Empir Econ
DOI 10.1007/s00181-012-0548-6

The effect of a law limiting upcoding on hospital admissions: evidence from Italy

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Received: 29 September 2010 / Accepted: 5 December 2011

Abstract Policy makers have made several attempts to limit hospitals' upcoding. We investigate the impact of a law introducing a minimum length of stay for discharges with complications. We analyze its effects on the probability of a discharge with complications, on its length of stay and on its reimbursement. We show that the policy has been effective in limiting upcoding, since, after the law, (1) the probability of a discharge with complications has decreased by 3%; (2) its length of stay has risen by 0.17 days more than the observed corresponding variation in the length of stay of a discharge in the control group; (3) the hospital's revenue on a discharge with complications has decreased by 8.5% more than the observed revenue change on a discharge in the control group. Furthermore, we find evidence of an ownership effect on upcoding, since not-for-profit and for-profit hospitals have been more affected by the law than public hospitals.

Keywords Upcoding · Length of stay · Logit model · Difference-in-difference model

JEL Classification C51 · I11 · I18 · L33

1 Introduction

Upcoding is a serious problem arising in the hospital sector in countries where a prospective payment system (PPS) has been adopted. Under this system hospitals receive

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Published online: 01 February 2012

a pre-determined, per-case payment based on diagnosis related groups (DRGs).[1] Upcoding may occur due to hospital managers exploitation of their private information: they may register patients in more severe DRGs to receive 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; and (2) selecting the most profitable treatment from other, viable treatments that may less expensive.[2] The second form of upcoding suggests that the patient receives treatments not necessarily required by her/his health status. This paper focuses on registering patients with complications, the most frequent type of upcoding.

In order to limit upcoding, a law was passed in 2007 in Lombardy, the most populated Italian region (with about 10 million residents), that was enacted in January of 2008. The law-modified hospitals' reimbursements for discharges in DRGs with complications, linking them to the patients' length of stay. We investigate how discharges in DRGs with complications, patients' length of stay, and hospitals' reimbursements have changed following the law's implementation. Hence, our aim is to assess whether the law has been effective in limiting upcoding, and to estimate its impact on regional health care costs.

Upcoding 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 but differ if the patient has complications (the so called top-code DRG) or not (the bottom-code DRG). In these DRG pairs, upcoding a patient means registering her/him as with complications even though the latter may not be present. To implement upcoding, it is enough to indicate in the Hospital Discharge Chart some information that make possible switching the discharge from the bottom-code DRG to the top-code DRG in the pair.

Policy makers have reacted in different ways to try 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 hospitals' incentives to engage in upcoding. Lombardy has recently adopted this type of law: in order to receive the higher reimbursement for discharges in DRGs with complications, it is no longer sufficient to simply register the patient in the top-code DRG of the pair. A pre-determined minimum threshold is now also required for each patient's length of stay. The threshold was adopted after observing that, in many DRG pairs, discharges with complications had lower length of stays than discharges without complications, a clear contradiction (patients with complications should receive,

[1] In countries where PPS is adopted, patients are classified into a DRG according to the clinical information reported in the hospital discharge chart: 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 DRG system has been adopted in the Lombardy Region in Italy since 1995.

[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.

on average, more health care treatments than patients without complications). Hence, before the law, for any discharge registered in a top-code DRG the hospital received a higher reimbursement, i.e., there was no link between the presence of complications in the patient and her/his discharge's length of stay. After the law, each hospital may choose to upcode a patient, but taking into account that to receive the higher top-code reimbursement it is necessary to increase her/his discharge's length of stay, i.e., upcoding has a higher opportunity cost (each bed is engaged on the same patient for a longer time).

To investigate the impact of this law on upcoding we examine information on 1,694,084 discharges in 138 hospitals in Lombardy during the period 2007–2008, in which there were 245,199 (14.5% of total) discharges in 86 DRGs with complications.[3] The data set has been extracted from an administrative source; thus provides information on the entire population, not just a sample of it.

Our main results are as follows: First, we find that the probability of a discharges in DRGs with complications decreased by 3% after the law. Second, the length of stay of a discharge with complications has increased by 0.17 days more than the corresponding variation in the length of stay of a discharge in the control group. This implies that in order to continue practicing upcoding, hospitals reacted strategically to the new law, slightly increasing the length of stay of discharges in DRGs with complications. This strategy has probably focused on those patients with hospitalization periods sufficiently close to the minimum length of stay threshold established for discharge with complications. Third, the reimbursement received by hospitals for a discharge in one of the DRG pairs distinguishing between patients with or without complications has decreased by 8.5% after the law. This reduction is the additional variation observed in the treated group discharges in comparison with the same period variation in reimbursement for discharges in the control group. Fourth, we find evidence that not-for-profit and for-profit hospitals were more engaged in upcoding than public hospitals. They exhibit a greater reduction in the probability of a discharge with complications, a greater increase in its length of stay and a greater reduction in its reimbursement.

These results have been obtained with the use of a logit model for estimating the impact of the law on the probability of a discharge with complications, and of a difference-in-difference model for measuring the effect on length of stays and reimbursements. We apply these models to panel data, taking into account for hospitals' fixed effect. In the difference-in-difference models we compare the difference before/after the law in the outcome of interest (i.e., the discharge's length of stay and its reimbursement) for the treated group and for the control group. The control group is comprised of the discharges in the 298 DRGs that does not distinguish between discharges with/without complications.[4]

[3] We have information on all the regional hospitals receiving public reimbursements for acute discharges.

[4] The discharges in the DRGs without complications (i.e., those registered in the bottom code of the DRG pair) have been excluded from the analysis on the length of stay since the law directly affects the discharges in the treated DRGs (i.e., those with complications) but also, indirectly affects the discharges in the DRGs without complications. The latter discharges should increase after the law implementation. Hence, including in the control group the discharges in DRGs without complications would not make the two groups independent. We are grateful to an anonymous referee for suggesting this issue. They are instead considered

Hence, the combined evidence that, after the law, the probability of a discharge in DRGs with complications decreased, and that hospitals strategically modified patients' length of stay, suggests that upcoding was widespread in hospitals of Lombardy and the law successfully limited it. Furthermore, the law had also a monetary effect.

Despite the importance of upcoding, few studies have analyzed it. Silverman and Skinner (2004) investigated whether hospitals' ownership affects upcoding using a sample of Medicare claims data.[5] Dafny (2005) examined U.S. hospitals' responses to a 1988 policy change that had a large impact on DRG reimbursements on 43% of Medicare hospital discharges. The author considered all the DRG pairs with and without complications and investigated nominal and real responses to price changes in which "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) analyzed the same data set to determine if hospitals replaced their managers if they did not exploit the upcoding opportunities after the 1988 policy change. These are interesting contributions, but they are limited to the same population group—the elderly that are covered by Medicare. Our study encompasses instead to entire population of discharges in hospitals of Lombardy regardless of age. Furthermore, we explicitly take into account the impact of patient characteristics on hospitals' discharges of patients with complications, a factor that is missing in the above-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) studied just the impact of a variation in the DRG reimbursements, which only indirectly affects the incentive to upcode.

Our article is also related to Liu et al. (2004) and to our previous contribution (Berta et al. 2010). Liu et al. investigated the impact of delivery laws on postpartum lengths of stay in the US. This paper provided a methodological reference for evaluating the impact of the law that was investigated in this contribution on the distribution of discharges' length of stay. Our previous contribution presented a proxy for measuring hospitals' upcoding activities and evaluated how the impact contributed to hospitals' efficiency in Italy. To the best of our knowledge, no previous contributions have attempted to assess the impact of a law which was explicitly introduced to limit upcoding.

This article is organized as follows. In Sect. 2, we describe the DRG system adopted in Lombardy and the main features of the law. In Sect. 3, we specify our empirical strategy, and in Sect. 4, we show the main features of the data set. Descriptive and econometric results are reported in Sect. 5, and Sect. 6 points out the main conclusions.

Footnote 4 continued
as part of the treated group (together with discharges with complications) when we investigate the impact of the law on the discharge's reimbursement. As just mentioned, the law has an effect on the discharges in DRGs without complications, that may increase after the law. Hence our aim is to estimate its impact on the per-discharge reimbursement that hospitals obtain in the DRG pairs distinguishing for the presence/absence of complications in the patient, as opposed to the group of DRGs not affected by the law.

[5] 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.

2 Background: the DRG system in Lombardy and the year 2008 law

In 1995, Lombardy adopted a DRG system wherein hospitals receive a pre–determined tariff for each discharge. Public regional reimbursements represent the vast majority of revenues for acute discharges in all hospitals of Lombardy: out-of-pocket reimbursements comprise only a tiny share of hospital revenues (only 2.2% of regional acute discharges, while the percentage of people with a private insurance in Italy is only 7%). In every Italian region universal coverage for health care services is provided by the Italian NHS, which was introduced in 1978. The NHS is funded through general taxation. Financial resources are then transferred to the various regions that are in charge of managing their individual systems. In Lombardy, all hospitals fulfilling certain requirements that are established and monitored by the regional officers belong to the mixed market hospital sector, comprised of public, private not-for-profit and private for-profit hospitals. The reimbursement that hospitals receive, for each discharge, is established by law at the beginning of each year. These tariffs are revised to take into account hospitals' costs, and may also be modified to correct possible distortions such as upcoding.

In Lombardy, the DRG classification includes 496 DRGs; among them, there are 99 pairs of DRGs with the distinction "patient with/without complications", i.e., a total of 198 DRGs. In each DRG, the tariff received for any hospital acute discharge is split in three parts. For instance, Fig. 1a shows the reimbursement that any type of hospital in Lombardy (i.e., public, for-profit and not-for-profit) received for a discharge in the DRG 010 ("Neoplasia of the nervous system with complications", the dashed line) and in DRG 011 ("Neoplasia of the nervous system without complications", the dotted-dashed line) in 2007. The tariff depends upon two patient length of stay's (LOS) thresholds: if the discharge has a LOS lower than 2 days (i.e., less than 2 nights in hospital) the hospital receives a reimbursement equal to 197 Euro (the 0–1 LOS range). Any discharge in DRG 010 with a LOS included between 2 and 34 days gives rise to a reimbursement from the regional government to the hospital equal to 3,727 Euro. Clearly, the hospital has an incentive to keep the patients' LOS *as low as possible* if the discharge falls within this interval. By only taking monetary terms into account, the best situation for an hospital is having a patient with a short LOS (e.g., equal to 2 to 3 days), and then replacing the patient with a new one. A patient with a long LOS yields instead a high opportunity cost for the hospital as more possible reimbursements (coming from additional discharges) are foregone.[6]

Moreover, as shown in Fig. 1b, discharges with a LOS greater than 34 days can be treated as outliers. The LOS distribution within each DRG is typically skewed and mostly concentrated in short LOSs. Hence, the relevant part of the tariff for the hospitals' budget is the upper-horizontal segment shown in Fig. 1a.

Figure 1a also presents the reimbursement transferred by the regional government to the hospital for each discharge in DRG 011, the one without complications (the dotted-dashed line). This reimbursement is always lower than the one for DRG 010 (with complications).

[6] For patients with a LOS greater than 34 days hospitals receive a reimbursement equal to Euro 3,727 plus Euro 148 for each incremental day after the day 34.

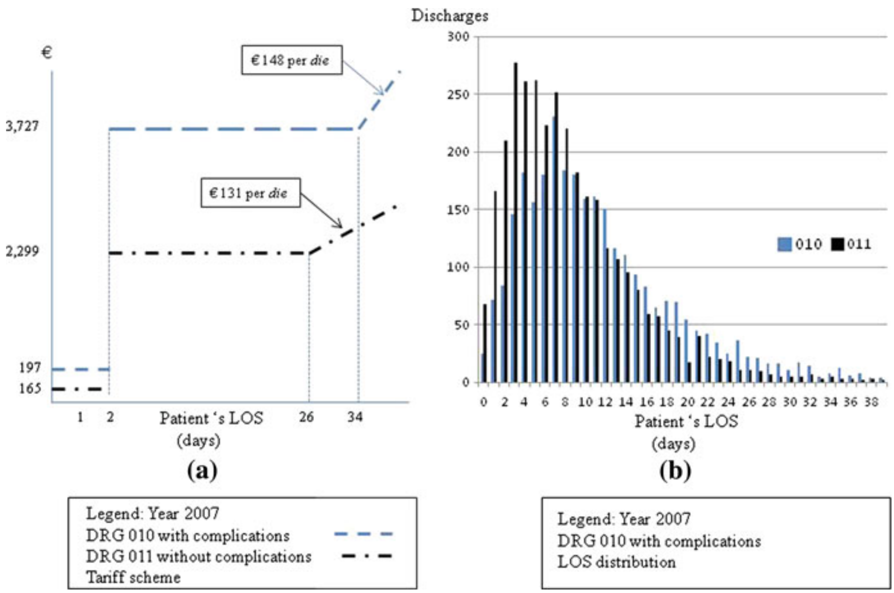

Fig. 1 Tariffs in DRGs pair 010–011 and discharges' LOS distribution

As shown by Dafny (2005), the spread between the tariff for the top-code DRG in the pair (i.e., the one with complications) and that for the bottom-code DRG (i.e., the one without complications) is the hospital's monetary incentive to engage in upcoding. Figure 2 shows that in 2007, before the law, upcoding a patient with a LOS equal or greater than 2 days in the DRG pair 010/011 yields a monetary gain (i.e., the spread) equal to Euro $3{,}727 - 2{,}299 = 1{,}428$.[7]

The regional government, being aware of the incentive to upcode as shown in Fig. 2, approved the Regional Act No. 5743/2007 law, with the specific goal of limiting upcoding. The law introduced an important change: hospitals, in 2008, received the higher reimbursement for a DRG with complications, only if the discharge's LOS reaches a minimum threshold, that is DRG-specific (i.e., it varies among the different DRGs with complications). Figure 2 shows that for the DRG pair 010/011, the LOS threshold is set at 6 days. Hence, any discharge coded with complications but with a LOS lower than 6 days was reimbursed as a discharge without complications.[8] The

[7] Euro 1,428 is the gain from upcoding if the patient's LOS is between 2 and 26 days (see Fig. 1a). If the LOS is between 26 and 34 days the gain is lower, because the reimbursement in DRG 011 is equal in this case to Euro 2,299 plus Euro 131 for each incremental day after the 26th one. For instance, if the LOS is equal to 30 days, the reimbursement in DRG 011 is Euro 2,299 plus Euro 524 (4 extra days reimbursed Euro 131 each), i.e., Euro 2,823. Hence the gain from upcoding a patient is equal to Euro 904. However discharges with such long LOS are exceptions, as shown in Fig. 1b.

[8] Health care regional officers justify this policy shift by asserting that a discharge in a DRG with complications with a LOS lower than a minimum time spell has no sufficient grounds to be reimbursed more, i.e., as a compensation for more intensive care. The analysis of hospital discharges that occurred during

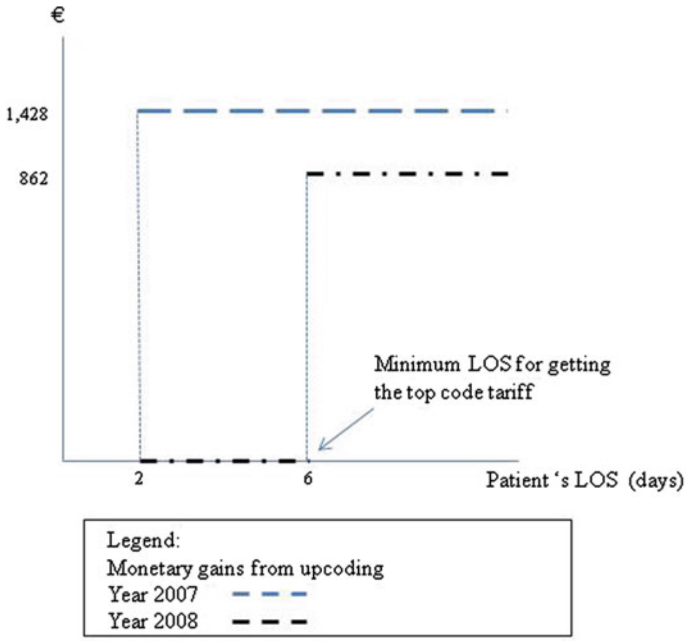

Fig. 2 Changes in upcoding incentives introduced by law

dotted-dashed line in Fig. 2 shows the incentive to upcode in year 2008: for any LOS between 2 and 6 days it is equal to 0. If, instead, the LOS is sufficiently high (i.e., greater than 6 days) there is still a monetary gain from upcoding a patient, which is equal to Euro 862.[9]

Table 1 shows the different minimum LOS thresholds for receiving a top-code reimbursement after the law, and the number of corresponding DRGs. There are 11 different thresholds, varying from a minimum of 3 days to a maximum of 13 days.

We exclude 13 DRGs pairs from the analysis since the minimum LOS threshold established by the law in order to get the top-code tariff is equal to 2 days, i.e., in these DRGs the possibility of receiving, after the law, a top-code reimbursement is not contingent upon the patient's LOS. It is sufficient to have a LOS equal to 2 days to receive both (1) a higher tariff that remains fixed for a long LOS interval, as shown in Fig. 1a (the first upward shift); and (2) the top-code tariff if the patient is registered in

Footnote 8 continued
the first semester of 2007 in the DRG pairs with and without complications has led the regional health care officers to adopt a LOS threshold for the DRGs with complications equal to the median per-patient LOS of the correspondent DRG without complications during that period. This LOS 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).

9 In 2008, the tariff for a discharge in DRG 010 with a LOS higher (or equal) to 2 days was Euro3,248, while the tariff for an equal LOS discharge in DRG 011 was Euro 2,386. Hence the incentive to upcode is Euro 862.

Table 1 Minimum LOS thresholds and DRGs with complications

LOS threshold	DRGs (number)
3	25
4	20
5	15
6	17
7	3
8	3
9	3
10	1
11	1
13	1

the DRG with complications. Hence in these 13 pairs, the law had no effect in limiting upcoding: the analysis is limited to 86 DRG pairs.

Although the law has reduced the incentive to upcode, it has not entirely eliminated it—hospitals may consider increasing the patient's LOS so that it reaches the minimum threshold, and then upcode the patient. This means that hospitals, in order to continue practicing upcoding, have to strategically modify their actions regarding the LOS distribution in each DRG with complications.

In Lombardy's hospital system, upcoding is a decision that has to be taken at the top level of an hospital's governance. The hospital's general manager is indeed lawfully responsible for all the coding activity performed in her/his hospital. Furthermore, from coding the patients hospitals receive the regional reimbursements which account for the vast majority of their revenues, as mentioned before. Hence coding guidelines are defined by the top-level executives. This implies that we can investigate whether the law has modified their behaviors by comparing data before and after its implementation.

3 Econometric approach

In this section, we present our research questions and the econometric approach we apply to investigate them. Our first testable hypothesis regards the probability of having a discharges in DRGs with complications before and after the law.

Research Hypothesis #1 (RH_1): There is a significant difference in the probability of a discharge with complications before and after the law.

In order to investigate the above research question, we implement a logit model where the dependent variable is equal to 1 when the discharge is in a DRG with complications and 0 if it is in any other DRG where there is no distinction between patients with or without complications. By estimating this model we can study whether there has been a significant change in the upcoding probability. Second, our aim is to investigate if the law changed the LOS of discharges in DRGs with complications, as shown in the following testable hypothesis.

Research Hypothesis #2 (RH_2): There is a significant difference in the LOS of a discharge with complications before/after the law in comparison with the same-period difference in the LOS of a discharge in a DRG with no distinction between patients with or without complications.

In this case we implement a difference-in-difference model where the dependent variable is the LOS of each patient during the year 2007 and 2008.[10] The treated group is given by the discharges in DRGs with complications while the control group is comprised of the discharges in DRGs where the possibility of complications in the patient is not accounted for. Discharges in DRGs without complications are not considered due to the following reasons: (1) they are influenced by the law (i.e., they should increase in 2008); and (2) they are not independent from the discharges in the treated group.[11] Last, our aim is to study the combined effect on public regional health care costs of the law. In this case we have to take into account hospitals' reimbursements. The law affected reimbursements both in DRGs with and without complications, since, after its implementation, it is more difficult (more likely) to register a patient in a DRG with (without) complications. The monetary effect of the law regards the average hospitals' reimbursement for a discharge in a DRG pair where a patient may have complications or not. The issue here is to analyze whether after the law there is a significant reduction in the hospitals' reimbursement for a discharge in a DRG pair with/without complications, in comparison with the observed trend for reimbursement in any other DRG. Hence our final research question is:

Research Hypothesis #3 (RH_3): There is significant difference in hospitals' reimbursement for a discharge in DRGs with/without complications before/after the law in comparison with the same-period difference in the reimbursement for a discharge without such distinction.

To investigate RH_3 we implement a difference-in-difference model where the dependent variable is the log transformation of the reimbursement received by an hospital for each discharge belonging to the treated and control groups. The treated group here is different than that designed for testing RH_2. In this case it is given by the reimbursements received for a discharge in all the DRG pairs distinguishing between presence/absence of complications in the patient, i.e., we include here in the treated group also the reimbursement for discharges in DRGs without complications.

As discussed by Besley and Case (2000) and Blundell and McCurdy (1999), any attempt to evaluate the impact of a policy on some variables should carefully consider two important issues: (1) the possible policy endogeneity; (2) the selection of treated

[10] The difference-in-difference model is a development of the potential outcome and counter factual analysis methodology (Imbens and Rubin 2009; Winship and Morgan 2007; Rubin 1974, 1975, 1978; Holland 1986; Heckman 2005; Schneider et al. 2007; Stuart 2007; Jin and Rubin 2009). See Jones (2009) for an overview of difference-in-difference applications to other health economics issues.

[11] The LOS increase may also bring a negative social effect if the patients' waiting time increases after the law. Unfortunately, it is not possible to control for this effect as no data are available for patients' waiting hospitalization time in Lombardy. However we have information regarding the beds-load factor in each regional hospital. The evidence is that (1) many hospitals have spare capacity; and (2) the load factor did not significantly increase after the law. In 2007, the average beds-load factor was equal to 79.5%, and slightly increased to 80.8% (+1.3%) in 2008, which still signals that hospitals are not congested.

and control groups if a difference-in-difference model is adopted. On the first issue, policy endogeneity means that some economic, political and demographic variables may have influenced the policy adoption. In turn, they are also the policy target. In our natural experiment, the policy was motivated, as described in the Introduction, by an exogenous medical treatment factor: before the law less health care treatments were observed in many discharges with complications than in discharges without complications, a clear medical contradiction. Hence, we may argue that policy's endogeneity is not an issue here.

Regarding the second issue by Besley and Case (2000) and Blundell and McCurdy 1999 argue that treated and control groups should have no other difference than the policy, that is applied only to the treated one. In our experiment treated and control groups differ also for medical treatments (while they share the same regional economic and political system, and the same potential demand): the possible presence of patients' complications only in the treated group. However, we take into account for patients' characteristics, that may be an important factor of difference between the two groups. Another possible time-varying variable influencing discharges in the two groups may be the impact of technological change. Hence, we include a proxy of technical progress in our regressors when it may affect a variable of interest: in our investigation technical progress may have an impact on the discharge's LOS, i.e., only in our second research question (patients with complications are not influenced by hospitals' technology but by exogenous factors such as the patients health status; reimbursements are instead exogenously defined by a regional law). The estimated coefficients of the policy impact on the treated group should then be sufficiently robust.

In our difference-in-difference models the treated group is composed of 86 DRGs with complications. The control group is instead comprised of all the 298 DRGs without distinction for the presence/absence of complications. We have monthly observations at the individual level, since our information are extracted from patients' hospital discharge charts.

We consider a 2-year panel (2007–2008) and apply a fixed effect model to take into account for hospitals' heterogeneity. In order to investigate the impact of the law on the probability of a discharge with complications we regress the following logit model:

$$\begin{aligned} y_{iht} = \alpha_0 + \sum_{k=1}^{7} \beta_k X_{iht} + \sum_{l=1}^{2} \zeta_l H_{ht} + \sum_{d=1}^{11} \eta_d M_{iht} + \sum_{v=1}^{137} \theta_v HOSP_h \\ + \alpha_1 POST_{iht} + \alpha_2 \{OWNNFP \times POST\}_{iht} \\ + \alpha_3 \{OWNFP \times POST\}_{iht} + \epsilon_{iht}, \end{aligned} \tag{1}$$

where i indexes individual discharges, h indexes hospitals ($h = 1, \ldots, 138$), t indexes years ($t = 1, 2$). The dependent variable is equal to 1 if the discharge is registered in a DRG with complications (and 0 otherwise). We control for patients' characteristics, given by the following set of covariates X_{iht}[12]: the patient's age (*AGE*, expressed in

[12] The statistical literature on health care evaluation (Goldstein and Spiegelhalter 1996) has highlighted the importance of the patient's characteristics (e.g., age, gender, comorbidities, health status, etc.) in testing

years), gender (*GENDER*, a dummy variable equal to 1 if the patient is male), comorbidity level (*CI*, i.e., a comorbidity index),[13] transit through an intensive-care-unit (ICU expressed as a percentage of patients), and the presence of particular pathologies such as: cardiovascular diseases (CARDIO expressed as percentage of patients), cancer (CANCER expressed as a percentage of patients), and admission through an emergency unit (EMERG expressed as a percentage of patients). H_{jtm} is a pair of hospital's characteristics that may affect output, i.e., the total number of discharges: we consider the number of beds (BEDS expressed as a number) and the beds-load factor (LF expressed as the ratio of total patients on available beds). We control also for month fixed effects through the monthly dummies M_{iht}, and for hospitals' fixed effects through the dummy variable $HOSP_h$.

The impact of the policy on the probability of a discharge with complications is captured by the dummy variable $POST$, equal to 1 if $t = 2$ (i.e., year 2008 when the new law has been implemented), and zero otherwise. Our aim is also to investigate whether hospitals with a specific ownership type has been more affected by the law than other types. We control for this ownership effect through the interaction terms between the dummy variables $OWNNFP$ (equal to 1 if the hospital is a not-for-profit organization and 0 otherwise) and $OWNFP$ (equal to 1 if the hospital is a for-profit organization and 0 otherwise) and the dummy variable $POST$. This implies that we take public hospitals as reference.

The second research hypothesis (i.e., RH_2) regards the impact of the law on the discharges' LOS. We implement the following difference-in-difference model:

$$
\begin{aligned}
y_{iht} = \alpha_0 &+ \sum_{k=1}^{7} \beta_k X_{iht} + \sum_{l=1}^{3} \zeta_l H_{ht} + \sum_{d=1}^{11} \eta_d M_{iht} + \sum_{v=1}^{137} \theta_v HOSP_h \\
&+ \alpha_1 POST_{iht} + \alpha_2 TREAT_{iht} + \alpha_3 \{POST \times TREAT\}_{iht} \\
&+ \alpha_4 \{OWNNFP \times POST\}_{iht} + \alpha_5 \{OWNFP \times POST\}_{iht} \\
&+ \alpha_6 \{OWNNFP \times TREAT\}_{iht} + \alpha_7 \{OWNFP \times TREAT\}_{iht} \\
&+ \alpha_8 \{OWNNFP \times POST \times TREAT\}_{iht} \\
&+ \alpha_9 \{OWNFP \times POST \times TREAT\}_{iht} + \epsilon_{iht},
\end{aligned} \tag{2}
$$

Footnote 12 continued
the robustness of outcomes regarding hospitals activities, such as the number of discharges of patients with complications, patients' age, and gender, etc.

[13] In medicine, comorbidity describes the presence of other diseases in addition to the primary one. Several indexes have been developed to quantify comorbidity (see 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.

where the dependent variable, LOS, is given by the number of days of each individual discharge. We take into account for patients' characteristics as in Model (1), while we modify the hospitals' characteristics H_{ht}. We consider again the number of beds ($BEDS$) but we exclude the beds-load factor, since there is an endogeneity problem with the dependent variable.[14] We tackle this issue by implementing an instrumental variable approach: the variable $NSURG$ (the number of surgery rooms in each hospital) is our instrumental variable for hospitals' utilization of their installed capacity. The variable $SURGDAYS$ (the number of active days in the surgery rooms of each hospital) is the only proxy available in our data set that may indicate the possible impact of technical change on treated and control groups (the assumption here is that technical progress may reduce the time spent by the patients in surgery rooms).

As before, we consider both month and hospital fixed effects. The policy impact is estimated by the $POST$ and $TREAT$ variables, and by their interaction terms. $TREAT$ is a variable equal to 1 if the LOS regards a discharge in a DRG with complications and 0 otherwise. The interaction term $POST \times TREAT$ identifies the impact of the law on the LOS of discharges with complications as a difference with the LOS of the discharges in the control group, always before/after the law. We control also for the ownership effect, through the interaction terms $OWNNFP \times POST \times TREAT$ and $OWNNFP \times POST \times TREAT$.

The last research question is investigated by implementing a difference-in-difference approach similar to Model (2). The only differences are: First, the dependent variable is the log transformation of the reimbursement obtained by hospital h on discharge i in time t. Therefore, the coefficient of interest indicates the percentage variation in individual reimbursement. Second, hospitals' characteristics are the same as in Model (1) (i.e., $BEDS$ and LF), since there is no endogeneity problem for beds-load factor here (the dependent variable is the reimbursement for individual discharges and not for their aggregate). Third, we include the variable $SPREAD$ which is given by the variation in the level of reimbursement in each DRG pair, i.e., it is the difference between the top code and bottom code tariff in DRG pairs with/without complications. This variable captures the impact of monetary incentives on the hospitals' admittance strategy: they may increase discharges in the more lucrative DRGs, through patients' selection.

4 The data set

Our main data source is provided by the Hospital Discharge Charts regarding the patients' discharges in Lombardy. The data are provided by the Health Care Department of the Lombardy Region. The HDCs 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 beds-load factor.

[14] The beds-load factor is computed as $LF = (\text{Average LOS} \times \text{discharges})/(\text{BEDS} \times 365\text{days})$. Hence the dependent variable LOS and the explanatory variable LF are highly correlated.

Table 2 Dependent and explanatory variables: descriptive statistics

	2007				2008			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Dependent variables								
Discharge with com. (%)	15	36	0	100	14	35	0	100
Discharge LOS (days)	7.02	8.92	0	561	7.68	9.06	0	523
Discharge reimb. (Euro)	3,486	4,974	0	273,530	3,552	5,174	0	443,610
Patients' characteristics								
Age (years)	49.76	29.58	0	109	49.72	29.82	0	108
Gender (male = 1)	0.51	0.50	0	1	0.51	0.50	0	1
Patients' health status								
Transit in ICU (%)	5.84	23	0	100	5.87	24	0	100
Cancer disease (%)	8.67	28	0	100	8.54	28	0	100
Comorbidity index	0.4	0.75	0	5	0.38	0.73	0	5
Discharge in emerg. (%)	6.91	25	0	100	7.04	26	0	100
Cardiovascular dis. (%)	17.59	38	0	100	17.56	38	0	100
Hospital's characteristic								
Beds	407	295	10	1,167	403	290	10	1,162
Beds-load factor (%)	82	10	27	100	84	10	30	100
Surgery rooms (number)	13.36	11.68	0	50	13.56	11.82	0	50
Op. surg. rooms (h)	584.08	561.54	0	2,707	594.94	603.73	0	2,708
For-profit (number)	34				34			
Not-for-profit (number)	16				16			
Public (number)	88				88			
DRGs' characteristics								
Spread 2008/2007 (%)					1.3	10	−55	83

Table 2 displays some details of the explanatory variables introduced in the econometric models. Among the 138 hospitals there was no changes in ownership during the 2007–2008 period. 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.

5 Results

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

5.1 Descriptive statistics on discharges

Table 3 shows some descriptive statistics regarding the dynamics of discharges in DRGs with complications (the treated group), in DRGs without complications, and in

Table 3 Descriptive statistics on the effects of the law

	2007	2008	% Change
Coded discharges			
DRGs with comp. (treated group)	126,323	118,876	−5.9
DRGs without comp.	138,116	136,804	−0.9
DRGs in control group	723,794	725,091	+0.2
Reimbursed discharges			
DRGs with comp. (treated group)	126,323	87,228	−30.9
DRGs without comp.	138,116	168,452	+22.0

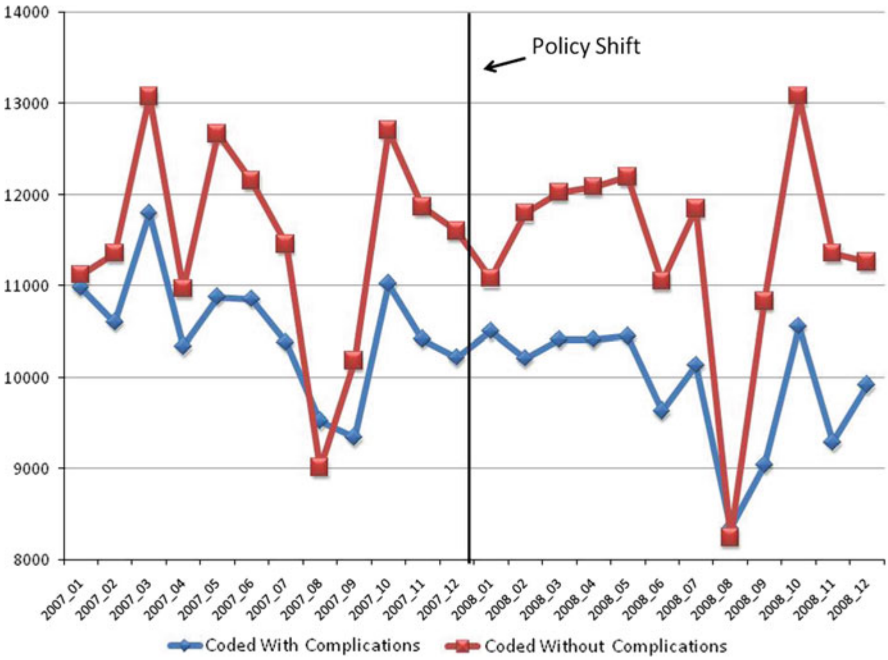

Fig. 3 Discharges in DRGs with and without complications in Lombardy

the DRGs belonging to the control group during the observed period. The total number of discharges with complications in 2007 is equal to 126,323, while after the law this number decreases to 118,876 (−5.9%). The same variable for the DRGs without complications is equal to 138, 116 in 2007 and to 136,804 in 2008. The variation in this case is equal to −0.9%. Figure 3 shows the monthly dynamic of coded discharges in DRGs with complications and without complications in years 2007–2008.

The number of discharges in the DRG control group is 723,794 in 2007 and 725,091 in 2008, with a small +0.2% increase. The situation is rather different if we consider the discharges reimbursed in DRGs with complications and without complications in years 2007 and 2008. Discharges reimbursed in DRGs with complications show a relevant decrease (-30.9%). On the contrary, discharges in DRGs without complications increased by $+22\%$.

5.2 Econometric results

The results of the logit model (1) estimating the impact of the law on the probability of discharge with complications is shown in Table 4. All variables regarding patients' characteristics have a significant impact on the probability of a discharge with complications. Age, gender, cancer disease, treatments in intensive-care-units, and comorbidity have a positive effect, while heart disease and admittance through the emergency unit have a negative impact. Heart diseases reduce the probability of a discharge with complications because these characteristics have a very broad medical application in Lombardy, so that they result to apply to all the population and not necessarily lead to a higher frequency of patients with complications. Similarly, being admitted through the emergency unit is a phenomenon applied to all population. The beds-load factor has a negative significant impact, meaning that hospitals with higher beds' utilization rates seem to admit fewer patients with complications. This may be due to less upcoding when patients are rationed or to patients' selection. Some month fixed effects are significant (all with a negative sign with the exception of August, a month with a very hot weather in Italy, that typically leads to an increase in the discharges of patients with complications).

The effect of the law is captured by the coefficient of the variable $POST$, that is negative and statistically significant. It implies a 3% reduction in the probability of a discharge with complications after the law. The reduction has been greater in not-for-profit and in for-profit hospitals than in public ones. Hence, we find a positive answer to the our first research question, and also identify the presence of an ownership effect.

Table 5 presents the estimated coefficient of the difference-in-difference model (2) applied to patients' LOS. Again all the variables for patients' characteristics are significant, with the exception of $GENDER$, that seems not to influence discharges' LOS. All these variables, when significant, increase the LOS, with the exception of heart diseases, that reduce instead the LOS, for the same explanation provided before.

Hospitals' capacity has a significant negative effect on the LOS: this means that patients' turnover is higher in large size hospitals, since they have discharges with shorter length of stay. We found no evidence of a technical change effect, neither of an impact of hospitals' utilization of the installed capacity. Month fixed effects are significant. Discharges' LOS is increased after the law, and it is longer in the treated group. However the most important result is that discharges' LOS increased more after the law in the treated group in comparison with the same-period variation in the control group. A discharge's LOS in the treated group has increased by 0.17 days more, after the law, than a discharge in the control group. Again the LOS increased more in not-for-profit (+0.29 days) and in for-profit (+0.33 days) hospitals than in public ones.

We can argue that the combined evidence obtained by regressing Model (1) and Model (2) show that upcoding was a widespread practice in the hospitals of Lombardy, and that not-for-profit and for-profit hospitals were more involved in it.

Table 4 Law effect on the probability of a discharges with complications

	Coeff.	SE
Intercept	−3.570***	0.147
AGE	0.030***	0.0001
GENDER	0.038***	0.005
ICU	0.416***	0.010
CARDIO	−0.771***	0.007
CANCER	0.524***	0.007
EMERG	−0.687***	0.010
CI	0.597***	0.003
LF	−0.276*	0.161
BEDS	0.0004	0.0003
JAN	−0.017	0.012
FEB	−0.038***	0.012
MAR	−0.021*	0.012
APR	−0.025**	0.012
MAY	−0.038***	0.012
JUN	−0.008	0.012
JUL	0.017	0.012
AUG	0.108***	0.012
SEP	−0.016	0.012
OCT	−0.033***	0.012
NOV	−0.050***	0.012
POST	−0.033***	0.006
$OWNNFP \times POST$	−0.041**	0.017
$OWNFP \times POST$	−0.034**	0.013

***$P < 0.01$; **$P < 0.05$; *$P < 0.1$
AGE patient's age, $GENDER$ percentage of male patients, ICU patients in intensive care units, $CARDIO$ percentage of heart-disease patients, $CARCER$ percentage of patients with cancer, $EMERG$ percentage of patients admitted through Emergency, CI comorbidity index, LF beds-load factor, $BEDS$ hospital's beds, $POST$ year 2008, $OWNNFP$ not-for-profit hospitals, $OWNFP$ for-profit hospitals, monthly dummies ($JAN, FEB, \ldots$)

Table 6 shows the results regarding our third research question, i.e., the impact of the law on discharges' reimbursements. Again, patients' characteristics are statistically significant and, in this case, all positive. This means that the different critical patients' health status features give rise to higher reimbursements. Both hospitals' capacity ($BEDS$) and its utilization (LF) are significant and have a positive effect on reimbursements: larger size hospitals receive higher per-discharge reimbursements. Moreover, those with higher capacity utilization rates get higher per-discharge reimbursements. This may be a signal that a more efficient management is also able to select the discharges yielding higher reimbursements. Many month fixed effects are, as usual, significant, and with negative sign. The variable $SPREAD$ is significant and with positive sign. The monetary incentive is strong and leads to higher per-discharge reimbursements.

The coefficient of the interaction term $POST \times TREAT$ is significant and negative. This implies that after the law the per-discharge reimbursement in DRGs with/without complications has decreased by 8.5%, after taking into account the same period variation in control group reimbursements. Hence the law had also a monetary impact.

Table 5 Law effect on discharges' LOS

	Coeff.	SE
Intercept	0.010	0.256
AGE	0.047***	0.0003
GENDER	0.012	0.013
ICU	6.923***	0.029
CARDIO	−1.145***	0.019
CANCER	2.969***	0.024
EMERG	1.440***	0.027
CI	1.518***	0.010
BEDS	−0.002**	0.001
NSURG	−0.005	0.026
SURGDAYS	0.00001	0.00001
JAN	−0.151***	0.031
FEB	−0.298***	0.031
MAR	−0.254***	0.030
APR	−0.206***	0.031
MAY	−0.185***	0.030
JUN	−0.166***	0.031
JUL	−0.181***	0.031
AUG	0.007	0.033
SEP	−0.357***	0.031
OCT	−0.236***	0.030
NOV	−0.136***	0.031
POST	0.073***	0.017
TREAT	2.252***	0.030
POST × *TREAT*	0.173***	0.041
OWNNFP × *POST*	−0.042	0.052
OWNFP × *POST*	−0.026	0.036
OWNNFP × *TREAT*	0.241***	0.092
OWNFP × *TREAT*	0.121*	0.070
OWNNFP × *POST* × *TREAT*	0.292**	0.131
OWNFP × *POST* × *TREAT*	0.330***	0.100

*** $P < 0.01$;
** $P < 0.05$; * $P < 0.1$
All variables as in Table 4, plus $NSURG$ number of hospital's surgery rooms, $SURGDAYS$ days of operation of hospitals' surgery rooms, $TREAT$ treated group

The ownership effect is still present: per-discharge reimbursement in treated DRGs is decreased by 5% in not-for-profit hospitals (with respect to the public ones) and by more (7.3%) in for-profit hospitals (again with respect to the public ones), always in comparison with control group reimbursements. Hence also our last research question received a positive answer. Since the average reimbursement in year 2007 for a discharge in a DRG with complications was equal to Euro 4,613, a 8.5% reduction in per-discharge reimbursement amounts to a saving of Euro 392 per discharge in DRGs with/without complications after the law.

Table 6 Law effect on per-discharge reimbursement

	Coeff.	SE
Intercept	6.987***	0.040
AGE	0.010***	0.000
GENDER	0.069***	0.001
ICU	0.936***	0.003
CARDIO	0.197***	0.002
CANCER	0.586***	0.002
EMERG	0.204***	0.003
CI	0.051***	0.001
LF	0.257***	0.043
BEDS	0.0002***	0.0001
JAN	−0.019***	0.003
FEB	0.002	0.003
MAR	−0.005	0.003
APR	−0.011***	0.003
MAY	−0.020***	0.003
JUN	−0.010***	0.003
JUL	−0.015***	0.003
AUG	−0.033***	0.003
SEP	−0.023***	0.003
OCT	−0.008***	0.003
NOV	−0.004	0.003
SPREAD	0.475***	0.012
POST	0.033***	0.002
TREAT	0.187***	0.003
POST × *TREAT*	−0.085***	0.005
OWNNFP × *POST*	−0.005	0.005
OWNFP × *POST*	−0.017***	0.004
OWNNFP × *TREAT*	0.027***	0.009
OWNFP × *TREAT*	0.008	0.007
OWNNFP × *POST* × *TREAT*	−0.050***	0.013
OWNFP × *POST* × *TREAT*	−0.073***	0.010

*** $P < 0.01$;
** $P < 0.05$; * $P < 0.1$
All variables as in Table 4, plus $SPREAD$ 2007/2008 DRG tariff variation, $TREAT$ treated group

We can then argue that (1) upcoding was a widespread practice in hospitals of Lombardy and (2) linking discharges in DRGs with complications to their length of stay is an effective incentive to limit it.

6 Conclusions

We have investigated the effects of a law explicitly designed to limit upcoding in the hospitals of Lombardy. The law introduces a minimum LOS for discharges registered in DRGs with complications. We have examined hospitals' response to the law by investigating its impact on the probability of a discharge in a DRG with complications, on its length of stay and on its reimbursement.

We found evidence that the policy has been effective in limiting upcoding, since the probability of a discharge with complications is significantly lower in 2008 (we estimated a 3% decrease). Second, discharges in DRGs with complications have a positive variation in their length of stay that is 0.17 days longer, after the law, than that observed for discharges in the control group. Third, we find that the law had also a monetary impact, since per-discharge reimbursements in the treated group are 8.5% lower, after the law, than the corresponding variation for the control group. Last we find evidence of an ownership effect on upcoding activity: not-for-profit and for-profit hospitals are more engaged in this distortion.

These insights enlarge the previous results on upcoding (Silverman and Skinner 2004 and Dafny 2005) as they have been obtained by applying new econometric approaches to this topic, by investigating a population-based data set (while previous contributions used data from a sample that included just elderly people), and by using data at the individual level.

Acknowledgements The authors are grateful to two anonymous referees for the helpful suggestions provided on a first version of the paper. Furthermore the great support received from Luca Merlino and Carlo Zocchetti in building the data set is acknowledged by the authors. This research has received funding from the University of Bergamo (grant 60MART10). Giuditta Callea has mainly contributed to Sects. 2 and 4.

References

Agency for Healthcare Research and Quality (2008) Healthcare cost and utilization project. Comorbidity Software Version 3.3. http://www.hcup-us.ahrq.gov/toolssoftware/comorbidity/comorbidity.jsp
Berta P, Callea G, Martini G, Vittadini G (2010) The effects of upcoding, cream skimming and readmissions on the Italian hospitals efficiency: a population–based investigation. Econ Model 27:812–821
Besley T, Case A (2000) Unnatural experiments? Estimating the incidence of endogenous policies. Econ J 110:672–694
Blundell R, McCurdy T (1999) Labor supply: a review of alternative approaches. In: Ashenfelter O, Card D (eds) Handbook of labor economics. Elsevier, Amsterdam
Charlson ME, Pompei P, Ales KA, MacKenzie CR (1987) A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis 40:373–383
Dafny LS (2005) How do hospitals respond to price changes? Am Econ Rev 95:1525–1547
Dafny LS, Dranove D (2009) Regulatory exploitation and management changes: upcoding in the hospital industry. J Law Econ 52:223–250
de Groot V, Beckerman H, Lankhorst G, Bouter L (2003) How to measure comorbidity: a critical review of available methods. J Clin Epidemiol 56:221–229
Elixhauser A, Steiner C, Harris DR, Coffey RM (1998) Comorbidity measures for use with administrative data. Med Care 36:8–27
Fossati A (2002) Economia Pubblica. Franco Angeli, Milan
Goldstein H, Spiegelhalter DJ (1996) League tables and their limitations: statistical issues in comparison of institutional performance. JRSS Ser A 159(3):385–443
Heckman J (2005) The scientific model of causality. Sociol Methodol 35:1–97
Holland PW (1986) Statistics and causal inference. J Am Stat Assoc 81:945–970
Imbens G, Rubin DB (2009) Causal inference in statistics, and in the social and biomedical sciences. Cambridge University Press, New York
Jin H, Rubin DB (2009) Public schools versus private schools: causal inference with partial compliance. J Educ Behav Stat 34:24–35

Jones AM (2009) Panel data methods and applications to health economics. In: Mills TC, Patterson K (eds) Palgrave handbook of econometrics. Volume II: applied econometrics. Palgrave MacMillan, Basingstoke
Liu Z, Dow WH, Norton EC (2004) Effect of drive-through delivery laws in postpartum length of stay and hospital charges. J Health Econ 23:129–155
McClellan M (1997) Hospital reimbursement incentives: an empirical analysis. J Econ Manag Strat 6:91–128
Mayes R (2007) The origins, development, and passage of Medicare's revolutionary prospective payment system. J History Med Allied Sci 62:21–55
Rubin DB (1974) Estimating causal effects of treatments in randomized and nonrandomized studies. J Educ Psychol 66:688–701
Rubin DB (1975) Bayesian inference for causality: the importance of randomization. In: The Proceedings of the social statistics section of the American Statistical Association, pp 233–239
Rubin DB (1978) Bayesian–inference for causal effects—ole of randomization. Annals of Statistics 6:34–58
Schneider B, Carnoy M, Kilpatrick J, Schmidt WH, Shavelson RJ (2007) Estimating causal effects using experimental and observational designs a think tank white paper. American Educational Research Association, Washington, DC
Silverman E, Skinner J (2004) Medicare upcoding and hospital ownership. J Health Econ 23:369–389
Simborg DW (1981) DRG creep: a new hospital-acquired disease. New Engl J Med 304(26):1602–1604
Southern DA, Quan H, Ghali WA (2004) Comparison of the Elixhauser and Charlson/Deyo methods of comorbidity measurement in administrative data. Med Care 42:355–360
Stuart EA (2007) Estimating causal effects using school-level data sets. Educ Res 36:187–198
Winship C, Morgan S (2007) Counterfactuals and causal inference. Cambridge University Press, Cambridge