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Effect of a law limiting upcoding on hospitals' admissions: Evidence from Italy

by

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Effect of a law limiting upcoding on hospitals' admissions: Evidence from Italy

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Abstract

Policy makers have made several attempts to limit hospitals upcoding. We investigate the impact on discharges with and without complications of a law introducing a minimum length of stay to discharges with complications. We implement a DID econometric model to assess the impact of the law and a logistic multilevel model to estimate whether hospitals reacted strategically to it by varying the patients' length of stay. We show that the policy has been effective in limiting upcoding, since the number of discharges with complications is significantly lower in 2008. We also show that hospitals have reacted strategically to the law by modifying the distribution of discharges' length of stay in DRGs with complications, in order to continue practicing upcoding. Furthermore, we provide evidence that upcoding is greater in private for–profit hospitals, that have been more affected by the law.

JEL classification: C51, I11, I18, L33
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1 Introduction

Upcoding is a serious problem arising in the hospital sector in countries where a Prospective Payment System (PPS) is adopted. Under this regime hospitals receive a pre–determined per–case payment based on Diagnosis Related Groups (DRGs).[1] Upcoding may arise because hospital's managers exploit their private information: they may register patients in more severe DRGs in order to get higher reimbursements (Simborg 1981). As shown by McClellan (1997), the two most common ways to practice upcoding are: (1) registering a patient with complications when the latter are not present; (2) selecting the most profitable treatment among all the feasible ones.[2] The second form of upcoding implies that the patient receives treatments not necessarily required by her/his health status. This paper focuses on registering patients with complications, the most frequent upcoding practice.

Upcoding through patients' complications might be implemented because the DRG classification scheme identifies a certain number of DRG pairs where, in each pair, the two DRGs share the same diagnosis and differ only for the presence of complications in the patient (the so called top code DRG)

[1] In countries where PPS is adopted, patients are classified into a DRG according to the clinical information reported in the Hospital Discharge Abstract (HDA): the choice of the DRG code depends on the list and sequencing of diagnoses and procedures, whether complications and comorbidities are present or not, and other factors such as age and gender. Hospitals receive a pre-determined rate for each discharge according to the assigned DRG. See Mayes (2007) for a complete description of the origin and the organization of the DRG system in the US. A similar regime is adopted in the Lombardy Region in Italy.

[2] An example of the second strategy may be a patient with ventricular arrhythmia. She/he may be registered in several DRGs: the ones where she/he receives only medical treatments (and here there are three options: "Cardiac arrest", "Cardiac arrhythmia with complications" and "Cardiac arrhythmia without complications"), or the DRG for electrophysiologic stimulation (involving more severe treatments) or the most expensive procedures such as the DRG for automatic inplantable cardiac defibrillator placement.

or not (the bottom code DRG). In these DRG pairs, upcoding a patient means registering she/he as with complications when instead the latter are not present. To implement upcoding it is enough to indicate in the HDA some information that allow switching the discharge from the bottom code DRG to the top code DRG in the pair.

Patients registered in the DRG with complications should need more care and treatments. To compensate hospitals for these higher costs, the DRG tariff is higher for patients with complications than that for patients without them. Hence hospital managers can exploit their private information about the patient's health status: they can register a patient without complications in the top code DRG in order to get the higher tariff. The absence of complications implies that no further treatments are practiced on the patient. Hence the hospital can get a higher reimbursement without incurring in higher costs. As a consequence, upcoding has a negative impact on health care expenditure, and thus needs to be under control.

Policy makers have reacted in different ways in trying to limit upcoding. For instance, laws introducing fines and criminal charges have been approved in the U.S. to deter this practice (Dafny (2005)). In other countries, laws have modified the PPS to decrease the hospitals' incentives to be engaged in upcoding. Lombardy, the most populated (10 million) Italian Region, has recently (2007) adopted this type of law.

Despite the importance of upcoding, few contributions have analyzed it. Silverman and Skinner (2004) investigate whether hospital ownership affects upcoding using a sample of Medicare claims data.[3] Dafny (2005) examines U.S. hospitals' responses to a 1988 policy change that generated a large impact on DRG reimbursements for 43% of Medicare hospital discharges. She

[3]Medicare is a social insurance program administered by the U.S. government, providing health insurance coverage to people who are aged 65 and over, or who meet other special criteria.

considers all of the DRG pairs with and without complications and investigates nominal and real responses to price changes, where "nominal" refers to hospital coding practices while "real" refers to the number of discharges and the intensity of care provided. Some years later Dafny and Dranove (2009) analyze the same data set to check whether hospitals replaced their managers if they did not exploit the upcoding opportunities involved in the 1988 policy change. These are interesting contributions, but they are limited to the same population group: the elderly (those covered by Medicare). Our study refers instead to all of the population, without any age restriction. Furthermore, we take explicitly into account the impact of patients' characteristics on hospitals' discharge rate of patients with complications, an ingredient missing in the mentioned contributions. Finally, we test the effects of a policy shift that has been implemented precisely to limit upcoding. Dafny (2005) and Dafny and Dranove (2009) analyze instead the impact of a variation in the DRG reimbursements, which only indirectly affects the incentive to upcode.

Our paper is also related to Liu *et al.* (2004) and to our previous contribution (Berta *et al.* (2010)). Liu *et al.* investigate the impact of delivery laws on postpartum length of stay in the US. This paper provides a methodological reference for evaluating the impact of the law investigated in this contribution on the distribution of discharges' length of stay. Our previous contribution provides a proxy for measuring hospitals' upcoding activities and evaluates its impact of hospitals' efficiency in Italy. To the best of our knowledge, no previous contributions have attempted to assess the impact of a law explicitly introduced to limit upcoding. This is precisely the goal of the paper.

As mentioned before, since Lombardy Region has introduced in 2007 a law that modifies the upcoding incentives, we investigate a natural experiment to test for the presence of upcoding in the regional hospitals and to analyze how they reacted to the policy shift. The law changed the tariff for top code DRG in each pair. More precisely, it introduced a minimum length of stay for patients registered in the top code DRG in order to obtain the corresponding reimbursement. If this temporal threshold is not fulfilled, the discharge is reimbursed at the tariff for the bottom code DRG. Clearly, the law's objective is to increase the average patients' length of stay in the DRGs with complications, in order to restore the correct relation between intensity of care, hospital costs and acknowledged reimbursements, i.e., to limit upcoding. Hence it is interesting to observe whether the law has been successful or not. To address this issue, we will analyze how the law affected two critical variables: the number of discharges in DRGs with and without complications before and after the law in all the hospitals of the Lombardy Region; the distribution of the length of stay in the top code DRGs. The latter variable has an impact on the patient's health status since short length of stays are correlated with poor health outcomes (Liu *et al.* (2004)).[4] We investigate these topics using a data set that covers all the regional hospitals (158) and 94 DRG pairs with and without complications (out of 99 that are included in the policy).[5] Our approach is similar to Dafny (2005), who considered 93 DRG pairs regarding Medicare discharges in the US. The analyzed period covers the years 2007 and 2008; this amounts to a study of 767,126 discharges.[6]

[4]Dafny (2005) classifies the effects of laws limiting upcoding into two categories: nominal and real effects. The former regards the number of discharges affected by upcoding and hence the nominal impact due to higher hospitals' reimbursements. The latter is instead the impact on the patients' intensity of care, such as the length of stay, the procedures implemented, the days in intensive care units, the death rate.

[5]Five pairs have been excluded because discharges in these DRGs have been recorded only for year 2008. This implies that they cannot be considered to study the effects of the policy on hospitals' behavior in years 2007 and 2008. Discharges are grouped into 523 DRGs, but only 236 (45%) of them belong to a pair of codes that share the same diagnosis. The coding of patients is set by the software produced by 3M, called *Grouper*, Version 19.

[6]Total discharges are higher than this figure because they include also active mobility—

Concerning the number of discharges in top and bottom code DRGs, the law introduced a difference between coded and reimbursed discharges with complications. By coded discharges we mean the assignment to a specific DRG obtained by applying the relevant information included in the patient's HDA (after the discharge). A reimbursed discharge with complications is instead the tariff which is payed by the Region to the hospital, that is based—after the introduction of the law—on two information: (1) the DRG code, (2) the patient's minimum length of stay. This implies that for each hospital there may be a difference between coded and reimbursed discharges in all the DRG pairs. This difference has an important implication for our analysis. If the hospital, for instance, does not take into account the monetary incentives related with the minimum length of stay, it may continue to register patients as before the introduction of the law. This might imply that the law had no effects on coded discharges in DRGs with complications. However, if the minimum length of stay is not achieved, the discharge will be considered as a without complications one, and reimbursed the tariff for the bottom DRG in the pair. This might imply that the policy induces a reduction in the number of reimbursed discharges with complications. In turn, such a reduction will have an impact on public health expenditure.

We control for the possible effects on coded and reimbursed DRGs by implementing a Difference–in–difference (DID) econometric model, where discharges in DRGs with complications are the treated outcomes, and those in DRGs without complications are the control ones.

The analysis of the distribution of patients' length of stay has instead two further objectives: first, to we want to observe whether the law had some real effects. Second, to test if hospitals have reacted strategically to the introduction of the law, by increasing the length of stay only of those

i.e., patients living outside Lombardy. However, since the policy reform excluded out–of–region discharges, we do not consider them in our analyses.

patients where there is still a monetary incentive to practice upcoding after the policy shift. Since the law incentives to increase the length of stay in DRGs with complications, hospitals need to consider the trade–off between higher revenues—coming for the higher tariff received for the DRG with complications— and higher costs—due to a longer patient's stay. This implies that after the introduction of the law may be convenient to practice upcoding only for those patients with length of stays sufficiently close to the minimum required threshold. For these patients hospitals may have an incentive to shift forward the length of stay, at least up to the threshold. On the contrary, increasing the discharge period may not be convenient for patients with short length of stays. If the number of discharges of some length of stays close to the threshold has decreased after the policy shift, this implies that hospitals reacted strategically to the law, in order to continue practicing upcoding. We investigate this effect using a logistic multilevel econometric model exploiting the hierarchical structure of a data set at the patient level.[7] This allows to estimate the change in the distribution of discharges' length of stay before and after the law.

The statistical literature on health care evaluation (Goldstein and Spiegelhalter (1996)) has highlighted the importance of the patient's characteristics in testing the robustness of outcomes regarding hospitals activities, such as the number of discharges of patients with complications. Hence we take this into account when estimating the econometric models. Furthermore, the health economics literature (see for example Steinbusch et al. (2007)), has pointed out that upcoding is positively related to some market characteristics, which include the presence of for–profit ownership.[8] Hence, we

[7]Upcoding on a patient is nested with the strategy adopted by a specific hospital. As underlined by Leyland and Goldstein (2001) and by Gelman and Hill (2006), it is necessary to use multilevel models in the health care sector since many outcomes are affected by hierarchical relationships between different institutions.

[8]Steinbusch et al. (2007) also consider the impact on upcoding of hospital size, fi-

investigate if there is a difference between public, private for–profit and private not–for–profit hospitals both in the level of upcoding activities—before and after the law—and in their strategic reaction to the policy shift, i.e., on the distribution of patients' length of stay in DRGs with complications.[9]

We find that the policy has been effective in limiting the amount of upcoding in the regional system since discharges in DRGs with complications are decreased after the introduction of the law. This result is robust since we have taken into account the impact of variations in patients' characteristics during the observed period. Hence it is the net effect of the law. Second, we observe that the impact of the policy on coded discharges in DRGs with complications is lower than that on reimbursed discharges in the same DRG categories. This implies that hospitals have partially continued to register patients with the same length of stays before and after the law, showing a certain degree of independence from monetary incentives. Third, the impact of the policy is stronger, both considering coded and reimbursed discharges, in private for–profit hospitals and in private not–for–profit hospitals. Hence we might argue that the upcoding activities was greater in these two hospital categories before the policy shift. Fourth, hospitals reacted strategically to the law by increasing the length of stays of those patients with complications and an expected hospitalization period sufficiently close to the minimum length of stay required for receiving a top code tariff. This means that managers are fully aware of the existence of upcoding incentives and exploit the

nancial situation, intra–regional differences, case–mix characteristics and control–system characteristics.

[9]Many previous contributions have found, for instance, that private and not–for–profit hospitals have different objective functions (Newhouse (1970), Pauly and Redisch (1973), Lakdwawalla and Philipson (1998) and Horwitz (2003)), pointing out that not–for–profit ones pursue social outcomes, while profit maximization is the objective of private hospitals. Hence private nor–for–profit hospitals may behave more similarly to public ones that private for–profit hospitals.

private information in order to increase the hospitals' revenues, adapting the behavior to the modified legal environment. Last, this strategic reaction is greater for private for–profit hospitals. Again this is a confirmation that private for–profit hospitals give more weight in health care management to monetary incentives than public and private not–for–profit ones.

Our results are similar to those obtained by Silverman and Skinner (2004) and Dafny (2005), since they found that upcoding activities in the US is greater in private for–profit hospitals.[10] However, differently from them, we perform some robustness tests for taking into account the impact of both patients' and hospitals' characteristics on discharges with complications. Moreover, our study is applied to a data set without age limitations.

The paper is organized as follows. In Section 2, we describe how the DRG reimbursements are designed in Lombardy and their relationship with patients' length of stays before and after the introduction of the law. In Section 3 we present a model of a hospital's response to the policy shift and we state our research questions. In Section 4, we introduce the DID and logistic multilevel models, while in Section 5 we show the main features of the data set. Descriptive and econometric results are reported in Section 6, and Section 7 points out the main conclusions.

2 Background: the DRG system in Lombardy and the 2007 policy shift

In 1995 Lombardy adopted a DRG system similar to the US one. Since then regional public, private for–profit and not–for–profit hospitals receive a pre–determined tariff for each of the 523 DRGs. Some of them are grouped in pairs, with or without complications. The tariff acknowledged in these pairs

[10] Silverman and Skinner investigate only few DRGs (i.e., respiratory infections and pneumonia), while Dafny analyses only a specific population group (the elderly).

depends on the patient's length of stay. For instance, Figure 1(a) shows the reimbursement hospitals receive for a discharge in the DRG 010 (Neoplasia of the nervous system with complications) and in the DRG 011 (Neoplasia of the nervous system without complications) in year 2007, before the law.

[Insert Figure 1 here]

The hospital receives Euro 165 (Euro 197) if the discharge is without (with) complications and has a length of stay maximum of zero–one day. If instead the discharge is without (with) complications but the length of stay is between 2 and 26 (34) days the tariff is Euro 2,299 (Euro 3,727). Clearly a patient with length of stay within 2 days and 26 (34) days gives to the hospital always the same reimbursement (e.g., Euro 2,299) but her/his cost is increasing with the length of stay. For this reason PPS has induced a general reduction in length of stay per discharge. As shown by Dafny (2005), the spread between the DRG with complications and that without complications—in this example Euro 3,727 - 2,299 = 1,428—is the monetary incentive to practice upcoding, i.e., to register a patient without complications in DRG 010 rather than in DRG 011. If the length of stay is greater than a rather large threshold, e.g., 26 days for DRG 011 and 34 days for the DRG 010 with complications, the patient is classified as an outlier, and the reimbursement is given by a per–die compensation (e.g., Euro 131 per day in DRG 011).

Since 1995, the regional government of Lombardy has periodically revised DRG rates. Such rates revision, besides being an instrument to adjust prices to cost and to inflation, has been used by regional health care officers to control hospitals' behavior. In 2007, the regional government approved a law, the Regional Act N. 5743/2007 in force since January 2008, with the specific goal to limit upcoding. Figure 1(b) presents the variation in the tariffs in the same pair due to the introduction of the law from the beginning of year 2008. There is an important change: a discharge coded in DRG 010 as with complications but with a length of stay between 2 days and 6 days will be reimbursed Euro 2,386, i.e., the tariff for DRG 011. The higher tariff (Euro 3,248) for DRG 010 can be obtained only if the length of stay is at least 6 days. Health care officers justify this shift by asserting that a discharges in a DRG with complications with a length of stay lower than a minimum time spell has no sufficient grounds to be reimbursed more as a compensation for more intensive care.[11]

3 A model of hospitals' responses to the law

The aim of this section is twofold: first we want to model the hospitals monetary incentives to upcode patients and their possible reactions to the introduction of the law; second, we will draw some testable predictions that will provide some empirical evidence on upcoding and hospitals' behavior.

We assume that the profit an hospital can get from a patient registered in a DRG with complications is the following one (we focus on the rather long time spell shown in Figure 1 where the tariff is fixed independently of the length of stay):

$$\pi_C = p_C - (u + \beta) \times x_C \tag{1}$$

where C is for with complications, p_C is the pre–determined tariff reimbursed

[11]The analysis of hospital discharges that occurred during the first semester of 2007 in the DRG pairs with and without complications has led the regional health care officers to adopt a threshold for the DRGs with complications equal to the median per–patient length of stay of the correspondent DRG without complications during the first semester of 2007. This length of stay extension is consistent with the medical definition of complications—i.e.,, an additional problem that arises following a procedure, treatment, or illness that generates the extension of one day in the length of stay in 75% of the cases (see Fossati (2002) for a medical definition of complications).

for a DRG with complications, u is the per–day hospitalization costs, β is the per–day extra costs due to the more intensive care required by a patient of type C and x_C is the length of stay. The profit obtained instead if a patient is registered in a DRG without complication is:

$$\pi_{NC} = p_{NC} - u \times x_{NC} \tag{2}$$

where NC is for without complications and p_{NC} is the pre–determined tariff reimbursed for that DRG type. In this case the hospital does not incur in the per–day extra costs β since the patient has no complications. Furthermore the length of stay x_{NC} should be different and lower than in case of complications. If the hospital's managers want to exploit the profit possibilities, they will try, by inspection of (1)–(2), to reduce the length of stay x as much as possible, in order to minimize costs. Furthermore, they may consider whether to register the patient with or without complications, by comparing $\pi_C \geq \pi_{NC}$. The latter is fulfilled when the following expression holds:

$$p_C - p_{NC} \geq u(x_C - x_{NC}) + \beta x_C \tag{3}$$

Hence the incentive for upcoding exists when the extra revenues are greater than extra–costs due to registering a patient with complications. The extra costs are given by two components: (1) the increase in hospitalization costs due to a longer length of stay; (2) the extra health care costs due to the more intensive care. Notice that if the hospital's managers are fully opportunistic, they will push profitability as much as they can by (1) not increasing the length of stay in case of a discharge with complications (i.e., $x_C = x_{NC}$) and do not perform any more intensive care, so that $\beta = 0$. In this case there is always an incentive to practice upcoding, since the left–hand side of (3) is positive while the right–hand side is 0.

The profit function π_C changes with the policy shift in year 2008 (while the function π_{NC} is unchanged). Its new expression is:

$$\pi_C = \begin{cases} p_C - (u+\beta) \times x_C & \text{if} \quad x_C \geq \hat{x} \\ p_{NC} - (u+\beta) \times x_C & \text{if} \quad x_C < \hat{x} \end{cases} \tag{4}$$

The law introduces a minimum length of stay $\hat{x}$ for a patient registered in a DRG with complications in order to get the higher tariff p_C. If this threshold is not met the tariff is the lower one p_{NC}. If we assume that, if the hospital's managers want to practice upcoding after the policy shift, they will just meet the length of stay threshold (i.e., in case of a patient with complications $x_C = \hat{x}$), the incentive can now be written as:

$$p_C - p_{NC} \geq u(\hat{x} - x_{NC}) + \beta x_C \tag{5}$$

If $\hat{x} > x_C$, i.e., the threshold is such that the patient's length of stay to get the tariff with complications is longer than that practiced on the same type of patient before the law, it is evident that the policy shift has reduced the upcoding incentives. However they are completely eliminated. More precisely, the condition (5) may be fulfilled for some length of stays and not fulfilled for others, depending on how large is its increase up to the threshold. For instance, in year 2007 there was no control on length of stays so that, in principle, no increase in x was required to get the higher tariff p_C. Hence for all length of stays (e.g. $x = 2$, $x = 3$ etc.) there was an incentive to upcode (especially if $\beta = 0$). In year 2008 a length of stay sufficiently close to the threshold $\hat{x}$ may be such that there is an incentive to upcode, because the extra costs $(u(\hat{x} - x_{NC}) + \beta x_C)$ are lower than the extra revenues $(p_C - p_{NC})$. However, this may not be true for length of stays not too close to $\hat{x}$.

Figure 2 shows the possible situations arising in DRGs with complications after the policy shift. Panel (a) presents the typical asymmetric distribution of length of stays in a DRG (Xiao et al. (1999), Felder (2009)). Panel (b)

reproduces this distribution and shows that there are two relevant length of stay areas: area A, where length of stays are sufficiently close to the threshold $\hat{x}$ so that it is still convenient to practice upcoding after the policy shift. However, this implies that the patients' length of stay increases so that after the law the frequency of length of stays in area A should be lower. On the contrary, the length of stays belonging to area B are those where there is no longer convenience to practice upcoding after the law, since this will imply an increase in costs not compensated by the tariffs' differential. If the latter is true we should observe that hospital's managers react strategically to the law, by exploiting upcoding only on those length of stays where it is still profitable. The reaction implies that the frequency of area A's length of stays is lower after the policy shift.

[Insert Figure 2 here]

Given the features of the law described in Section 2 and the model of hospitals' incentives toward upcoding, we can now set up our research questions. Since the law affects the DRGs with complications we can classify the discharges in these DRGs as the treated group, while the discharges in the DRGs without complications are the untreated group. Clearly, the treatment is given by the law, enforced in year 2008. Furthermore, the law discriminates between coded and reimbursed discharges. The differences between them might signal that hospitals reacted in some way independently from the monetary incentives embedded in each discharge. Hence we can then state our first testable hypotheses.

Research Question 1 (RQ_1): There is a significant change between 2007 and 2008 in the number of coded discharges in the treated DRGs group (with complications) in comparison with those in the untreated group (without complications).

Research Question 2 (RQ_2): There is a significant change between 2007 and 2008 in the number of reimbursed discharges in the treated DRGs group (with complications) in comparison with those in the untreated group (without complications). The magnitude of this change is greater than that on coded discharges.

Furthermore we want to control for hospitals' ownership, given the possible heterogeneity in their objective functions. This means that hospitals with different ownership types respond to the policy shift differently. For instance, private for–profit hospitals may have more incentives to exploit all the monetary incentives embedded in the DRG tariffs. Thus, we can also investigate the following testable hypothesis.

Research Question 3 (RQ_3): Public and private not–for–profit hospitals are less engaged in the significant change between 2007 and 2008 in the number of discharges in the treated DRGs group than private for–profit hospitals. This is true both for coded and reimbursed discharges.

Last, we examine if hospitals managers react strategically to the law by increasing only some length of stays in the DRGs with complications, as shown in Figure 2. Hence our final research questions are:

Research Question 4 (RQ_4): There is a significant change between 2007 and 2008 in the distribution of discharges with length of stays sufficiently close to the minimum length of stay required for reimbursing the top code DRG tariff.

Research Question 5 (RQ_5): Private for–profit hospitals exhibit a greater change between 2007 and 2008 in the distribution of discharges with length of stays close to the minimum length of stay required for reimbursing the top code DRG tariff than private not–for–profit and public hospitals.

The above research questions are studied using a DID approach (RQ_1–

RQ_3) and a logistic multilevel model (RQ_4 and RQ_5), which are described in the next section.

4 Methodology

In order to measure the impact of the 2008 Lombardy policy change on hospitals' upcoding activity, we adopt one of the most common methods used in applied economics to evaluate the effect of policy interventions, i.e., the DID approach.[12]

In this paper, we use a non–conventional DID approach since the discriminating factor between the treated and untreated groups is not the belonging to a particular geographic area, to a specific ownership form, or to a group of pathologies to which the policy is addressed, but rather to discharges in treated and untreated DRGs. We perform a population–based analysis since we consider the entire population and not just a sample. Given the non–normality of the output distribution, we apply a log transformation of the dependent variable (i.e., treated or untreated discharges), and then we implement the OLS estimates. The DID econometric model is applied to coded discharges first and then to the reimbursed ones. This regards research questions RQ_1–RQ_3.

We consider a two–year panel on monthly data of hospital discharges (both coded and reimbursed) for the years 2007 and 2008. We define y_{ijtm} as the number of discharges in all DRGs of group i ($i = 1, 2$, where 1 stands for treated) in hospital j in year t and month m. Hence, we can write the following model:

[12] The DID is a development of the potential outcome and counterfactual analysis methodology (Imbens and Rubin (2009), Winship and Morgan (2007), Rubin (1974, 1975, 1978), Holland (1986), Heckman (2005), Schneider *et al.* (2007), Stuart (2007) and Jin and Rubin (2008)). See Jones (2009) for an overview of DID applications to other health economics issues.

$$y_{ijtm} = \alpha T + \sum_{l=1}^{11} \gamma_l (TM_l) + \delta I_{jt} + \sum_{k=1}^{7} \beta_k X_{k,ijtm} + \zeta H_{jtm} + \epsilon_{ijtm}, \tag{6}$$

where $j = 1, \ldots, 138$; $m = 1, \ldots, 12$; and $t = 2007, 2008$. T is the year dummy variable, equal to 1 if $t = 2008$ and zero otherwise, M_l is the month dummy variable, equal to 1 if $l = m$ and zero otherwise. I_{jt} is a binary variable that takes a value equal to 1 if the discharges in hospital j in year t regards the treated group and zero otherwise. $X_{k,ijtm}$ is a set of patient's health status characteristics in group i, hospital j, time t, and month m; H_{jtm} is a set of hospital j's characteristics at time t and month m; while ϵ_{ijtm} is the error term. By using monthly dummies, it is possible to control for possible seasonal patterns. In this context, the estimate of δ is the monthly average DID estimator—i.e.,, the effect of the policy on the number of discharges in the treatment group on an average month.

If we take the 12–month–first difference we get:

$$\begin{aligned} y_{ij,2008,m} - y_{ij,2007,m} = \alpha + \gamma_m M_m + \delta(I_{j,2008} - I_{j,2007}) + \\ + \sum_{k=1}^{7} \beta_k (X_{k,ij,2008,m} - X_{k,ij,2007,m}) + \zeta(H_{j,2008,m} + \\ - H_{j,2007,m}) + (\epsilon_{ij,2008,m} - \epsilon_{ij,2007,m}). \end{aligned} \tag{7}$$

If we denote $\Delta = \Delta_{12m}$ as the 12–month differences we can write:

$$\Delta y_{ijm} = \alpha + \gamma_m M_m + \delta \Delta I_{jm} + \sum_{k=1}^{7} \beta_k \Delta X_{k,ijm} + \zeta \Delta H_{jm} + \Delta \epsilon_{ijm}. \tag{8}$$

Table 1 lists the patient's characteristics X_{ijtm} added to the model. Including these variables in the regression may help performing a robustness test on the estimated effect of the law. The variables that have been considered include age (AGE), gender ($MALE$), transit through an intensive–care–unit (ICU), presence of particular pathologies such as cardiovascular diseases ($CARDIO$) and cancer ($CANCER$), admission through an emergency unit ($EMERG$), and comorbidity ($COMORB$).[13] We consider the hospital's available beds ($BEDS$) as a proxy of its production characteristic, and its ownership (OWN), a multinomial variable equal to 0 in case of private not–for–profit hospital, to 1 if the hospital is private not–for–profit and to 2 if it is a public one.

Variable name	Variable description
Patient's characteristics	
AGE_{ijtm}	Patients' average age
ICU_{ijtm}	% of patients that spent at least one night in an ICU
CV_{ijtm}	% of patients affected by cardiovascular diseases
$CANC_{ijtm}$	% of patients affected by cancer
EM_{ijtm}	% of patients admitted in emergency
$GEND_{ijtm}$	% of males
CI_{ijtm}	Comorbidity Index
Hospital's characteristic	
OWN_{jtm}	Hospital's ownership
$BEDS_{jtm}$	Number of available beds

Table 1: List of the Exogenous Variables

[13]In medicine, comorbidity describes the presence in a patient of other diseases in addition to the primary one. Several indexes have been developed to quantify comorbidity (see de Groot *et al.* (2003)). The most widely used are the Charlson Comorbidity Index (see Charlson *et al.* (1987)) and the Elixhauser Index (see Elixhauser *et al.* (1998)). They consider the coded presence of some secondary diagnoses not linked with the principal one (i.e., the main reason of discharge), such as heart attacks, chronic pulmonary disease, diabetes, cancer, or AIDS. The Elixhauser Index considers a list of 30 comorbidities, while the Charlson Comorbidity Index is limited to only a list of 17. Recent studies (see Southern *et al.* (2004)) point out that the Elixhauser comorbidity measurement outperforms the Charlson model in predicting mortality. We adopt the Comorbidity Software, Version 3.3 developed as part of the Healthcare Cost and Utilization Project (HCUP) by the Agency for Healthcare Research and Quality (2008) to compute the Elixhauser Index.

If, by applying OLS to Eq. (8), we obtain a statistically significant and negative coefficient for δ, then we can accept RQ_1–RQ_3, i.e., there is a significantly difference between the changes in the number of discharges in treated and untreated groups during the years 2007 and 2008. This may be interpreted as an evidence of a diffuse upcoding practice within the regional system before the introduction of the law.

Our further research questions (i.e., RQ_4–RQ_5) regard the identification of possible hospitals' strategic reaction to the law, concentrated on changing the distribution of the length of stays in DRGs with complications. In dealing with this issue, we take into account that in the health care sector the data have a hierarchical structure: patient h's length of stay in a specific DRG of hospital j depends both on patient's characteristics and on the ability of that hospital. As pointed out by Leyland and Goldstein (2001) and by Gelman and Hill (2006), not using a multilevel approach lead to two types of errors: (1) the "ecological fallacy"—i.e., individual effects are drawn from estimates aggregated at the group level; (2) the "atomistic fallacy"—i.e., group effects are drawn from estimates at the individual level. Hence, to investigate RQ_4–RQ_5, we adopt a logistic multilevel model, where the dependent variable is binary, since observations are taken now at the patient's level in each hospital. We define z_{hjtm} as a binary variable that is equal to 1 if patient h, in hospital j, in year t, and month m, has a discharge LOS following in area A of Figure 2(b), and 0 otherwise. Our observations are taken from each patient's HDA. Hence, z_{hjtm} measures the probability that patient h is subject to upcoding by hospital j, practiced by increasing the her/his length of stay after the introduction of the law. Within this framework, the data maintain a hierarchical structure, since the probability that patient h is subject to upcoding depends on the hospital where she/he has been admitted. Thus, the following logistic multilevel model is the most appropriate framework:

$$z_{hjtm} = \alpha + \sum_{k=1}^{7} \beta_k X_{k,hjtm} + \zeta H_{jtm} + \gamma_m M_m + u_{jt} + \delta YEAR + \epsilon_{hjtm}, \quad (9)$$

where the error term is split into two components: the first level error component (the bottom of the hierarchy—the patient), ϵ_{hjtm}; and the second level error component (the top of the hierarchy—the hospital), u_{jt}. The latter is a random variable distributed as $N(0, \sigma^2)$. $YEAR$ is a dummy variable equal to 1 if $t = 2008$. Hence, to test whether hospitals with different ownerships are differently engaged in reacting strategically to the law by varying the frequency of length of stays we regress Eq. (9), and take into of the interaction between the ownership variable (OWN) and the after law enforcement period (I).

5 The data set

As already mentioned, our main data source is the HDAs regarding the patients' discharges in Lombardy. We consider the 94 DRG pairs that share the same principal diagnosis and differ for the presence of complications during the years 2007 and 2008. The data are provided by the Health Care Department of the Lombardy Region. The HDAs include several types of information regarding the patient (gender, age, and residence), the hospital (regional code), and the discharge (DRG, length of stay, principal and secondary diagnoses, principal and secondary procedures). This data set has been linked with other information—always provided by the Lombardy Health Care Department—regarding some hospitals' features such as the number of beds and the ownership.[14]

[14]Information is recorded in Access. The data are not public under Italian privacy law. The Health Care Department of the Lombardy Region may be contacted for discussing the provision of the data with the aim of scientific publications.

Table 2 displays some details of the explanatory variables introduced in the DID and multilevel models. We considered 138 hospitals, with no changes in ownership during the period 2007–2008. The majority are public (64%); private for–profit are 25% of the total, while private not–for–profit ones are only 11% of the total.

	2007				2008			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Patient's characteristics								
Age	62.08	9.98	23.13	79.72	62.51	9.99	22.82	80.10
Gender (Male = 1)	0.53	0.19	0.00	1.00	0.53	0.19	0.00	1.00
Patient's health status								
Transit in ICU	0.05	0.09	0.00	0.62	0.05	0.09	0.00	0.64
Cancer disease	0.16	0.31	0.00	1.00	0.16	0.31	0.00	1.00
Comorbidity index	0.55	0.39	0.01	1.59	0.53	0.38	0.01	1.45
discharge in emergency	0.06	0.17	0.00	0.99	0.06	0.18	0.00	0.99
Cardiovascular disease	0.10	0.28	0.00	1.00	0.10	0.28	0.00	0.99
Hospital's characteristic								
Beds	184	186	4	1167	186	186	10	1162
For–profit (number)	34				34			
Not–for–profit (number)	16				16			
Public (number)	88				88			

Table 2: Explanatory Variables: Descriptive Statistics

6 Results

In this section, we present our econometric results, providing some empirical evidence regarding our research questions. We split the results into two parts. First we show some descriptive statistics regarding the discharges in DRGs with and without complications in Lombardy before and after the policy shift. Then we present the econometric estimates.

6.1 Descriptive statistics on discharges with and without complications

Table 3 shows some descriptive statistics regarding the dynamics of discharges in treated and untreated DRGs over the observed period. The total number of discharges without complications in 2007 (both coded and reimbursed, since there is no discrimination in that year) is equal to 251,467. In year 2008 coded discharges with complications are 126,787 (-6%), while reimbursed discharges show a relevant decrease (-30%). On the contrary, discharges in DRGs without complications (representing in year 2007 about 65% of the discharges in the pairs) increased by 14%.

	2007		2008	
Coded Discharges in:	Number	%	Number	%
Untreated Group	251,467	65.09	254,018	66.71
Treated Group	134,854	34.91	126,787	33.29
Reimbursed Discharges in:	Number		Number	
Untreated Group	251,467	65.09	286,706	75.29
Treated Group	134,854	34.91	94,099	24.71

Table 3: Descriptive Statistics

Figure 3 shows the dynamic of coded discharges with complications and without complications in years 2007–2008. Coded discharges without complications show a small increase in the majority of months during 2008 (in comparison with 2007), while coded discharges with complications are almost in all months of 2008 slightly lower than that of 2007.

[Insert Figure 3 here]

Figure 4 presents instead the dynamic of reimbursed discharges with and without complications. It is evident that reimbursed discharges without complications went up in each month of 2008, while those with complications exhibit a significant monthly reduction. Hence, this first evidence confirms that discharges in treated DRGs, affected by the law, have decreased.[15]

[Insert Figure 4 here]

6.2 Econometric results

The reduction in upcoding displayed in Table 3 and in Figure 3 may be due to the policy shift but also to other reasons, such as a variation in the population health status or in the hospital's production capacity. Hence we estimate the DID model shown in equation (8) without and with patients' and hospitals' characteristics, to test the robustness of our estimates. The results regarding the effect of the policy on coded discharges are shown in Table 4.

[Insert Table 4 here]

Model 1 provides estimates without considering the impact of patients' and hospitals' characteristics. The coefficient of the variable I is negative and statistically significant. This implies that the policy has been successful because there is a significant reduction in coded discharges in DRGs with complications in comparison with coded discharges in DRGs without complications. There is no monthly effect. Model 2 regards estimation including the patients' and hospitals' characteristics. Again the coefficient of the variable I is negative and significant but with a smaller absolute value. Hence not considering the dynamics of patients' health status and of hospitals' capacity may lead to overestimates of the policy effect. In model 2 there is a positive monthly regarding April (probably due to Eastern holidays) and a negative statistically significant impact of patient's age, days in intensive

[15] The two sharp decreases observed in the untreated group are related to discharges in August, a period where, in Italy, all activities are reduced for holidays.

care units, being affected by cancer, and comorbidity index. These estimates imply, as expected, that the two–year monthly variation is lower when the patient's age increases, when they spend some days in intensive care units, when they are affected by cancer and when the health status is relatively "bad." Last, there is a positive statistically significant impact of hospitals' capacity. The R–squared for Model 2 (with patients' and hospitals' characteristics) is sufficiently high for a DID model.

[Insert Table 5 here]

The results for reimbursed discharges are shown in Table 5. The most important result is that the magnitude of the variable estimating the impact of the policy is greater in absolute value than that shown for coded discharges. This is true both for Model 1 and 2. This difference implies that hospitals continued to register patients in DRGs with complications even if their length of stay was lower than the minimum threshold required to get the higher tariff. These discharges have been coded as with complications but reimbursed as without complications. In our view this result cannot be due to mistakes in coding patients, but rather it is a signal that many hospitals treat patients without paying too much attention to the monetary implications of their decisions. Hence the policy may have not changed the level of health services received in hospitals while it has produced an important reduction the reimbursements to hospitals acknowledged by the Lombardy Region. Regarding the other variables, the April effect is now significant both in Model 1 and 2, while among patient's characteristics also the variable gender is significant, with a positive effect, i.e., the two–year monthly variation is higher when the patient is male. The answer is then positive to both RQ_1 and RQ_2.

[Insert Table 6 here]

Table 6 shows the estimates of the variable I, i.e., the impact of the policy in the number of coded and reimbursed discharges, among hospitals' with different ownership. All estimates regard Model 2, i.e., including the effects of patients' and hospitals' characteristics. The absolute variable of the coefficient is always lower for public hospitals. The greater impact for coded discharges is in private not–for–profit hospitals while for reimbursed discharges is for private for–profit hospitals. Hence we might draw two consequences: (1) public hospitals are less affected by the policy; (2) private for–profit hospitals have the greatest impact on reduced reimbursements. The first result confirms RQ_3, i.e., public hospitals are less engaged in upcoding than the other hospital types. The second result might be interpreted as a signal that private for–profit hospitals pay a lot of attention to the monetary incentives embedded in patients' discharges.

The hospitals' strategic responses to the policy shift, i.e., the change in the frequency of discharges with the length of stay sufficiently close to the minimum threshold required by the law for reimbursing the higher tariff in the pair, have been investigated by regressing the logistic multilevel model shown in Eq. (9). The results are shown in Table 7. Model 3 provides the estimates without taking into account the ownership effect and its interaction with the treatment variable I. The latter are instead included in Model 4.

[Insert Table 7 here]

In Model 3 the impact of the variable I is negative and statistically significant. This implies that hospitals have reacted to the law by increasing the length of stays especially in those discharges with expected length of stay sufficiently close to the minimum threshold. This seems to suggest that they have done this in order to practicing upcoding, as predicted by the theoretical model presented in Section 3. Furthermore many variables related to patients' characteristics are significant: among them, age, days in intensive care units, being affected by cancer and the comorbidity index have a negative effect. This implies that the probability of a discharge with a length of stay close to the 2008 threshold is lower if these patients characteristics are greater. Cardiovascular diseases, admissions through emergency units and being a male increases instead this probability. All these effects allow to identify the net impact of the treatment. In Model 4 the most interesting results are: (1) the dummy variable for private for–profit hospitals is positive and statistically significant and (2) the interaction between the treatment effect and private for–profit hospitals is negative and statistically significant. These results imply that (1) during the observed period the distribution of discharges with length of stay close to the minimum length of stay threshold is greater in private for–profit hospitals; (2) the strategic reaction to the policy enforced in year 2008 has been particularly relevant in this type of hospitals. This evidence confirms that private for–profit hospitals are sensible to monetary incentives when providing health care services and therefore they are more likely to be engaged in upcoding and in identifying any feasible opportunities embedded in the PPS, such as a variation in patients' length of stay only when it is profitable, not for health care considerations. Hence the answers to both RQ_4 and RQ_5 are both positive.

7 Conclusions

We have investigated the effects of a law explicitly designed to limit upcoding in the hospitals of Lombardy, the most populated Italian region. The law introduces a minimum length of stay for discharges registered in DRGs with complications. We have modeled hospitals' responses to the policy shift and we have identified the possible strategy that allow to continue practicing upcoding when it is profitable. This strategy implies a strategic change in the distribution of discharges length of stays in DRGs with complications.

We found evidence that the policy has been effective in limiting upcoding, since the number of reimbursed discharges with complications is significantly lower in 2008. This effect is also present when we take into account changes in patients' and hospitals' characteristics between 2007 and 2008. The impact of the law is greater when we consider reimbursed discharges with complications, an effect having positive consequences for the public health expenditure. Furthermore, public hospitals exhibit the smaller treatment effect. Last, we have shown that hospitals have reacted strategically to the law by modifying the distribution of discharges length of stay in DRGs with complications, in order to practice upcoding. This has been done by increasing the length of stay of patients with expected hospitalization periods sufficiently close to the minimum threshold imposed by the law. We provide evidence that this effect is greater in private for–profit hospitals.

These insights enlarge the previous results (Silverman and Skinner (2004) and Dafny (2005)) since they have been obtained by applying new econometric approaches (the DID and logistic multilevel models), by taking into account of hierarchical structure in the data and by investigating a population–based data set (while previous contributions used data coming from a sample covering only elderly people).

	Model 1		Model 2	
	Coefficient	t–ratio	Coefficient	t–ratio
Constant	0.2165***	6.2677	0.1046***	3.3775
January	0.0512	1.0915	0.0424	1.0236
February	0.0432	0.9215	0.0334	0.807
March	-0.0358	-0.7633	-0.0373	-0.899
April	0.1112	2.3706	0.0878***	2.1167
May	0.0181	0.3856	0.0014	0.033
June	-0.0373	-0.7943	-0.0516	-1.2441
July	0.0397	0.8461	0.0254	0.6132
August	-0.0309	-0.6582	-0.0609	-1.4678
September	0.0408	0.8701	0.0218	0.5258
October	0.0332	0.7068	0.0152	0.3661
November	-0.0165	-0.3508	-0.0445	-1.0731
AGE			-0.0237***	-14.9769
ICU			-1.316***	-8.2217
CV			0.0634	0.7614
CANCER			-0.2463***	-2.5683
EM			-0.0896	-0.4986
GEN			0.0857	1.3863
CI			-0.1641***	-6.1649
BEDS			0.0018***	2.6601
I	-0.533***	-27.8223	-0.2535***	-13.1165
Observations	276			
R–squared	0.19		0.37	
*** $P < 0.01$				
dependent variable: log of y_{ijtm}				

Table 4: DID Estimation of Coded Discharges in Treated and Untreated Groups

	Model 1		Model 2	
	Coefficient	t–ratio	Coefficient	t–ratio
Constant	0.3281***	9.8307	0.2546***	8.4863
January	0.0522	1.1505	0.0521	1.2898
February	0.0332	0.7318	0.0334	0.8269
March	-0.0381	-0.8397	-0.0339	-0.8398
April	0.1061***	2.3402	0.0938***	2.3217
May	0.012	0.2655	-0.0013	-0.0319
June	-0.0388	-0.8557	-0.0484	-1.199
July	0.0338	0.7454	0.0256	0.6346
August	-0.0161	-0.3546	-0.0311	-0.7696
September	0.0397	0.8755	0.0244	0.6049
October	0.0381	0.8397	0.0265	0.6567
November	-0.0154	-0.3403	-0.0362	-0.8966
AGE			-0.0151***	-9.7386
ICU			-1.0778***	-7.8387
CV			0.0619	0.7738
CANCER			-0.5292***	-6.0865
EM			-0.3188***	-2.0343
GEN			0.1841***	3.0755
CI			-0.2432***	-9.519
BEDS			0.0022***	3.397
I	-0.9368***	-50.606	-0.6833***	-36.6419
Observations	276			
R–squared	0.43		0.55	
*** $P < 0.01$				
dependent variable: log of y_{ijtm}				

Table 5: DID Estimation of Reimbursed Discharges in Treated and Untreated Groups

Ownership	Coded discharges	Reimbursed discharges
Public	-0.2243***	-0.6455***
Private For–profit	-0.2826***	-0.7602***
Private Not–for–profit	-0.3608***	-0.7486***
Observations	176	
R–squared	0.39	
*** $P < 0.01$		
dependent variable: log of y_{ijtm}		

Table 6: DID Estimation of ownership treatment effects

	Model 3		Model 4	
	Coefficient	t–ratio	Coefficient	t–ratio
Constant	-0.7819***	-11.4464	-0.851***	-6.4933
January	0.0486	1.9043	0.0486	1.905
February	0.0905***	3.5408	0.0903***	3.5324
March	0.0455	1.7976	0.0453	1.7916
April	0.0290	1.124	0.029	1.1215
May	0.0562***	2.2029	0.0562***	2.203
June	0.0249	0.9618	0.0242	0.9332
July	0.0678***	2.6353	0.0672***	2.6089
August	0.095***	3.5724	0.0948***	3.5641
September	0.0515	1.9442	0.0506	1.911
October	0.0057	0.2226	0.0056	0.2171
November	-0.0282	-1.0706	-0.0286	-1.0843
AGE	-0.0099***	-32.4398	-0.0099***	-32.4109
ICU	-0.6237***	-26.1622	-0.6229***	-26.1235
CV	0.0746***	4.855	0.0736***	4.7927
CANCER	-0.1257***	-8.6127	-0.126***	-8.6346
EM	0.0584***	2.5724	0.0587***	2.5864
GEN	0.1981***	18.654	0.1981***	18.6543
CI	-0.0702***	-11.6674	-0.0707***	-11.7418
BEDS	0.0001	0.53	0.0002	1.1354
YEAR	-0.0776***	-7.3682	-0.0864***	-2.4251
PUB			-0.0583	-0.4468
PROF			0.3578***	2.4472
YEAR*PUB			0.0415	1.1026
YEAR*PROF			-0.1201***	-2.7607
Observations	276			
*** $P < 0.01$				
dependent variable: log of z_{ijtm}				

Table 7: Hospitals' change in frequency of discharges length of stay in top code DRGs

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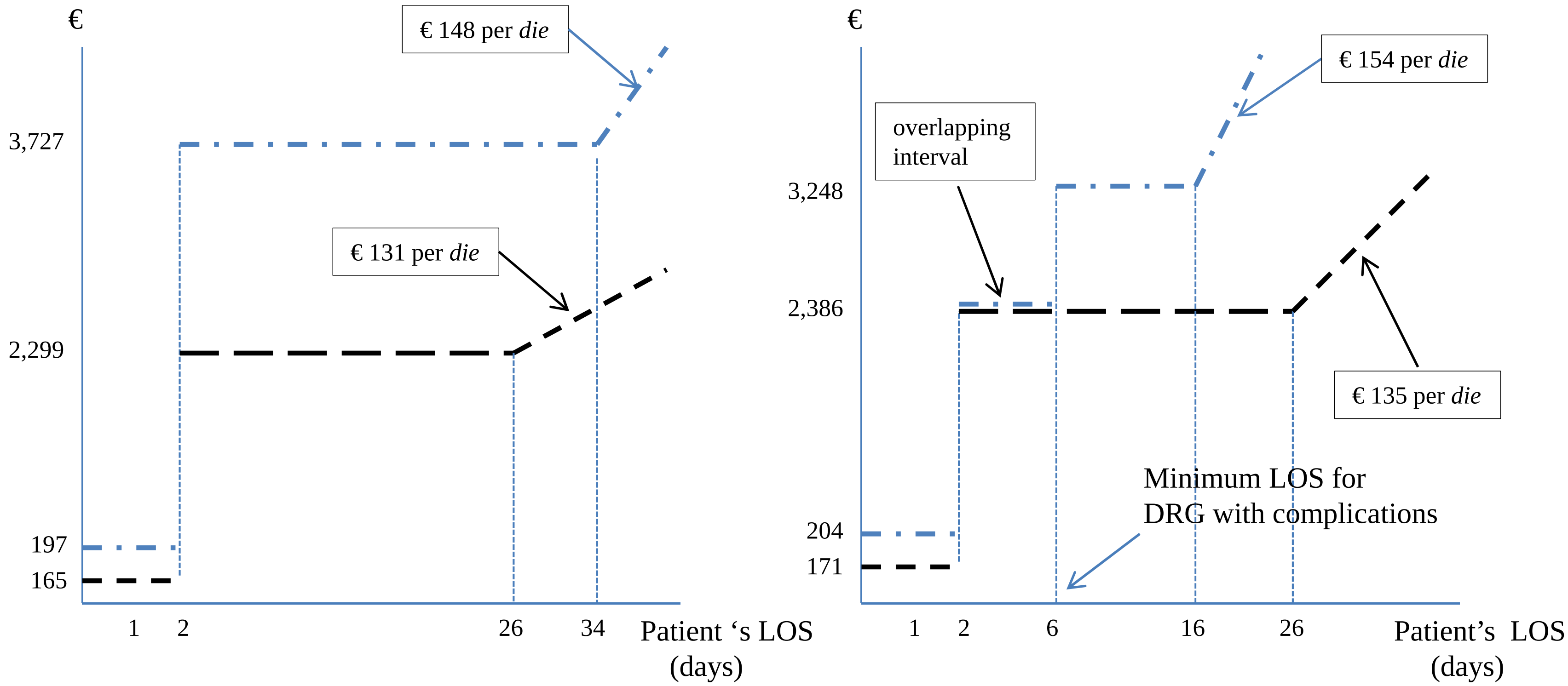
Fig. 1 Tariffs in DRGs with and without complications

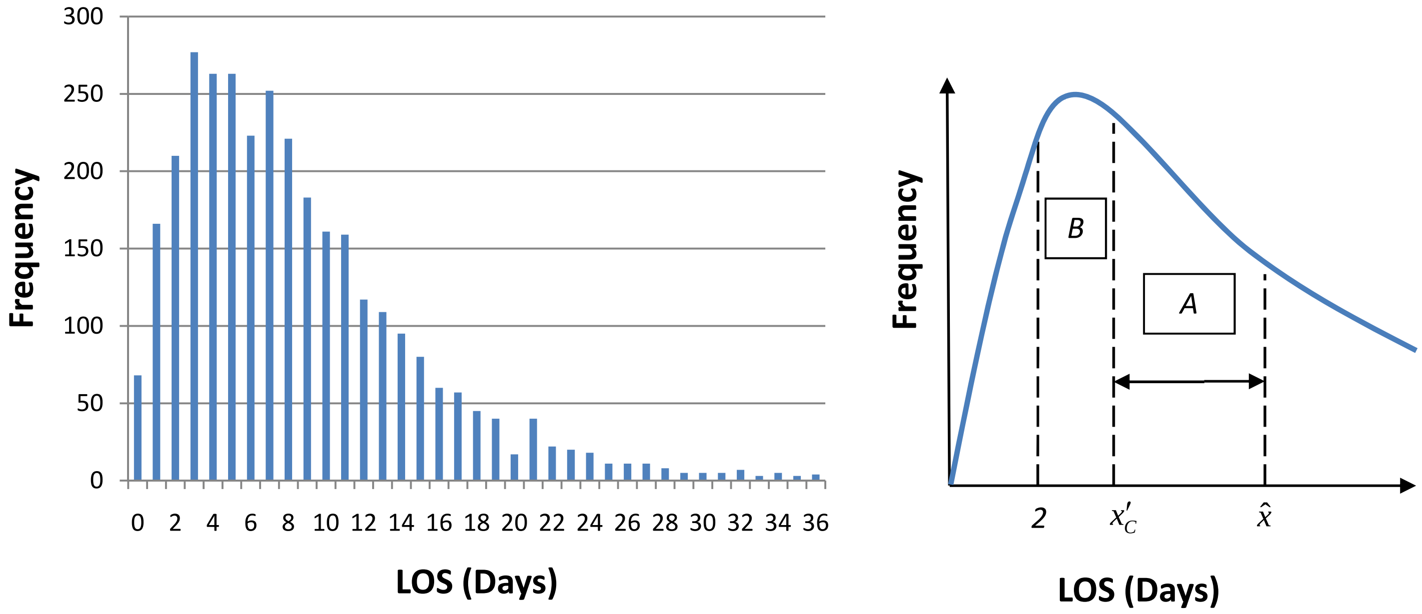


(*a*) (*b*)

Legend: Year 2007
DRG 011 without complications
DRG 010 with complications

Legend: Year 2008
DRG 011 without complications
DRG 010 with complications

Fig. 2 Incentives to change the frequency length of stay in DRGs with complications



(*a*) (*b*)

Fig 3: Dynamics of coded discharges in DRGs With and Without complications

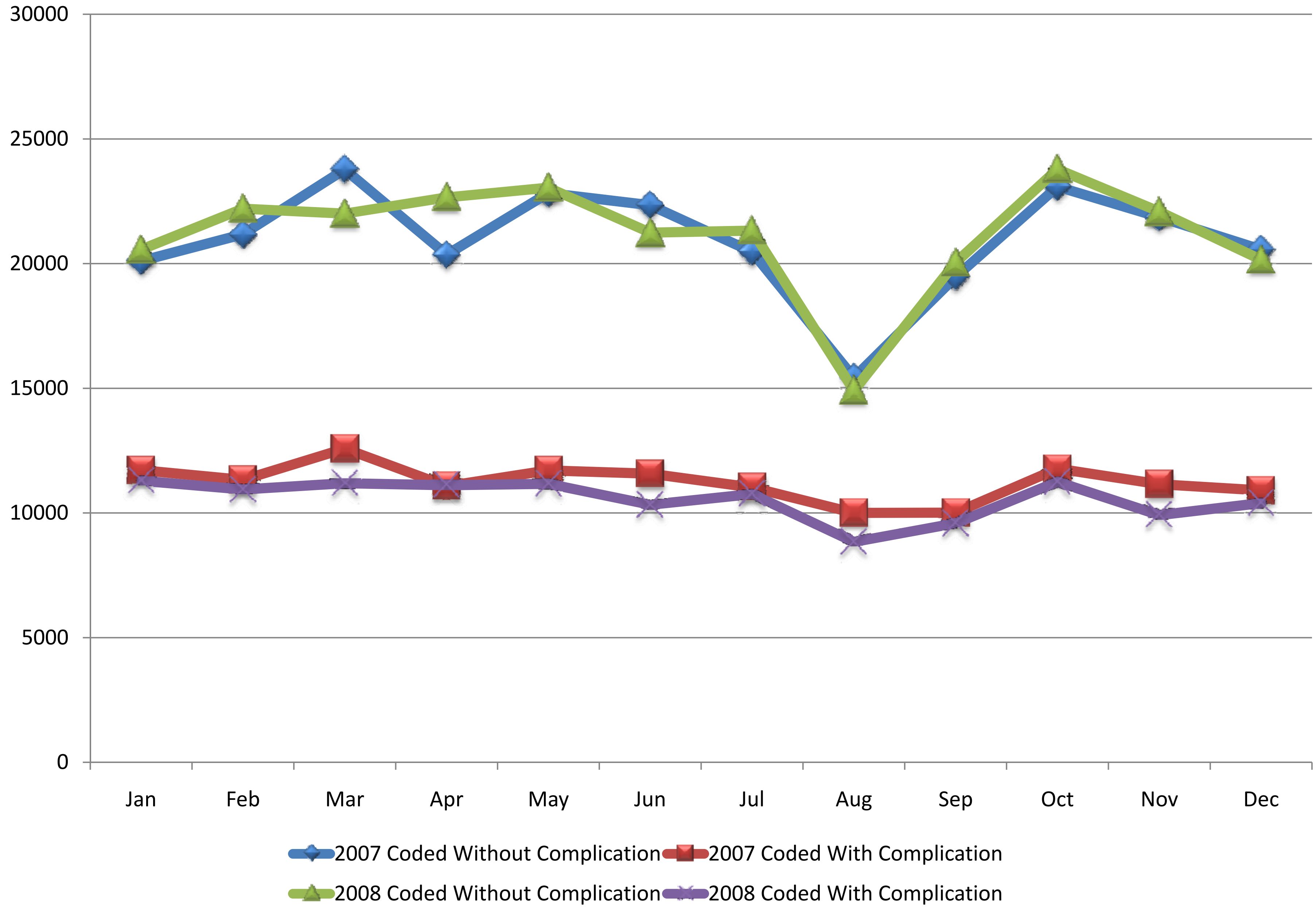


Fig 4: Dynamics of reimbursed discharges in DRGs With and Without complications