage differences in personnel employment as implied by the model, comparing hospitals by legal status. Table 8 gives the percentage gaps, based on the coefficients of the dummy variables indicating hospital categories in Tables 6-7. These coefficients are typically estimated with precision, being significantly different from zero at the $10^{-3}$ level for MDs, nurses and administrative staff. The teaching public hospitals are the reference here. To obtain the percentage values of Table 8, we simply compute $100(\exp(\text{Coefficient}) - 1)$.

[46] On these tables, a star $^{*}$ indicates significance at the 10% level; two stars $^{**}$ indicate significance at the 5% level; three stars $^{***}$ indicate significance at the 1% level. To shorten the Tables 6-7, we do not display the estimated coefficient of activity dummies, indicating the presence or absence of the different types of stays. There are 11 such dummies and they are generally significant, but not always. We also do not show the coefficients on Home Hospitalization and Long-term stays: these variables are not very significant. We show the crucial coefficients, and the most important types of stays.

[47] This effect seems to be driven by the fact that small public hospitals welcome more seniors, who stay longer and whose pathologies are less demanding in terms of personnel. These hospitals tend to act as nursing homes.

Table 6: Demand for Labor Inputs, IV Estimation

| | Assist. Nurses | MDs | Nurses | Admin. Staff |
|---|---|---|---|---|
| Inpatient STAC | 0.158*** | 0.219*** | 0.158*** | 0.171*** |
| | (0.021) | (0.019) | (0.019) | (0.020) |
| Outpatient STAC | 0.036*** | 0.085*** | 0.041*** | 0.060*** |
| | (0.014) | (0.014) | (0.013) | (0.014) |
| Emergency Department | 0.334*** | 0.265*** | 0.308*** | 0.224*** |
| | (0.046) | (0.051) | (0.044) | (0.042) |
| Psychiatry Department | 0.092** | 0.131*** | 0.155*** | 0.077* |
| | (0.038) | (0.040) | (0.044) | (0.043) |
| Sessions | 0.089*** | 0.072*** | 0.106*** | 0.078*** |
| | (0.008) | (0.008) | (0.007) | (0.008) |
| Follow-up and Rehab. | 0.301*** | 0.157*** | 0.260*** | 0.199*** |
| | (0.055) | (0.044) | (0.052) | (0.054) |
| Ext$^{al}$ Consultations | 0.013 | 0.064*** | 0.061*** | 0.103*** |
| | (0.022) | (0.022) | (0.020) | (0.023) |
| For Profit | −1.050*** | −0.206* | −0.474*** | −0.416*** |
| | (0.121) | (0.106) | (0.109) | (0.126) |
| Non-Profit | −0.742*** | −0.231*** | −0.335*** | −0.047 |
| | (0.098) | (0.081) | (0.087) | (0.101) |
| Public | −0.520*** | −0.338*** | −0.311*** | −0.139 |
| | (0.093) | (0.082) | (0.081) | (0.101) |
| Specialization | −0.098*** | −0.131*** | −0.104*** | −0.053 |
| | (0.035) | (0.034) | (0.033) | (0.038) |
| Training | 0.041 | −0.036 | 0.140** | −0.016 |
| | (0.072) | (0.069) | (0.058) | (0.076) |
| Research | 0.037 | 0.138*** | 0.072** | 0.166*** |
| | (0.031) | (0.049) | (0.030) | (0.045) |
| Casemix | 2.534*** | 1.262* | 3.207*** | 2.196*** |
| | (0.772) | (0.663) | (0.733) | (0.797) |
| Av. Patient Age | 0.003 | −0.002 | 0.006*** | −0.0002 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Casemix×Av. Patient Age | −0.027*** | −0.019** | −0.044*** | −0.028*** |
| | (0.010) | (0.008) | (0.009) | (0.010) |
| Constant | −4.276*** | −3.993*** | −5.096*** | −3.722*** |
| | (0.753) | (0.765) | (0.685) | (0.677) |
| Observations | 3,948 | 3,948 | 3,948 | 3,948 |
| Adjusted $R^2$ | 0.840 | 0.848 | 0.869 | 0.842 |

Table 7: Demand for Labor Inputs, Ordinary Least Squares

| | Assist. Nurses | MDs | Nurses | Admin. Staff |
|---|---|---|---|---|
| Inpatient STAC | 0.155*** | 0.220*** | 0.160*** | 0.174*** |
| | (0.018) | (0.016) | (0.016) | (0.017) |
| Outpatient STAC | 0.034*** | 0.080*** | 0.045*** | 0.053*** |
| | (0.011) | (0.010) | (0.010) | (0.010) |
| Emergency Department | 0.296*** | 0.255*** | 0.272*** | 0.257*** |
| | (0.044) | (0.041) | (0.040) | (0.040) |
| Psychiatry Department | 0.064** | 0.087*** | 0.128*** | 0.030 |
| | (0.027) | (0.029) | (0.033) | (0.033) |
| Sessions | 0.086*** | 0.066*** | 0.110*** | 0.073*** |
| | (0.007) | (0.006) | (0.006) | (0.007) |
| Follow-up and Rehab. | 0.273*** | 0.159*** | 0.226*** | 0.195*** |
| | (0.035) | (0.029) | (0.029) | (0.030) |
| Ext$^{al}$ Consultations | 0.027** | 0.068*** | 0.051*** | 0.083*** |
| | (0.013) | (0.013) | (0.012) | (0.013) |
| For Profit | −0.964*** | −0.166* | −0.478*** | −0.419*** |
| | (0.097) | (0.086) | (0.089) | (0.104) |
| Non-Profit | −0.699*** | −0.214*** | −0.322*** | −0.084 |
| | (0.085) | (0.074) | (0.077) | (0.091) |
| Public | −0.495*** | −0.339*** | −0.335*** | −0.160* |
| | (0.078) | (0.070) | (0.068) | (0.085) |
| Specialization | −0.099*** | −0.120*** | −0.088*** | −0.043 |
| | (0.030) | (0.030) | (0.028) | (0.034) |
| Training | 0.088 | −0.020 | 0.159*** | −0.036 |
| | (0.061) | (0.056) | (0.050) | (0.066) |
| Research | 0.024 | 0.143*** | 0.064* | 0.200*** |
| | (0.036) | (0.043) | (0.033) | (0.045) |
| Casemix | 2.288*** | 1.429** | 3.285*** | 2.619*** |
| | (0.771) | (0.607) | (0.709) | (0.762) |
| Average Patient Age | 0.002 | −0.001 | 0.006*** | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Casemix×Av. Patient Age | −0.023** | −0.020*** | −0.044*** | −0.034*** |
| | (0.010) | (0.008) | (0.009) | (0.010) |
| Constant | −3.074*** | −3.933*** | −3.740*** | −2.961*** |
| | (0.564) | (0.549) | (0.515) | (0.548) |
| Observations | 6,916 | 6,916 | 6,916 | 6,916 |
| Adjusted $R^2$ | 0.843 | 0.845 | 0.863 | 0.838 |

To fully appreciate the meaning of the figures on Table 8, we need a few simple calculations. For instance, the fact that for-profit (hereafter FP) hospitals have 37.7% less nurses than public teaching hospitals (hereafter TP) also yields, using the IV estimates of Table 6,

$$X^{tp} = \exp(0.474)X^{fp} = 1.606X^{fp},$$

recalling that $x = \ln(X)$, meaning that teaching public hospitals employ 60% more registered nurses than for-profit hospitals. The same type of computation tells us that public teaching hospitals employ 39% more nurses than private non-profit hospitals and 36% more than ordinary public hospitals. These differences are huge. The fact that all percentages in Table 8 are negative shows that the public teaching hospitals seems to be the least efficient.

Table 8: Labor demand differences, in percentage, relative to teaching hospitals, taking the severity of cases and research activity into account; 2015-2019.

| | Medic. Doctors | | Regist. Nurses | | Assist. Nurses | | Admin. Staff | |
|---|---|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| For Profit | −15.3% | −18.6% | −38.0% | −37.7% | −61.9% | −65.0% | −34.2% | −34.0% |
| Non-Profit | −19.3% | −20.6% | −27.5% | −28.5% | −50.3% | −52.4% | −08.0%† | −00.5%† |
| Public | −28.7% | −28.7% | −28.5% | −26.7% | −39.0% | −40.5% | −14.8%† | −13.0%† |
| † *non-significant* | | | *IVs: log-outputs lagged 2 years* | | | | | |

With 4 exceptions, all the percentage values of this table are obtained from regression coefficients that are estimated with precision and are significant at the 1% level.

**A shortage of doctors in ordinary public hospitals?** At first glance, Table 8 shows that private hospitals are not using doctors more efficiently than the public teaching hospitals: for instance, using IV estimates, for-profit hospitals employ 14% more MDs than ordinary public hospitals for the same list of outputs.[48] In fact, private hospitals of both kinds and public teaching hospitals are using more doctors than the ordinary public institutions. This confirms the well-known fact, illustrated by anecdotal evidence, that, in France, relatively small, provincial or suburban public hospitals suffer from a shortage of MDs. For the interpretation of the results of Table 8, it is important to keep in mind that we controlled for a full list of output measures, including research, training of students and the average severity of cases treated by the hospital.

**Excess employment of nurses.** In contrast, public teaching hospitals, are employing 60% more nurses than the private sector, for a given vector of stays, as indicated above. The gap is even bigger if we consider the assistant-nurses: with IV estimates, we find that there are 2.85 times more assistant-nurses in public teaching hospitals as compared to for-profit hospitals.[49]

[48] With IV estimates, we have $X^{fp} = \exp[-.206 + .338]X^p = 1.141X^p$, and with OLS estimates, we find $X^{fp} = \exp[.173]X^p = 1.192X^p$, for doctors.

[49] Indeed, with Table 6, column (1), we obtain that the ratio of assistant-nurses in teaching to assistant nurses in for-profit hospitals is $\exp(1.05) = 2.85$.

There are explanations for this observation, and we'll come back to possible interpretations below. We can also check that the private for-profit sector is much more efficient in terms of non-medical administrative staff. We observe that the OLS and IV results are quite close. This confirms that IV estimation does not seem to be essential to understand our data.

There are some Political-Economy explanations for these results: it is known that large public hospitals, located in major French cities, mainly teaching hospitals (*i.e.*, the *CHU*), have been massively used by local politicians as policy tools to fight local unemployment. Many nurses and more specifically, too many less-qualified assistant nurses have been hired and tenured as civil servants, *i.e.*, with lifetime employment contracts, during the 30 years preceding 2010 (see Clark and Milcent (2011), (2018)). The consequences of this policy, even if the governance of public hospitals was changed after 2009, are still extremely visible.[50] To this peculiar form of human-resources management, we must probably add explanations derived from the *soft budget constraint* theories (cf. Kornai *et al.* (2003)). The regulator cannot credibly force the largest public hospitals to rationalize the production of health care. In addition, due to employment protection laws in the public service, personnel adjustments are very slow.[51]

**Robustness.** Further results checking robustness are presented in Appendix C. We tested variants of the list of activities and variants of the dependent variables (mainly separating surgery from medicine and obstetrics). We also study a model with the lagged dependent variable added as a regressor, estimated by the system GMM method à la Blundell-Bond. The results show that the legal-status dummies are always significant and always lead to the same conclusions about comparisons of efficiency. In contrast, the controls for the average severity of cases do not always work very well. Yet, we will see below that the severity indices do have a significant impact on the average length of stays.

### 4.3 The Common Support Problem

The fact that we imposed a common specification and pooled all types of hospital, even if we distinguish them by means of legal-status dummies, may be an overly strong assumption, causing what is sometimes called a common support problem. As indicated above, in the next section, we will overcome this difficulty by estimating different models for different categories of hospitals. We propose here a robustness test based on a special subsample of hospitals that cannot easily be classified — they could be private or public. We first try to predict the legal status of each hospital using a Multinomial Logit model, and select the sub-sample of all hospitals that have a sufficiently large probability of belonging to all 4 categories. This task is almost

[50] In a nutshell, and to summarize a long story, before 2009, the Mayor of the city was the chairman of the hospital board. An act passed in 2009 (*i.e.*, the *HPST act*) substantially changed the power of local politicians in the hospital boards.

[51] Our results are not very surprising: Donahue (1989) reports that government agencies providing municipal services employ 20 to 30 percent more workers for a given output level than do private contractors, in the United States.

impossible because the public teaching hospital status is very easily predicted by a combination of observable characteristics, like size and research activity.

So, we restrict the test to the three other categories, excluding all the teaching hospitals (*i.e.,* *CHU*s) from the sample. Then, we specify the Multinomial Logit as predicting legal status, based on the following variables: the percentages of activity in inpatient STAC, outpatient STAC, sessions, while controlling for the presence or absence of inpatient and outpatient medicine, surgery, plus the presence of sessions, long-term care, follow-up care activities and casemix. We choose a threshold of 10%, meaning that we select all hospitals that have a probability of at least 10% of belonging to any of the three categories. This threshold selects at least 25% of the institutions in each category.

Figure 1 shows both the percentage of hospitals of each category (left panel) and the absolute number of hospitals selected in each category (right panel), when we require that all selected individuals have at least a 10% probability of being public, private for-profit or private non-profit. We see that many hospitals are lost, but wee keep 25% of ordinary public hospitals, and around 50% of the for-profit and non-profit hospitals, respectively.

Figure 2 plots the density of the predicted probability (*i.e.*, propensity score) of being a private for-profit hospital, conditional on the true legal status. The left panel shows this density in the full sample; the right panel shows the same distributions in the selected sub-sample. We see that the selection based on propensity score has generated distributions that are less divergent, putting much less weight on the extreme propensities.

Next, we re-estimated the labor-demand model with the selected sub-sample and the results are presented in Table 9. We easily see that the crucial estimated coefficients are still significant. The legal-status dummies keep the same sign and the same order of magnitude as in the complete sample: the coefficients for nurses and assistant-nurses are still negative and sizable, while the legal-status coefficients of the demand for doctors are positive, confirming the already noted fact that ordinary public hospitals probably suffer from a shortage of doctors.

We will now discuss the results obtained with a more flexible model in which a different input-demand function is estimated separately for each of the 4 hospital types and 4 different personnel categories. This approach will permit us to compute a decomposition in the fashion of Oaxaca and Blinder, comparing public and private hospitals.

Figure 1: Selection of Hospitals with a Minimal 10% Predicted Probability of Belonging to All Three Categories

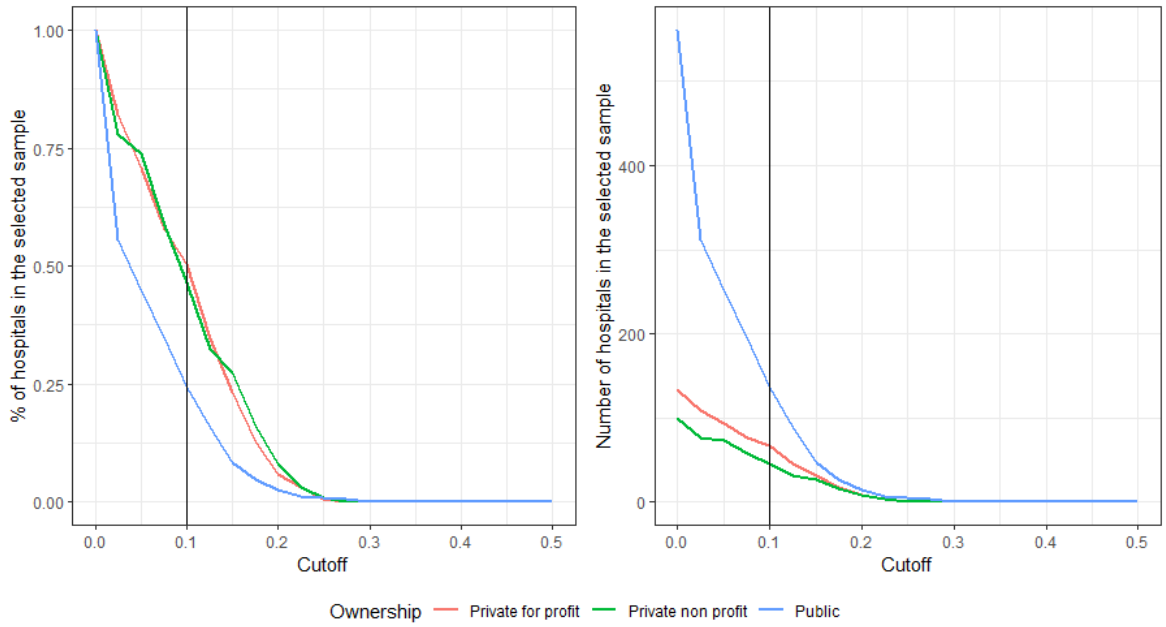



Figure 2: Predicted Probability Density of Being Private For-Profit, Knowing the Real Legal Status, in Full and Selected Samples

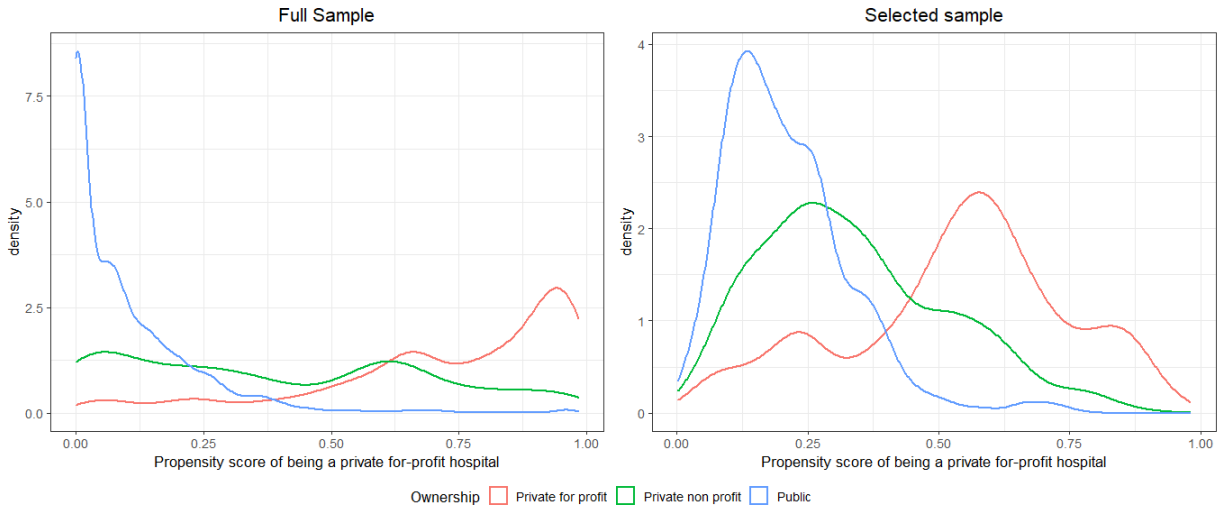


Table 9: Demand for Labor Inputs, Estimated with a Selected Sample of Hospitals

| | Assist. Nurses | MDs | Nurses | Admin. Staff |
|---|---|---|---|---|
| Inpatient STAC | 0.233*** | 0.323*** | 0.301*** | 0.184*** |
| | (0.061) | (0.045) | (0.056) | (0.049) |
| Outpatient STAC | 0.046*** | 0.075*** | 0.071*** | 0.038*** |
| | (0.016) | (0.016) | (0.015) | (0.015) |
| Emergency Department | 0.326*** | 0.279*** | 0.291*** | 0.307*** |
| | (0.061) | (0.055) | (0.051) | (0.053) |
| Sessions | 0.056*** | 0.045*** | 0.067*** | 0.076*** |
| | (0.012) | (0.012) | (0.012) | (0.012) |
| Follow-up care and Rehab. | 0.282*** | 0.214*** | 0.276*** | 0.246*** |
| | (0.069) | (0.051) | (0.051) | (0.050) |
| Psychiatry Department | 0.066** | 0.034 | 0.062* | 0.023 |
| | (0.029) | (0.035) | (0.034) | (0.048) |
| External Consultations | 0.029 | 0.039** | 0.026 | 0.104*** |
| | (0.023) | (0.019) | (0.020) | (0.023) |
| For-Profit | −0.523*** | 0.159* | −0.213** | −0.119 |
| | (0.103) | (0.094) | (0.083) | (0.102) |
| Non-Profit | −0.248*** | 0.149** | 0.011 | 0.151* |
| | (0.075) | (0.068) | (0.065) | (0.082) |
| Specialization | −0.034 | −0.022 | 0.038 | −0.010 |
| | (0.070) | (0.057) | (0.059) | (0.065) |
| Casemix | 5.420*** | 2.812* | 5.948*** | 7.928*** |
| | (1.484) | (1.543) | (1.430) | (1.861) |
| Av. Patient Age | 0.006* | 0.003 | 0.017*** | 0.004 |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Casemix×Av. Patient Age | −0.071*** | −0.038* | −0.088*** | −0.102*** |
| | (0.020) | (0.020) | (0.019) | (0.023) |
| Constant | −3.844*** | −3.211*** | −3.515*** | −2.750*** |
| | (0.770) | (0.732) | (0.639) | (0.727) |
| Number of observations | 1,841 | 1,841 | 1,841 | 1,841 |
| Adjusted $R^2$ | 0.816 | 0.841 | 0.891 | 0.858 |

Note: To shorten the table, the coefficients of 13 control variables (mostly activity indicators) included in this regression are not displayed. Significance is indicated by * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$. Ordinary public hospitals are the reference category. The teaching public hospitals are excluded from the sample. All hospitals in the sample have a predicted probability of belonging to each of the three categories that is larger than 10%. The propensity score is estimated thanks to a Multinomial Logit predicting the legal status of hospitals.

### 4.4 Productivity Differences: Counterfactuals

Our sub-sample estimates of input-demand functions allow us to compute counterfactual employment levels for each hospital and each period. If $x_{it}$ is the logarithm of some category of personnel and $y_{jit}$ is the log-output of activity $j$ in hospital $i$ at time $t$, we have specified the log-linear regression, describing the conditional demand for personnel as $x_{it} = a^s + b^s y_{it} + c^s z_{it} + \epsilon_{sit}$, where $y_{it} = (y_{1it}, \ldots, y_{Lit})$ is the vector of outputs (or activities); $z_{it}$ is a vector of control variables; $(a^s, b^s, c^s)$ is a vector of parameters. Given estimations $\hat{a}^{fp}, \hat{b}^{fp}$, $\hat{c}^{fp}$, obtained with the sub-sample of for-profit hospitals, denoted $FP$, we can predict the counterfactual demand $\hat{x}^{fp}_{it} = \hat{a}^{fp} + \hat{b}^{fp} y_{it} + \hat{c}^{fp} z_{it}$ of, say, a public hospital $i$ characterized by $(x_{it}, y_{it}, z_{it})$ at time $t$: this is, for short, the demand for personnel of hospital $i$ in year $t$ if $i$ was transformed into a private for-profit institution. We also compute the predicted demand of hospital $i$, using the regression estimated in the sub-sample of public hospitals, denoted $\hat{x}^{p}_{it} = \hat{a}^{p} + \hat{b}^{p} y_{it} + \hat{c}^{p} z_{it}$, where $p$ indicates ordinary public hospitals. Let in addition $P$ denote the subset of ordinary public hospitals. Next, we compute all the differences $\hat{x}^{p}_{it} - \hat{x}^{fp}_{it}$. Given that these are differences in logarithms, to obtain ratios, we take the exponential of the differences, and we compute the median of these ratios as follows,

$$M_p = \underset{it \in P}{Median} \left( \exp(\hat{x}^{p}_{it} - \hat{x}^{fp}_{it}) \right),$$

where we consider all the observations $(i, t)$ in the sub-sample of ordinary public hospitals $P$. We also compute the standard deviation $\sigma_p$ of the ratio, that is, the square root of

$$\sigma_p^2 = \frac{1}{N_p} \sum_{it \in P} (exp(\hat{x}^{p}_{it} - \hat{x}^{fp}_{it}) - \mu_p)^2 \quad \text{where} \quad \mu_p = \frac{1}{N_p} \sum_{it \in P} exp(\hat{x}^{p}_{it} - \hat{x}^{fp}_{it}),$$

and where $N_p$ is the number of observations in $P$. So, the predicted employment of each public hospital is compared to the predicted employment of the same hospital if it were a private for-profit institution, based on the same vector of outputs and controls. The same statistic can be computed with the sub-sample of private non-profit hospitals, denoted $NP$, and with the sub-sample of public teaching hospitals, denoted $PT$. The values of $M_{tp}$, $M_{np}$ and $M_p$ for the 4 categories of personnel are given in Table 10. Each entry gives four figures: on the first row, the first number on the left is the median counterfactual ratio, the second number between brackets is the bootstrapped standard deviation of the median ratio; on the second row, in italics, the first number on the left is the standard deviation of the ratio itself, *i.e.*, $\sigma_s$, with $s = p, tp, np$, and the second number, between brackets, is the bootstrapped estimation of the standard deviation's standard deviation.

Table 10: Ratios of the predicted employment of different categories of personnel, divided by their counterfactual predicted value, computed with the estimated factor demand of private for-profit hospitals

| | Assist. Nurses | MDs | Reg. Nurses | Admin. Staff |
|---|---|---|---|---|
| Public Teaching Median $M_{tp}$ | 2.1 (0.66) | 1.82 (0.63) | 1.97 (0.55) | 1.98 (0.45) |
| Standard Dev. $\sigma_{tp}$ | *0.49 (0.93)* | *0.63 (0.53)* | *0.44 (1.11)* | *0.6 (1.66)* |
| Private Non-Profit Median $M_{np}$ | 1.14 (0.12) | 1.04 (0.15) | 1.23 (0.11) | 1.47 (0.15) |
| Standard Dev. $\sigma_{np}$ | *0.28 (0.21)* | *0.23 (1.14)* | *0.16 (0.41)* | *0.46 (0.29)* |
| Ordinary Public Median $M_p$ | 1.31 (0.2) | 0.93 (0.19) | 1.17 (0.18) | 1.48 (0.21) |
| Standard Dev. $\sigma_p$ | *0.18 (0.19)* | *0.15 (0.15)* | *0.15 (0.13)* | *0.22 (0.2)* |

*Note* : The table provides the median of the predicted personnel demanded by hospitals of one of 3 categories (public teaching, private non-profit and ordinary public hospitals) divided by the counterfactual predicted personnel demand of a private for-profit hospital with the same output and control vector. To make sure that institutions are on an equal footing, we set a zero value for training, psychiatric dept. stays and long-term care stays. The standard deviation of the median ratio is bootstrapped and presented between brackets next to the right of the median. The second line, in italics, gives the standard deviation of the distribution of ratios and the bootstrapped value of the standard deviation of the standard deviation. For instance, the figures for assistant-nurses in Public Teaching hospitals indicate that teaching hospitals employ 2.1 times more of this type of personnel than the for-profit hospitals with the same activity vector. The bootstrapped standard deviation of 2.1 is .66. The bootstrap procedure used 50 replications for each entry. Bootstrapping is applied at the level of the hospital and not at the level of the observation $it$.

The figures of Table 10 are very striking; they confirm that public teaching hospitals seem to be very inefficient, because the median counterfactual ratio indicates that teaching hospitals employ approximately 2 times more employees than their for-profit counterpart. The rest of the table more or less confirms the results obtained with a simple regression on pooled data: firstly, that the non-profits are less efficient, except for the employment of doctors, and secondly, that the ordinary public hospitals employ less doctors but more of the 3 other categories of personnel.

The for-profit hospitals and clinics do not contribute to training, so that we cannot estimate the coefficient of the teaching variable for these hospitals. To put all hospitals on an equal footing, and particularly, to avoid penalizing the public teaching hospitals, we set the training indices and the number of psychiatry stays equal to zero for every hospital in the computations of Table 10. In spite of this conservative choice, we find that the differences between the public and private for-profit institutions are huge on average. Yet, the differences between private non-profit and private for-profit institutions are smaller than the public-private differences. In Table 10, we again find the result that the employment of doctors in ordinary public hospitals would not change if they were "privatized". In contrast, the changes are large if we privatize the teaching hospitals, or if we consider the registered and assistant-nurses.

**Robustness**. We computed a number of robustness checks for these results. In Appendix E, we study the impact of hospital size on the value of counterfactual ratios. We also computed the entire table of results with a Translog specification of the demand for inputs, using a Lasso

algorithm to pick the best regressors. A Translog specification is justified because it leads to a more flexible specification of the underlying technological constraints. Yet, the results obtained are quite close and do not change the conclusions.

# 5 Further Robustness Checks and Interpretations

We will now present some additional results. We firstly discuss the impact of legal status on the average length of stay, which itself depends on days spent by patients at the hospital. We show that the casemix index has a differential impact on the average length of stay, depending on the type of ownership. Secondly, we apply the Oaxaca-Blinder[52] decomposition method to hospitals. Instead of comparing the wages of male and female workers and decompose the difference in explained and unexplained parts, we compare the input demands of public and private hospitals.

## 5.1 Average Length of Stay and Severity

The fact that our model explains employment levels as a function of the number of stays could be understood as reduced form for a more complicated model in which the number of employees of a certain kind depends on the number of days spent by patients in the hospital. This point of view can shed light on an important mechanism explaining why public and private hospitals are different in their use of personnel. The number of days is by definition the average length of stay multiplied by the number of stays, or, taking logarithms, $\log(\text{Days}) = \log(ALOS) + y$. Next, it is reasonable to assume that the demand for personnel depends on the number of days, so that we have

$$x = \beta y + \beta \log(ALOS) + \zeta_0,$$

where $\zeta_0$ is a random disturbance. If in addition, we assume that ALOS depends on severity, we can write

$$\log(ALOS) = \delta_0 \text{Casemix} + \delta_1 z + \zeta_1,$$

where $\zeta_1$ is another random error term, and, substituting $\log(ALOS)$ in the equation explaining $x$, we obtain the model studied above, in which inputs are explained by outputs, casemix and other controls.

We now more specifically study the linear regression of *ALOS* on *Casemix*, average patient age and controls, with interactions between the casemix index and legal-status dummies. This regression sheds light on an interesting difference between small and large hospitals. The results are presented in Table 11. Large hospitals are here defined as having a size larger than the median, where size is measured by the total number of stays. First, Table 11 shows that the coefficients of legal-status dummies are very significant. The small for-profit hospitals use on average 2.8 days less per stay than public institutions.

[52] See Oaxaca (1973), Blinder (1973).

The impact of the average patient age is of the same order of magnitude: the results indicate, for instance, that the ALOS is 4.7 days longer if the average age is above 70 in small hospitals. The impact of average patient age is not significant in large institutions. In the case of large hospitals, the important variable is our Casemix index. The interactions of Casemix with legal status show that the slope of the line giving ALOS as a linear function of Casemix is much higher, while the intercept is much smaller, in large for-profit hospitals. Figure 3 shows the coefficients of the linear-affine relationship between Casemix and ALOS, as given by the results of the rightmost column of Table 11: it is striking that the slope of the Casemix-ALOS linear relationship is almost 6 times larger in for-profit hospitals. More precisely, an increase in severity by 0.1 (10 points) yields an increase in ALOS of 2.8 days in the for-profit sector, while the equivalent figure is only .5 days in public teaching hospitals. These coefficients are identified thanks to the diversity of private for-profit institutions, some of them treating more severe cases on average.

This shows that the for-profit institutions adjust ALOS to average severity much more than the public institutions. A likely interpretation is that the private sector has a much more flexible organization. In other words, the interpretation seems to be that for-profit hospitals optimize more, while the public hospitals do not adjust personnel to average severity. The smaller coefficient on Casemix of public hospitals is likely to be one of the sources of public sector inefficiency.

Figure 3: Reaction of ALOS to Severity in Large Hospitals

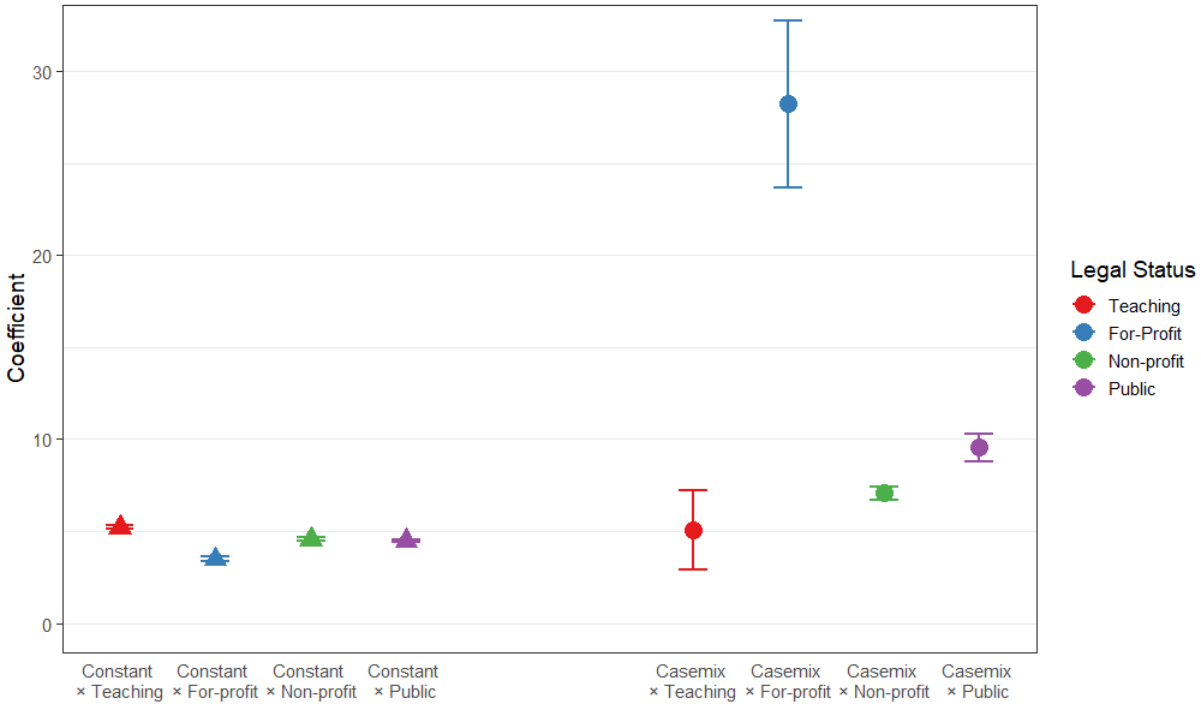


Table 11: Regression of Average Length of Stay on Severity of Cases and Legal Status

| | *No control for patient age* | | *Control for patient age* | |
|---|---|---|---|---|
| Hospital Size | *Small* | *Large* | *Small* | *Large* |
| For-Profit | $-2.991^{***}$ | $-1.716^{***}$ | $-2.810^{***}$ | $-1.721^{***}$ |
| | (0.369) | (0.081) | (0.346) | (0.082) |
| Non-Profit | $-0.124$ | $-0.639^{***}$ | $-0.137$ | $-0.642^{***}$ |
| | (0.373) | (0.077) | (0.455) | (0.083) |
| Ordinary Public | $1.069^{***}$ | $-0.691^{***}$ | 0.500 | $-0.698^{***}$ |
| | (0.301) | (0.059) | (0.360) | (0.064) |
| $40 \leq$ Av. Patient Age $\leq 70$ | | | $2.585^{***}$ | 0.001 |
| | | | (0.089) | (0.042) |
| $70 \leq$ Av. Patient Age | | | $4.772^{***}$ | $-0.109$ |
| | | | (0.168) | (0.111) |
| Teaching×Casemix | $4.372^{***}$ | $5.045^{***}$ | 1.089 | $5.044^{***}$ |
| | (0.827) | (1.043) | (1.016) | (1.106) |
| For-Profit×Casemix | $3.695^{***}$ | $28.141^{***}$ | 1.121 | $28.204^{***}$ |
| | (1.154) | (2.260) | (1.019) | (2.326) |
| Non-Profit×Casemix | 0.239 | $7.054^{***}$ | $-2.596^{***}$ | $7.064^{***}$ |
| | (0.611) | (0.130) | (0.480) | (0.175) |
| Ordinary Public×Casemix | $1.859^{***}$ | $9.496^{***}$ | $-0.096$ | $9.542^{***}$ |
| | (0.140) | (0.349) | (0.315) | (0.395) |
| Constant | $7.678^{***}$ | $5.189^{***}$ | $5.060^{***}$ | $5.193^{***}$ |
| | (0.322) | (0.075) | (0.370) | (0.050) |
| Observations | 3,390 | 3,739 | 3,343 | 3,737 |
| $R^2$ | 0.479 | 0.562 | 0.536 | 0.562 |

Note: To shorten the table, the coefficients of 13 control variables (mostly activity indicators) included in this regression are not displayed. Significance is indicated by $^{*}$ for $p < 0.1$; $^{**}$ for $p < 0.05$; $^{***}$ for $p < 0.01$. Teaching public hospitals are the reference category here. The dependent variable is ALOS in days. Equations are estimated by OLS. Hospital size is measured by the total number of stays per year; small hospitals are below the median of the size distribution.

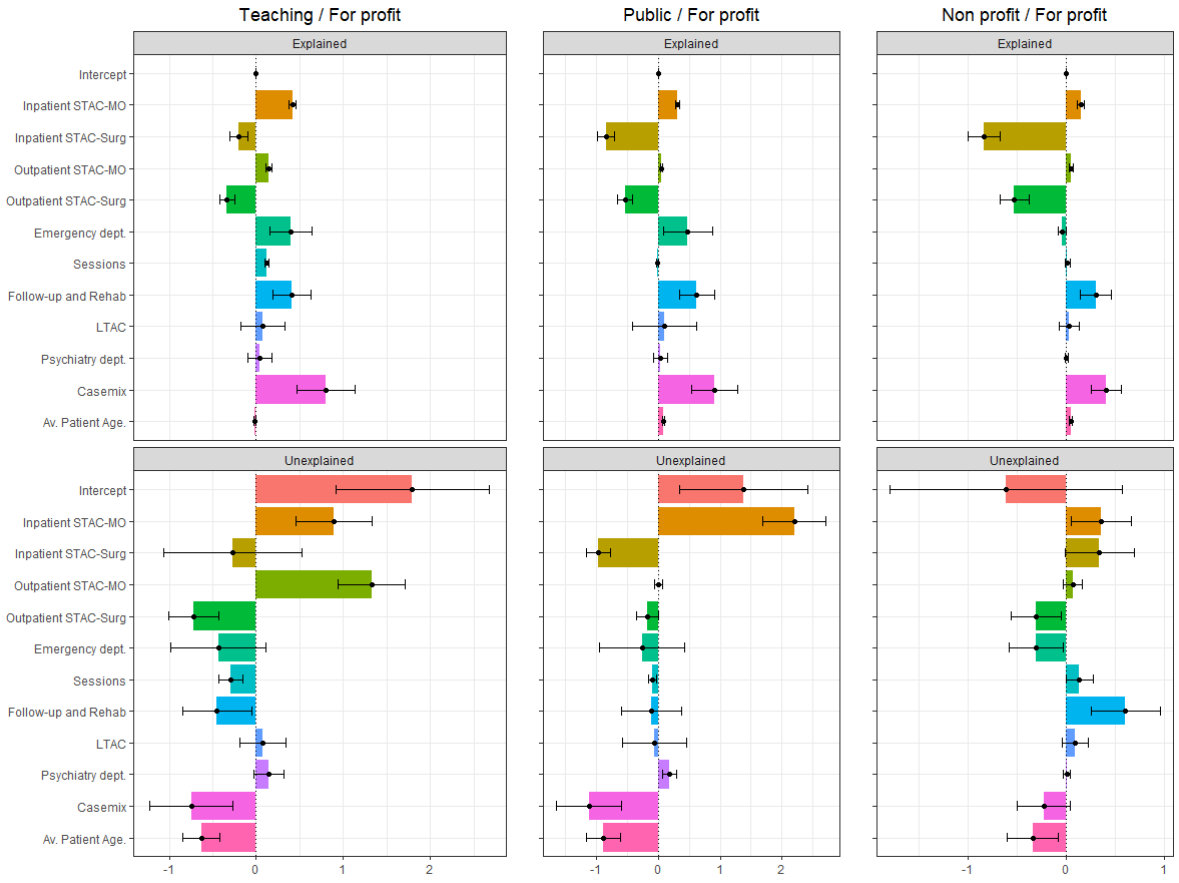
## 5.2 Oaxaca-Blinder Decomposition of Hospital Differences

We now apply the Oaxaca-Blinder decomposition, well-known in Labor Economics, to study the differences between public and private hospitals. The decomposition is typically used to compare the earnings of females with males, the latter being the reference. Here, the for-profit hospitals will be the point of comparison. The employment levels are predicted by the log-linear model studied above. We take the estimated demands for some input $k$ in subsample $s$, where $s$ is in $\{p, np, fp, tp\}$, that is, $x = \hat{a}^s + \hat{b}^s y + \hat{c}^s z$ and we express the difference between two sub-sample averages, denoted $\bar{x}^s$ for some $s$. Taking for instance the public and for-profit categories we have

$$\bar{x}^p - \bar{x}^{fp} = \underbrace{(\bar{y}^p - \bar{y}^{fp})\hat{b}^p + (\bar{z}^p - \bar{z}^{fp})\hat{c}^p}_{\text{explained}} + \underbrace{(\hat{a}^p - \hat{a}^{fp}) + (\hat{b}^p - \hat{b}^{fp})\bar{y}^{fp} + (\hat{c}^p - \hat{c}^{fp})\bar{z}^{fp}}_{\text{unexplained}},$$

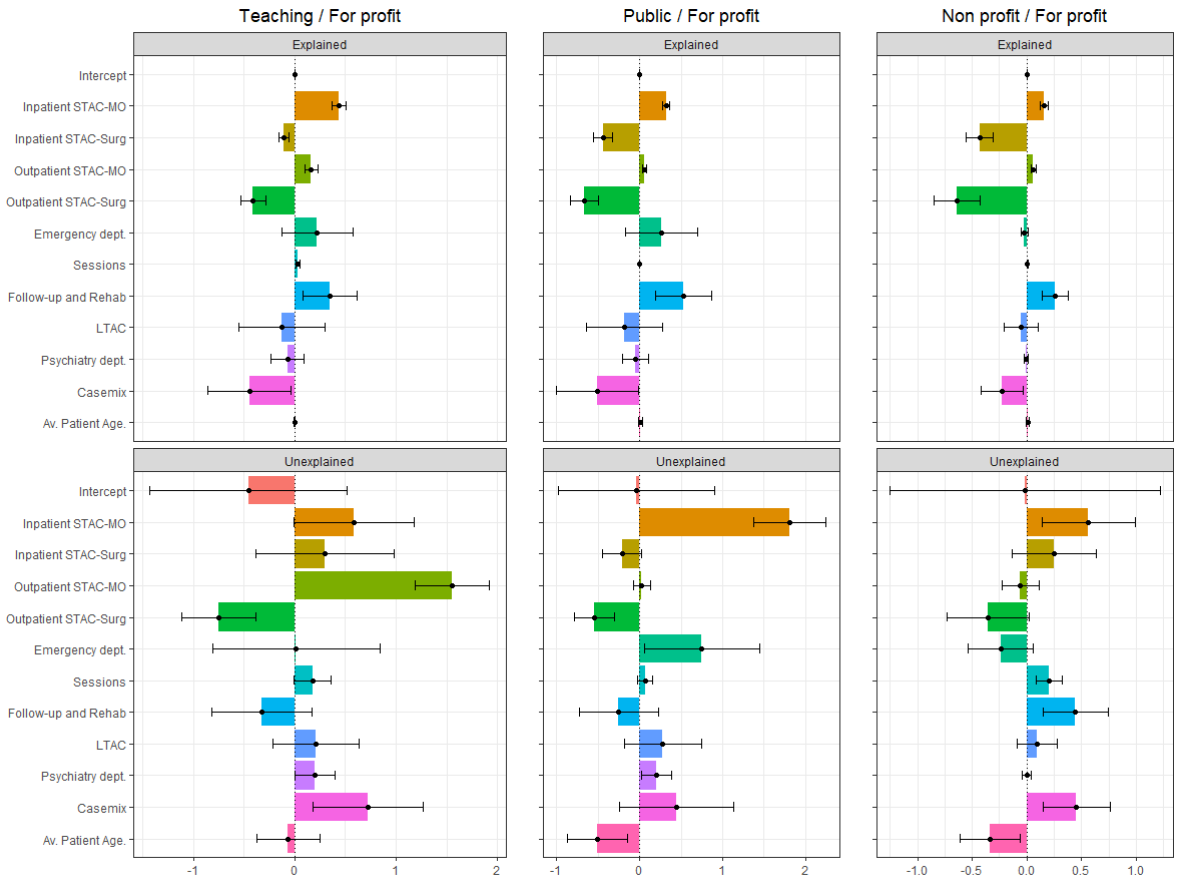
where the first two terms on the right-hand side are the explained part of the difference $\bar{x}^p - \bar{x}^{fp}$, in other words, the difference explained by different activity levels and values of controls, on average, and where the last three terms form the *unexplained* part, due to different coefficients in the public and for-profit sectors. The model is estimated by OLS in the respective sub-samples.

Figure 4: Oaxaca-Blinder Decomposition of the Demand for Nurses



The results are presented on Figure 4 in the case of registered nurses, and on Figure 5 in the case of doctors (and surgeons). The top left panel of Figure 4 gives the "explained" contributions to the difference between the average demand for nurses in teaching hospitals and in for-profit hospitals, as indicated above. The explanatory variables are listed on the side. A positive contribution on a given line indicates that the teaching hospital has a higher average value of the corresponding activity or control variable. The middle-top and the rightmost top panel give the equivalent contributions when the comparison is between ordinary public and for-profit and between non-profit and for-profit hospitals, respectively. The bottom panels give the "unexplained" part of each decomposition: for instance, in the bottom-left panel, the contribution is positive on a given line, corresponding to a given variable, if the estimated coefficient of the teaching public is higher than the coefficient of the for-profit equation for this variable.

Figure 5: Oaxaca-Blinder Decomposition of the Demand for Doctors




Looking at Fig. 4, we first see that, apart form the fact that the severity of cases is higher and plays a bigger role in the comparison of teaching and for-profit hospital, the most important contributions are "unexplained", namely: *(i)*, a higher intercept in the teaching hospitals; *(ii)*, a higher coefficient on inpatient and outpatient medicine STAC stays, both implying a higher demand for nurses in public hospitals; *(iii)*, a higher reaction to average severity and average

patient age in the for-profit hospitals.

If we now look at the decomposition for doctors, on Figure 5, we again see that the most important contributions are *unexplained*, meaning differences attributed to estimated coefficients, namely: *(i)*, the most important difference is now due to coefficients on inpatient and outpatient STAC stays in medicine and obstetrics, leading to a higher demand for doctors in the teaching public hospitals; *(ii)*, in contrast, outpatient surgery requires more surgeons in the for-profit hospitals; and *(iii)*, the average severity of cases now requires more doctors in public hospitals as compared to for-profit hospitals. In general, it seems clear that the development of outpatient STAC stays in medicine and obstetrics requires significantly more personnel in public hospitals, for reasons that are "unexplained".

# 6 Conclusion

Using an almost exhaustive panel of French hospitals during the pre-Covid period, 2015-2019, based on official public data, we studied the comparative efficiency of four categories of healthcare providers: ordinary public, teaching public, for-profit and not-for-profit private hospitals. Our comparison is based on the estimation of conditional labor-demand functions, explaining the employment levels of several categories of personnel as a function of a list of hospital outputs. The inputs are mainly: the physicians and surgeons; the registered nurses, the assistant-nurses and administrative staff workers. The list of output measures includes inpatient and outpatient short-term acute-care stays, emergency department stays, treatment sessions, long-term stays, etc. Based on estimation results, we compare groups of hospitals according to ownership and legal status, considering different efficiency measures. We show that there exist large, significant and robust differences in the employment levels of the various categories of personnel of the four groups of hospitals. The public hospitals employ on average much more nurses, assistant nurses and administrative workers than the for-profit hospitals, conditional on the same vector of outputs. The public teaching hospitals, *i.e.*, the largest hospitals in France, are even less efficient. These results are obtained while controlling for the average severity of cases (*i.e.*, the official casemix index), the research and training (*i.e.*, higher education) activities. For instance, we find that the public hospitals employ 60% more registered nurses than the teaching hospitals, conditional on the same output vector. We conjecture (but do not prove) that these results are due to a combination of several factors: underinvestment of public hospitals in the ambulatory, same-day medicine and surgery; resistance to change; weak credibility of government commitments (*i.e.*, soft-budget constraint problems); the fact that public hospitals have been used in the past as tools to fight local unemployment. Further research will study the relative importance of these, or other factors more specifically.

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# A Appendix. Additional Elements on the Data and Descriptive Statistics

## A.1 Additional Elements on Hospital Personnel and Indicators

The public SAE data base is the source of several common difficulties. The survey is potentially very rich but there are missing data.[53] For this reason, the use of some variables may cause a substantial drop in sample size. We were therefore forced to find compromises between number of observations and richness of the description. In any case, our results are very robust. The general conclusions that we obtain do not depend on fine choices made to select a working sample from the SAE database. The productivity differences that we show are very significant and always lead to same conclusions, with nuances.

**Medical Doctors and Surgeons.** In the case of doctors working in private hospitals (physicians and surgeons), we only have a count. This may of course pose a measurement-error problem since some doctors work only part-time. Most of the doctors (and surgeons) in public hospitals are full-time employees, earning a salary, while most of the private sector doctors are independent practitioners (*i.e., médecins libéraux*). The problem of estimating the number of full-time equivalent doctors cannot easily be solved given the current state of the SAE survey; the data base does not provide the full-time equivalent number of doctors (*i.e.*, *équivalents temps-plein*). Yet, if we find that doctors are more productive in the private sector, given that some are working only part time, we are only underestimating their true productivity, and the productivity difference with the public sector would typically be a lower bound.

We do not observe the hours of physicians. There is a small proportion of wage-earning physicians in the for-profit sector (5 MDs per clinic on average, but 39 independent practitioners on average per clinic). In contrast, there are few independent practitioners in the public sector. Table 12 provides some details. We chose to aggregate all MDs. The fact that our models are log-linear ensures that an error in the rate of conversion of independent practitioners into full-time equivalent doctors will in essence affect regression constants. The choice we made was to add all full-time and one half of all part-time doctors and to subtract one half of the doctors that are also university teachers (*i.e.*, members of the medical school faculty). Our results are not very sensitive to the other possible conventions. For instance we also tried counting all doctors with the same weight or counting part-time doctors as half-time: these conventions lead to very similar results.

[53] The Covid years 2020-2021 pose a particular problem in this respect.

Table 12: Count of MDs per Hospital. Years 2016-2019

| | Average number per hospital | |
|---|---|---|
| | Salaried Physicians | Independent Practitioners |
| Ordinary Public | 46 | 4,5 |
| Private For Profit | 5 | 39 |
| Private Non-Profit | 14 | 22 |
| Public Teaching | 228 | 2 |

**Nurses.** In France, there exists "registered" (or ordinary) nurses, without specialization (*i.e., sans spécialité*), nurses with specialization (*i.e., avec spécialité*) and chief nursing officers (*i.e., infirmiers-cadres*). We call them simply registered nurses. The count of each of the three types is not always known, because some hospitals have not provided the detailed figures. We obtain a large sample if we include a hospital-year when the FTE-registered nurse without specialization is not lacking.

The assistant-nurses (*i.e., aides-soignants*) form a distinct group of less qualified care personnel. We singled out this category because it is a well-known, numerous group of workers, at least in the public sector, and the private-public productivity differences are huge.

**Specialization Index.** Our specialization index is computed with the help of the Open CCAM database, which is itself extracted from the PMSI files. In the Open CCAM database, each medical procedure is identified by an identifier called *CCAM code*. The identifier has 4 letters describing the treatment plus a 3 digit number used to differentiate treatments of the same family. The first two letters correspond to a part of the body or physiological function treated. The third letter corresponds to the action performed during the procedure and the fourth letter corresponds to the path taken by the doctors to accomplish their task.

This coding system is used to construct a specialisation index that measures the diversity of CCAM codes in each hospital. However, directly calculating an entropy index based on the full CCAM codes diversity can be misleading. Consider a hospital specialized in cardiac surgery; while it may perform a wide array of procedures, all these procedures are related to heart or cardiac care. As a consequence, we aggregated procedures based on the first two letters of their codes, resulting in 170 distinct anatomy-based groups of procedures. We then computed an entropy statistic to assess the diversity of these groups in the hospital's activity. The specialisation index for hospital $i$ in year $t$ is defined as follows,

$$Specialization_{it} = \sum_{g \in G_{it}} p_{git} \ln(p_{git}),$$

where $G_{it}$ is the set of procedure groups conducted by hospital $i$, and $p_{git}$ is the proportion of

procedures from group $g$ within the overall activity of hospital $i$ in year $t$. The hospital is more specialized when the specialization index is larger.

## A.2 Descriptive Statistics Tables

We present here some standard descriptive statistics on the main input and output variables used in the analysis above. Table 13 gives the averages of the main output variables, and (between square brackets) the proportion of hospitals in which the activity is nonzero. Table 14 and 15 give the averages and standard deviations of other important variables in the 4 categories of hospitals.

Table 13: Descriptive Statistics: Average Number of Stays, Employment Levels and Percentage of Hospitals with a Given Activity or Personnel Category

| | Teaching | For-Profit | Non-Profit | Ordinary Public |
|---|---|---|---|---|
| *Activity* | | | | |
| Inpatient STAC-MO | 14111.6 [95.4%] | 2093.8 [79.2%] | 2982 [86.4%] | 5553.9 [98.5%] |
| Outpatient STAC-MO | 5816.8 [92.8%] | 495.5 [58.5%] | 995.8 [64.3%] | 797.1 [62.8%] |
| Inpatient STAC-Surg | 4704 [66.4%] | 2785 [80.1%] | 1484.6 [46.5%] | 1240.6 [44.4%] |
| Outpatient STAC-Surg | 2462.2 [62.5%] | 6222.8 [82.1%] | 2149.4 [46%] | 1086.8 [44.8%] |
| Emergency | 24752.1 [51.3%] | 4762 [23.3%] | 4757.2 [18.8%] | 14377.5 [55.8%] |
| Psychiatry | 1477.8 [28.9%] | 54.1 [1.4%] | 79.7 [4.7%] | 1876.2 [19.1%] |
| Sessions | 13839.4 [85.5%] | 4735.9 [83.5%] | 9544.3 [77.5%] | 3798.1 [71.2%] |
| Follow-up Rehab. | 756.5 [56.6%] | 563.4 [21.1%] | 658.5 [45.1%] | 419.5 [77%] |
| External Consult. | 197062.5 [97.4%] | 177.2 [8.4%] | 35811 [56.3%] | 59307.8 [74.3%] |
| LTAC | 54.1 [27%] | 21.6 [0.4%] | 40.3 [11.3%] | 31.6 [37.6%] |
| Home Hospit. | 718.2 [8.6%] | 442.4 [2.7%] | 1012.8 [7%] | 294.3 [14.7%] |
| *Personnel* | | | | |
| FTE Assist. Nurses | 407.9 [100%] | 39.5 [100%] | 58 [100%] | 132.4 [100%] |
| Count of Doctors | 228.7 [100%] | 45.5 [100%] | 44.7 [100%] | 58.2 [100%] |
| FTE Reg. Nurses | 534.5 [100%] | 69.6 [100%] | 96.2 [100%] | 165.6 [100%] |
| FTE Admin. | 220.8 [100%] | 27.6 [100%] | 58.1 [100%] | 75.6 [100%] |

*Note* : The table provides the average value of the variable in 4 hospital categories (public teaching, private non-profit and ordinary public hospitals). The figure indicated in square brackets is the percentage of hospitals in which the variable is nonzero.

Table 14: Distribution of Activities in Hospitals (in %)

| | Teaching | For-Profit | Non-Profit | Ordinary Public |
|---|---|---|---|---|
| % Inpatient MO | 0.25 *(0.17)* | 0.11 *(0.15)* | 0.26 *(0.26)* | 0.31 *(0.22)* |
| % Outpatient MO | 0.14 *(0.15)* | 0.03 *(0.11)* | 0.09 *(0.17)* | 0.03 *(0.09)* |
| % Inpatient Surg. | 0.06 *(0.08)* | 0.16 *(0.14)* | 0.06 *(0.10)* | 0.02 *(0.04)* |
| % Outpatient Surg. | 0.04 *(0.09)* | 0.37 *(0.28)* | 0.10 *(0.18)* | 0.03 *(0.06)* |
| % Emergency | 0.23 *(0.25)* | 0.11 *(0.20)* | 0.10 *(0.22)* | 0.32 *(0.31)* |
| % Psychiatry | 0.04 *(0.14)* | 0.00 *(0.05)* | 0.01 *(0.08)* | 0.05 *(0.16)* |
| % Sessions | 0.14 *(0.18)* | 0.17 *(0.29)* | 0.25 *(0.37)* | 0.05 *(0.10)* |
| % Follow-up Rehab. | 0.17 *(0.24)* | 0.18 *(0.25)* | 0.28 *(0.25)* | 0.23 *(0.28)* |
| % LTAC | 0.02 *(0.03)* | 0.01 *(0.02)* | 0.05 *(0.06)* | 0.02 *(0.03)* |

*Note* : The table provides the average value of the percentage of activity in total number of stays variable in 4 hospital categories (public teaching, private non-profit and ordinary public hospitals). The figure indicated between brackets is the standard deviation of the corresponding variable.

Table 15: Average Values of Severity Indices and Other Variables

| | Teaching | For-Profit | Non-Profit | Ordinary Public |
|---|---|---|---|---|
| Casemix | 0.19 *(0.14)* | 0.04 *(0.09)* | 0.12 *(0.18)* | 0.22 *(0.17)* |
| Casemix-Surg. | 0.09 *(0.05)* | 0.02 *(0.01)* | 0.04 *(0.03)* | 0.07 *(0.05)* |
| Casemix-MO | 0.17 *(0.13)* | 0.14 *(0.14)* | 0.19 *(0.18)* | 0.26 *(0.16)* |
| Beds+ Slots | 542.71 *(429.22)* | 151.11 *(104.37)* | 153.51 *(134.04)* | 203.09 *(204.16)* |
| Operating Rooms | 13.74 *(15.16)* | 8.39 *(6.27)* | 4.78 *(6.16)* | 3.93 *(5.51)* |
| OR/$10^3$ Surg. Stays | 7.61 *(46.23)* | 1.33 *(4.70)* | 1.94 *(3.18)* | 2.45 *(4.72)* |
| Imaging Machines | 3.60 *(3.93)* | 0.82 *(1.48)* | 1.23 *(2.08)* | 1.24 *(1.77)* |
| Imaging/Bed | 5.50 *(7.39)* | 4.41 *(7.77)* | 7.50 *(13.90)* | 4.12 *(4.78)* |
| Specialization | -2.70 *(0.81)* | -2.52 *(0.88)* | -1.95 *(1.11)* | -2.27 *(1.09)* |

*Note* : The table provides the average value of the variables in 4 hospital categories (public teaching, private non-profit and ordinary public hospitals). The figure indicated between brackets is the standard deviation of the corresponding variable.

# B A Structural Interpretation: The Conditional Factor-Demand Model

## B.1 Some Advantages of Input-demand over Production Functions

A simple production function approach will typically require the use of some production aggregate; in contrast, a conditional input-demand model is less demanding and with such a model, we can remain relatively agnostic as to the nature of the appropriate formula for the aggregation of outputs and use as many different "products" as desired, provided that the data supports the estimation of the parameters. This is a first advantage of conditional factor-demand functions.

Secondly, these factor demands can be derived from a production function. A generalized, multi-output Cobb-Douglas model, presented below, provides a justification for our econometric specification and sheds light on the relationship between the production function and the conditional input-demand approaches.[54]

Thirdly, to estimate the input-demand functions, we do not need to observe the complete list of inputs. In particular, we do not need to estimate a demand for the various forms of physical capital, and it does not matter much if we do not have a good measure of capital.

Finally, our approach has some other advantages for estimation. A production function approach would study something like $\bar{\mathbf{y}} = F(x) + \eta$, where $\bar{\mathbf{y}} = h(y)$ is a production index, $x$ is a vector of log-inputs, $y$ is a vector of log-outputs and $\eta$ is an error term. In contrast, we consider here the regression of inputs on outputs, that is, a relationship of the form $x = g(y) + \epsilon$, where $\epsilon$ is a random-error vector with a zero mean. For identification of the input-demand coefficients, we can use OLS if we assume that output measures are exogenous, *i.e.*, $\mathbb{E}(\epsilon \,|\, y) = 0$. In contrast, under this assumption, and under consistency of production and input-demand functions, it is almost immediate that $\eta$ is correlated with $x$, so that the production function in econometric form is potentially plagued by the endogeneity bias problem, even when the input-demand form is not. For a proof of this point see the next subsection. To sum up, the assumption that output $y$ is exogenous in input-demand functions could be relatively acceptable[55], but the assumption that $x$ is exogenous in the production function equation is not reasonable. Yet, we still have some doubts about the mean-independence of $y$ and $\epsilon$, even conditional on controls $z$, and even in sub-samples: this is why we also use some classic instrumental variable estimators based on lagged output variables.

[54] The estimation of conditional input-demand functions could be performed while imposing cross-equation constraints on the parameters, these constraints being suggested by the model of Appendix B, but the structural interpretation of our model is neither necessary nor essential here.

[55] This is true if patients have the right to choose the hospital, and if hospitals can adjust the workforce in the short run, which is approximately true, in France.

## B.2 Structural Interpretation

When it comes to evaluating differences in productivity, a production function clearly permits such assessments and allows for simple comparisons between hospitals. Given a list of inputs $x$ we can estimate the production $\hat{y}$ of a firm (*i.e.*, hospital) and this production can be compared to actual production $y$. Some hospitals lie below the regression line, some lie above. But more generally, we can estimate production functions for distinct groups of firms, say, type A and type B, and compare hospitals by means of counterfactuals: just predict the production of a type-A firm if it had the same vector of inputs $x$ but was endowed with the production function of a type B firm.

To provide a justification for our econometric model, and to fix ideas, assume that hospitals are characterized by a multi-output production function. Let $Y_j$ be the production of product $j$ (for instance, inpatient STAC stays, oupatient STAC stays, emergency department stays, etc). Assume that there are $L$ products indexed by $j$. Let now $X_k$ be the quantity of input $k$, with $k = 1, \ldots, K$. Some inputs are unobserved. The four observed factors here are the doctors, FTE registered nurses, FTE assistant nurses and hospital administrators. The generalized Cobb-Douglas model is the following functional link between inputs and outputs,

$$\prod_j Y_j^{\beta_j} = A \prod_k X_k^{\alpha_k},$$

where $A > 0$, $\alpha_k > 0$, $\beta_j > 0$ are parameters, and we assume that $\sum_j \beta_j = 1$. The latter constraint, that the sum of the $\beta_j$ powers is equal to 1, is imposed without loss of generality.[56] The interpretation of this model is that a production capacity $AX_1^{\alpha_1} \ldots X_K^{\alpha_K}$ is obtained thanks to inputs $X_k$, and can be allocated, with imperfect substitution possibilities, between the outputs $Y_j$. We denote $Y = \prod_j Y_j^{\beta_j}$. A natural interpretation is that $Y$ is an aggregate production index. [57]

We can now derive the conditional input-demand functions. Let $w_k$ be the price of input $k$. Conditional input demands, denoted $X_k^*(Y, w)$, minimize the input expenditure $\sum_k w_k X_k$ subject to the technological constraint $A \prod_k X_k^{\alpha_k} \geq Y$. If $\lambda$ is the Lagrange multiplier of the constraint, we necessarily have $X_k^* = \lambda \alpha_k Y / w_k$ for each $k$. Since the technological constraint is satisfied as an equality at the minimum, we easily derive,

$$\lambda Y = \left(\frac{Y}{\gamma}\right)^{\frac{1}{\alpha}} \quad \text{defining} \quad \alpha = \sum_k \alpha_k, \quad \text{and} \quad \gamma = A \prod_k \left(\frac{\alpha_k}{w_k}\right)^{\alpha_k}.$$

Since we know the value of $\lambda Y$, the conditional input demands $X_k^*(Y, w)$ can be expressed as functions of $Y$, $w$ and parameters. Taking logarithms, defining $x_k = \ln(X_k)$ and $y_j = \ln(Y_j)$, we find,

$$x_k^* = \sum_j \frac{\beta_j}{\alpha} y_j + a_k, \quad \text{where} \quad a_k = \ln\left(\frac{\alpha_k}{w_k}\right) - \frac{\ln(\gamma)}{\alpha}.$$

[56] If not, we could change the values of $A$ and the $\alpha_k$s.

[57] We could also assume that the index has a CES form, that is, $Y = (Y_1^\sigma + \cdots + Y_L^\sigma)^{\frac{1}{\sigma}}$. The simplest production function model, aggregating all outputs (*i.e.*, stays), is obtained if we set $\sigma = 1$.

To put this model in econometric form, we add a random error term with a zero mean, denoted $\epsilon_k$, on the right-hand side. For each observed input $k$, we have,

$$x_k^* = \sum_j b_j y_j + a_k + \epsilon_k, \qquad \text{with} \qquad b_j = \frac{\beta_j}{\alpha}.$$

The input prices $w_k$ are not observed, and, even if we observed these prices, they do not vary during the period, or vary only in a negligible way in real terms during the four years of the observation period. As a consequence, we can treat the $a_k$ as constants attached to each input $k$, or, in a more flexible way, as functions of control variables $z_{it}$, such as the hospital characteristics (legal status, size, etc). The addition of control variables is legitimate since $\gamma$ depends on $A$ and the latter parameter can typically be specified as a function of controls.

We can now briefly discuss the identification conditions in our factor-demand model. Suppose we have a production function equation (in log-linear form) $y = \delta + \sum_k \alpha_k x_k + \eta$, where $y = \sum_j \beta_j y_j$ is the aggregate log-output index, $\eta$ is a random error term with $\mathbb{E}(\eta) = 0$ and $\delta = \ln(A)$. On the other hand, we derived input demand functions $x_k = \sum_j b_j y_j + a_k + \epsilon_k$, with $b_j = \beta_j/\alpha$, as explained above. The terms $a_k$ may depend on exogenous controls without any problem. If we add up the $\alpha_k x_k$, we find $\sum_k \alpha_k x_k = (y/\alpha) \sum_k \alpha_k + \sum_k \alpha_k a_k + \sum_k \alpha_k \epsilon_k$. Rearranging terms, we find

$$y = \sum_k \alpha_k x_k - \sum_k \alpha_k a_k - \sum_k \alpha_k \epsilon_k.$$

Consistency with the production function imposes that $\delta = -\sum_k \alpha_k a_k$, and $\eta = -\sum_k \alpha_k \epsilon_k$.

Now, if we want to estimate the input demand functions by OLS, it is sufficient to assume that $y_j$ is exogenous in the input-demand equations for all $j$, that is, more precisely, $E(\epsilon_k|y_j) = 0$ for all $(k, j)$. But assuming this, we immediately find that, for all $\ell = 1, \ldots, K$, $\text{Cov}(x_\ell, \eta) = -\sum_k \alpha_k \text{Cov}(\epsilon_\ell, \epsilon_k)$. It follows that we have $\text{Cov}(x_k, \eta) \neq 0$ except under very special conditions with a zero probability.[58] It follows that the $x_k$s are generically endogenous in the production function equation. The assumption that $\mathbb{E}(\eta|x) = 0$ is not reasonable. In addition, since we do not observe all the inputs $k = 1, \ldots, K$, the unobserved inputs are in the error term $\eta$ and for this reason alone, the $x_k$s are endogenous in the production function equation, but it would be relatively more reasonable to assume $\mathbb{E}(\epsilon_k|y_j) = 0$.

[58] Note that if the $\epsilon_k$ are uncorrelated, that is, $\text{Cov}(\epsilon_\ell, \epsilon_k) = 0$ for all $k \neq \ell$, then $\text{Cov}(x_k, \eta) = -\alpha_k \text{Var}(\epsilon_k) < 0$.

# C Robustness of Results Obtained with Pooled Data

Table 16: Demand for Labor Inputs, for Medicine, Obstetrics and Surgery. IV Estimation

| | Assist. Nurses | MDs | Nurses | Admin. Staff |
|---|---|---|---|---|
| For Profit | $-0.813^{***}$ | $-0.249^{**}$ | $-0.398^{***}$ | $-0.512^{***}$ |
| | (0.102) | (0.105) | (0.105) | (0.118) |
| Non-Profit | $-0.672^{***}$ | $-0.349^{***}$ | $-0.378^{***}$ | $-0.048$ |
| | (0.090) | (0.094) | (0.094) | (0.103) |
| Public | $-0.454^{***}$ | $-0.408^{***}$ | $-0.295^{***}$ | $-0.139$ |
| | (0.077) | (0.082) | (0.078) | (0.102) |
| Research | 0.036 | $0.151^{***}$ | $0.084^{***}$ | $0.190^{***}$ |
| | (0.027) | (0.046) | (0.031) | (0.051) |
| Casemix | 1.592 | 0.975 | 2.235 | $2.427^{***}$ |
| | (1.314) | (1.087) | (1.407) | (0.857) |
| Av. Patient Age | 0.003 | 0.0004 | $0.008^{***}$ | $-0.0002$ |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| Casemix×Av. Patient Age | $-0.016$ | $-0.018$ | $-0.035^{**}$ | $-0.032^{***}$ |
| | (0.016) | (0.014) | (0.017) | (0.011) |
| Observations | 3,948 | 3,948 | 3,948 | 3,948 |
| Adjusted $R^2$ | 0.871 | 0.862 | 0.883 | 0.830 |

Note: To shorten the table, the coefficients of 17 control variables included in this regression are not displayed. Significance is indicated by $^{*}$ for $p < 0.1$; $^{**}$ for $p < 0.05$; $^{***}$ for $p < 0.01$. Teaching hospitals are the reference category. IVs are log-outputs lagged two years.

## C.1 Variants with Surgery, Medicine and Obstetrics

Are the above results robust? We studied a number of variants, adding some controls, changing the dependent variables or re-estimating in some sub-samples. We generally find that the legal status dummies remain significant and in essence, yield the same results on productivity differences. When we add controls, the controls for the severity of cases tend to lose some significance. For instance, if we control more finely for surgical activities, the impact of casemix on the number of doctors becomes barely significant.

To test the impact of medicine alone, we first re-estimate the model of Tables 6-7 with a variant of dependent variables. In this variant, the demand for personnel is limited to personnel allocated to Medicine, Surgery and Obstetrics activities. The results are presented in Table 16. We easily see that the key legal status indicators are still significant and negative (particularly in the first three columns), showing that for-profit, non-profit and ordinary public hospitals are more efficient than teaching hospitals. The controls for the severity of cases are less convincing.

Table 17: Demand for Labor Inputs, Separating Surgery and Medicine, with added Controls; IV Estimation

| | Assist. Nurses | MDs | Nurses | Admin. Staff |
|---|---|---|---|---|
| For Profit | $-1.048^{***}$ | $-0.187^{*}$ | $-0.472^{***}$ | $-0.416^{***}$ |
| | (0.112) | (0.110) | (0.099) | (0.125) |
| Non-Profit | $-0.777^{***}$ | $-0.272^{***}$ | $-0.339^{***}$ | $-0.102$ |
| | (0.089) | (0.086) | (0.079) | (0.102) |
| Public | $-0.482^{***}$ | $-0.344^{***}$ | $-0.264^{***}$ | $-0.146$ |
| | (0.085) | (0.085) | (0.074) | (0.103) |
| Research | $0.045^{**}$ | $0.136^{***}$ | $0.085^{***}$ | $0.159^{***}$ |
| | (0.023) | (0.043) | (0.022) | (0.041) |
| Specialization | $-0.062^{*}$ | $-0.217^{***}$ | $-0.097^{***}$ | $-0.099^{***}$ |
| | (0.033) | (0.031) | (0.028) | (0.033) |
| Average Patient Age | 0.002 | $-0.004^{*}$ | $0.004^{**}$ | $-0.004$ |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Casemix-Medicine | $1.195^{**}$ | $1.467^{***}$ | $2.426^{***}$ | $1.571^{***}$ |
| | (0.588) | (0.499) | (0.528) | (0.542) |
| Casemix-Surgery | $4.027^{*}$ | 3.610 | $5.310^{**}$ | $-2.644$ |
| | (2.339) | (2.553) | (2.331) | (2.588) |
| Av. Age×Casemix-Medicine | $-0.013^{*}$ | $-0.022^{***}$ | $-0.036^{***}$ | $-0.021^{***}$ |
| | (0.008) | (0.007) | (0.007) | (0.008) |
| Av. Age×Casemix-Surgery | $-0.070^{*}$ | $-0.049$ | $-0.082^{**}$ | 0.057 |
| | (0.037) | (0.041) | (0.037) | (0.044) |
| Observations | 3,949 | 3,949 | 3,949 | 3,949 |
| Adjusted $R^2$ | 0.873 | 0.855 | 0.900 | 0.854 |

Note: To shorten the table, the coefficients of 29 control variables included in this regression are not displayed. Significance is indicated by $^{*}$ for $p < 0.1$; $^{**}$ for $p < 0.05$; $^{***}$ for $p < 0.01$. Teaching hospitals are the reference category. IVs are log-outputs lagged two years.

We next consider a variant of the model including surgery, and in which surgery, on the one hand, and medicine plus obstetrics, on the other hand, are measured by different output variables, both for inpatient and outpatient stays, and in which we add a number of controls describing medical equipment more precisely. The added controls are the following: if the hospital practices neurosurgery; if it practices grafts; if it practices cardiac surgery; if there exists a dialysis service; the number of operating rooms; the number of medical imaging machines. We finally distinguish the severity of cases in surgery and medicine (*i.e.*, Casemix-Surgery and Casemix-Medicine). The crucial coefficients are displayed in Table 17. The first rows of this table confirm our earlier findings, we have the same ranking and approximately the same values of the coefficients of legal-status indicators. The coefficients of casemix indices are positive and non-negligible; they are estimated with precision for medicine in all categories of personnel, and for surgery, in the

demand for registered nurses.

### C.2 System GMM estimation à la Blundell-Bond

Finally, we also estimated the model using the System GMM method (à la Blundell-Bond), introducing a lagged dependent variable in the regression: we treat the lagged log-input, labour-demand variables as endogenous, but the log-output variables and controls are treated as orthogonal to residuals. The small number of periods is likely to be the main reason for non-significant coefficients $\beta$ when the log-stays, appearing on the right-hand side, are instrumented by their lagged first-differences, as suggested by Blundell and Bond (1998). The lagged first-differences appear to be weak instruments for the levels of the right-hand side variables. But, when log-stays are not instrumented, we obtain good results that confirm our earlier findings. The results are presented in Table 18. It is remarkable that the addition of the lagged dependent variable yields significant coefficients between .3 and .7, with administrative personnel being the most persistent, and more interestingly, the lagged dependent variable is not leading to non-significant $\beta$ coefficients on log-stays. Finally, the coefficients of legal-status dummies are, in essence, the same as before.

Table 18: Demand for Labor Inputs, with Lagged Labor Demand System GMM Estimation

| | Assist. Nurses | MDs | Reg. Nurses | Admin. Staff |
|---|---|---|---|---|
| Lagged Labor Demand | 0.317*** | 0.495*** | 0.499** | 0.661*** |
| | (0.10) | (0.13) | (0.24) | (0.10) |
| Inpatient STAC | 0.208*** | 0.143*** | 0.149** | 0.063*** |
| | (0.04) | (0.04) | (0.07) | (0.02) |
| Outpatient STAC | 0.009 | 0.049*** | 0.012* | 0.023*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Emergency Department | 0.126*** | 0.083** | 0.089 | 0.075** |
| | (0.05) | (0.04) | (0.05) | (0.03) |
| Sessions | 0.086*** | 0.044*** | 0.070** | 0.029*** |
| | (0.01) | (0.01) | (0.03) | (0.01) |
| Research | 0.003 | 0.051** | 0.022 | 0.051** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Specialization | -0.126*** | -0.091*** | -0.094* | -0.011 |
| | (0.03) | (0.03) | (0.05) | (0.01) |
| Casemix | 1.178 | 0.635 | 1.075 | 0.985*** |
| | (0.86) | (0.57) | (0.92) | (0.38) |
| Av. Patient Age | 0.001 | -0.000 | 0.004* | 0.000 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Casemix×Av. Patient Age | -0.010 | -0.009 | -0.016 | -0.013*** |
| | (0.01) | (0.01) | (0.01) | (0.00) |
| For-Profit | -0.539*** | -0.092 | -0.173* | -0.155** |
| | (0.11) | (0.07) | (0.10) | (0.07) |
| Non-Profit | -0.443*** | -0.139* | -0.174* | 0.016 |
| | (0.09) | (0.07) | (0.10) | (0.04) |
| Public | -0.298*** | -0.182*** | -0.135 | -0.027 |
| | (0.07) | (0.07) | (0.08) | (0.04) |
| Constant | -0.834* | -0.872** | -0.756* | -0.199 |
| | (0.50) | (0.40) | (0.46) | (0.27) |
| Observations | 5260 | 5260 | 5260 | 5260 |

Note: To shorten the table, the coefficients of 13 control variables (mostly activity indicators) included in this regression are not displayed. Significance is indicated by * for $p < 0.1$; ** for $p < 0.05$; *** for $p < 0.01$. Teaching public hospitals are the reference category here. The system GMM method is used to estimate parameters: the equation is estimated simultaneously in first differences and in levels. The levels of the endogenous variable are instrumented by lagged first differences and the first differences are instrumented by the corresponding lagged levels. The log-outputs on the right-hand side are not instrumented here. The dependent variable uses the staff allocated to medicine, obstetrics and surgery only.

# D Appendix. Autocorrelation of Output Measures

The regressions studied here are of the form $x_{it} = Rx_{i,t-1} + \Gamma z_{it} + \nu_{it}$, where $\nu_{it}$ is a random vector with a zero mean, $R$ and $\Gamma$ are coefficient matrices, and $z_{it}$ are activity indicators. Tables 19 and 20 display the estimated coefficients of $R$, the $11\times11$ matrix of first-order autocorrelation coefficients of the vector of output measures. The diagonal elements are very significant, positive, ranging from .28 to .93, the most persistent types of stays being the most important: inpatient and outpatient STAC and Sessions. The off-diagonal elements of $R$ are typically not significantly different from zero, or, if significant, are of a smaller order of magnitude than the diagonal coefficients.

Table 19: Matrix of Autoregression Coefficients; Stays Explained by Lagged Stays, 1

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Inpatient STAC-MO | Outpatient STAC-MO | Inpatient STAC-Surg | Outpatient STAC-Surg | Emergency | Psychiatry |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L.In. STAC-MO | **0.93**$^{***}$ | 0.09$^{***}$ | 0.02$^{***}$ | 0.03$^{***}$ | 0.02$^{***}$ | 0.003 |
| L.Out.STAC-MO | 0.01$^{***}$ | **0.71**$^{***}$ | 0.01$^{***}$ | $-0.04^{***}$ | 0.02$^{***}$ | 0.0001 |
| L.In.STAC-Surg | 0.003 | 0.08$^{***}$ | **0.77**$^{***}$ | 0.18$^{***}$ | 0.06$^{***}$ | $-0.002$ |
| L.Out.STAC-Surg | 0.003 | $-0.08^{***}$ | 0.02$^{***}$ | **0.38**$^{***}$ | $-0.0000$ | $-0.005$ |
| L.Emergency | 0.01 | 0.12$^{***}$ | 0.06$^{***}$ | 0.04$^{***}$ | **0.48**$^{***}$ | 0.004 |
| L.Psychiatry | $-0.004$ | 0.01 | 0.0003 | $-0.03^{**}$ | 0.005 | **0.58**$^{***}$ |
| L. Sessions | 0.01$^{***}$ | $-0.01^{*}$ | 0.01$^{***}$ | 0.004 | 0.02$^{***}$ | 0.003 |
| L.Follow-up Rehab. | 0.01 | 0.02 | 0.02$^{***}$ | 0.04$^{***}$ | 0.002 | 0.01 |
| L. External Consult. | 0.002 | 0.03$^{***}$ | 0.001 | $-0.02^{***}$ | 0.004$^{**}$ | $-0.001$ |
| L.LTAC | $-0.003$ | 0.09$^{**}$ | 0.02 | 0.07$^{***}$ | 0.04$^{***}$ | 0.003 |
| L.Home-Hosp | 0.001 | $-0.02$ | 0.01 | 0.04$^{***}$ | 0.01 | 0.01 |
| Observations | 5,367 | 5,367 | 5,367 | 5,367 | 5,367 | 5,367 |
| Adjusted $R^2$ | 0.99 | 0.94 | 0.99 | 0.98 | 0.99 | 0.99 |

Table 20: Matrix of Autoregression Coefficients; Stays Explained by Lagged Stays, 2

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Sessions | Follow-up and Rehab. | External Consul$^{tions}$ | LTAC | Home Hospital$^{tion}$. |
| | (7) | (8) | (9) | (10) | (11) |
| L.Inpatient STAC-MO | $0.02^{**}$ | $0.01^{**}$ | $0.11^{***}$ | $-0.002$ | 0.004 |
| L.Outpatient STAC-MO | $0.01^{**}$ | $0.01^{***}$ | $0.08^{***}$ | 0.0002 | $0.01^{***}$ |
| L.Inpatient STAC-Surg | $0.04^{***}$ | $-0.01$ | $0.08^{***}$ | $0.01^{**}$ | 0.004 |
| L.Outpatient STAC-Surg | $-0.02^{**}$ | $0.03^{***}$ | $-0.08^{***}$ | 0.001 | $0.01^{***}$ |
| L.Emergency | $0.05^{***}$ | $-0.01$ | $0.17^{***}$ | 0.003 | $-0.01^{***}$ |
| L.Psychiatry | 0.01 | $-0.01$ | $0.05^{**}$ | $-0.01$ | $-0.005$ |
| L.Sessions | $\mathbf{0.91}^{***}$ | 0.003 | $0.05^{***}$ | $-0.002$ | $0.003^{***}$ |
| L.Follow-up Rehab. | 0.01 | $\mathbf{0.50}^{***}$ | 0.01 | $0.02^{***}$ | $-0.001$ |
| L.External Consult. | $-0.004$ | 0.0003 | $\mathbf{0.27}^{***}$ | $-0.001$ | 0.0002 |
| L.LTAC | $-0.01$ | $0.09^{***}$ | $-0.14^{***}$ | $\mathbf{0.57}^{***}$ | $0.03^{***}$ |
| L.Home Hosp. | 0.01 | 0.01 | 0.02 | 0.001 | $\mathbf{0.28}^{***}$ |
| Observations | 5,367 | 5,367 | 5,367 | 5,367 | 5,367 |
| Adjusted $R^2$ | 0.97 | 0.99 | 0.97 | 0.98 | 0.98 |

# E Robustness of Results Obtained with Counterfactual Computations

Table 21: Ratios of the predicted employment of different categories of personnel, divided by their counterfactual predicted value, computed with the estimated factor demand of private for-profit hospitals: evaluation on small and large institutions

| **Small Hospitals** (below median size) | | | | |
|---|---|---|---|---|
| | Assist. Nurses | MDs | Reg. Nurses | Admin. Staff |
| Public Teaching $M_{tp}$ | 2.9 (0.55) | 1.47 (0.26) | 1.75 (0.33) | 1.95 (0.32) |
| $\sigma_{tp}$ | *1.37 (0.55)* | *0.55 (0.26)* | *0.41 (0.33)* | *1.34 (0.32)* |
| Non-Profit $M_{np}$ | 1.51 (0.16) | 1.06 (0.11) | 1.38 (0.13) | 1.52 (0.14) |
| $\sigma_{np}$ | *0.53 (0.16)* | *0.24 (0.11)* | *0.31 (0.13)* | *0.42 (0.14)* |
| Ordinary Public $M_p$ | 1.54 (0.14) | 0.85 (0.11) | 1.28 (0.12) | 1.49 (0.14) |
| $\sigma_p$ | *0.32 (0.14)* | *0.13 (0.11)* | *0.28 (0.12)* | *0.44 (0.14)* |
| **Large Hospitals** (above median size) | | | | |
| | Assist. Nurses | MDs | Reg. Nurses | Admin. Staff |
| Public Teaching $M_{tp}$ | 2.14 (0.8) | 2.09 (0.9) | 2.17 (0.95) | 2.34 (0.9) |
| $\sigma_{tp}$ | *0.41 (0.8)* | *0.49 (0.9)* | *0.31 (0.95)* | *0.46 (0.9)* |
| Non-Profit $M_{np}$ | 1.1 (0.18) | 1.01 (0.23) | 1.27 (0.24) | 1.72 (0.37) |
| $\sigma_{np}$ | *0.16 (0.18)* | *0.24 (0.23)* | *0.09 (0.24)* | *0.64 (0.37)* |
| Ordinary Public $M_p$ | 1.38 (0.3) | 1.04 (0.34) | 1.26 (0.31) | 1.63 (0.33) |
| $\sigma_p$ | *0.13 (0.3)* | *0.13 (0.34)* | *0.09 (0.31)* | *0.1 (0.33)* |

*Note* : The table provides the median of the predicted input demand of a hospital of one of 3 categories (public teaching, private non-profit and ordinary public hospitals) divided by the counterfactual predicted demand of a private for-profit hospital with the same output and control vectors. Computations and displayed statistics are the same as in Table 10 except that the median ratios have been computed separately for the sub-samples of small and large hospitals.

It is legitimate to ask if hospital size plays a role in relative differences. We take the number of stays as a measure of hospital size, dividing the sample into two subsets: the institutions above and below the median size, as measured by the total number of stays. The results are given by Table 21. We see that the results do not differ very much in small hospitals. There are some differences though: the inefficiency problems of small teaching hospitals seem worse when we look at assistant nurses; the shortage of doctors seems worse in small ordinary public hospitals.

Finally, to test robustness, we re-estimated the model in sub-samples, but using a Translog spec-

ification,combined with a Lasso algorithm, to select the most relevant predictors of employment in each of the categories, then we recomputed the same statistics: these appear on Table 22. The results of Table 22 confirms the earlier findings, except that the ordinary public hospitals seem more inefficient in their use of doctors as in the previous results.

Table 22: Ratios of the predicted employment of different categories of personnel, divided by their counterfactual predicted value, computed with the estimated factor demand of private for-profit hospitals

| **Estimation with a Translog Specification combined with a Lasso Algorithm** | | | | |
|---|---|---|---|---|
| | Assist. Nurses | MDs | Reg. Nurses | Admin. Staff |
| Public Teaching $M_{tp}$ | 2.24 (0.42) | 1.74 (0.29) | 1.92 (0.29) | 1.99 (0.39) |
| $\sigma_{tp}$ | *0.93 (0.79)* | *0.51 (0.22)* | *0.65 (0.37)* | *3.31 (1.49)* |
| Non-Profit $M_{np}$ | 1.27 (0.09) | 1.13 (0.09) | 1.4 (0.09) | 1.58 (0.14) |
| $\sigma_{np}$ | *0.41 (0.25)* | *0.28 (0.09)* | *0.22 (0.17)* | *0.42 (0.41)* |
| Ordinary Public $M_p$ | 1.6 (0.25) | 1.21 (0.18) | 1.51 (0.2) | 1.73 (0.21) |
| $\sigma_p$ | *0.31 (0.35)* | *0.31 (0.18)* | *0.3 (0.55)* | *24.07 (0.67)* |

*Note* : The table provides the median of the predicted labor demand of a hospital in one of 3 categories (public teaching, private non-profit and ordinary public hospitals) divided by the counterfactual predicted demand of a private for-profit hospital with the same output and control vector. Computations and displayed statistics are the same as in Table 10 except that the model has been re-estimated, in sub-samples, with a Translog specification, using a Lasso algorithm to pick the regressors.

# F Online Appendix: Sub-sample Estimation of Personnel-Demand Functions

## F.1 Assistant Nurses

Table 23: Sub-sample Estimation of Demand for Assistant-Nurses

| | Teaching | For-Profit | Non-Profit | Ordinary Public |
|---|---|---|---|---|
| Inpatient STAC | 0.533*** | 0.150*** | 0.102** | 0.365*** |
| | (0.082) | (0.028) | (0.049) | (0.061) |
| Outpatient STAC | 0.099** | 0.007 | 0.005 | 0.041*** |
| | (0.050) | (0.027) | (0.024) | (0.014) |
| Emergency | 0.106* | 0.207*** | 0.375*** | 0.243*** |
| | (0.062) | (0.076) | (0.083) | (0.050) |
| Sessions | 0.030 | 0.103*** | 0.041** | 0.057*** |
| | (0.027) | (0.010) | (0.018) | (0.012) |
| Follow-up Rehab. | 0.168*** | 0.172** | 0.377*** | 0.209*** |
| | (0.060) | (0.070) | (0.074) | (0.048) |
| LTAC | 0.336*** | | 0.425 | 0.090*** |
| | (0.068) | | (0.355) | (0.033) |
| Psychiatry | 0.021 | | 0.208** | 0.055 |
| | (0.032) | | (0.105) | (0.036) |
| Ext. Consult. | 0.060* | 0.029 | 0.132*** | −0.030* |
| | (0.034) | (0.033) | (0.029) | (0.016) |
| Research | −0.033 | 0.067** | 0.018 | −0.158 |
| | (0.108) | (0.032) | (0.047) | (0.271) |
| Training | −0.034 | | −0.061 | 0.145 |
| | (0.081) | | (0.093) | (0.122) |
| Specialization | 0.085 | −0.177*** | −0.141** | −0.002 |
| | (0.109) | (0.060) | (0.070) | (0.041) |
| Casemix | 1.844* | 5.051** | 2.388** | −0.145 |
| | (1.050) | (2.440) | (1.019) | (1.331) |
| Av. Patient Age | 0.003 | 0.0003 | 0.004 | −0.00000 |
| | (0.003) | (0.003) | (0.003) | (0.004) |
| Casemix×Av. Patient Age | −0.021 | −0.045 | −0.034** | 0.008 |
| | (0.016) | (0.028) | (0.014) | (0.017) |
| Constant | −2.473*** | −1.062 | −2.990*** | −2.619*** |
| | (0.900) | (0.937) | (1.089) | (0.571) |
| Presence of Activity Indicators | | | | |
| I(Inpatient MO) | 3.356*** | −0.166** | −0.676** | 1.643*** |

| | | | | |
|---|---|---|---|---|
| | (0.612) | (0.078) | (0.340) | (0.526) |
| I(Outpatient MO) | 0.100 | $-0.113^{**}$ | $-0.149$ | $-0.004$ |
| | (0.359) | (0.045) | (0.127) | (0.059) |
| I(Inpatient Surg.) | 0.196 | 0.015 | $-0.242$ | $-0.149^{*}$ |
| | (0.152) | (0.170) | (0.199) | (0.077) |
| I(Outpatient Surg.) | 0.035 | $-0.050$ | 0.291 | $0.182^{**}$ |
| | (0.133) | (0.231) | (0.227) | (0.081) |
| I(Sessions) | $0.492^{***}$ | $0.137^{*}$ | 0.113 | $0.129^{**}$ |
| | (0.175) | (0.071) | (0.121) | (0.055) |
| I(Emergency) | 0.997 | $1.719^{**}$ | $3.404^{***}$ | $2.212^{***}$ |
| | (0.645) | (0.759) | (0.850) | (0.428) |
| I(Follow-up Rehab.) | $0.768^{**}$ | $0.694^{*}$ | $1.726^{***}$ | $1.024^{***}$ |
| | (0.355) | (0.410) | (0.482) | (0.291) |
| I(Home Hosp.) | 0.176 | $-0.270^{**}$ | 0.001 | $-0.098^{***}$ |
| | (0.124) | (0.111) | (0.154) | (0.032) |
| I(LTAC) | $-0.609^{***}$ | | $-0.945$ | $-0.048$ |
| | (0.232) | | (1.182) | (0.109) |
| I(Psychiatry) | $-0.061$ | $0.549^{***}$ | $-1.306^{*}$ | $-0.250$ |
| | (0.264) | (0.108) | (0.678) | (0.302) |
| I(Ext.Consult.) | $-0.858^{**}$ | $-0.265$ | $-1.231^{***}$ | $0.375^{**}$ |
| | (0.385) | (0.244) | (0.289) | (0.164) |
| I(Research) | $-0.114$ | $-0.126^{*}$ | $-0.326^{**}$ | $-0.099^{*}$ |
| | (0.134) | (0.066) | (0.144) | (0.055) |
| Observations | 686 | 2,488 | 870 | 2,872 |
| Adjusted $R^2$ | 0.839 | 0.694 | 0.723 | 0.877 |

## F.2 Registered Nurses

Table 24: Sub-sample Estimation of Demand for Registered Nurses

| | Teaching | For-Profit | Non-Profit | Ordinary Public |
|---|---|---|---|---|
| Inpatient STAC | 0.489*** | 0.165*** | 0.109** | 0.375*** |
| | (0.079) | (0.024) | (0.049) | (0.055) |
| Outpatient STAC | 0.107** | 0.035 | 0.034 | 0.046*** |
| | (0.047) | (0.022) | (0.025) | (0.016) |
| Emergency | 0.099* | 0.263*** | 0.227** | 0.230*** |
| | (0.052) | (0.067) | (0.115) | (0.051) |
| Sessions | 0.052** | 0.106*** | 0.113*** | 0.062*** |
| | (0.024) | (0.008) | (0.021) | (0.012) |
| Follow-up Rehab. | 0.091* | 0.121* | 0.389*** | 0.182*** |
| | (0.053) | (0.070) | (0.070) | (0.040) |
| LTAC | 0.239*** | | 0.288 | 0.027 |
| | (0.068) | | (0.238) | (0.029) |
| Psychiatry | 0.079** | | 0.295** | 0.135*** |
| | (0.034) | | (0.127) | (0.048) |
| Ext. Consult. | 0.080*** | 0.041 | 0.088*** | 0.005 |
| | (0.029) | (0.030) | (0.030) | (0.016) |
| Research | 0.010 | 0.054 | 0.081* | −0.309 |
| | (0.077) | (0.036) | (0.043) | (0.263) |
| Training | 0.068 | | 0.018 | 0.152 |
| | (0.065) | | (0.079) | (0.113) |
| Specialization | 0.058 | −0.119** | −0.154** | 0.001 |
| | (0.100) | (0.050) | (0.072) | (0.043) |
| Casemix | 2.637*** | 1.420 | 3.757*** | −0.031 |
| | (1.003) | (2.700) | (1.092) | (1.556) |
| Av. Patient Age | 0.003 | 0.011*** | 0.010** | −0.001 |
| | (0.003) | (0.003) | (0.004) | (0.003) |
| Casemix×Av. Patient Age | −0.034** | −0.021 | −0.055*** | −0.0001 |
| | (0.014) | (0.031) | (0.015) | (0.019) |
| Constant | −1.756** | −1.690* | −2.418* | −2.355*** |
| | (0.867) | (0.883) | (1.332) | (0.513) |
| Presence of Activity Indicators | | | | |
| I(Inpatient MO) | 3.154*** | 0.012 | −0.360 | 1.674*** |
| | (0.581) | (0.064) | (0.343) | (0.471) |
| I(Outpatient MO) | 0.375 | −0.038 | 0.096 | −0.017 |
| | (0.308) | (0.039) | (0.139) | (0.059) |

| | | | | |
|---|---|---|---|---|
| I(Inpatient Surg.) | 0.049 | 0.015 | $-0.419^{*}$ | $-0.176^{**}$ |
| | (0.190) | (0.157) | (0.232) | (0.077) |
| I(Outpatient Surg.) | 0.027 | 0.028 | 0.200 | $0.158^{*}$ |
| | (0.180) | (0.203) | (0.255) | (0.090) |
| I(Sessions) | $0.377^{**}$ | $0.182^{***}$ | $0.327^{***}$ | $0.205^{***}$ |
| | (0.163) | (0.064) | (0.126) | (0.055) |
| I(Emergency) | 0.878 | $2.273^{***}$ | $1.923^{*}$ | $2.081^{***}$ |
| | (0.548) | (0.666) | (1.149) | (0.440) |
| I(Follow-up Rehab.) | 0.329 | 0.602 | $2.063^{***}$ | $0.992^{***}$ |
| | (0.312) | (0.424) | (0.445) | (0.249) |
| I(Home Hosp.) | 0.100 | $-0.211^{**}$ | $-0.108$ | $-0.127^{***}$ |
| | (0.142) | (0.107) | (0.139) | (0.029) |
| I(LTAC) | $-0.555^{**}$ | | $-0.936$ | 0.035 |
| | (0.224) | | (0.804) | (0.096) |
| I(Psychiatry) | $-0.390$ | $0.513^{***}$ | $-1.734^{**}$ | $-0.704^{*}$ |
| | (0.263) | (0.156) | (0.847) | (0.383) |
| I(Ext.Consult.) | $-0.976^{***}$ | $-0.382$ | $-0.855^{***}$ | 0.119 |
| | (0.324) | (0.234) | (0.294) | (0.166) |
| I(Research) | $-0.027$ | $-0.160^{***}$ | $-0.136$ | $-0.135^{**}$ |
| | (0.114) | (0.056) | (0.143) | (0.053) |
| Observations | 686 | 2,488 | 870 | 2,872 |
| Adjusted $R^2$ | 0.905 | 0.704 | 0.753 | 0.915 |

### F.3 MDs

Table 25: Sub-sample Estimation of Demand for MDs

| | Teaching | For-Profit | Non-Profit | Ordinary Public |
|---|---|---|---|---|
| Inpatient STAC | 0.425*** | 0.212*** | 0.270*** | 0.393*** |
| | (0.081) | (0.025) | (0.042) | (0.041) |
| Outpatient STAC | 0.123*** | 0.086*** | 0.042** | 0.037* |
| | (0.047) | (0.021) | (0.021) | (0.019) |
| Emergency | 0.118* | 0.137** | 0.127* | 0.310*** |
| | (0.068) | (0.064) | (0.073) | (0.042) |
| Sessions | 0.069** | 0.056*** | 0.069*** | 0.040*** |
| | (0.029) | (0.009) | (0.018) | (0.012) |
| Follow-up Rehab. | 0.087 | 0.086 | 0.314*** | 0.112*** |
| | (0.060) | (0.067) | (0.069) | (0.041) |
| LTAC | 0.160** | | 0.026 | 0.068** |
| | (0.071) | | (0.147) | (0.035) |
| Psychiatry | 0.045 | | 0.211* | 0.093** |
| | (0.033) | | (0.118) | (0.046) |
| Ext. Consult. | 0.131*** | 0.056 | 0.101*** | 0.027 |
| | (0.029) | (0.042) | (0.027) | (0.019) |
| Research | 0.028 | −0.033 | 0.109*** | 0.088 |
| | (0.090) | (0.038) | (0.040) | (0.235) |
| Training | −0.101 | | −0.014 | 0.029 |
| | (0.067) | | (0.076) | (0.122) |
| Specialization | −0.062 | −0.202*** | −0.083 | −0.028 |
| | (0.103) | (0.053) | (0.075) | (0.041) |
| Casemix | 1.816** | −5.028** | 1.669* | −0.941 |
| | (0.841) | (2.340) | (0.888) | (1.454) |
| Av. Patient Age | 0.001 | −0.0005 | −0.001 | −0.004 |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Casemix×Av. Patient Age | −0.027** | 0.060** | −0.021* | 0.010 |
| | (0.012) | (0.027) | (0.012) | (0.017) |
| Constant | −2.932*** | −1.142 | −2.410** | −3.596*** |
| | (1.004) | (0.844) | (1.007) | (0.523) |
| Presence of Activity Indicators | | | | |
| I(Inpatient MO) | 2.811*** | 0.077 | 0.428 | 1.934*** |
| | (0.592) | (0.079) | (0.288) | (0.349) |
| I(Outpatient MO) | 0.219 | −0.032 | 0.002 | −0.064 |
| | (0.310) | (0.038) | (0.088) | (0.080) |

| | | | | |
|---|---|---|---|---|
| I(Inpatient Surg.) | 0.136 | 0.462** | −0.252 | −0.116 |
| | (0.146) | (0.192) | (0.191) | (0.083) |
| I(Outpatient Surg.) | 0.100 | −0.319 | 0.103 | 0.136 |
| | (0.130) | (0.196) | (0.192) | (0.102) |
| I(Sessions) | 0.656*** | 0.122* | 0.075 | 0.109* |
| | (0.181) | (0.071) | (0.118) | (0.060) |
| I(Emergency) | 1.097 | 1.147* | 1.076 | 2.675*** |
| | (0.709) | (0.636) | (0.730) | (0.376) |
| I(Follow-up Rehab.) | 0.461 | 0.618 | 1.796*** | 0.596** |
| | (0.348) | (0.410) | (0.439) | (0.253) |
| I(Home Hosp.) | 0.179** | −0.093 | 0.141 | −0.060 |
| | (0.072) | (0.086) | (0.134) | (0.039) |
| I(LTAC) | −0.406* | | −0.163 | −0.227* |
| | (0.227) | | (0.535) | (0.124) |
| I(Psychiatry) | 0.009 | 0.294*** | −1.295* | −0.514 |
| | (0.246) | (0.091) | (0.768) | (0.379) |
| I(Ext.Consult.) | −1.535*** | −0.380 | −0.990*** | −0.101 |
| | (0.327) | (0.280) | (0.279) | (0.185) |
| I(Research) | −0.148 | −0.147*** | −0.209 | −0.026 |
| | (0.119) | (0.055) | (0.129) | (0.049) |
| Observations | 686 | 2,488 | 870 | 2,872 |
| Adjusted $R^2$ | 0.912 | 0.713 | 0.839 | 0.895 |

## F.4 Administrative Staff

Table 26: Sub-sample Estimation of Demand for Administrative Personnel

| | Teaching | For-Profit | Non-Profit | Ordinary Public |
|---|---|---|---|---|
| Inpatient STAC | 0.438*** | 0.156*** | 0.093* | 0.395*** |
| | (0.117) | (0.024) | (0.048) | (0.058) |
| Outpatient STAC | 0.128** | 0.050*** | 0.051** | 0.022 |
| | (0.057) | (0.018) | (0.026) | (0.021) |
| Emergency | 0.068 | 0.304*** | 0.112 | 0.260*** |
| | (0.046) | (0.056) | (0.095) | (0.055) |
| Sessions | 0.082** | 0.055*** | 0.102*** | 0.054*** |
| | (0.034) | (0.007) | (0.021) | (0.015) |
| Follow-up Rehab. | 0.021 | 0.154** | 0.318*** | 0.142*** |
| | (0.085) | (0.070) | (0.070) | (0.042) |
| LTAC | 0.229* | | 0.195 | 0.039 |
| | (0.117) | | (0.261) | (0.042) |
| Psychiatry | 0.005 | | 0.011 | 0.042 |
| | (0.052) | | (0.185) | (0.049) |
| Ext. Consult. | 0.140*** | 0.047* | 0.131*** | 0.003 |
| | (0.031) | (0.028) | (0.026) | (0.017) |
| Research | 0.099 | 0.030 | 0.081 | −0.035 |
| | (0.093) | (0.029) | (0.056) | (0.223) |
| Training | −0.081 | | −0.024 | 0.024 |
| | (0.088) | | (0.065) | (0.165) |
| Specialization | 0.024 | −0.133*** | −0.155* | 0.059 |
| | (0.150) | (0.049) | (0.083) | (0.052) |
| Casemix | 1.771 | 1.334 | 1.234 | 1.616 |
| | (1.486) | (1.871) | (1.027) | (1.781) |
| Av. Patient Age | 0.004 | 0.0004 | −0.002 | 0.001 |
| | (0.005) | (0.003) | (0.004) | (0.004) |
| Casemix×Av. Patient Age | −0.030 | −0.014 | −0.017 | −0.022 |
| | (0.023) | (0.022) | (0.014) | (0.022) |
| Constant | −2.180** | −2.498*** | −0.476 | −3.073*** |
| | (1.078) | (0.790) | (1.189) | (0.591) |
| Presence of Activity Indicators | | | | |
| I(Inpatient MO) | 2.555*** | −0.061 | −0.509 | 1.929*** |
| | (0.778) | (0.054) | (0.330) | (0.355) |
| I(Outpatient MO) | 0.125 | −0.067* | −0.014 | −0.013 |
| | (0.364) | (0.036) | (0.143) | (0.076) |

| | | | | |
|---|---|---|---|---|
| I(Inpatient Surg.) | 0.162 | 0.154 | −0.321 | −0.175** |
| | (0.181) | (0.224) | (0.244) | (0.088) |
| I(Outpatient Surg.) | 0.375** | −0.063 | 0.217 | 0.041 |
| | (0.170) | (0.220) | (0.233) | (0.106) |
| I(Sessions) | 0.638*** | 0.126** | 0.365*** | 0.107 |
| | (0.227) | (0.055) | (0.125) | (0.069) |
| I(Emergency) | 0.518 | 2.727*** | 1.003 | 2.365*** |
| | (0.472) | (0.551) | (0.954) | (0.477) |
| I(Follow-up Rehab.) | −0.037 | 0.818* | 1.509*** | 0.720*** |
| | (0.503) | (0.422) | (0.437) | (0.260) |
| I(Home Hosp.) | 0.250** | −0.177** | −0.063 | −0.135*** |
| | (0.111) | (0.079) | (0.131) | (0.036) |
| I(LTAC) | −0.465 | | −0.691 | −0.108 |
| | (0.370) | | (0.858) | (0.144) |
| I(Psychiatry) | 0.379 | 0.427*** | 0.043 | −0.056 |
| | (0.359) | (0.154) | (1.158) | (0.400) |
| I(Ext.Consult.) | −1.671*** | −0.382* | −1.115*** | 0.141 |
| | (0.383) | (0.218) | (0.242) | (0.177) |
| I(Research) | 0.060 | −0.104** | −0.602*** | 0.025 |
| | (0.129) | (0.043) | (0.148) | (0.057) |
| Observations | 686 | 2,488 | 870 | 2,872 |
| Adjusted $R^2$ | 0.832 | 0.733 | 0.789 | 0.870 |