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Optimal Healthcare Contracts: Theory and Empirical Evidence from Italy*

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Abstract

In this paper we investigate the nature of the contracts between a large health-care purchaser and health service providers in a prospective payment system. We model theoretically the interaction between patients choice and cream-skimming by hospitals. We test the model using a very large and detailed administrative dataset for the largest region in Italy. In line with our theoretical results, we show that the state funded purchaser offers providers a system of incentives such that the most efficient providers both treat more patients and also treat more difficult patients, thus receiving a higher average payment per treatment.

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Keywords: Patients choice, Cream skimming, Optimal healthcare contracts, Hospitals, Lombardy.

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1 Introduction

The basis upon which many providers of health care across the world are paid for the services they provide is the principle of Diagnosis Related Groups (DRG). First introduced for Medicare payments in 1983 (Fetter, 1991), this payment mechanism reimburses hospitals that perform a given treatment by an amount determined as a notional cost for similar treatments.[1] Relative to a retrospective reimbursement system, this reduces health care costs (Ellis and McGuire, 1990), since it gives providers little incentive to perform costly unnecessary treatments. However, tying the overall reimbursement to the overall number of patients, when the cost of treating each may vary considerably, makes a hospital's financial position very sensitive to the patient mix of the various DRGs it provides. The patient mix is affected both by *patient choice* and by *cream skimming*. When patients are able to choose where they are treated, those who know they have more complex prognoses have stronger incentives to seek admission to hospitals they perceive to be of better quality. Cream skimming is the hospital practice to refuse treatment, implicitly or explicitly, to more "expensive" patients. Some theoretical literature (Newhouse, 1996, Ellis and McGuire, 1986, Sappington and Lewis, 1999 among others) has identified the incentive for cream skimming provided by a DRG based payment system as a drawback which may reduce the benefits deriving from its incentives for cost reduction (Street et al., 2011).[2] Both patient choice and cream skimming are reasons to doubt that the patient mix is uncorrelated to the specific characteristics of the hospital.

[1]A comprehensive discussion of the details of the implementation of DRG based payments in eleven European countries is in Cots et al. (2011).

[2]The potential for cream skimming is present when the features of a supplier's customers affect the supplier's cost of providing the good or service. Beside health care, this is clearly the case in financial markets (Ellis and McGuire, 1986), in the regulation of utilities (Laffont and Tirole, 1990), and, most closely related, the provision of education, with both studied theoretical (Epple and Romano, 2008) and empirical (Altonji et al., 2015, Figlio and Stone, 2001) analyses of cream skimming of the best students by private schools competing with state schools.

The first part of the theoretical analysis in this paper (Section 2.1) confirms rigorously that cream skimming and patient choice amplify each other's effect on the hospitals' patient mix: if a hospital is unsuited to treat a certain patient for a given DRG, then both the hospital and the patient prefer treatment to occur in a more suitable hospital. As a consequence, the difference in case mix between hospitals increases both with the parameter measuring the patients' ability to choose hospitals, proxied in the model with the relative importance of delaying treatment and being treated at an inconvenient hospital, and on the ability of the hospital to "dump" patients, which is determined by the legal and institutional environment.

Of course the suitability of the match between patients with different complexity and hospitals with different skills in the treatment of a given DRG is not just a private matter between the hospitals and the patients, but has also the social concern that scarce resources, highly skilled hospitals, should be allocated where they are most needed, namely the most complex patients. To the extent that more complex cases are also more expensive to treat, an inflexible DRG payment system would give *all* hospitals, not just the least suitable ones, an incentive to turn away patients whose treatment would cost more than the fixed DRG reimbursement. In fact, De Fraja (2000) shows that, in the natural situation where hospitals are in a better position than the purchaser to understand the nature of a specific patient's clinical condition, the socially optimal health contract is such that *hospitals that treat a higher proportion of their potential patient pool for a given DRG receive a higher average reimbursement for that given DRG*. *Prima facie*, it may be seen counterintuitive that cost efficient providers receive a *higher* average payment per treatment. But this is so as to induce them to accept more complex patients, which would be inefficient to treat in less efficient hospitals.

The flexibility of the optimal reimbursement system is in fact reflected in the pattern of payments made by a very large public purchaser in the north of Italy.

The diagrams in Figure 2 below strongly suggest that the official reimbursement tariff is an initial reference value, with actual payments often diverging from this value. This deviation from the official refund rate is of course within the health authority's contractual rules, according to which reimbursement can be increased when a DRG is associated with other specific interventions, or when it requires the use of more expensive materials, or reduced, when delivered in clearly defined, simpler settings, calling for "low-intensity surgery", or when the outcome falls short of a target quality, and other circumstances, as explained in more detail in Section 2.2.

These adjustments to the tariff are incorporated in the theoretical analysis in Section 2.2. While they must be based on observable and contractible parameters, to the extent that there is correlation between these and characteristics of the patient which are observed by the provider but not by the health authority, the provider's information advantage is reduced by a payment system that compensates hospitals that treat more complex and expensive patients. This implies, as shown in Proposition 4, that providers which are more efficient in the provision of a given DRG receive in practice a higher *average* reimbursement for that DRG and treat a higher fraction of the potential patient pool for that DRG, that is the for whom the hospital is nearest among those which provide the DRG they need.

We test the theoretical model using a rich administrative dataset, described in Section 3, which contains detailed information on all the treatments carried out in 2013 on behalf of the health purchaser of Lombardy. With over 10 million residents it is the most populous region in Italy, and it accounts for about one fifth of the country's GDP. The OLS estimations in Table 2 confirm that, indeed, hospitals that treat more patients relative to their potential demand, that is hospitals that in theory have more complex patients, are paid more on average for a given treatment than hospitals which appear to treat fewer of their potential patients.

While there might be other explanations for this finding, it is consistent with two important assumptions on the behaviour of purchasers and providers of health care. The first is that the contracts negotiated between the regional health authority and its healthcare providers satisfy the efficiency conditions outlined in a simple case by De Fraja (2000) and developed for the more complex many-hospital, many-DRG case in the theoretical part of this paper. The second is that, just as shown by Einav et al. (2017) and Eliason et al. (2018) for the providers of long-term acute-care for Medicare patients, hospitals respond to incentives generated by these contracts in the manner predicted by the theoretical model presented in Section 2.

This result is robust to changes in the definition of "nearest hospital", both in terms of how distance is measured, miles or travel time, and by the coarseness of the measure of distance: it seems plausible that patients needing a potentially serious hospital treatment may disregard small enough differences in the distance to different hospitals. As we just said, one likely interpretation of our findings is that when contracts are designed by the health purchaser in the socially efficient manner and hospitals respond to the incentives these contracts determine in the manner predicted by the theory. Thus interpretation gains further indirect confirmation from the results obtained by splitting the sample in emergency and non-emergency hospitalisations, and according to the ownership and mission of the hospitals. One would expect patient choice and cream skimming to operate more weakly for emergency hospitalisations: indeed this is what we report in column (5) in Table 4. And, like Eliason et al. (2018), we also find that private for profit hospitals respond more strongly to the incentive scheme than public hospitals and not-for-profit ones (columns (6)-(8) in Table 4).

The paper is organised as follows. In Section 2, we develop the theoretical background, first proposing a simple model to study the interaction of the choices of a population of patients and two competing providers which can potentially treat them (Section 2.1), and subsequently, in Section 2.2, extending the model in De Fraja (2000) to the characteristics of the contracts entered by providers in Italy. The data is described in detail in Section 3, and the empirical strategy in Section 4. Section 5 presents our results, which confirm the theoretical hypothesis of a positive correlation between average payment per DRG and the fraction of the potential patients treated, and a brief conclusion is in Section 6. An appendix contains further robustness tests, and additional material.

2 Theoretical background

We study the provision of health care to a large population of patients who may need treatment for a wide range of DRGs. This provision, funded by the taxpayer, is managed by a health authority, which proposes contracts to a large number of hospitals for the treatment of the patients who need care, and, following treatment, reimburses the provider on the basis of the agreed contractual terms.

Formally we study a three stage game, with three sets of players: (i) the health authority, which chooses the health-care contracts to offer, (ii) the hospitals providing the services, which choose their admission practices for their various services, and (iii) the patients, who choose which hospitals they want to be treated by. These three sets of players choose in each stage in that order, and we study the game backwards, beginning with the last.

2.1 The individual admission decision

We study first the patients' choices, taken when the healthcare contracts and the hospitals admission practices are in place. In principle, a patient may seek admission to any of the H hospitals offering to treat the DRG she needs. Naturally, whether a patient needing a treatment is in fact treated at a given hospital depends on both parties, the hospital and the patient, agreeing to this. This is because while patients are allowed by law to choose where they receive treatment, hospitals have an incentive to "dump", that is to avoid treating, certain patients. In the simple model of this section we show that, if patients and hospitals have at least some discretion in the treatment decisions, then patients' choice amplifies the effect of the provider's cream skimming. This happens because patients may understand that they could be turned away by some hospitals, and, if so, eschew them in the first place to avoid the possible waste of time and effort. That is, if hospitals practice cream skimming, patients may not seek treatment there in the first place; unlike Groucho Marx, they do not seek admissions to hospitals which would *not* accept them. Thus cream skimming and patients' choice are the two sides of the same coin: they are both unobservable and have similar effects on the observable hospitalisation decision. This is not a drawback for our paper, as its focus is on the efficiency of the patient-provider matching, not what determines it.

In this subsection, we concentrate on the choices, the patients' and the providers', that lead a patient who needs a given DRG to be treated at a given hospital. At this stage, the contracts between the provider and the health authority, including the tariff for the DRG in question, are all fixed. In the next subsection, we introduces the principles that inspire the specific funding mechanism used by the regional health authority in Lombardy.

We consider a very simple model, based on the standard industrial economics Hotelling set-up (Tirole, 1988): in the original model, consumers are distributed along a linear road, and choose in which of the two shops located at the opposite ends of the road they do their shopping. We posit instead a population of patients who need a given DRG. These patients are distributed along a interval $[-z, z]$ with density $F(u)$: $F(-z) = 0$, $F(z) = 1$. They can receive the treatment they need from one of the two hospitals, which are located in $-z$ and z. A patient incurs a travel cost which is proportional to the distance between her location and the location of the hospital she is treated by.[3] Thus a patient located in $u \in [-z, z]$ has a travel cost $(z + u)\,\tau$ if she is treated at the hospital in $-z$, and a cost $(z - u)\,\tau$ if she is treated at the hospital in z. Receiving treatment brings the patient a benefit of $b > 0$.

Patients also differ according to their idiosyncratic health status, which the hospital can learn after a pre-admission medical visit. In Section 2.2, we focus on the observability of some of the patients' characteristics, but in the simple model of this section, we simplify the analysis by assuming that a fraction η of the patients are simple to treat, and the rest are complex. The latter are more likely to experience complications, they have overall poorer health, more uncertain recovery time, and so on. Variables referring to the two types of patients are labelled E and H, acronyms for "easy" and "hard".

The hospitals differ in the *cost* of providing health care, but the *quality* of care they provide is identical, both for simple and for complex patients.

The cost of treating simple patients is such that the net hospital benefit, given by the difference between the refund for the treatment paid by the health authority and the cost of provision, is strictly positive for both hospitals. Both hospitals therefore are willing to admit all the simple patients that knock on their door. Hospitals instead differ in their cost to treat complex patients. Specifically, in the "low cost" hospital, the difference between refund and actual cost is positive, but for the "high cost" hospital the actual cost of performing the treatment in a satisfactory manner exceeds the associated DRG payment, and so its net "profit" is negative: one may think of complex cases requiring equipment not owned or personnel not employed by the "high cost" hospital, which would then need to incur the cost of procuring them on an ad hoc basis for the specific treatment of a complex patient. In short, a high cost hospital has a financial incentive not to treat a complex patient. It

[3] This cost includes the monetary, time, and inconvenience cost incurred by the patient and her family and friends during the treatment, and so it may include also ease of parking a car, and the type of non-medical amenities available.

might try to avoid doing so either explicitly, by informing them that is unable to treat them, or implicitly, for example by advising them that they would be better off if they went to a different hospital. We assume that a hospital's ability to turn down patients is determined by a parameter $\sigma \in [0,1]$. σ is a measure of cream skimming: when a complex patient seeks admission to a high cost hospital, she is turned down with probability σ. The value of σ is determined by the accuracy of the pre-admission assessment procedure, by formal or informal appeals by the patient, or by individual physicians' decisions out of line with the hospital's financial interest. When $\sigma = 0$, there is no cream skimming, that is all patients are treated in whatever hospital they seek admission to.

To determine the equilibrium allocation of patients to hospitals, we assume, without loss of generality, that the high cost hospital is located in $-z$, and the low cost one in z. Notice that simple patients will choose only on the basis of the "travel" cost since they are always treated by their first choice hospital, and so simple patients located in $x < 0$ prefer the high cost hospital, and vice versa, patients in $x \geq 0$ go to the low cost hospital; as the set of patients in $x = 0$, who are indifferent between the two hospitals has measure zero in $[-z, z]$, there is no loss in generality in assuming that they all go to the low cost hospital.

Next consider complex patients. Even though the quality of treatment is the same in the two hospitals, they do care about the type of the hospital they seek to be admitted: if $\sigma > 0$, they run the risk to be turned away, which entails stress and delays, and they might therefore seek admission to the low cost hospital even when it is further away than the high cost one.[4] In order to ensure sufficient importance of the distance travelled and the cost of travel and to ensure that all patients prefer to be treated, we assume that $\tau \in \left(\frac{1-\eta}{\left(\frac{2-\sigma}{\sigma}\right)^2 + 1 - \eta} \frac{b}{z}, \frac{b}{z} \right)$. Formally, if patients maximise their expected payoff, given a benefit of being turned away of 0, a complex patient located

[4]This assumes that patients have precise information about their own type. Adding some uncertainty on their part would not alter the qualitative features of the equilibrium.

in $x \in [-z, z]$ receives a payoff $b - (z - x)\tau$ if she goes to the low cost hospital and $(b - (z + x)\tau)(1 - \sigma)$, if she goes to the high cost hospital. She is indifferent between hospitals when she is located in $x = \frac{-\sigma}{2-\sigma}\left(\frac{b}{\tau} - z\right) < 0$. Thus complex patients face a trade-off: if they are only slightly nearer to the high cost hospital, they may choose to travel to the low cost one, which implies a longer trip, but a higher probability of being treated, rather than risk being turned away, and having to delay the admission. We can summarise this discussion formally.

Proposition 1. *Complex (respectively simple) patients seek admission to the low cost hospital if and only if their location x satisfies* $x \geq \frac{-\sigma}{2-\sigma}\left(\frac{b}{\tau} - z\right)$ *(respectively* $x \geq 0$*).*

With this preliminary result, we can establish the link between cream skimming and patients' choice on the one side, and the number and types of patients who are treated by each hospital in equilibrium on the other.

Towards this goal, we concentrate on two measures of the patient mix, ξ and ψ. The first, ξ, is the proportion of the total patients treated for the DRG in question who receive treatment in the low cost hospital, relative to the proportion that would be treated in the absence of cream skimming or patients' choice. And the second, ψ, is the proportion of the patients treated for this DRG in the low cost hospital who are "complex" patients, again relative to the proportion that would be treated in the absence of cream skimming or patients' choice.

Proposition 2. *Let F be uniform in* $[-z, z]$. *Then:*

$$\frac{\partial \xi}{\partial \sigma} > 0, \qquad \frac{\partial \xi}{\partial \tau} < 0, \qquad \frac{\partial \psi}{\partial \sigma} > 0, \qquad \frac{\partial \psi}{\partial \tau} < 0. \tag{1}$$

Proof. Begin by deriving the equilibrium values of ξ and ψ. Let G be the total number of patients who are treated at the low cost hospital; from Proposition 2, G is given by the sum of $\eta(1 - F(0))$, the simple patients for whom the nearer hospital is the low cost one, and $(1 - \eta)\left(1 - F\left(\frac{-\sigma}{2-\sigma}\left(\frac{b}{\tau} - z\right)\right)\right)$, the complex patients for whom the nearer hospital is the high cost one, and those who live near enough the mid point of the line that they are willing to incur the extra travel cost to avoid the risk of being turned away by the high cost hospital. When τ is at its maximum value, $\tau = \frac{b}{z}$, so that all patients seek admission to the nearest hospital, or when $\sigma = 0$, so that hospitals do not practice cream skimming, the number of patients in the low cost hospital is $1 - F(0)$. Similarly, B, the total number of patients treated at the high cost hospital is given by the sum of $\eta F(0)$ and $(1-\sigma)(1-\eta) F\left(\frac{-\sigma}{2-\sigma}\left(\frac{b}{\tau} - z\right)\right)$. The remaining $\sigma F\left(\frac{-\sigma}{2-\sigma}\left(\frac{b}{\tau} - z\right)\right)$ patients are not treated, and receive a 0 payoff. Given the assumption of a uniform density in $[-z, z]$, $F(u) = \frac{1}{2}\left(1 + \frac{u}{z}\right)$ and so ξ is given by:

$$\xi = \frac{\frac{G}{G+B}}{1 - F(0)} = \frac{1}{2} \frac{b\sigma(1-\eta) + \tau z(2(1-\sigma) + \sigma\eta)}{b\sigma^2(1-\eta) + 2\tau z(2(1-\sigma) + \sigma\eta)} \tag{2}$$

Conversely, to determine ψ, we need G_H, the number of complex patients treated in the low cost hospital,

$$\psi = \frac{\frac{G_H}{G}}{1-\eta} = \frac{b\sigma + 2\tau z(1-\sigma)}{b\sigma(1-\eta) + \tau z(2(1-\sigma) + \sigma\eta)} \tag{3}$$

The proposition is now obtained simply carrying out the differentiation.

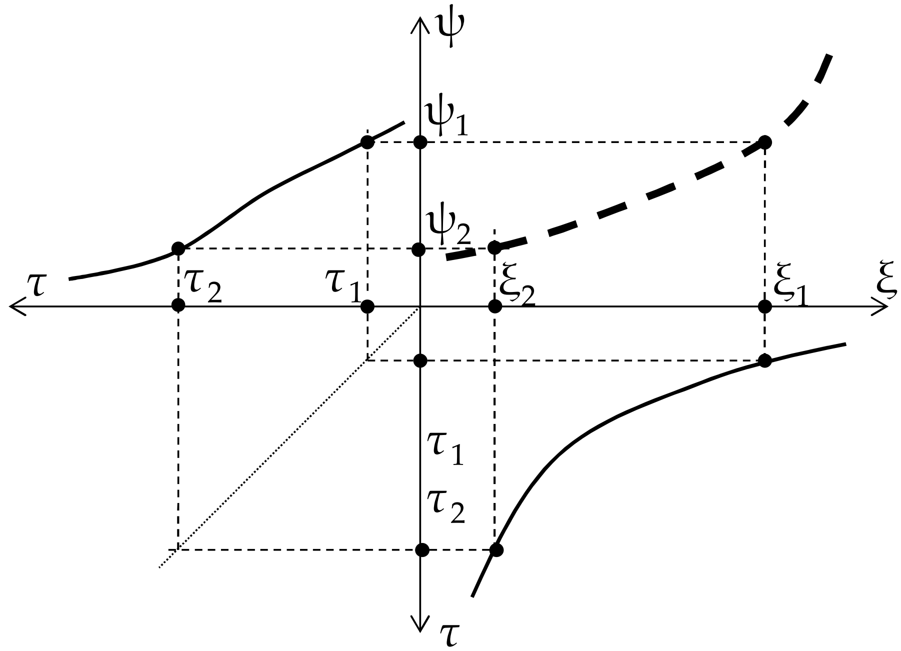
$$\frac{\partial \xi}{\partial \sigma} = \frac{(1-\eta) z\tau b\sigma^2 \left(\left(\frac{\sigma-2}{\sigma}\right)^2 + \left(1 - \frac{b}{z\tau}\right)(1-\eta)\right)}{\left(2\tau z(2(1-\sigma) + \sigma\eta) + b\sigma^2(1-\eta)\right)^2}$$

which is positive if $\tau > \frac{1-\eta}{\left(\frac{2-\sigma}{\sigma}\right)^2 + 1 - \eta}$, as assumed. □

In words, if the hospitals become more able to practice cream skimming, that is if σ increases, or if it becomes easier for patients to travel to the hospital of their choice, that is if τ decreases, then (i) the number of patients treated in the low cost hospital increases, and (ii) the proportion of its patients who are complex also increases.

Recall that σ and τ are not observable. They, however, can be left behind the scenes in the quest for the link between the variables of interest in this paper, namely the observable variables ξ, the number of patients treated in a hospital, and ψ, the proportion of these patients whose diagnosis is complex, both these variables

Figure 1:
The equilibrium patient mix.



Note: The relationship between ξ, the proportion of patients who are treated in a good hospital, and ψ, the proportion of these patients who are complex to treat, in the equilibrium of the model described in Section 2.1. The travel cost of patients, τ, a measure of their ability to choose hospital, is not observable.

measured relative to the baseline value they would have in the absence of choice by patients and hospitals. We do this in Figure 1, for τ, the unit travel cost for patients. To see how this diagram is built up, consider a given value of τ, say τ_1. Given the other parameters, the values of ξ and ψ associated to this value of τ, call them ξ_1 and ψ_1, are obtained by setting $\tau = \tau_1$ in (2) and (3) as shown in the south-east (ξ) and the north-west (ψ) diagrams. The slope of these relationships is determined in (1). ξ_1 and ψ_1 are the coordinates on the (ξ, ψ) cartesian space in the north-east quadrant of the values of these variables corresponding to τ_1, and must therefore lie on the $\psi(\xi)$ relation. Repeating the process for another value of τ, say $\tau = \tau_2$, determines another such point (ξ_2, ψ_2), and so on: the entire relation is traced by the range of feasible values of τ. The positively sloped relationship between ξ and

ψ illustrated in Figure 1 indicates a positive correlation between the number of patients treated, ξ, and the percentage of these patients who are more expensive to treat, ψ. Exactly the same argument would hold if we had factored out σ, the measure of cream skimming. To sum up, when choice increases, a low cost hospital treats more patients and more complex patients. Note that the correlation between ξ and ψ is spurious, as both are caused by the unobservable variables τ and σ. As we will see, while the data allows us to determine accurately the proportion of patients treated by a hospital relative to the potential pool, ξ, the other variable in the north-east quadrant of Figure 1, the proportion of the hospital's patients who are complex, is not observable. In the next section, therefore, we establish a positive link between the complexity of a patient's treatment, which is unobservable, and the reimbursement received by the hospital which treated her, which is instead observable, and thus we can define a testable link between variables measured in the data. This link is the one explored in the empirical analysis presented in Section 5.

2.2 The providers' problem

Section 2.1 establishes that, for a given DRG, more efficient hospitals, those whose cost of treating a complex patient does not exceed the payment they receive for the treatment, treat *more* of their fair share of patients needing this DRG; and also that they end up with a patient mix such that they have more "complex" patients than would be determined by the allocation that would emerge in the absence of patient choice and cream skimming, and consequently they have higher cost than they would with a patient mix reflecting population averages.

The question may therefore be asked as to why the health authority does not separate the exemplar DRG studied in Section 2 into two, a "standard DRG" and a "DRG with complications", with reimbursement that cover the cost of each, and give hospital the choice whether to offer one or both. This would provide better incentives, and does in fact happen to some extent in the Italian setting we study. To

Table 1:
The Lombardy DRG prospective payment system in 2013.

Variable	N	Mean	St.Dev.	Min	Max
Base refund for day treatment (€)	538	3133	7068	25	76,240
Refund for treatment with overnight stay (€)	538	5628	9221	428	101,344
Threshold for flat refund (days)	538	22.98	18.87	2	138
Refund per day exceeding the threshold (€)	538	238	171	45	1149

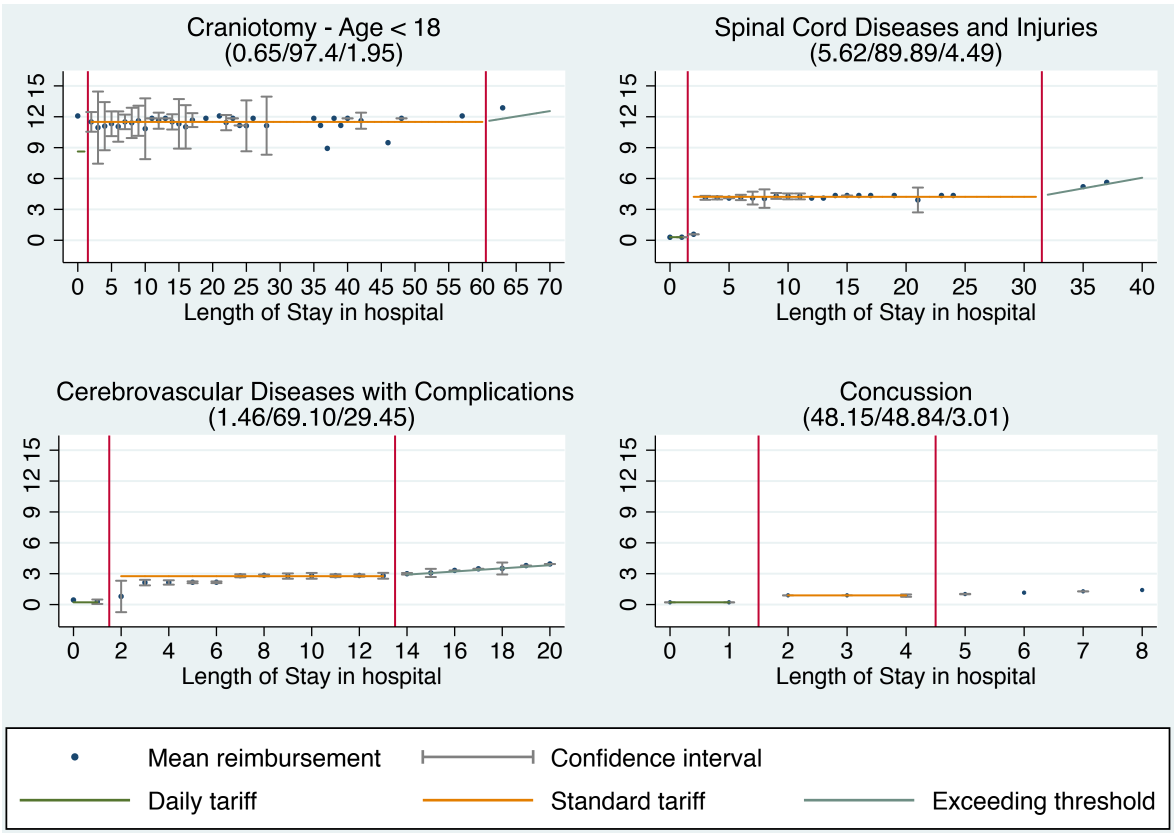
Note: Summary statistics for the parameters of the prospective payment system adopted by the Lombardy region in 2013 to reimburse hospitalisations completed in the region's hospitals and classified as one of the 538 DRGs of the system.

see how, it is necessary to look into some details of the system. Each hospitalisation is allocated on discharge to one of 538 DRGs, and in principle refunded according to a schedule characterised by four parameters. The first is the basic refund for treatments that require less than a 24-hour stay in the hospital. The second is a flat refund for hospitalisations that require up to a threshold number of overnight stays: this flat refund gives no incentives to keep patients in the hospital longer than it is necessary. This threshold is the third parameter. Hospitalisations that need to exceed the threshold are reimbursed according to a daily rate, which is the fourth parameter. Figure 2 describes these parameters for four DRGs. For example, DRG 3, a craniotomy on an under 18, determined in 2013 a reimbursement of €8,625.62 if the patient is discharged within 24 hours, of €11,501.49 if she stays less than 60 days, and an additional €329.33 *per day*, for stays exceeding 60 days. Analogously for the other DRGs. Aggregate descriptive statistics of these parameters[5] are collected in Table 1.

But not all craniotomies are equal. To capture the difference in complexity of treatment within each DRG, the health authority reimburses, in addition to the "base" tariff for a given DRG, supplementary amounts depending on the values of

[5]This system follows ICD-9-CM (1996), and defines 538 DRGs using (the Italian translation of) the 24th edition of the DRG classification. The baseline price for each DRG is revised regularly, reflecting information on hospitals' costs, perceived distortions or to influence the hospitals' overall supply.

Figure 2:
Lombardy's DRG Reimbursement Scheme.



Note: The reimbursement scheme for four DRGs in Lombardy, with the actual payments in 2013. In each panel, the horizontal axis measures the number of days spent in hospital, and the vertical axis the tariff and the average reimbursement measured in thousand of euros. The solid line is the baseline payment. This changes from one to two days, it remains constant up to a threshold, and it increases at a *per diem* rate beyond the threshold. The dots in correspondence of the integers values on the horizontal axes are the actual average reimbursements and the 95% confidence intervals. The second line in the title is the percentage of treatments that fell into the three groups (one day or less, up to the threshold, beyond the threshold).

some observable parameters, which reflect the probable complexity of the condition of the patient in question, pre-existing complicating conditions, comorbidities, age, sex, discharge status, and so on, and the characteristics of the particular treatment provided, such as use of special materials, details of the diagnosis, the adopted procedures, hospitalization settings, and so on. Divergence can occur also as a consequence of subsequent checks on the admission and treatment records, or if a patient is re-admitted within 40 days of discharge. They also reflect the overall cost and services provided by the hospital: for example, refunds to providers without an A&E (Accident and Emergency) department receive 3% less than the tariff, those with a "high intensity" A&E department receive 5% more. Each of the K possible combinations of all these factors can be summarised in a single score, κ_k, $k = 2, \ldots, K$, thus creating a parameter vector $(\kappa_1, \ldots, \kappa_K)$. The result of these additional payments is also shown in Figure 2, which reports, for each possible length of the hospital stay, the average actual reimbursement, and the 95% confidence interval around this average. The figures strongly suggest that, in practice, actual reimbursements for each DRG can differ considerably, even for treatments that require the same number of nights spent in hospital.

The process of differentiating treatments within the same DRG cannot however be pushed too far. There is a limit in the potential for describing each possible detail of every individual case. Typically, patients can differ in characteristics, general state of health, fitness, and so on, which a medical check-up would reveal with a reasonable degree of precision, but which are harder and too costly to measure or describe in detail *ex-ante*, and hence unsuitable as the basis of a formal contract or of an algorithm for the determination of the reimbursement for a given treatment.[6] We measure this set of unobservable characteristics with a single dimensional parameter, u, which varies continuously[7] in an interval $[\underline{u}, \overline{u}] \subset \mathbb{R}$. A higher value of u indicates the presence of many potential reasons to make treatment difficult, and so give more incentive to the hospital to try to "dump" such patients, either by refusing treatment or by more subtle discouragements.

[6]Consider for example the difference between BMI and "general health". Only the former can sensibly be included in a reimbursement formula: a significant premium for patients whose general health is classified as poor would give hospitals incentives to classify all patients in this category. The conceptual framework is therefore that provided by the literature on incomplete contracts (Hart, 1988 and Tirole, 1999).

[7]Thus we have u taking a continuum of values, and κ a discrete number of them. This reflects that facts that combinations of age and preconditions take one of a number of possible values, whereas unobservables are more nuanced, but different assumptions on the domain of the parameters κ and u would give similar results.

To model differences in a hospital's efficiency, we extend the simple binary classification of Section 2.1 and capture differences among hospitals with a more nuanced hospital-DRG specific parameter, $\gamma_t^h > 0$. We write provider h's cost of performing DRG t on a given patient with characteristics (u, κ) as

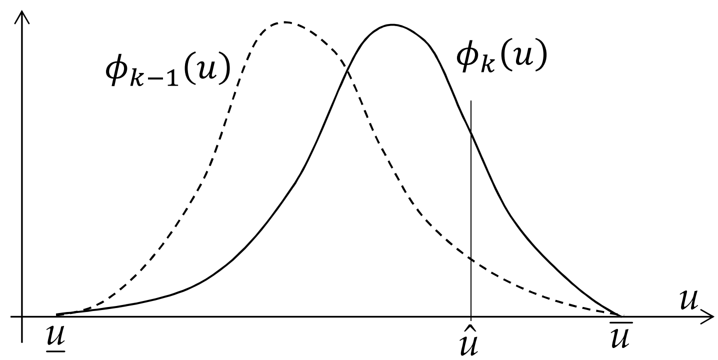
$$\gamma_t^h c^t (u, \kappa) . \tag{4}$$

Denoting partial derivatives with a subscript, we order u and κ so that $c_u^t (\cdot) > 0$ and $c_\kappa^t (\cdot) \geqslant 0$: higher values of u or κ indicate more expensive patients to treat. We assume $c_{uu}^t (\cdot) \geqslant 0$ and $c_{u\kappa}^t (\cdot) \geqslant 0$: the two sets of a patient's characteristics have similar effects on cost of provision. We also introduce the technical assumption that $c_{uu\kappa}^t (\cdot) \leqslant 0$: this suggests that the rate of increase in cost is "not too high", and could be replaced at the cost of greater algebraic complexity in the proof of Proposition 4.

While there are many examples of individuals with unfavourable observable characteristics who experience a smooth and trouble-free treatment in hospital, and vice versa, the existence seems plausible of a positive correlation between the observable and the unobservable characteristics: a patient with high κ is more likely to have high u. We capture this formally by positing that the distribution of u in $[\underline{u}, \overline{u}]$ depends on κ. Specifically, let $\Phi_k^h (u)$ be the distribution of u for patients in provider h characterised by the observable κ_k, with $\Phi_k^h (\underline{u}) = 0$, $\Phi_k^h (\overline{u}) = 1$ and density $\phi_k^h (u) = \Phi_k^{h\prime} (u)$. The superscript h indicates that different hospitals serve in general populations with different distributions of the unobservable characteristics, and the general equilibrium nature of the allocation of patients to hospitals make these distribution endogenously determined. The positive correlation between κ and u is captured formally as follows.

Assumption 1. *For every $k = 2, \ldots, K$, for every $h = 1, \ldots, H$, $\Phi_{k-1}^h (u) > \Phi_k^h (u)$ for $u \in (\underline{u}, \overline{u})$. That is $\Phi_k^h (u)$ first order stochastically dominates $\Phi_{k-1}^h (u)$.*

Figure 3:
First order stochastic dominance.



*N*ote: The dashed line is the density of patients with low cost observable characteristics (low κ); the solid line for higher κ patients. There are proportionally more patients with u below a given value among those in the low κ group.

In words, when the observable characteristics indicate higher cost of treatment, then it is more likely that the unobservable characteristics also push the cost up. This assumption is illustrated in Figure 3. This depicts the density function of u for two groups of patients with different levels of the observable characteristics, κ_{k-1} and κ_k, with $\kappa_{k-1} < \kappa_k$. Consider a certain level of "difficulty" for a given DRG, the level implied by the vertical line, drawn at the abscissa $\hat{u}$. As the picture shows, when κ takes the high value κ_k, which is bad news in terms of observable characteristics, there are more patients with a value of u worse, that is higher, than the threshold. Assumption 1 requires that this is true for every possible threshold.

We can now determine the solution to the provider's choice of the patients that it would like to admit. Consider a provider h with idiosyncratic cost parameters $\{\gamma_t^h\}_{t=1}^T$, faced with a set of unit payments, fixed at this stage, one set for each the different DRGs it can offer. There is no loss of generality in taking the case where $\sigma = 1$, that is where every patient can be dumped: when a hospital is unable to refuse admissions to some of its patients, then the cost of treating them is unavoidable and corresponds to a reduction in the available budget. Put differently, we concentrate on the discretionary subset of the potential patients treated by the hospital.

Let therefore

$$p_t(\kappa_k), \qquad k = 1, \ldots, K, \quad t \in T \tag{5}$$

denote the payment offered by the purchaser to its hospitals for carrying out DRG t when the severity of the observable variables is given by κ_k.

Importantly, the health authority also creates a link among all the DRGs offered by each provider by its requirement that the annual total payment received by a hospital for all the DRGs it offers should not exceed a maximum determined at the beginning of the year.[8] We denote this cap on the budget as P^h.

Proposition 3. *Let T be the set of DRGs provided by hospital h. Then hospital h treats patients characterised by parameters (u, κ_k) if and only if $u \leq u_{kt}^h$, where where u_{kt}^h is the solution to*

$$\frac{\gamma_t^h c_u^t(u, \kappa_k)}{1 + \lambda^h} = p_t(\kappa_k), \qquad k = 1, \ldots, K, \quad t \in T, \tag{6}$$

and λ^h is a Lagrange multiplier, whose value depends on the overall cap negotiated with the provider, P^h.

Proof. To lighten notation, we normalise the number of potential patients to 1 and the cost parameter correspondingly. Begin by noting that, if provider h decides to treat for DRG t n_{kt}^h patients with observable characteristics κ_k, then it will treat those with unobservable characteristics below u_{kt}^h, where u_{kt}^h satisfies

$$n_{kt}^h = \int_{\underline{u}}^{u_{kt}^h} \phi_k^h(u)\, du = \Phi_k^h\left(u_{kt}^h\right), \tag{7}$$

This is because, given that provider h observes the type of each patient and knows the overall distribution of the characteristics of the patients who require the treatment during the year, it can choose to treat only those with the most favourable characteristics, *viz* those

[8] Although this maximum, which differs noticeably from provider to provider, is not set in stone, as it may be renegotiated towards the end of the financial year, we proceed by writing hospital h maximisation problem when this constraint needs to be satisfied.

with $u \leqslant u_{kt}^h$.

Thus the problem of provider h can simply be stated as:

$$\max_{\left\{\left\{u_{kt}^h\right\}_{k=1}^K\right\}_{t=1}^T} \sum_{t=1}^T \sum_{k=1}^K \left(p_t\left(\kappa_k\right) \Phi_k^h\left(u_{kt}^h\right) - \int_{\underline{u}}^{u_{kt}^h} \gamma_t^h c^t\left(u, \kappa_k\right) \phi_k^h\left(u\right) du \right) \tag{8}$$
$$\text{s.t.: } \sum_{t=1}^T \sum_{k=1}^K p_t\left(\kappa_k\right) \Phi_k^h\left(u_{kt}^h\right) \leqslant P^h.$$

The proposition follows in a straightforward manner from solving problem (8). □

Recall that γ_t^h is the hospital h's cost parameter for DRG t. Total differentiation of (6) shows that $\frac{du_{kt}^h}{d\gamma_t^h} = -\frac{c_u^t(\cdot)}{\gamma c_{uu}^t(\cdot)} < 0$: as the efficiency of the provider increases, that is as its cost parameter γ_t^h decreases, it chooses to treat more patients, and hence it admits more difficult ones.

Using (7) in the proof of Proposition 3, the total number of patients treated in hospital h for DRG t is given by:

$$N_t^h = \sum_{k=1}^K \Phi_k^h\left(u_{kt}^h\right).$$

Analogously, if we let $\overline{p}_t^h$ be the average payment to hospital h for the treatments it performs under DRG t, $\overline{p}_t^h$ is given by

$$\overline{p}_t^h = \frac{\sum_{k=1}^K p_k \Phi_k\left(u_{kt}^h\right)}{\sum_{k=1}^K \Phi_k\left(u_{kt}^h\right)}, \tag{9}$$

2.3 The health authority's overall decision.

De Fraja (2000) studies the welfare maximising contract proposed by a purchaser to a single provider for a single DRG, for a specific κ. He shows that a purchaser will negotiate contracts with providers which are such that providers which accept to treat more patients will receive a higher payment per treatment. This to ensure that more efficient hospitals treat the more expensive patients. The extra payment needs to be finely tuned: high enough to induce efficient providers to accept "expensive" patients, while at the same time low enough to dissuade less efficient providers from pretending to be efficient and treating the "expensive" patients, who, for optimality, need to be treated at the more efficient hospitals. This feature of the optimal contract requires the price schedule designed by the health authority to satisfy the following plausible constraint.

$$\kappa_{k_1} > \kappa_{k_2} \quad \text{implies} \quad p_t\left(\kappa_{k_1}\right) > p_t\left(\kappa_{k_2}\right). \tag{10}$$

That is, the purchaser chooses prices, for each DRG, which increase with the severity of the observed characteristics κ.

We can now state and prove the main result of this section.

Proposition 4. *Let $K > 1$. (i) N_t^h decreases with γ, and (ii) for suitably chosen prices satisfying (10), $\overline{p}_t^h$ decreases with γ.*

Proof. Note that the solution to (6) depends on γ_t^h, which we make explicit in what follows by writing $u_{kt}^h = u_{kt}^h(\gamma)$. (i), the first part of the statement of the proposition, is established immediately by differentiation:

$$\frac{\partial N_t^h}{\partial \gamma} = \sum_{k=1}^{K} \phi_k^h\left(u_{kt}^h(\gamma)\right) \frac{\partial u_{kt}^h(\gamma)}{\partial \gamma} = -\sum_{k=1}^{K} \phi_k^h\left(u_{kt}^h(\gamma)\right) \frac{c_u(\cdot)}{\gamma_t^h c_{uu}(\cdot)} < 0.$$

Consider (ii) next. For future reference, we note that total differentiation yields

$$\frac{\partial}{\partial \kappa}\left(\frac{\mathrm{d}u_{kt}^h(\gamma)}{\mathrm{d}\gamma}\right) = \frac{-1}{\gamma_t^h c_{uu}(\cdot)}\left(c_{u\kappa}(\cdot) - \frac{c_u(\cdot)\, c_{uu\kappa}(\cdot)}{c_{uu}(\cdot)}\right). \tag{11}$$

This, given the technical assumption on $c_{uu\kappa}(\cdot)$, is negative.

We next proceed by induction on K, the number of possible observable types. We compact notation in the proof by omitting the subscripts t and k and the superscript h, and, when no confusion can arise, also the argument of the functions, as well as writing p_k as a shorthand for $p_t(\kappa_k)$. Finally, for clarity, we denote by $\overline{p}_x$ the value of (9) for $K = x$: that is, $\overline{p}_x$ is the average reimbursement for a typical DRG received by a typical hospital when the number of possible combinations of factors affecting the reimbursement is x. We begin by showing that the assert holds for $K = 2$. The algebraic section of the online appendix shows that developing (9) for $K = 2$, one obtains

$$\frac{\partial \overline{p}_2}{\partial \gamma} = \frac{(p_2 - p_1)\,\phi_2(\cdot)\,\phi_1(\cdot)}{(\Phi_1(\cdot) + \Phi_2(\cdot))^2}\left(\frac{\partial u_2}{\partial \gamma}\frac{\Phi_1(\cdot)}{\phi_1(\cdot)} - \frac{\partial u_1}{\partial \gamma}\frac{\Phi_2(\cdot)}{\phi_2(\cdot)}\right).$$

Now note that we have (i) $p_2 > p_1$ by (10), (ii) $\frac{\partial u_2}{\partial \gamma} < \frac{\partial u_1}{\partial \gamma} < 0$, from (11), and (iii) Lemma 1 in De Fraja (2016) shows that if Φ_2 first order stochastically dominates Φ_1, then $\frac{\Phi_1(\cdot)}{\phi_1(\cdot)} > \frac{\Phi_2(\cdot)}{\phi_2(\cdot)}$, so that the last term in the above is negative. Therefore, $\frac{\partial \overline{p}_2}{\partial \gamma} < 0$, which establishes the first step of the induction process. Next, assuming to have shown that the assert holds for $K-1$, we show that it holds also for K.

Write the average payment (9) as

$$\overline{p}_K = \frac{\sum_{k=1}^{K-1} p_k \Phi_k(\cdot) + p_K \Phi_K(\cdot) + \overline{p}_{K-1}\Phi_K(\cdot) - \overline{p}_{K-1}\Phi_K(\cdot)}{\sum_{k=1}^{K} \Phi_k(\cdot)}; \tag{12}$$

next, use the fact that

$$\overline{p}_{K-1} = \frac{\sum_{k=1}^{K-1} p_k \Phi_k(\cdot)}{\sum_{k=1}^{K-1} \Phi_k(\cdot)},$$

and so

$$\sum_{k=1}^{K-1} p_k \Phi_k(\cdot) = \overline{p}_{K-1} \sum_{k=1}^{K-1} \Phi_k(\cdot),$$

to write (12) as:

$$\overline{p}_K = \overline{p}_{K-1} + \frac{\left(p_K - \overline{p}_{K-1}\right)\Phi_K(\cdot)}{\sum_{k=1}^{K} \Phi_k(\cdot)}. \tag{13}$$

Now differentiate (we refer again to the online Appendix):

$$\begin{aligned}\frac{\partial \overline{p}_K}{\partial \gamma} =& \frac{\partial \overline{p}_{K-1}}{\partial \gamma}\left(1 - \frac{\Phi_K(\cdot)}{\sum_{k=1}^{K} \Phi_k(\cdot)}\right) + \\ & \frac{p_K - \overline{p}_{K-1}}{\left(\sum_{k=1}^{K} \Phi_k(\cdot)\right)^2} \sum_{k=1}^{K}\left(\frac{\partial u_K}{\partial \gamma}\frac{\Phi_k(\cdot)}{\phi_k(\cdot)} - \frac{\partial u_k}{\partial \gamma}\frac{\Phi_K(\cdot)}{\phi_K(\cdot)}\right)\phi_k(\cdot)\,\phi_K(\cdot).\end{aligned} \tag{14}$$

Recall that we have $\frac{\partial \overline{p}_{K-1}}{\partial \gamma} < 0$ by the induction hypothesis, and $p_K > \overline{p}_{K-1}$ by (10), the assumption that prices are increasing with κ; thus $\overline{p}_{K-1}$ is a weighted average of prices all lower than p_K. Next consider the terms in the sum: $\phi_k(\cdot)\,\phi_K(\cdot)$ are all positive. The same result on first order stochastic dominance used in the first step of the induction process shows that the terms in the brackets are all negative except when $k = K$, in which case it is 0. This shows that $\frac{\partial \overline{p}_K}{\partial \gamma} < 0$ and completes the proof. □

Thus, if a provider's patient mix is endogenous, then (i) more efficient hospitals treat more of their potential patients, and (ii) even though they are more efficient, they receive a higher average price per DRG: this is a consequence of their greater willingness to treat more expensive patients.

It is worth considering the empirical counterpart of Proposition 4. The unobservable hospital efficiency, γ_t^h, determines the variables σ and k, cream skimming and patients choice, also unobservable. These two variables together create an association between the attractiveness of the hospital to its "natural" patients, ψ, which is observable, and the average complexity of its patient mix, ξ, which is not. However, while ξ is not directly observable, Proposition 4 shows that, when there is correlation between u and κ, ξ is positively correlated with the reimbursement, which instead is directly observable. In other words, Proposition 4 can be summarised as showing that, for appropriately chosen prices that solve the purchaser's optimisation problem, *a higher proportion of patients treated is correlated with a higher average payment*. Given the rules imposing a constant payment for each DRG, this correlation, if it found to exist, must be caused by correlations with other variables, some observable, such age, sex, comorbidities, hospital size and the like, which can be controlled for, but others are unobservable and so are directly reflected in the reimbursement. This theoretical results informs the empirical analysis of this paper: the *unobserved* variable, the provider's relative efficiency in providing the different DRGs, is positively correlated to two *observable* variables, the proportion of the potential total number of treatments actually carried out and the average payment for this DRG.

3 The Data

Our data covers the universe of hospitalisations in 2013 in Lombardy, the largest region in Italy, and one of the wealthiest and best educated in Europe. Its population of 10 million makes it similar in size to Ohio or Portugal, with density as high as New Jersey's and the Netherlands'.

From around twenty-five years ago, a series of reforms fully devolved to the Italian regions the responsibility for the financing and the provision of health care, albeit with a national fund intended to mitigate regional differences. Lombardy was the first region fully to take advantage of these reforms: in 1997 it created a quasi-market for health care built on the pillars of (i) separation between the purchaser, Lombardy's regional government acting through its fifteen health authorities, and providers, the hospitals, (ii) competition between private and public providers, and (iii) patients' freedom to choose the hospital where they are treated (Brenna, 2011).

In 2013, the year of our data, healthcare in Lombardy was provided by around 200 hospitals, some public, some private for profit, others private not for profit, generating 1.5 million discharges per year at an overall cost of approximately €18 billion. The reimbursement to hospitals was based on a long established prospective payment system based on the Diagnosis Related Groups (DRGs).

Milan, the region's administrative, financial and cultural capital accounts for approximately 15% of the region's population, and correspondingly, does not monopolise health care provision, which is indeed available through a network of providers that cover the region's territory in the densely populated area south of the Alps. The map in Figure A1 in the Appendix, which depicts the location and size of hospitals in the region, illustrates this.

Our dataset, which covers the universe of all hospitalisations for the year 2013, is very rich in the information it contains. There is some demographic information on the patient, such as age, gender, referring physician, and municipality and postcode of residence. It also contains detailed information on the specific hospitalisation: the dates of admission and discharge, the portion of the schedule according to which the reimbursement was calculated, and of course the actual reimbursement paid to the provider. The clinical information included is the condition which caused the hospitalisation, the principal diagnosis, and up to five co-diagnoses. Similarly, we have information on the principal procedure provided to the patient and up to five secondary procedures. Both diagnoses and procedures are coded according to the internationally agreed classification of diseases (ICD-9-CM, 1996). Furthermore, our data reports whether a special-care unit was used, the wards in which the patient was cared for, and the DRG code assigned to the hospitalisation.

4 Econometric strategy

The theoretical analysis in Section 2 hinges around the idea that patients have a "natural" hospital for treatment, one that is, they would choose if they had no information whatsoever about the overall quality of the service they would receive should they seek admission at the hospital. If all patients were treated by their natural hospital, and if the matching of patients to their natural hospital were independent of the patients' characteristics observed by both the hospital and the health authority, then the average payment for a given DRG received by the various hospitals would be similar. However, as the theoretical analysis showed, to the extent that patients know something about the hospitals and in turn the hospitals know something about the patients which the data are unable to capture, the allocation of patients to hospitals is not random, but instead such that more difficult hospitalisations are more likely to occur in some hospitals than in others in a systematic way. As the theory section explains, we have an *unobserved variable*, the quality of the DRG in the hospital, which is correlated both with the hospital ability to attract patients and its willingness to treat them, *and* with the adjustments to the payment schedule determined by the idiosyncratic characteristics of a given hospitalisation, as set out in Assumption 1. Because of the strict link between the DRG and the payment explicit in the contract between purchaser and provider, any correlation we find between payment and attractiveness, after controlling for the observables, cannot be caused by an (average) causal link between patient-mix at DRG level and reimbursement for a given hospitalisation within DRG t at hospital h, for the simple reason that it is ruled out by the regional rules, and must therefore be explained by correlation with unobserved variables, consistently with the ideas and results of the theoretical analysis the structure of the payment system offered by the Lombardy region to its hospitals conducted in Section 2.

We look for this spurious correlation by estimating the following OLS regression for the rich administrative dataset described in Section 3.

$$p_{ith} = \rho A^{j}_{th} + \alpha a^{j}_{ith} + \boldsymbol{\beta}\mathbf{X}_{ith} + DRG_t + HOSP_h + WARD_w + GP_p + MONTH_m + \epsilon_{ith}. \tag{15}$$

While the estimation of (15) is a standard cross-section OLS with DRG, hospital, ward, referring physician, and month of admission fixed effects, care must be taken in the selection of the sample and in the construction of the variables, and this section explains in detail our approach in these respects. The dependent variable is straightforward: p_{ith} is the percentage deviation of the reimbursement paid to hospital h for hospitalisation i from the official tariff for DRG t: $\frac{\text{reimbursement}_{ith} - \text{tariff}_{it}}{\text{tariff}_{it}}$.

The coefficient of interest is that of the first variable on the right-hand side, A^{j}_{th}, a measure of what we may call the *attractiveness* of being treated by hospital h for DRG t. As we explain below, the superscript $j \in \{1, 2, 3, C\}$ identifies alternative plausible concepts according to which a hospital is classified as natural. The theoretical model predicts the coefficient ρ to be positive: a more "attractive" hospital is paid more. A^j_{th} is constructed from the second variable on the RHS, a^j_{ith}, which in turn measures the extent by which patients are treated by their "natural" hospitals. Following some of the literature on patients' choice and hospital competition (LeGrand, 2009, or Brekke et al., 2011 among many others), we base the determination of whether or not a hospital is "natural" on the relative location of the patient and all the region's hospitals which provide the DRG she needs (Kessler and McClellan, 2000). Thus, for every given hospitalisation, we divide all the hospitals offering the DRG for which the patient is hospitalised into two groups, the hospitals that are natural for the patient, and all the others. The variable a^j_{ith} (with a a mnemonic for "away") is a dummy that takes value 0 if hospitalisation i was of a patient treated for DRG t and resident in location ℓ was *not* in one of her natural hospitals. Thus $a^j_{ith} = 1$ means that hospitalisation i did *not* take place in a hospital which was natural for the hospitalised patient.

We turn now to these alternative concepts of being a natural hospital for a patient, indexed by $j \in \{1, 2, 3, C\}$. In the first and simplest case, there is only one natural hospital, and that is the one nearest to the patient among those, in the region, that offers DRG t. Distance is defined as the shortest road distance between the centroid of the intersection of the patient's municipality and postcode of residence.[9] Thus $a^1_{ith} = 1$ if there is a hospital other than h with a shorter road route than hospital h.[10] The next measure is the variable a^2_{ith}. This takes value 0 if the patient receives treatment in any hospital h in the nearest 10% of the region's hospitals which provide DRG t, and 1 otherwise: for example, if 85 hospitals pro-

[9]Postcodes and municipalities are both partitions of the region, but are not nested: there are postcodes that contain more than one municipality, and municipalities with many postcodes: their intersection, the finest residence information for the patient, partitions Lombardy into 1582 subareas.

[10]It could be argued that distance could be measured as travel time rather than miles. In our data, the two are highly correlated (0.955), which makes it somehow pointless to report both sets of results, which are anyway identical to a very high approximation.

vide DRG t, then the nearest nine are all natural for the location where the patient of hospitalisation i lives. Similarly, a^3_{ith} takes value 0 if hospital h is no further than 10% more than her nearest hospital where DRG t is available, and 1 otherwise. That is, if a patient's nearest hospital is 77km, then we deem natural all the hospitals which are up to 84.7km away from the location where the patient lives.[11]

The last concept of natural hospital, is the one we choose as our preferred specification. It diverges slightly from the consideration of distance, by combining it with the municipality of residence. We define a dummy a^C_{ith} (the superscript C stands for commune, or municipality) taking value 0 if hospitalisation i was in the hospital nearest to the patient hospitalised or if the hospital and the patient are in the same municipality. and 1 otherwise. Most municipalities have at most one hospital, and so for the patients resident in these, $a^C_{ith} = a^1_{ith}$. It is only for municipalities with more than one hospital offering DRG t that the two can be different. These tend to be the larger towns and cities, where the local transport system and road network may suggest that distance is not the best proxy for convenience, and where travel by car may not be the preferred way for patient to travel to the hospital, with bus and underground routes and timetables more likely to determine convenience for patients living there.

The variable a^j_{ith} constructed, we can now define the main variable of interest, namely A^j_{th}, the attractiveness of hospital h for DRG t. A hospital is attractive if *local residents are treated by it*. We therefore build our measure of attractiveness A^j_{th} using information on the hospital which treated the patients needing DRG t whose natural hospital is h. The general formula we use is defined according to the potential

[11]For both a^2_{ith} and a^3_{ith} we have also considered different numerical thresholds: for example, we have set $a^2_{ith} = 0$ if the hospital where the hospitalisation took place was in the nearest 15%, 20%, 25%, and 30% of the region's hospitals which provide DRG t, and $a^2_{ith} = 1$ otherwise. Conversely, we have set $a^3_{ith} = 0$ if the patient was treated in a hospital that was no further than 20%, 30%, 40%, and 50% more than her nearest hospital which provides DRG t. None of the regression results are altered in a significant way.

Table 2:
Summary statistics

Variable	Daily mean	Daily sd	Standard mean	Standard sd	Extra Treshold mean	Extra Treshold sd
Reimbursement in €	1,472.36	1,364.81	3,645.31	4,172.49	7,555.23	12,974.01
% Deviation from tariff	0.061	0.463	0.034	0.184	0.033	0.191
Far from hospital dummy: a^1	0.420	0.494	0.506	0.500	0.542	0.498
Far from hospital dummy: a^2	0.800	0.400	0.857	0.350	0.870	0.337
Far from hospital dummy: a^3	0.483	0.500	0.569	0.495	0.603	0.489
Far from hospital dummy: a^C	0.478	0.500	0.550	0.497	0.601	0.490
DRG attractiveness measure A^1	0.201	0.401	0.142	0.349	0.131	0.336
DRG attractiveness measure A^2	0.516	0.499	0.431	0.495	0.397	0.489
DRG attractiveness measure A^3	0.468	0.499	0.382	0.486	0.356	0.478
DRG attractiveness measure A^C	0.581	0.493	0.493	0.499	0.457	0.498
Length of hospital stay (normalised)	0.810	0.391	0.28	0.25	1.93	1.42
Age of patient	48.91	23.70	53.54	26.95	60.38	24.33
Female patient	0.465	0.499	0.535	0.499	0.559	0.496
DRG reputation index	0.089	0.110	0.073	0.103	0.061	0.078
Emergency admission	0.022	0.147	0.069	0.254	0.107	0.309
At least one comorbidity	0.155	0.362	0.369	0.482	0.521	0.499
DRG size in hospital×hospital	16.35	36.70	58.99	119.04	7.19	16.52
Ward externality	0.012	0.039	0.010	0.037	0.007	0.026
No. of DRG offered by hospital	57.41	56.78	82.79	82.68	52.77	61.39
Death within 30 days	0.036	0.185	0.040	0.196	0.102	0.302
Transfer to extra wards	0.010	0.100	0.038	0.192	0.138	0.344
Number of observations	131,499		698,549		51,669	

Note: Summary statistics of the dataset used in the regression. See main text for explanation of the definition and the construction of the variables, and for the observations excluded from the dataset.

demand of patients:

$$A_{th}^{j} = \frac{N_{th}^{jc}}{N_{th}^{jp}} \qquad j = 1, 2, 3, C. \tag{16}$$

In (16), the denominator N_{th}^{jp} is the number of discharges that would take place for DRG t in hospital h if patients had no quality related preference and if all hospitals treated all the patients that turn up at the door needing a treatment for DRG t. This is calculated as the count of the hospitalisations for DRG t that would determine a value $a_{ith}^{j} = 0$ if it had taken place at hospital h. For measures which allow for multiple natural hospitals, we assume that patients choose randomly, and so a hospital-

Table 3:
Correlations between measures of "natural hospital" and of "attractiveness"

	a^1	a^2	a^3	a^C
a^1	1			
a^2	0.569***	1		
a^3	0.655***	0.932***	1	
a^C	0.587***	0.775***	0.717***	1

	A^1	A^2	A^3	A^C
A^1	1			
A^2	0.464***	1		
A^3	0.497***	0.907***	1	
A^C	0.417***	0.881***	0.799***	1

Pairwise correlations	
A^1-a^1	-002
A^2-a^2	0.104***
A^3-a^3	0.053***
A^C-a^C	0.178***

Note: *** $p \leqslant 0.01$. Correlations between the variable measuring whether a patient is treated by their "natural" hospital, a^j, and the attractiveness of the hospital where they are treated, A^j, $j = 1, 2, 3, C$. See the text for the definition of the various measure

isation with N local hospitals adds $\frac{1}{N}$ to the count. Thus N_{th}^{jp} is hospital h's potential demand for DRG t, hence the superscript p. Conversely, the numerator N_{th}^{jc} is the number of the patients in the set of those that form the denominator who have been treated at hospital h for DRG t. Their ratio, A_{th}^{j} in (16), thus measures the percentage of the potential local demand for DRG t directed to hospital h that is in fact treated in hospital h.

While there is a mechanical link among the four variants of these two variables, a_{ith}^{j} and A_{th}^{j}, for example $a_{ith}^{1} = 0$ implies $a_{ith}^{j} = 0$ for $j = 2, 3, c$, the correlations among them are not very high, as shown by the summary statistics table, Table 2, and by Table 3 which reports the correlations between four versions of the dummy "away", on the LHS, and of the hospital's attractiveness, on the RHS. The lower part of the table, which reports the pairwise correlation between $a_{ith}^{j} = 0$ and $A_{th}^{j} = 0$, shows the lack of mechanical correlation, even though one variable is constructed from the values of the other.

The vector $\mathbf{X}_{ith}$ contains the other covariates we control for. At the hospitalisation level, we include the gender of the patient and their age, squared to account for possible non-linearities, with young and elderly patients potentially more complex, and the length of their hospital stay, the difference between the day of admission and the day of discharge.[12] To account for the very wide differences between the normal required stay for different procedure, illustrated by Table 1 and Figure 2 we normalise it as the ratio between the number of days in hospital and the "standard treatment" threshold for that DRG. This threshold is 60 days for a craniotomy on a young patient, and so a hospitalisation for a craniotomy which requires 37 nights in hospital would be classified as having a length of stay of $37/60 = 0.616$.

We include a dummy indicating an emergency admission: although in most cases patients and their family may not have much choice as to which hospital they are admitted following an emergency, ambulance drivers and other medical personnel serving emergency are directed by hospitals as to the suitability of a given patient being admitted: thus, even for emergencies, the link between the patient's and the hospital's location is not inflexible. As one would expect, this variable is highly concentrated in some DRGs, with 12 of them have over 90% of the admissions classified as emergencies, and around 2/3 having less than 1% emergency admissions.

We also include a measure of the reputation of DRG t in hospital h. To construct it we exploit the freedom patients have to choose a provider outside their region of residence.[13] We define the reputation of DRG t in hospital h, q_t^h, as the percentage of hospitalisations of patients who are resident outside Lombardy. This captures the idea that patients who travel from outside the region to be treated for a given DRG in Lombardy are approximately equidistant from all the hospitals in the region, and so will choose them only of the basis of what they perceive to be the likely quality

[12]Which is therefore subject to a measurement error, as would be the case for a patient admitted at 11pm and discharged at 1am the next day being recorded as an overnight stay.

[13]In 2013, almost one tenth of the discharges were from patients not resident in Lombardy. When a patient from outside the region is treated by a Lombard provider the latter is normally refunded on a national scale of charges by the region (or country) of residence of the patient treated.

of service they will receive.[14]

This measure of reputation clearly takes the same value for all hospitalisations in for DRG t in hospital h. It assumes that patients outside the region have some knowledge which allows them to assess the quality of the DRG they need. One may argue that knowledge may be more generic: it stands to reason that *cardiology* in a certain hospital may have a good reputation, without the public being au fait with the performance of each the various specific DRGs which require the cardiology ward. In other words there is a reputation externality bestowed by the wards which are involved in the delivery of the treatment required for hospitalisation i, which we also measure using the proportion of hospitalisations of patients coming from outside the region. The data record up to four wards where a patient has been admitted in the course of the hospitalisation. Because each hospitalisation may need different wards, this is not necessarily the same for all hospitalisations for DRG t in hospital h. In detail, to construct this *ward externality index* for hospitalisation i, we proceed as follows. Let $\mathcal{W}_h$ be the set of the wards in hospital h, and let them be indexed by w. Let d^h_{with} be the number of days spent by the patient in ward w during hospitalisation i, which took place in hospital h and was refunded according to DRG t. The reputation of this stay is q_{th}, obtained as described above as the proportion of the patients treated by hospital h for DRG t who are residents outside Lombardy. The reputation of ward w in hospital h is the average reputation of the DRGs that went through ward w, with weights the number of days:

$$q_{wh} = \frac{\sum_{i \in I_{th}} d_{with} q_{th}}{\sum_{i \in I_{th}} d_{with}},$$

where I_{th} is the set of hospitalisation for DRG t in hospital h. Now the reputation of

[14] Of course patients living just outside the regions border may seek admission to a hospital in Lombardy precisely because it is the most convenient for them. We run regression including a dummy for hospitals near the border, but neither on its own nor interacted with the quality measure, it had any effect on the results.

the wards for hospitalisation i is simply:

$$Q_{ith} = \frac{\sum_{w \in \mathcal{W}_h} d_{with} q_{wh}}{\sum_{w \in \mathcal{W}_h} d_{with}}.$$

Notice of course that the number of days spent in most wards is 0, given that only up to four wards are reported in the data.

The very fact of requiring transfers to different wards might be an indication of complications, whether expected or unexpected, which may increase the reimbursement. We therefore include one categorical variable which takes value 1 if the given admission has involved transfers to additional wards. The number of patients treated for DRG t in hospital h in the year may be correlated with the "experience" of the medical teams, and thus also influence the hospital's willingness to take more difficult patients and the patients' desire to be treated there. This is the variable *DRG size in hospital*. We measure this both in absolute terms and as the ratio to the total number in the region, with no difference in results.

We use the information on the clinical diagnoses coded in the data to include the complete set of comorbidity measures obtained applying the Elixhauser algorithm (Elixhauser et al., 1998). This algorithm produces 30 dummies, each for a specific comorbidity, such as "obesity", "cardiac arrhythmias", "uncomplicated hypertension" and so on. Summary statistics for these comorbidities are in the appendix together with the estimated coefficients in our preferred specification. Finally, we include in the specification in (15) a set of fixed effects to control for other possible sources of spurious correlation between p and A, such as, for example, different level of general health in the various provinces of Lombardy, different propensity to refer patients by different general practitioners, or different overall efficiency in different hospitals. Fixed effects at the DRG level capture the obvious differences between clinical conditions grouped in each DRG. There might be relevant characteristics of the hospital which affect the reimbursement:

this unobserved heterogeneity is captured by the hospital fixed effect. We also include ward fixed effects, to account for differences in the variability of the refund correlated to the specialism. The socio-economic conditions of the patients can also affect the complexity of treating them. While we have no specific information about these, the municipality where a patient lives and the referring physician, are likely to be highly correlated with a person's socio-economic background: in the small municipalities population is fairly homogeneous, and in the larger ones, anecdotal evidence indicates that physicians tend to serve patients of similar location and social class. Together, these two variables afford considerable granularity, given that we have 8,877 different physicians and 1,544 municipalities. Approximately 10% of the hospitalisations do not report the information about the referring physician;[15] for these, we impute the physician using information on the patient's municipality and postcode. Table A3 in the Appendix confirms that using alternative procedures to proxy information about the patient socio-economic background, or omitting observations where the referring physician is missing leaves all results effectively unchanged.

The final sample for most regressions is obtained from the universe of the hospitalisations in Lombardy in 2013 which were refunded on the standard tariff, that is excluding daily hospitalisations and those exceeding the threshold We also exclude hospitalisations of patients not residing in Lombardy and all those younger than 2 years: the justification for the latter is that neonatal cases are subject to different sources of variation, and are best excluded; changing the cut-off age does not change the results. Finally, the month of admission may account for different admission policies by the hospital as the end of the financial year approaches and the likely importance of the budget constraint becomes better known to the hospital.

[15]One may think that these missing values might be concentrated in emergency admissions. This however is not the case 10.1% versus 11.45% for emergency ones.

5 Results

Our main results are reported in Table 4. This reports the estimates obtained using our preferred indicators for the attractiveness of the hospital and for the categorical variable that indicates whether the patient is local, A^C and a^C respectively, and on the other covariates and fixed effects discussed in the previous section.

We begin with Column (1). It shows the results of a baseline model which includes only the hospital's attractiveness and the "away" dummy, and controls for the DRG, the hospital, the ward, and the month of admission fixed effects. Here the attractiveness of the hospital where a given DRG is performed does not have a statistically significant effect on the reimbursement; instead, less is refunded for patients who are not "local" to the hospital.

In the second column of Table 4, we include the patients and DRG covariates, including the dummies for the comorbidities; in the third we add the demographic fixed effects, as the combination of the fixed effect for the referring physician and the municipality of residence as explained at the end of Section 4. The quantitative differences between columns (2) and (3) are negligible, suggesting that differences in socio-demographic characteristics of the patient are captured by the other covariates. Comparing these to column (1), show that the inclusion of controls for comorbidities in the regressions is necessary for a correct specification: many are statistically significant, and the signs of the coefficients for A^C and a^C change: the effect of the "away" dummy disappears, and the coefficient of interest, the attractiveness of the hospital, reported in the first row, acquires statistical significance and has the expected sign. To get a handle on the coefficient for A^C in our preferred specification, column (3), consider a patient treated at the average DRG-hospital. Suppose this hospital became one standard deviation more attractive, then the reimbursement for the treatment received by the hospital would increase by 1.84%. This is a considerable effect, given that the system is based on the principle that all

Table 4:
Reimbursent for hospitalisations.

Dependant variable % Δ tariff	(1) No Controls	(2) Controls	(3) + GP FE	(4) Emerg.	(5) Daily	(6) No Profit	(7) Priv. Profit	(8) Public
DRG attractiveness, A^C	0.0048	0.0187***	0.0184***	0.0112	0.0140***	0.0291	0.0233*	0.0139**
	0.005	0.006	0.006	0.008	0.005	0.022	0.014	0.006
Far from hospital, a^C	-0.0022***	-0.0006	-0.0005	0.0003	0.0000	-0.0007	0.0002	-0.0005
	0.001	0.001	0.001	0.001	0.000	0.002	0.001	0.001
Length of hospital stay		0.2136***	0.2135***	0.1119***	0.0018	0.2268***	0.2310***	0.2102***
		0.007	0.007	0.006	0.003	0.031	0.014	0.007
Age of patient		0.0003***	0.0003***	0.0008**	0.0003***	-0.0003	0.0004	0.0003***
		0.000	0.000	0.000	0.000	0.000	0.000	0.000
Age^2		-0.0013*	-0.0010	-0.0054**	-0.0025**	0.0042	-0.0031	-0.0012
		0.001	0.001	0.002	0.001	0.003	0.002	0.001
Female patient		0.0029***	0.0030***	0.0021*	-0.0008	0.0029	0.0031***	0.0030***
		0.001	0.001	0.001	0.001	0.002	0.001	0.001
DRG reputation		-0.0037	-0.0029	0.0332	-0.0064	0.0525	0.0103	-0.0213
		0.016	0.015	0.036	0.012	0.045	0.023	0.024
Emergency admission		0.0283***	0.0282***		0.0388***	0.0517***	0.0428***	0.0227***
		0.003	0.003		0.005	0.014	0.010	0.003
DRG size in hospital		-0.0327***	-0.0326***	-0.0287	-0.0254	-0.1071	-0.0178	-0.0292**
		0.012	0.012	0.021	0.021	0.068	0.045	0.012
Ward externality		-0.0115	-0.0092	-0.1486	0.1547***	0.1737	0.0031	-0.0940
		0.045	0.045	0.096	0.057	0.159	0.041	0.062
Patient transferred		0.0025	0.0025	0.0006	0.0638***	0.0048	0.0012	0.0016
		0.003	0.003	0.002	0.006	0.006	0.004	0.003
Fixed Effects Included								
Comorbidities FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Referring GP FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	686,357	686,357	686,089	46,769	127,128	58,715	100,673	524,480
R-squared	0.274	0.337	0.347	0.405	0.971	0.468	0.439	0.343

Note: ***$p \leqslant 0.01$, **$p \leqslant 0.05$, *$p \leqslant 0.1$. Estimation of (15). Column (1) includes only the attractiveness of the hospital for the DRG, and the dummy for for patient living away from the hospital, as well as DRG, hospital, ward, and month of admission fixed effects. The second column adds clinical characteristics of the hospitalisation. Column (3) adds the residence and physician fixed effects. Column (4) is the sample of the hospitalisations classified as emergencies. The same regression is run in column (5) for the sample of the hospitalisations refunded on the "no overnight stay" tariff. Columns (6)-(8) split the main sample by hospital type (private not for profit, private for profit and publicly owned hospitals). In these columns the sample is hospitalisations which were refunded with the standard payment. In all columns, standard errors are clustered at hospital times DRG level.

treatments for a given DRG are reimbursed at the same rate. The positive sign of the attractiveness coefficient suggests that hospitals which are "better" at attracting and admitting local patients are refunded more, which, our theoretical analysis suggests, could be on the basis on a formula which corrects the fixed DRG payment by guaranteeing a higher reimbursement for patients whose observable conditions are positively correlated with unobservable factors that make treatment more complex and hence more costly.

The coefficients for most of the other covariates are all plausible. Reimbursement increases with the length of the hospital stay: recall that this is due only to the greater complexity of hospitalisations requiring a longer stay, as the estimations are conducted on hospitalisations whose reimbursement is independent of the length of the hospital stay. Older and female patients appear to determine a higher reimbursement. The DRG and wards specific reputation measures have no additional explanatory power once we control for the hospital, the quality of health care provision is fully captured. On the other hand hospitals that perform more treatments for a given DRG appear to be reimbursed less on average, as indicated by the negative sign for *DRG size in hospital*. This could be rationalised by a combination of specialist hospitals concentrating on fewer but more difficult cases and learning by doing in larger hospitals, which can probably better match treatments patients and personnel. The effects of transfers is small and not statistically significant, suggesting that the likely higher complexity of cases where the patient is transferred to another ward is fully captured by other observable variables. Emergency admissions, unsurprisingly, cost more, an effect no doubt partly due to the adjustment to reimbursement according to the type of A&E services available in the hospital, as explained in Section 2.2.

Emergency admissions are further studied in Column (4). It provides an indirect confirmation that our explanation of the positive coefficient for the attractiveness of the hospital in column (3), our preferred specification, by suggesting that where cream skimming and patient choice are less likely to be an influential determinant of the patient mix, then a hospital's ability to attract its local patient is unable to explain differences in the reimbursement received by the hospital, which the lack of statistical significance for A^{C}_{ith} suggests to be the case. See also column (4) in Table A4 in the Appendix, which reports the results obtained running the main regression on the sample of the non-emergency hospitalisations only: results are qualitatively unchanged.

Column (5) repeats the analysis for the hospitalisations that are refunded on the "day" hospital schedule, which account for about 15% of the total. Some of these do involve an overnight stay, as it would be the case where the patient is admitted the day prior to that arranged for the procedure, and so the length of stay variable must be interpreted as a dummy for night stay. In many cases, there are morning and afternoon shifts for some simple procedures, which nevertheless requires a few hours preparation: the "morning" patients may be admitted the evening before, and discharged at lunchtime, the afternoon ones may be admitted in the morning and discharged at the end of the afternoon. Note that if this were the case, and if the allocation to morning and afternoon shifts were random, the *length of stay* dummy would not be statistically significant, which we find to be the case in our sample. The attractiveness of the hospital does instead affect the reimbursement just as for normal hospitalisations: thus, as we suggest in Section 4 there is some flexibility even for daily hospitalisation. Some of the other covariates differ from their corresponding values in column (3), notably those for emergency admissions, which however are only 2.2% of the total for this category, and for the ward externality.

The last three columns of Table 4 split the sample of column (3) into the three subsamples defined by ownership of the hospital, whether public or private, and, for the latter, according to whether or not it may distribute profits. In other environments these type of institutions have been shown to pursuit different admission or discharge practices (for example Bayindir, 2012, Eliason et al., 2018). Results indicate that reimbursements to "for profit" hospitals are more responsive to attractiveness than reimbursements to public hospitals. Not-for-profit hospitals instead seem to command reimbursements unrelated to their ability to attract their natural patients.

Table 5 contains a set of robustness tests; more are in the Appendix. Its first three columns show that the choice of our measure for a "natural" hospital does not affect the results in any qualitative way. They report the estimated coefficients for the same specification as in column (3) in Table 4, but with the other three measures of the natural hospital for a patient, a^1-a^3, as discussed above, in Section 4: natural hospitals being respectively the nearest, any that is among the 10% nearest hospitals, and any that is at most 10% further away than the nearest. All the reported coefficients are not statistically significantly different from each other.

Column (4) in the Table replace the percentage deviation of the reimbursement from the tariff with the log of the reimbursement as the dependent variable. There is a marked increase in R^2. The reason is that much of the variability in the reimbursement is due to the DRG which determines it. To gain some intuition, consider the extreme case where all hospitalisations are reimbursed exactly according to the tariff, with just a minuscule homoschedastic random error in each reimbursement. When the LHS variable is $\log\left(p_{it}^h\right)$, the R^2 would clearly be very close to 1, as all the variation in payments would be due to differences in the DRG tariff, and so fully accounted for by the DRG fixed effect. By the same token, when the dependent variable is the percentage deviation form the tariff all the variation is due to the random error, and the R^2 would be effectively 0. As it happens, R^2 when the DRG fixed effects are the only explanatory variables is 0.879 when the LHS variable is $\log\left(p_{it}^h\right)$, and 0.213 when it is the percentage deviation; this last figure

Table 5:
Robustness: changes in the construction of variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	%Δ tariff	%Δ tariff	%Δ tariff	$\log(Y)$	%Δ tariff	%Δ tariff
Location of "natural" patient	$j=1$	$j=2$	$j=3$	$j=C$	Medical	Surgical
DRG attractiveness, A^j	0.0194***	0.0182***	0.0278***	0.0258***	0.0064	0.0208**
	0.006	0.005	0.007	0.008	0.006	0.008
Far from hospital, a^j	-0.0008	-0.0000	-0.0004	-0.0027***	-0.0016**	0.0005
	0.001	0.001	0.001	0.001	0.001	0.001
Length of hospital stay	0.2135***	0.2134***	0.2136***	0.3600***	0.2815***	0.0714***
	0.007	0.007	0.007	0.011	0.011	0.005
Age of patient	0.0003***	0.0003***	0.0003***	0.0004***	0.0004***	0.0002*
	0.000	0.000	0.000	0.000	0.000	0.000
Age^2	-0.0010	-0.0010	-0.0010	-0.0012	0.0001	-0.0026***
	0.001	0.001	0.001	0.001	0.001	0.001
Female patient	0.0030***	0.0030***	0.0030***	0.0050***	0.0028***	0.0024***
	0.001	0.001	0.001	0.001	0.001	0.001
DRG reputation	-0.0062	-0.0052	-0.0077	-0.0194	-0.0570***	0.0013
	0.016	0.016	0.016	0.022	0.019	0.022
Emergency admission	0.0283***	0.0282***	0.0283***	0.0362***	0.0244***	0.0410***
	0.003	0.003	0.003	0.005	0.003	0.005
DRG size in hospital	-0.0287**	-0.0287**	-0.0322***	-0.0515**	-0.0253*	-0.0061
	0.011	0.011	0.011	0.021	0.014	0.028
Ward externality	-0.0070	-0.0091	-0.0075	-0.0381	-0.0868**	0.0636
	0.045	0.045	0.045	0.049	0.044	0.060
Patient transferred	0.0026	0.0025	0.0026	-0.0001	0.0126***	0.0124***
	0.003	0.003	0.003	0.003	0.004	0.003
Observations	686,089	686,089	686,089	686,056	418,017	267,177
R-squared	0.347	0.347	0.347	0.896	0.361	0.403

Note: $^{***}p \leqslant 0.01$, $^{**}p \leqslant 0.05$, $^{*}p \leqslant 0.1$. Columns (1)-(3) differ from the baseline specification (Column (3) in Table 4) only in the measures for attractiveness and the "far from hospital" dummy, which are computed according to A^i and a^i, with $i = 1, 2, 3$. Column (4) is the same specification but with the dependent variable given by the log of the reimbursement, instead of the percentage deviation from the tariff. Columns (5) and (6) consider the two subsamples of hospitalisations classified as medical and surgery. Comorbidity, DRG, hospital, ward, and month of admission fixed effects included in all columns.

suggest that DRGs differ somewhat in their propensity to require deviations form the contractual tariff. Thus the variable of interest, the DRG attractiveness at the hospital, and the other controls increase the R^2 from what is explained starting point value obtained in the DRG fixed effects only regression. All the coefficients in column (4) are similar to those in column (3) in Table 4, except for the dummy indicating a patient living far from the hospital.[16]

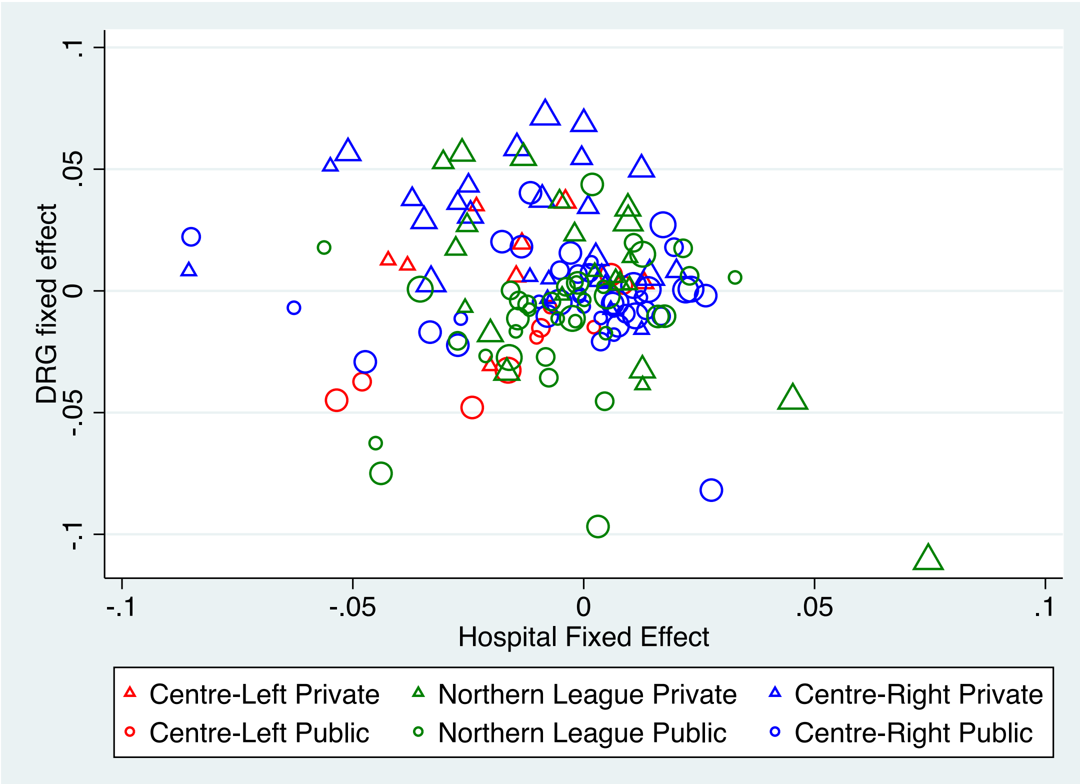
The last two columns in Table 5 split the sample in medical and surgical DRG. The comparison between them and our main regression highlights how the effect is mainly driven by the latter, with the coefficient for attractiveness losing statistical significance in the subsample of medical DRGs. This suggests greater importance of cream skimming and patient choice in hospitalisations involving surgery.

Further robustness tests are reported in the Appendix: in Table A3, we show that capturing demographic and socio-economic background with different combinations of location and referring physician fixed effect does not affect our results. Table A4 modifies the sample to account for the possibility of different reimbursements patterns for the patients who die during or immediately after the hospitalisation, to include the hospitalisation whose length exceeded the threshold, and to exclude the emergency admission. None of these changes in the sample changes the results compared to the main regression.

We end the paper by hinting at a possible way to study whether the negotiation between hospitals and the regional authority is affected by political pressure. One can imagine an environment model where local politicians try to influence the amount of funds that their local hospital receives from the regional centre. To do so, they might utilise their more precise information of local conditions to influence the minute details of the reimbursement rules, namely the extra-payments associated with the various κ_k in Section 2.2. Thus, for example, if in a given province the

[16]The sign of this coefficient has two possible explanations, compatible with each other, and in line with the theoretical analysis of Section 2.1. Some patients go to the local hospital irrespective of their health status: the model predict that they will be admitted with probability $(1-\sigma)$: thus the average unobservable complexity, and consequently the reimbursement, is higher for local patients. Alongside this "patient choice" explanation, a similar one could come from a "cream-skimming" perspective. Hospitals maybe more reluctant to dump local patients, who, for example, are just above the threshold for admission: it seems unfair (and inefficient) to force them to travel a long distance, and to make it difficult for relatives to visit. This "unselfish" decision would be unnecessary for a patient who is anyway travelling from afar. That is, when a patient is near the admission threshold, the hospital would only try to dump those who are not local. That this happens when the dependent variable is the log of the reimbursement suggest that this effect is more likely to be at work for more expensive, hence more serious, treatments.

Figure 4:
Fixed effect and political colour.



Note: Hospital fixed effect (horizontal axis) and average DRG fixed effect for the DRGS provided by the hospital (vertical axis) for hospital located in areas with different parties enjoying political control. The size of the symbol indicates the size of the hospital.

local politician knew that its constituents are more likely than the regional average to suffer from diabetes, they might try to convince those negotiating the contract to give higher adjustments to the tariffs for the DRGs whose patients are more likely to be affected by diabetes, and, if the politician in charge at regional level is in the same party as the provincial politician, would also be more likely to succeed. This extra payment would be obviously captured by the diabetes comorbidity dummy and, if the postulated political pressure is effective, would also be reflected in the hospital fixed effect and in the DRG fixed effects for the DRG offered by the hospital. Figure 4 illustrates the outcome of this simple exercise. It plots the hospital fixed effects of the various hospitals and the average fixed effects of the DRG they offer on the axes, together with the quartile of the revenue distribution in the region's hospitals, measured by the size of the symbol, whether they are public (circles) or private (triangle), and finally according to the party which governed the province where the hospital is located, a centre-left coalition, the regional Northern League, and a centre-right coalition.

We have also run two very simple regressions, where the fixed effects are estimated from dummies indicating the party in power, as well as the quartile size dummies. The idea is that those hospitals located in provinces controlled by the centre-right, the same parties which run the region at the time of the contract negotiation, namely the second half of 2012, should benefit form higher reimbursements, other things equal, either because of more "generosity" towards the hospitals, or towards the combinations of DRG offered by the hospital. These are the estimations:

$$FH_h^H = -\underset{.0049}{.006} - \underset{.0049}{.004}CR_h - \underset{.0072}{.0024}CL_h + \varepsilon_h, \tag{17}$$

$$FH_h^{DRG} = -\underset{.006}{.011} + \underset{.006}{.015}^{***}CR_h - \underset{.0088}{.0133}CL_h + \varepsilon_h. \tag{18}$$

In the above CR_h and CL_h are dummies taking value 1 if hospital h is in a province controlled by the centre-right (respectively centre-left) coalition, and the error term contains also size dummies. There is in (18) a hint of a slightly higher payment for DRGs that were more prevalent in hospitals in province controlled by the same coalition as the region, whereas the reimbursement to hospitals appears unaffected by these considerations, as none of the "party" coefficients are significant in (17).

6 Concluding remarks

Purchasers of health services in many countries use DRG payment systems to reimburse the providers they contract with. The general philosophy of this system is that each hospitalisation within a DRG is refunded equally. The efficiency properties of any system adopted in practice depend crucially on the minute details of the way in which this principle is implemented. This paper proposes a theoretical underpinning of the manner in which the DRG idea is applied by one large purchaser, a very large Italian region, and subsequently tests the theory on the universe of the contracts negotiated by this purchaser, over a one year period of health care provision. We find suggestive evidence that the contracts which governed the provision determined allocations of patients to hospitals in line with those which would result when the contract negotiated satisfy some simple optimality principles, specifically that more efficient hospitals admit more complex patients.

The theoretical analysis and the way in which it is used to interpret the available individual data on hospitalisations are clearly transferable to other environments which adopts a DRG system to reimburse providers, adjust the payments dictated by the higher cost of provision for specific situations and for patients with relatively well defined characteristics and comorbidities.

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A Appendix

A.1 Algebraic derivations

In this section, we develop step-by-step some of the formulae used in the proof of Proposition 4. We begin with $\frac{\partial \overline{p}_2}{\partial \gamma}$. Differentiate (9) with respect to γ, taking into account the dependence of u_{kt}^h on γ, and rearrange repeatedly.

$$\frac{\partial \overline{p}_2}{\partial \gamma} = \frac{\left(p_1 \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} + p_2 \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma}\right) (\Phi_1 (\cdot) + \Phi_2 (\cdot)) - \left(\phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} + \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma}\right) (p_1 \Phi_1 (\cdot) + p_2 \Phi_2 (\cdot))}{(\Phi_1 (\cdot) + \Phi_2 (\cdot))^2}$$

$$\begin{aligned} = (\cdot) \Big(& p_1 \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} \Phi_1 (\cdot) + p_2 \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} \Phi_1 (\cdot) + p_1 \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} \Phi_2 (\cdot) + p_2 \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} \Phi_2 (\cdot) \\ & - \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} p_1 \Phi_1 (\cdot) - \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} p_1 \Phi_1 (\cdot) - \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} p_2 \Phi_2 (\cdot) - \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} p_2 \Phi_2 (\cdot) \Big) \end{aligned}$$

$$= \frac{p_2 \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} \Phi_1 (\cdot) + p_1 \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} \Phi_2 (\cdot) - \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} p_1 \Phi_1 (\cdot) - \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} p_2 \Phi_2 (\cdot)}{(\Phi_1 (\cdot) + \Phi_2 (\cdot))^2}$$

$$= \frac{p_2 \left(\phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} \Phi_1 (\cdot) - \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} \Phi_2 (\cdot)\right) + p_1 \left(\phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} \Phi_2 (\cdot) - \phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} \Phi_1 (\cdot)\right)}{(\Phi_1 (\cdot) + \Phi_2 (\cdot))^2}$$

$$= \frac{(p_2 - p_1) \left(\phi_2 (\cdot) \frac{\partial u_2}{\partial \gamma} \Phi_1 (\cdot) - \phi_1 (\cdot) \frac{\partial u_1}{\partial \gamma} \Phi_2 (\cdot)\right)}{(\Phi_1 (\cdot) + \Phi_2 (\cdot))^2}$$

$$= \frac{(p_2 - p_1) \phi_2 (\cdot) \phi_1 (\cdot)}{(\Phi_1 (\cdot) + \Phi_2 (\cdot))^2} \left(\frac{\partial u_2}{\partial \gamma} \frac{\Phi_1 (\cdot)}{\phi_1 (\cdot)} - \frac{\partial u_1}{\partial \gamma} \frac{\Phi_2 (\cdot)}{\phi_2 (\cdot)}\right)$$

We continue by deriving the value of $\overline{p}_K$, given in (13):

$$\overline{p}_K = \frac{\overline{p}_{K-1}\sum_{k=1}^{K-1}\Phi_k(\cdot) + p_K\Phi_K(\cdot) + \overline{p}_{K-1}\Phi_K(\cdot) - \overline{p}_{K-1}\Phi_K(\cdot)}{\sum_{k=1}^{K}\Phi_k(\cdot)}$$

$$= \frac{\overline{p}_{K-1}\sum_{k=1}^{K}\Phi_k(\cdot) + \left(p_K - \overline{p}_{K-1}\right)\Phi_K(\cdot)}{\sum_{k=1}^{K}\Phi_k(\cdot)}$$

$$= \overline{p}_{K-1} + \frac{\left(p_K - \overline{p}_{K-1}\right)\Phi_K(\cdot)}{\sum_{k=1}^{K}\Phi_k(\cdot)}$$

And finally we differentiate the above with respect to γ, to obtain (14).

$$\frac{\partial\overline{p}_K}{\partial\gamma} = \frac{\partial\overline{p}_{K-1}}{\partial\gamma} + \frac{\left(\left(p_K - \overline{p}_{K-1}\right)\phi_K(\cdot)\frac{\partial u_K}{\partial\gamma} - \frac{\partial\overline{p}_{K-1}}{\partial\gamma}\Phi_K(\cdot)\right)\sum_{k=1}^{K}\Phi_k(\cdot) - \left(p_K - \overline{p}_{K-1}\right)\Phi_K(\cdot)\sum_{k=1}^{K}\phi_k(\cdot)\frac{\partial u_k}{\partial\gamma}}{\left(\sum_{k=1}^{K}\Phi_k(\cdot)\right)^2}$$

$$= \frac{\partial\overline{p}_{K-1}}{\partial\gamma}\left(1 - \frac{\Phi_K(\cdot)}{\sum_{k=1}^{K}\Phi_k(\cdot)}\right) + \frac{\left(p_K - \overline{p}_{K-1}\right)\phi_K(\cdot)\frac{\partial u_K}{\partial\gamma}\sum_{k=1}^{K}\Phi_k(\cdot) - \left(p_K - \overline{p}_{K-1}\right)\Phi_K(\cdot)\sum_{k=1}^{K}\phi_k(\cdot)\frac{\partial u_k}{\partial\gamma}}{\left(\sum_{k=1}^{K}\Phi_k(\cdot)\right)^2}$$

$$= \frac{\partial\overline{p}_{K-1}}{\partial\gamma}\left(1 - \frac{\Phi_K(\cdot)}{\sum_{k=1}^{K}\Phi_k(\cdot)}\right) + \frac{p_K - \overline{p}_{K-1}}{\left(\sum_{k=1}^{K}\Phi_k(\cdot)\right)^2}\left(\phi_K(\cdot)\frac{\partial u_K}{\partial\gamma}\sum_{k=1}^{K}\Phi_k(\cdot) - \Phi_K(\cdot)\sum_{k=1}^{K}\phi_k(\cdot)\frac{\partial u_k}{\partial\gamma}\right)$$

$$= \frac{\partial\overline{p}_{K-1}}{\partial\gamma}\left(1 - \frac{\Phi_K(\cdot)}{\sum_{k=1}^{K}\Phi_k(\cdot)}\right) + \frac{p_K - \overline{p}_{K-1}}{\left(\sum_{k=1}^{K}\Phi_k(\cdot)\right)^2}\sum_{k=1}^{K}\left(\phi_K(\cdot)\frac{\partial u_K}{\partial\gamma}\Phi_k(\cdot) - \Phi_K(\cdot)\phi_k(\cdot)\frac{\partial u_k}{\partial\gamma}\right)$$

$$= \frac{\partial\overline{p}_{K-1}}{\partial\gamma}\left(1 - \frac{\Phi_K(\cdot)}{\sum_{k=1}^{K}\Phi_k(\cdot)}\right) + \frac{p_K - \overline{p}_{K-1}}{\left(\sum_{k=1}^{K}\Phi_k(\cdot)\right)^2}\sum_{k=1}^{K}\left(\frac{\partial u_K}{\partial\gamma}\frac{\Phi_k(\cdot)}{\phi_k(\cdot)} - \frac{\partial u_k}{\partial\gamma}\frac{\Phi_K(\cdot)}{\phi_K(\cdot)}\right)\phi_k(\cdot)\,\phi_K(\cdot)$$

A.2 Further Tables: **Descriptive statistics, coefficients, and robustness tests.**

Table A1:
Descriptive Statistics - Local Health Authorities

Local Health Authority	Daily	Standard	Extra-Treshold
Bergamo	12.8	10.5	9.0
Brescia	14.5	14.4	10.5
Como	5.5	5.8	4.7
Cremona	3.3	4.4	3.9
Lecco	3.5	3.6	3.6
Lodi	2.0	2.6	2.6
Mantua	2.6	3.8	3.4
Milan	14.2	13.8	18.5
Milan Province 1 (Legnano)	8.5	9.1	11.2
Milano Province 2 (Melegnano)	6.8	6.2	6.3
Monza e Brianza	9.4	8.1	7.5
Pavia	6.7	5.9	6.1
Sondrio	1.7	1.6	1.4
Varese	7.6	9.1	10.4
Valcamonica-Sebino	0.9	1.1	1.0

Note: Percentage of the hospitalisations in each of the 15 local health authorities in the region.

Table A2:
Descriptive Statistics and coefficients - Comorbidities

Comorbidities	Daily	Standard	Extra-Treshold	β	Std. Error
Cogestive Heart Failure	1.1	5.5	11.8	-0.0073***	0.003
Cardiac Arrhythmias	3.6	5.9	11.3	0.0003	0.002
Valvular Disease	0.3	1.6	4.1	-0.0012	0.003
Pulmonary Ciruclation Disorders	0.2	0.8	1.3	0.0064	0.005
Peripheral Vascular Disorders	1	2	2.8	-0.0102*	0.006
Hypertension, Uncomplicated	1.9	4.7	5.2	0.0117***	0.002
Paralysis	0.1	0.2	0.4	-0.0171*	0.010
Other Neurological Disorders	0.6	2	3	0.0210***	0.005
Chronic Pulmonary Disease	0.5	3.4	4.6	0.0014	0.003
Diabetes, Uncomplicated	0.9	3.3	5.4	0.0078***	0.002
Diabetes, Complicated	0.3	1	1.6	0.0084	0.005
Hypothyroidism	0.1	0.5	0.9	0.0022	0.019
Renal Failure	1.2	3.1	6.2	-0.0120***	0.003
Liver Disease	0.4	1.9	3	-0.0323*	0.019
Peptic Ulcer Disease Excluding Bleeding	0	0	0.1	0.0162	0.025
AIDS/HIV	0	0.3	0.2	0.0294*	0.016
Lymphoma	0.3	0.8	2	0.0119	0.016
Metastatic Cancer	0.9	3.3	4.6	0.0192*	0.010
Solid Tumor Without Metastasis	4	7.8	8.6	-0.0118**	0.005
Rheumatoid Arthritis/Collagen Vascular	0.1	0.5	1.1	0.0186***	0.006
Coagulopathy	0.1	0.3	0.7	-0.0116	0.009
Obesity	0.2	0.8	0.6	0.0177**	0.009
Weight Loss	0.3	0.6	2.1	0.0345***	0.006
Fluid and Electrolyte Disorders	0.3	1.2	2.4	0.0251***	0.004
Blood Loss Anemia	0.1	0.6	1.9	0.0270***	0.006
Deficiency Anemia	0.1	0.7	1.2	0.0469***	0.005
Alcohol Abuse	0.3	0.7	0.8	0.0061	0.008
Drug Abuse	0.1	0.3	0.2	0.0082	0.012
Psychoses	0.2	1.1	1.1	0.0080	0.006
Depression	0.1	0.8	0.8	0.0264***	0.006
Hypertension, Complicated	0.39	1.33	1.7	baseline	

Note: Percentage of the hospitalisations where the patients was diagnosed to have each of the co-morbidities, in the three categories of hospitalisation reimbursements, columns (1)-(3), and estimated coefficients and standard errors for the fixed effects in the main regression: column (3) in Table 4. In column (4), $^{***}p \leqslant 0.01$, $^{**}p \leqslant 0.05$, $^{*}p \leqslant 0.1$.

Table A3:
Robustness Checks. Varying the sample and the fixed effects

Dependent Variable %Δ tariff	GP not missing (1)	GP not missing (2)	GP not missing (3)	Full Sample (4)	Full Sample (5)	Include Extra Thr. (6)
DRG attractiveness, A^C	0.0200***	0.0196***	0.0199***	0.0196***	0.0184***	0.0231***
	0.006	0.006	0.006	0.006	0.006	0.006
Far from hospital, a^C	-0.0009	-0.0007	-0.0008	-0.0007	-0.0005	-0.0003
	0.001	0.001	0.001	0.001	0.001	0.001
Length of hospital stay	0.2159***	0.2156***	0.2157***	0.2155***	0.2135***	0.3493***
	0.007	0.007	0.007	0.007	0.007	0.016
Age of patient	0.0004***	0.0004***	0.0004***	0.0004***	0.0003***	0.0003***
	0.000	0.000	0.000	0.000	0.000	0.000
Age^2	-0.0020**	-0.0021**	-0.0019**	-0.0021**	-0.0010	-0.0033***
	0.001	0.001	0.001	0.001	0.001	0.001
Female patient	0.0032***	0.0033***	0.0032***	0.0034***	0.0030***	0.0037***
	0.001	0.001	0.001	0.001	0.001	0.001
DRG reputation	-0.0042	-0.0029	-0.0034	-0.0027	-0.0029	0.0044
	0.016	0.016	0.016	0.016	0.015	0.016
Emergency admission	0.0289***	0.0291***	0.0289***	0.0291***	0.0282***	0.0135***
	0.003	0.003	0.003	0.003	0.003	0.003
DRG size in hospital	-0.0310***	-0.0306***	-0.0311***	-0.0304***	-0.0326***	-0.0294
	0.012	0.011	0.012	0.011	0.012	0.018
Ward externality	-0.0016	-0.0002	-0.0023	-0.0011	-0.0092	0.0057
	0.046	0.046	0.046	0.046	0.045	0.047
Patient transferred	0.0029	0.0028	0.0029	0.0027	0.0025	0.0335***
	0.003	0.003	0.003	0.003	0.003	0.005
Extra Threshold						0.0201
						0.017
Observations	611,202	610,975	611,200	610,973	686,089	737,247
R-squared	0.338	0.348	0.340	0.350	0.347	0.564
Fixed Effects Included						
Referring GP FE	No	Yes	No	Yes	No	No
Municipality FE	No	No	Yes	Yes	No	No
GP + Municipality FE	No	No	No	No	Yes	Yes

Note: ***$p \leqslant 0.01$, **$p \leqslant 0.05$, *$p \leqslant 0.1$. The columns differ in the fixed effects and the samples. Columns (1)-(3) take the subsample of the observations for which the referring physician is not missing; they differ in the fixed effects included, as shown at the bottom of the Table. Standard errors clustered at hospital times DRG level. Comorbidity, DRG, hospital, ward, and month of admission fixed effects included in all columns.

Table A4:
Further Robustness Checks.

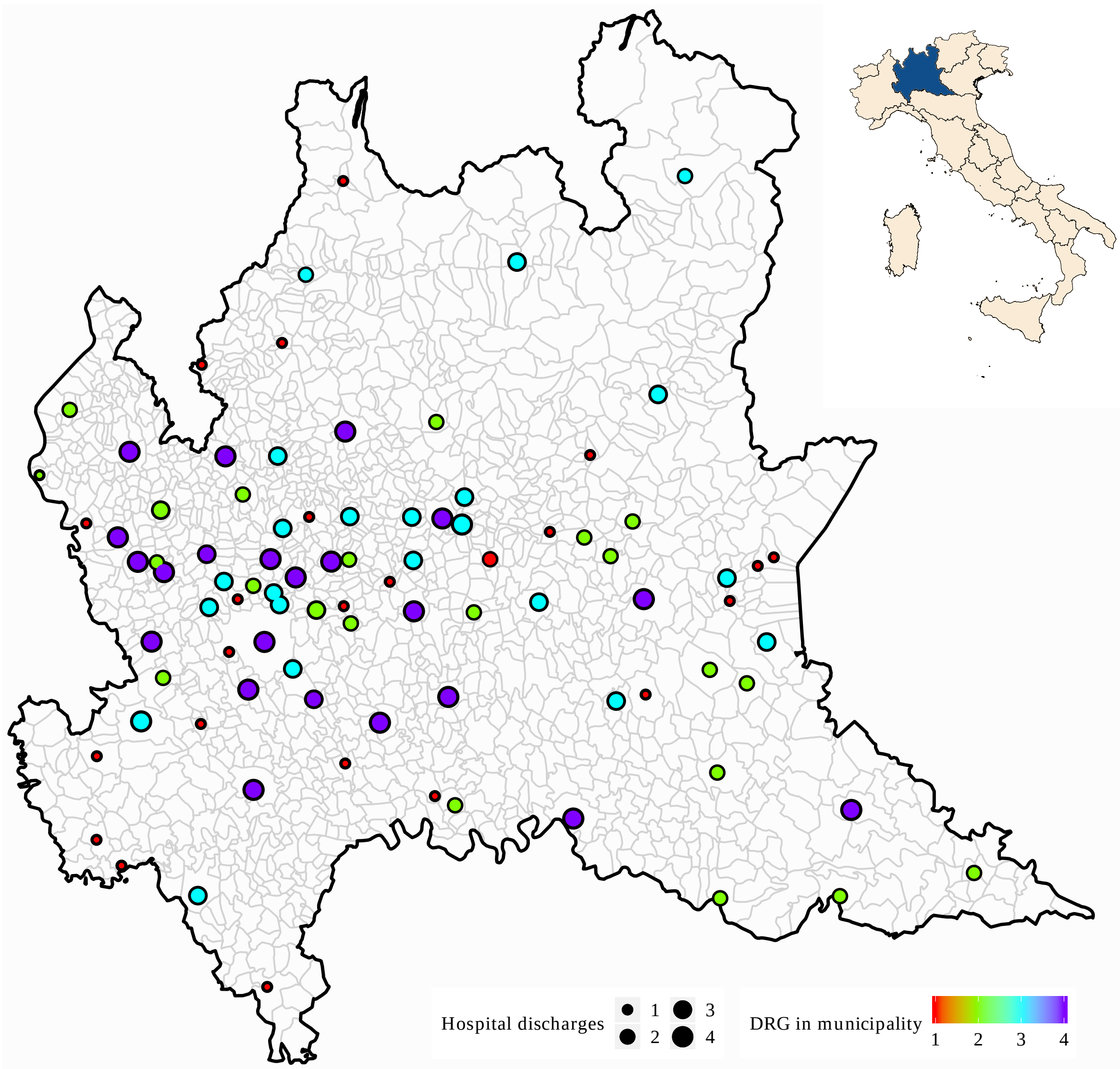
Dependent Variable % Δ tariff	(1) Baseline	(2) No Dead	(3) No hosp Dead	(4) No Emerg.
DRG attractiveness, A^C	0.0184***	0.0196***	0.0195***	0.0201***
	0.006	0.006	0.006	0.006
Far from hospital, a^C	-0.0005	-0.0006	-0.0006	-0.0006
	0.001	0.001	0.001	0.001
Length of hospital stay	0.2135***	0.2139***	0.2150***	0.2194***
	0.007	0.007	0.007	0.007
Age of patient	0.0003***	0.0003***	0.0003***	0.0002**
	0.000	0.000	0.000	0.000
Age^2	-0.001	-0.0013*	-0.0013*	-0.0007
	0.001	0.001	0.001	0.001
Female patient	0.0030***	0.0029***	0.0030***	0.0031***
	0.001	0.001	0.001	0.001
DRG reputation	-0.0029	-0.0048	-0.0045	-0.004
	0.015	0.016	0.015	0.016
DRG size in hospital	-0.0326***	-0.0337***	-0.0329***	-0.0358***
	0.012	0.012	0.012	0.012
Ward externality	-0.0092	-0.0037	-0.0029	0.0005
	0.045	0.043	0.046	0.046
Patient transferred	0.0025	0.0042	0.0034	0.0036
	0.003	0.003	0.003	0.003
Emergency admission	0.0282***	0.0305***	0.0296***	
	0.003	0.003	0.003	
Observations	686,089	658,302	671,388	638,022
R-squared	0.347	0.351	0.348	0.351

Note: *** p⩽0.01. ** p⩽0.05. * p⩽0.1. Column (1) is column (3) in Table 4. In column (2) we exclude observations if the patient has died in hospital or within 30 days of discharge; and in column (3) those when they have died while in hospital. Column (4) excludes emergency hospitalisations. In al cases, standard errors clustered at hospital times DRG level; comorbidity, DRG, hospital, ward, and month of admission fixed effects included.

A.3 Hospitals location

The map shows that hospitals are well spread across the region, both in terms of discharges and in terms of available DRGs. The north-west portion of the region is more mountainous and scarcely populated.

Figure A1:
Location and output of hospitals in Lombardy.



Note: Location of the hospitals in Lombardy (Italy). The partition is given by the different municipalities. Hospitals in the same municipality have been aggregated. The size of the dot represents the number of hospitalisations, and the intensity of the colour the number of different DRGs available.