Upcoding in a National Health Service: the evidence from Portugal

Keywords: upcoding; diagnosis-related groups; public hospitals; price spread

1 INTRODUCTION

Upcoding has been documented empirically in US hospitals and the Medicare system there.[1] However, empirical evidence addressing the issue in the context of European health systems is scarce.[2] To the best of my knowledge, there is no evidence for a large set of DRGs in the context of a National Health Service (NHS). This is somewhat surprising as patient classification systems are now common in many countries, many of which have an NHS and use diagnosis-related group (DRG)-like systems to pay providers of health care.

The use of prospective payment based on patients classification systems has become widespread. A crucial feature of payments by episode is the coding of each patient. In the US, the first country to have payments to health providers based on DRGs, a concern often raised was that of upcoding. The practice of upcoding consists of shifting the DRG of a patient to another DRG yielding a higher payment from the third-party provider. Dafny (2005) focused on the US hospitals' responses to price changes of the DRGs. She found that hospitals upcoded patients in order to increase profits through reimbursements, and hospitals upcoded more in the DRGs in which the price increase was greater. Moreover, upcoding occurred chiefly in the for-profit hospitals, and there was no increase in intensity or quality of care.[3]

Lave (1985) pointed out that compression was occurring in the US DRG prices, in the sense that high cost DRGs had been set lower than their actual costs and low cost DRGs had been set higher, and that might have important implications on DRG creep. Carter and Ginsburg (1985) explained that of the

[1] See Silverman and Skinner (2004) and Dafny (2005) for recent accounts of upcoding.
[2] Upcoding is also known as DRG creep in the related literature.
[3] Similar conclusions were found by Silverman et al. (1999) and Silverman and Skinner (2004).

8.4% accumulated case-mix index (CMI) increase from 1981 to 1984, 3.3% could be due to upcoding.[4] Hsia et al. (1988) found an error rate of 20.8% in the DRG codes from 1984 to 1985. Steinwald and Dummit (1989) argued that of the 20% CMI increase in the US from 1983 to 1988 only 8% was due to formal changes in DRG weights, suggesting upcoding as the culprit for the remaining increase. Carter et al. (1990) decomposed the 2.4% increase in the CMI of the US hospitals between 1986 and 1987 and found that one third of that value was due to upcoding. Psaty et al. (1999) calculated the potential upcoding costs per year for heart failure procedures in the US from 1986 to 1993, highlighting the size of the problem.

There is a small number of studies considering markets outside the US. Using Hungarian data, Kroneman and Nagy (2001) found no relationship between implementation of DRGs and the increase in CMI from 1992 to 1995. Rauner and Schaffhauser-Linzatti (2002) identified cost reduction and improvement in quality indexes following the implementation of PPS in Austria in the year of 1997. Xirasagar and Lin (2006) found that large public teaching hospitals are more likely to admit patients in need of hernia operation and cataract surgery than for-profit and not-for-profit hospitals in Taiwan. Berta et al. (2010) found no evidence of upcoding behaviour related to hospital ownership in the Italian NHS, and Jürges and Köberlein-Neu (2013) also found no evidence of upcoding for neonatology-related DRGs in Germany.[5]

Kuhn and Siciliani (2013) provide a recent theory treatment of upcoding.

[4]CMI is a measure of the complexity of episodes treated in a hospital, which is used in the calculation of a hospital budget. The index is calculated from DRG weights, and a proxy of the total number of patients treated in the hospital. Consequently, upcoding is correlated with higher CMI.

[5]Berta et al. (2010) analyse the effects of distortions induced by prospective payment system (PPS) on hospitals' technical efficiency. Also, Berta et al. (2012) evaluate a measure to disencourage upcoding behaviour, both using Italian data.

Their focus is on how quality, "manipulative effort", and auditing interact with the payment rule defined by a third-party payer to a provider. From their model it follows quite naturally that higher prices generate higher manipulative efforts and higher output and more auditing effort reduces upcoding. Moreover, the price instrument influences quality provided but auditing does not.

Considering that countries with an NHS also adopt patient classification systems and PPS to their public hospitals, the very same question can be asked: do we observe upcoding in the public health sector? Should it be a concern in the context of the NHS?[6] Our analysis shows that upcoding can also be present in an NHS system, though the link between episode coding and funding is weaker than in private markets. The estimated cost of upcoding is quite small.

The study was done with Portuguese NHS data for the years from 2001 to 2008. A politically-driven change in DRG prices in the year of 2006 provides an exogenous source of variation, not related to evolution in hospital costs, that may have an impact on hospital decisions. This enables us with variation to identify upcoding behaviour within an NHS framework. Since the changes in prices are not equally important to all DRGs, we trace whether shifts in DRG coding toward higher priced DRGs were stronger in those cases in which the relative price of a DRG changed the most.

The main contribution of the paper is the identification of upcoding for a large group of DRGs in a public health system. The hospitals respond to price changes including more patients into the DRGs that are more profitable. No distinction

[6]Steinbusch et al. (2007) conducted a comparative study amongst American, Australian, and Dutch case-mix reimbursement systems, pointing out the variables that could motivate or inhibit upcoding.

across statutes of hospitals is detected regarding upcoding behaviour. However, the financial burden is small: the upcoding induces an estimated average increase of 0.04% in cost.[7] Therefore, this is an evidence that supports the adoption or maintenance of DRG-like payment systems in NHSs.

The paper is organized into 7 sections. Section 2 describes the Portuguese NHS and the exogenous politically-driven change in prices. Section 3 describes a simple model generating our empirical predictions. Section 4 explains the methodology used, and section 5 discusses the results obtained. Section 6 has the concluding remarks.

2 THE PORTUGUESE HEALTH SYSTEM

Portugal has an NHS since 1979, and in the early 1980s a version of the US DRG was introduced.[8] The implementation started in 1989, which modified the incentives to produce and improve health goods, and the system has been adjusted over time.

During the early years there was no clear link between the budget that each public hospital received and its activity, which offered little incentive for upcoding. Budgets were revised annually based on historic costs, or deficits were run carelessly in the expectation that sooner or later fresh money from the Government would arrive. Thus, the soft-budget constraint effect rendered relatively irrelevant the "price" given to each DRG and they were revised sporadically and without a

[7] The result is aligned with those previous findings for other European health systems like Italy, Germany, Hungary and Austria (Kroneman and Nagy, 2001; Rauner and Schaffhauser-Linzatti, 2002; Berta et al., 2010, 2012; Jürges and Köberlein-Neu, 2013).

[8] It was the result from an agreement between the Ministry of Health and Yale University to assess the consequences of using DRG-like systems in the NHS.

sound underlying cost analysis.

In 2002 a change occurred in the Portuguese NHS. The Parliament approved a legal regime for hospital administration through the Law 27/2002 - November 8^{th}. According to the new legislation, public limited corporation (PLC) hospitals could be transformed into public entrepreneurial organisations named as *Entidade Pública Empresarial* (EPE) hospitals. Their control and supervision became a duty of both the Ministries of Health and Finance. The effective transformation of PLCs into EPE hospitals took place in the middle of 2005 through the Law-decree 93/2005, from July 7^{th}.

Therefore, the major change in hospital management rules was witnessed in the year of 2005. The budgeting process brought hospital budgets at the beginning of the year closer to expected costs, and management performance came under closer scrutiny. Even though no public hospital has become bankrupt, a clear hardening is seen in the budget constraint. The more entrepreneurial-like management rule was introduced in nearly half of the public hospitals: 32 hospitals changed their statute from PLC to EPE.[9] This change was politically-driven, to signal the Government's intention of keeping hospitals within the public sector.

The EPE hospitals have to define the health services to be provided through a contract with the Ministry of Health, describing the expected activity and overall budget for the next year.[10] Information from the DRGs is used to establish the terms of the contracts. These changes introduced the financial incentive for

[9] The release of different accountability documents is one of the changes, for example, as well as more freedom in contracting human resources and procuring hospital consumables.

[10] Having the EPE hospitals as a benchmark, in terms of management rules and budgeting process, the new regulation gives indirect incentives for entrepreneurial-like management rules in *Setor Público Empresarial* (SPA) hospitals as well.

upcoding, as greater complexity of recorded cases would bring more funds in the future. Upcoding delivers benefits to the hospital and can therefore become a matter of concern to the purchaser of care.

2.1 The coding process

The coding process in Portugal is realized by clinicians, but not by the same clinicians that provide direct care and collect information about patient's health and medical conditions. This choice of doctors rather than other health professionals was made by historic reasons. In 1989, when the implementation of DRGs occurred, it was easier and faster to train clinicians to code clinical episodes, given the supply of just graduated doctors in the job market. This is particular to the Portuguese system as the same task is performed by nurses in Spain, or by coding specialists in the US.

The process of coding is composed by three phases. In the first phase, the patients receive medical care and the clinician records information about patients' characteristics, diagnoses and medical procedures. The second stage is the phase where the episodes are classified into DRGs, by a group of clinicians, at *Gabinete da Codificação*. The last phase is the auditing period, where clinical processes are evaluated to verify whether the provided information and the DRG codes are in accordance with medical guidelines. This duty is made by auditing clinicians that not only conclude the processes, but also randomly audit them.

2.2 The policy change

Initial prices and weights for DRGs were set based on Maryland values in 1989, and then adjusted in ad hoc ways over the years. Portuguese hospitals do not have an accounting system allowing to compute cost per patient or per DRG. Thus, adjustments in prices and weights are decided internally to the NHS financing body. This process makes these changes exogenous from the point of view of the hospital and external analysts.[11]

The Portuguese DRG prices changed in 2003 and remained stable until early 2006, when another set of prices was fixed. In 2007, a change of equal size and for all DRGs was set.[12] The changes in DRG weights are almost equal to the ones in prices, making the correlation between changes in DRG prices and weights roughly equal to one. No further adjustment occurred in 2008. The price setting was exogenously determined and politically-driven. Therefore, the Portuguese NHS provides a natural test to assess the extent of upcoding in an NHS.

Despite the declaration that changes are due to accommodate real costs and reasonable profit level, the changes are not based in any study to define optimal prices and weights, from the economic point of view. It is also stated that variation in demographic conditions and epidemiological profile of the population were taken into account to set the new prices and weights. However, epidemiological variations are more evident across the regions of the country rather than for the entire country over a short period of time, and the prices and weights are set nationally.[13] These

[11] A concern would be that either price and weight changes could be anticipated by hospitals or even induced by them, by cost allocation decisions or treatment choices within DRG pairs.

[12] The relevant changes in DRG prices and weights were defined through *Portarias* 567/2006 - June 12^{th} and 132/2003 - February 5^{th}, which are legal instruments issued by the Ministry of Health.

[13] Adjustment for severity level is made by the CMI, which is required to obtain a fairer

facts suggest that those factors were not taken into account for the price and weight setting, at least in a clear way. The adoption of new technologies is other important driver of hospital cost increase, at least in the first stage of adoption. Nevertheless, the adjustment was mainly to reduce DRG prices and weights.[14]

Using the 2006 DRGs price change, we seek to understand how hospitals respond to price increases or decreases: do they maintain on the same behaviour pattern, given that the reasons for changes in price are mainly to adjust hospital costs; or do the hospitals behave strategically (upcoding) taking into account that control instruments are not powerful enough to oversee every hospital action?

3 A BRIEF ILLUSTRATIVE MODEL

To provide a background to our empirical procedure and the design of the robustness checks on the evidence of upcoding, we use a simple model. There is an exogenous demand, unaffected by coding decisions, at the pair of closely related DRGs: $n = x_1 + x_2$, where x_1 refers to top DRG and x_2, to bottom DRG, which corresponds to the true demand.

The observed treatment is defined as $u = x_1 + g$ and $d = x_2 - g$, where g measures the extent of upcoding (moving patients from bottom DRG to top DRG).

The objective function of the hospital is given by the profits less the cost of

reimbursement of the services provided. Epidemiological differences are one of the reasons for such refinement in hospital budgets.

[14]The complete set of DRGs prices and weights is available at AUTHOR'S WEBSITE.

upcoding:

$$V = p_1 u + p_2 d - c_1 x_1 - c_2 x_2 - 0.5 s g^2 \tag{1}$$

where the last term aggregates all costs from upcoding into a quadratic cost function (auditing, detection, and fines & ethical costs). The cost c_i is independent of coding, and upcoding levels depend on price differences between the top and bottom DRGs. This is the basis of the empirical strategy, borrowed in part from Dafny (2005). Under Equation 1, the first-order condition for the choice of g depends only on s, the cost parameter of upcoding, and $(p_1 - p_2)$, the price difference between the two DRGs of the same pair.

The fraction of top DRG in a pair of DRGs is defined as:

$$f = \frac{x_1}{x_1 + x_2} + \frac{g}{x_1 + x_2} \tag{2}$$

Under constant x_1 and x_2, f and g move in the same direction. If x_1 and x_2 move due to other reasons - real effects, then inference is more complicated and it is necessary to accommodate these facts into the empirical analysis. For this reason, the drivers of the ratio $x_1/(x_1 + x_2)$ need to be studied carefully.

4 THE EMPIRICAL APPROACH

We follow closely the empirical strategy laid down by Dafny (2005), in which demand is exogenous to the hospital.[15] To her main equation, we added other control

[15] From Dafny (2005), equation (3): $fraction_{pt} = \alpha + \varsigma pair_p + \delta year_t + \psi \Delta spread_{p,88-87} \times post + \varepsilon_{pt}$.

variables, namely, age and gender of patients, and characteristics of hospitals.[16] Moreover, our sample is composed by hospitals operating under two distinct legal regimes within the NHS, the SPA and EPE hospitals.

Given the existence of well defined catchment areas for the Portuguese NHS hospitals, exogeneity of demand is the reasonable assumption. Although some auditing exists, we do not have information on its results, and we cannot explore this dimension of the problem. Since DRGs have been in place since the mid-1980s and coding accuracy has been audited since the beginning, we do not expect a major influence of this element.

4.1 Data

The database used is organized by the *Administração Central do Sistema de Saúde* (ACSS). It is composed of hospital discharges from all NHS hospitals or hospital centres (the Portuguese DRG database).[17] The sample size is 54,593 DRG-pair level observations, per hospital and year. There are 104 hospitals and hospital centres, but not all of them have been active in all periods as few hospitals merged to create hospital centres. Data range from 2001 to 2008 (unbalanced panel).

We selected 112 pairs of DRGs, each of them corresponding to two similar DRGs that differ only by having or not having complications.[18] For example, the DRG pair 1 is composed of DRGs 7, "peripheral & cranial nerve & other nerve system procedures with complications", and 8, "peripheral & cranial nerve & other

[16] Different from Dafny (2005), the age of patients is not only other explanatory variable, it provides an indirect way to detect the upcoding behaviour, under some assumptions.

[17] The exception is *Amadora-Sintra* hospital due to particular hospital management characteristics not present in other hospitals.

[18] It was originally 145 DRG pairs, but there was lack of observations for 33 DRG pairs.

nerve system procedures without complications".

The rationale behind the DRGs selection has to do with the likelihood of upcoding detection: the ability to identify a patient wrongly coded, between two DRGs that differ only in the level of complication of the disease, requires a specific knowledge that in general only doctors have. Hence, the purchaser must proceed with auditing and it is costly. In such scenario, the upcoding might be profitable, if not detected.[19]

4.2 Variables

The dependent variable is the fraction of patients coded in the top DRG, $fraction_{dit}$, which accounts for the percentage of patients coded in the DRG with complications in each pair of DRGs, by hospital and year:

$$fraction_{dit} \equiv \frac{\text{N of cases in top code DRG}_{dit}}{(\text{N of cases in top code DRG} + \text{N of cases in bottom code DRG})_{dit}} \quad (3)$$

where d indexes the pair of DRGs, i indexes the hospital, and t indexes the year.

Our interest lies in the relationship of the $fraction_{dit}$ with the $spreadp$, which is defined as the spread of prices in a given DRG pair, from 2003 to 2006. This latter is the politically-driven exogenous variable, which is constructed in two steps. First, we take the difference between the value paid to the hospital for an episode classified in the DRG with complications minus the value paid for an episode of DRG without complications. Similar to Dafny (2005), p. 1533, equation (2), we

[19] Auditing does exist and codification of patients is performed by specially trained physicians. These factors help to suppress the extent of upcoding. However, little information is available about these audits.

define:

$$spreadp_{dT} = \begin{pmatrix} \textit{DRG price in} \\ \textit{the top code} \end{pmatrix}_{dT} - \begin{pmatrix} \textit{DRG price in} \\ \textit{the bottom code} \end{pmatrix}_{dT} \tag{4}$$

where d indexes the DRG pair and T indexes the year, which is 2003 or 2006, the periods of unequal DRGs price changes. The DRG price is common to all hospitals. Second, given this absolute value, we take the difference from 2003 to 2006.[20] Therefore, the spread of prices is defined as:[21]

$$spreadp_d = spreadp_{d06} - spreadp_{d03} \tag{5}$$

As an example, the pair 32 is composed of DRGs 110 and 111. The value of price spread in 2003 ($spreadp_{3203}$), €5,943.18, is the difference between the DRG prices €12,586.84 (DRG 110) and 6,653.66 (DRG 111). We then obtained the $spreadp_d$ for this pair by taking the difference of price spreads in 2006 and 2003, after performing the same calculation for price spread in 2006. For this specific pair of DRGs the spread of prices fell by 90.43%.[22]

The average age of patients in the pair of DRGs (m_age_pair), was calculated as the mean age of all patients coded with the DRGs that correspond to each pair, by hospital and year. For the mean age of patients coded in the DRGs with and

[20]The full year is used as an approximation, though the new prices went into effect only in the middle of the year.

[21]The $spreadw_d$ is calculated using the spread of weights, defined as:

$$spreadw_{dT} = \begin{pmatrix} \textit{DRG weight in} \\ \textit{the top code} \end{pmatrix}_{dT} - \begin{pmatrix} \textit{DRG weight in} \\ \textit{the bottom code} \end{pmatrix}_{dT}$$

$$spreadw_d = spreadw_{d06} - spreadw_{d03}$$

[22]For the majority of DRG pairs, price and weight changes are perfectly correlated.

without complication of each pair (m_age_cc and m_age_sc), the calculation followed the same logic, but split by DRG. Average number of secondary diagnoses in the pair, bottom and top DRGs ($m\_secdiag\_pair$, $m\_secdiag\_cc$ and $m\_secdiag\_sc$), and percentage of females (p_female_pair, p_female_cc and p_female_sc) were calculated in an analogous manner. Still, number of in-hospital days is used as other explanatory variable. The number of discharged patients per year (*dp*), occupied beds (*beds*), CMI, and *cost* were obtained from hospitals or ACSS reports.

[Table I here]

The sample has an average of 37.97% of patients coded in the top DRG. Age of the patients in the pair of DRGs is around 58 years old, average number of secondary diagnoses is 2.14 and almost half of them are female. Average number of in-hospital stay is 8.09 days. For hospitals, the average number of discharged patients is approximately 13,000 per year, number of beds is 344, and individual cost is €5,160.2.

Considering the important role of age in the process of upcoding, it is presented further descriptive statistics. In particular, for the top coded DRGs, we calculated the average age and its relation with gender, with secondary diagnoses, with length of stay and with cases of transfer from one to other hospital.[23]

[Figure 1, 2, 3 and 4 here]

Regardless of subgroup, the average age is increasing over the years (ageing population). The average age is higher for the subgroup of woman and also for the subgroup of patients with more than five secondary diagnoses. However, higher length of stay or being a transfer case is not associated with older patients. On the

[23] In particular for these analyses, the unit of observation used was DRG rather than pair of DRGs.

contrary, patients that stayed in hospital less than a month are older on average. Also, on average, the transfer cases from one to another hospital are more likely to happen for younger patients.

4.3 Model specification

The relevant equation to be estimated has the following form:[24]

$$\begin{aligned} fraction_{dit} = \alpha + \psi_1 spreadp_d \times post + \beta_1 m\_age\_cc_{dit} + \beta_2 m\_age\_sc_{dit} \\ + \rho_1 m\_secdiag\_cc_{dit} + \rho_2 m\_secdiag\_sc_{dit} + \phi_1 p\_female\_cc_{dit} \\ + \phi_2 p\_female\_sc_{dit} + \lambda X_i + \gamma H_i + \delta year_t + \epsilon \end{aligned} \tag{6}$$

where the ψ_1 vector measures the marginal effect of changes in the variation of price spread. The β_1 and β_2 capture the impact of patient's mean age in the DRGs that belongs to a pair (same logic for ρ and ϕ). They also work as a control for the (possible) increase in severity of cases over time. The variable *post* is a dummy variable that equals zero if the observation is from 2003 to 2005 (the new prices are not applicable for these years), and equals one otherwise (from 2006 to 2008).

Hospital characteristics coefficients (λ) of *dp*, *beds*, CMI, and *cost* have different relationships with the upcoding issue. Discharged patients, length of stay, and cost may or may not be directly associated with upcoding. Whenever upcoding

[24]For DRG weight analysis, the estimated equation is:

$$\begin{aligned} fraction_{dit} = \alpha + \psi_2 spreadw_d \times post + \beta_1 m\_age\_cc_{dit} + \beta_2 m\_age\_sc_{dit} \\ + \rho_1 m\_secdiag\_cc_{dit} + \rho_2 m\_secdiag\_sc_{dit} + \phi_1 p\_female\_cc_{dit} \\ + \phi_2 p\_female\_sc_{dit} + \lambda X_i + \gamma H_i + \delta year_t + \epsilon \end{aligned}$$

does not imply a different course of action but merely a distinct classification code (and the corresponding payment), the observed number of discharged patients and costs will be independent of the extent of upcoding. On the other hand, if classification of patients into a different DRG leads immediately to another treatment protocol, yearly average costs per patient treated at the hospital level are positively associated with the extent of upcoding. The number of beds that a hospital has is usually defined in the construction phase, or subsequent adjustments take place at spaced intervals of time. It is therefore unlikely to be correlated contemporaneously with upcoding. A different situation appears for the CMI. Systematic upcoding also creates an upward pressure in the CMI. Because its final value is computed normalizing the index to the average national value, common upgrading to all hospitals does not necessarily change the relative position of each hospital. Nonetheless, it is potentially an endogenous variable.

The δ vector of coefficients can be interpreted as the mean impact of the price changes on all pairs (similar interpretation to γ).

Estimation of the coefficients is performed using panel data analysis, considering fixed-effects at the level of DRG pairs (hospital fixed-effects were also computed). To correct for potential autocorrelation and clusters, robust standard errors clustered at DRG pairs were used.

A different analysis is performed to assess the role of age in the potential upcoding behaviour. Suppose that older patients are on average more complex cases, and recall that upcoding means moving some of the more complex cases from the lower DRG to the top DRG. Given the association of age with case complexity, this means moving some of the older patients from the bottom DRG to the top DRG, in which they will be amongst the youngest within that DRG. Thus, average age of patients in both DRGs decreases and there is upcoding, under the assumption of positive association between case complexity and age of patient. We aim to answer the following question: "do hospitals upcode taking into account the age of the patients?" Hence, we define:

$$\Delta age\_cc_{dit} = m\_age\_cc_{dit} - m\_age\_pair_{dit} \tag{7}$$

$$\Delta age\_sc_{dit} = m\_age\_sc_{dit} - m\_age\_pair_{dit} \tag{8}$$

where the dependent variables measure the difference between the mean age of patients coded in the DRG with complications (without complications) and the mean age in the pair of DRGs, for each pair, hospital and year. These two variables are then used to estimate the coefficients of the following equations:

$$\Delta age\_cc_{dit} = \alpha + \lambda X_i + \gamma H_i + \delta year_t + \epsilon \tag{9}$$

$$\Delta age\_sc_{pit} = \alpha + \lambda X_i + \gamma H_i + \delta year_t + \epsilon \tag{10}$$

where the years range from 2001 to 2008.

5 RESULTS

5.1 The evidence of upcoding

Estimation results are presented in Table III. The estimates from model 1 show that variation in spread of prices is positively correlated with the share of patients in the top DRG (model 1). Including fixed effects at DRG pairs, the effect is vanished (model 2). However, the inclusion of hospital dummies in model 3, besides the fixed effects, brings back the evidence of upcoding. The dummy variables for the years from 2006 until 2008, which coincide with the years of price changes, are statistically significant. The estimated coefficient of spread has a positive sign, implying that larger price changes are associated with a higher share of patients in the top DRG. Including the mean age of patients as a control variable does not change the results (model 4).

The average age in other DRGs not included in the DRG-pair analysis is used to control for the development of age over time.[25] From Table II, the average age of patients classified into those DRGs is smaller than in our sample, for every year.

[Table II here]

The estimations in model 5 using *ageOther* as an explanatory variable gives us stronger evidence of upcoding. The estimated coefficient for this variable has negative sign - the fraction of patients coded in the DRG with complications is negatively affected by the average age of the patients in other DRGs (episodes in the same hospital and period). Even after including such control for the effect of ageing population, we still observe that the policy change has a significant impact to shift patients from the bottom to the top code DRG. Furthermore, *ageOther* loses significance as we include other control variables.

[Table III here]

Considering that coding process of DRGs has three phases and involves three

[25] We thank an anonymous referee for this suggestion.

kind of clinicians (the clinicians, the coding clinicians and the auditing clinicians), it is also useful to look into the pattern of secondary diagnoses that have been originally recorded and lately associated to the DRGs, to strengthen the idea of upcoding rather than a scenario where the population health has worsened. These type of information is reported by "original" clinicians rather than coding clinicians (the ones finally responsible for the DRG coding).[26]

[Table IV here]

There is a persistent increase in the number of secondary diagnoses along the years (except for 2008). Such pattern was expected, given that the number secondary diagnoses is a proxy for severity level of the cases, which was hypothesized to be positively correlated with age that also increased along the years. There is a persistent increase in the number secondary diagnoses in relation to main diagnosis - from 1.80 in 2001 to 2.38 in 2008. This could indicate that the population became sicker in the last years, or that hospitals started recording more comorbidities.

At first, it is expected that average patients coded in the bottom DRG have fewer associated secondary diagnoses. However, it could be the case that these variables are also taken into consideration, when deciding to upcode a patient.[27]

We carefully studied how secondary diagnoses are associated to the DRGs that were used in the DRG-pair analysis. The goal was to obtain a list of secondary diagnoses that started being more frequently recorded after 2006. It is noteworthy

[26]On the second column of table IV, the total number of main diagnoses, which corresponds to total number of DRGs used to build the pairs of DGRs, is slightly bigger than what is used to form the pairs, due to availability of hospital information data merged for that analysis.

[27]Another consideration to deepen the investigation of upcoding would be to use the chronic conditions of the patients as an incentive for upcoding. In this case, the unit of observation would need to be the patient and a probabilistic model of whether the patient would be coded in the top DRG or not could be defined. The data used here do not allow for this type of analysis, but we mention as a suggestion.

that some secondary diagnoses just started being coded in 2006, the year of policy change, and this weakens the hypothesis of a sicker population. For example, there was a pronounced intensification in the coding V5866 after 2005, which refers to long-term use of aspirin. It is not likely that such a high increase in aspirin use actually occurred. It seems more plausible that clinicians started coding more secondary diagnoses as a way to ease the task of upcoding for coding clinicians.

Nevertheless, a definitive answer for the role of secondary diagnoses is given by running a regression model that controls for the number of secondary diagnoses. In model 6, we include the control variable *m_secdiag_pair* to check if upcoding result is robust. Controlling for the average number of secondary diagnoses, percentage of females and days stayed in the hospital, at the level of DRG pairs, the result is that estimated coefficients do not support the hypothesis of upcoding (models 6, 7 and 8).

The variable *totdays_pair* has the potential to be endogenous, considering that patients coded in the top DRG, with complications, are supposed to stay more days in the hospital. Taking this potential endogeneity into consideration, plus the fact that core results remain unchanged from model 7 to 8, *totdays_pair* is excluded from further use. Model 9 then has the mean age of patients in the top and bottom DRGs as explanatory variables. There is evidence of upcoding as the coefficient of *spreadp_post* is statistically significant.[28] Referring back to Equation 2, it becomes clear that age is an important driver of the proportion of patients in the top DRG of a pair. Different from Dafny (2005), the age of the patients has a very important role in the upcoding process.

[28]Robustness check changing the fixed effects from the DRG pairs to hospital level reveals the strength of the results, which remain mainly unchanged. For a recent discussion of statistical inference with clustered data, see Cameron and Miller (2015).

The variable *m_secdiag_pair* is also split between top and bottom code DRGs, to control for the fact that number of secondary diagnosis could influence the decision of upcoding a patient (model 10). This result strengthens the empirical evidence of upcoding. Therefore, upcoding is not a consequence of change in health status of the population - represented in this case by an increase in the number of secondary diagnoses, which is a proxy for severity of cases treated in a hospital. Upcoding is a result of the price incentives given by the spread of prices in the bottom and top DRGs.

The last and most preferred specification also includes the percentage of females split between top and bottom code DRGs. The results remain roughly equal to those in model 10.[29] The number of discharged patients, beds, and cost are negatively correlated with the fraction of patients in the top DRG, whereas the opposite is true for CMI and length of stay in most of the models.[30] It is worthwhile to mention the estimated coefficient sign associated with cost. The fraction of upcoded cases is not positively associated to cost, something hypothesized for upcoding to represent a change in protocols due to more severe cases being treated, instead of just an opportunistic behaviour situation.

The unbalanced panel nature results from mergers of hospitals into hospital centres over the years. These are groups of hospitals under the same management teams. No significant closures took place. Robustness checks can be done removing from the sample hospitals that become hospital centres or by creations of "simulated" hospital centres prior to their actual creations. This later version

[29]The analysis using *spreadw* (the changes in weights of the DRGs) obtains results that are similar to the price changes, and are available at AUTHOR WEBSITE.

[30]Larger hospitals are the ones that have a higher technological differentiation that may not be fully captured by the CMI.

creates an "artificial" balanced panel without losing data. The results are robust to those checks.

We provide an example of the impact of the spread of prices on the share of patients coded in the DRG with complications. Consider the specific pair of DRGs that refers to simple pneumonia and pleurism (DRG pair 22), with and without medical complications. Suppose that the Government set hypothetical new DRG prices resulting in €100 increase in the spread, which induces upcoding behaviour.[31] In this particular case it was found that 17 extra episodes would be included in the top DRG in one year with an associated upcoding cost of €10,395.

[Table V here]

Distinction between pure public hospitals (SPA) and more private management -like hospitals (EPE) is potentially important. We test for it allowing time dummies and the marginal incentive to upcode to be different according to the statutory type of the hospital. The two groups of hospitals do not behave differently in the upcoding matter. In the model there is an intercept term for EPE hospitals, and the variable $spread\_postEPE$ allows the measure of marginal incentive for upcoding to be different between hospital statutes. Neither is statistically significant. The incentive for upcoding is, according to these results, independent of the statutory nature of hospitals.

Other sensibility analyses of the upcoding results were conducted. We considered the possibility of upcoding under the distinction of having medical or surgical pairs of DRGs, and also the possibility of upcoding subjected to two different

[31] The €100 was defined in a way to represent an almost 10% increase in the average spread of prices in 2006, which was €1,128 (this average was calculated from the difference between the top and bottom DRGs in all 112 DRG pairs included in the sample).

scenarios in which there is either a negative or positive spread of prices. For the first model, which accounts for differences between the type of DRG, being it a medical or surgical one, upcoding effect was not identified. In the second model, considering asymmetric exposure to DRG price change, there was no modification in the main conclusions.[32] A model allowing for heterogeneous hospital upcoding behaviour based on volume of activity, with results not presented in the paper, rendered no remarkable differences. High and low volume hospital regressions show similar evidence of upcoding.

We constructed an index to measure the complexity of the cases transferred in and out of each hospital, and the received cases (transfer in) showed to be statistically significant, meaning that the greater the complexity of cases received by a hospital, the higher is the share of patients coded in the top DRG, which was naturally expected.

5.2 Age effects

Age can be a discriminating variable that is associated with episode complexity, as mentioned before. To assess its role in the upcoding we consider the average age in the top DRG and in the bottom DRG.

[Figure 5 here]

Figure 5 shows the growth rate of the average age in the pairs of DRGs. Even at this aggregate level some empirical facts are worth noting. First, the evolution before and after 2006 seems to be different. In the first years of the sample the

[32]One would expect upcoding to appear more easily with DRG price increases. Moreover, DRG price decrease should be linked to a “downcoding”.

average age within each pair of DRGs is increasing but at an intermediate rate between the top DRGs growth rate of patients' average age and the bottom DRGs growth rate. However, after 2006, we see a clear shift toward average age at the DRG-pair level increasing faster than in the bottom and the top DRGs (except for 2008). This can only result from a composite change, characterized by a slower growth in average age of both bottom and top DRGs, caused by moving older patients from the bottom to top DRGs.

If age is associated with high complexity and is used as a signal for how severe the case is, a change in the criterion for inclusion of younger ages in the top DRG will result in a testable empirical prediction. One more time, if upcoding takes more patients but less complicated cases to the top DRG, and assuming age to be positively correlated to severity of the case, we will observe average age decreasing in both DRGs of the pair. The alternative is that the patient mix has worsened over time, implying that average age of patients increases over time in both DRGs of each pair, and in a way unrelated to the change in DRG prices.

Thus, the two situations have different implications regarding the coefficient of interest and can be tested. We are interested in the overall trend of average age in the top and bottom DRGs of the pairs, and in the marginal effect associated with the magnitude of the price change. The scenario of worsening cases leads to a positive trend over time in both top and bottom DRG and a statistically non-significant coefficient of price change. The upcoding scenario implies a negative trend of the mean age in the top DRG and bottom DRG, reinforced by price sensitivity - a more pronounced effect is expected when relative prices change more.

[Table VI here]

Table VI shows the estimates related to the role of age. Taking first the results for the top DRG within each pair, we observe that the difference between age in the top and in the pair of DRGs is increasing in absolute terms for all years but 2002. The estimated coefficients became statistically significant from 2006 onwards, with average age in the top DRG decreasing relative to average age in the pair. For the bottom DRG a slightly different picture emerges, as the difference decreases only in 2002 and 2006, but is statistically non-significant in all years. It means that average age within the bottom DRG is evolving at a slower pace than the average across the pairs of DRGs in 2002 and 2006.[33]

Taking both results, we have support for the basic factual evidence of Figure 5, which is consistent with the presence of upcoding that is happening through a shift of older patients from the bottom to the top DRG, where they are relatively younger.

5.3 A longer-term view

An important issue to be addressed is whether the current upcoding trend is a long-term historical trend or it started with the price changes of DRGs in 2003. Above we addressed only the 2006 price change, which may simply reinforce a change that had already come into being through a 2003 price change.

Using the simplest regression model, without the impact of DRG price changes and adding two initial years to the previous regressions, we find that years 2001-2003 seem to be somewhat different than the others. The same behaviour is

[33] The regressions including the change in relative prices do not improve the results.

observed for the full model. The magnitude of the coefficients are greater after 2003, but much larger after 2006, coinciding with the time of DRG price changes. Hence, the first price changes that occurred in 2003 may have created some incentives for upcoding, but another shift seems to take place in 2006, with the latest change in DRG relative prices.

[Table VII here]

6 Upcoding size and cost

We estimated the total upcoding size and cost, considering the same hypothetical increase of €100 in the DRGs spread of prices, as we did for DRG pair 22, this time for the full set of episodes. The results are summarized in Table VIII.

[Table VIII here]

An increase of €100 in the spread of prices would lead to a larger fraction of patients to be coded in the top DRG. The average share of patients coded in the top DRG would change from 37.97% to 38.05%. Multiplying the average number of DRG episodes in a year by these shares and taking the difference between the two values yields the total number of upcoded cases that would be coded in the top DRG, following the incentive given by the price spread increase.

Supposing that all hypothetical upcoded cases would have a cost that equals the average cost of all top code DRG prices, €3,366, the upcoded cases would represent an extra cost of €377,815 in a given year. By using back-of-the-envelop calculations, the average upcoding burden represents 0.04% in the Portuguese

NHS.[34] This is a conservative estimation, considering that upcoding would occur in a DRG with average price and not in the most expensive DRGs.

The upcoding size represents a small amount of the average total cost in the sample. In quantitative terms, this result indicates that upcoding has a minor economic impact, suggesting that DRG-like payment system is adequate to the Portugese NHS.

7 FINAL REMARKS

Earlier research reports that US hospitals were quick to react to DRG price changes and to profit considerably from upcoding (Dafny, 2005). Classifying patients in those DRGs that allowed for a higher payment, and doing so more when the favourable price change was stronger, provided evidence for upcoding.

A natural issue is whether upcoding is specific to the US or if it can be found in other health systems as well. This question is especially important as many countries over the last decades have introduced patient classification systems. Purchasers of health care, i.e. Governments (through NHS or illness funds) or health insurance companies, are increasingly turning to patient classification systems for providers' payment.

Upcoding is a reimbursement problem, with no direct impact on patients health care. Of course, misuse of health care budget might indirectly affect health care through crowding effect, if overspending for patient A's treatment results in underspending for patient B. The analysis of this indirect effect is beyond the

[34] $AVGCOST_{total} = (146,343 \times 3366) + (238269 \times 2138) = 1,002,019,758$. $AVGCOST_{upcoding} = 377,815/1,002,019,758 = 0.0004$.

scope of the paper.

We use data from an NHS with the following features: demand to each hospital is basically exogenous, as patients have to comply with Government-defined catchment areas for each hospital; hospitals have to classify patient episodes into a DRG-like system; hospitals are not paid on an episode-by-episode basis but yearly budgets have been increasingly based on the DRGs and the DRG mix that the hospital provides; DRG prices are set by Government ruling and have infrequent changes, and the background studies supporting the new prices are not known to hospitals. Thus, price changes can be seen as exogenous from the point of view of hospitals.

Our results provide a mild support for upcoding, which can be described as an increase in the share of top DRG within pairs of DRGs. It has increased from 2001 to 2008, and more so in recent years. Moreover, not only has upcoding been occurring above what would be predicted by the simple ageing of population, it has been more important when the price change was stronger. This points to the conclusion that even within NHS, management of hospitals does respond to incentives for upcoding patients. However, the quantitative impact of upcoding is small justifying the adequacy of DRG-like payment method for the Portuguese NHS. The results might extend to other NHSs.

The contribution of the paper to the literature is at least two-fold. It is provided qualitative evidence of upcoding in a NHS context. Comprehending a wide set of DRGs, the study also offers a measurement of upcoding size.

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Appendices

A Figures

Figure 1: Age - gender

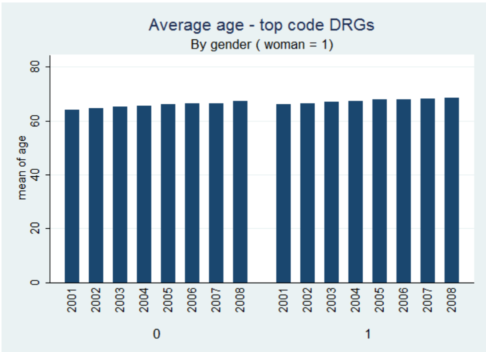


Figure 2: Age - secondary diagnoses

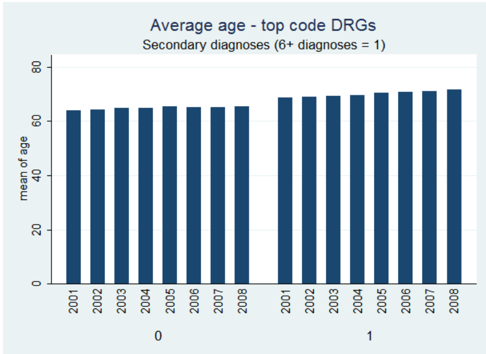


Figure 3: Age - length of stay

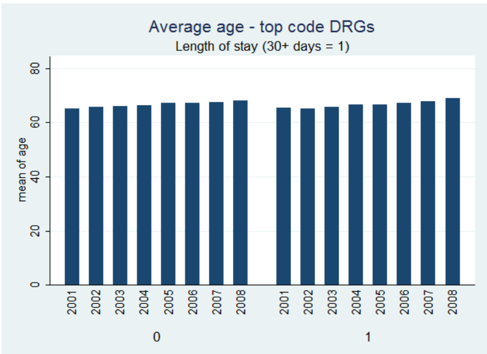


Figure 4: Age - transfer

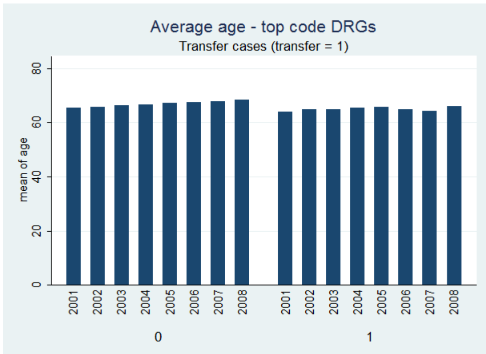
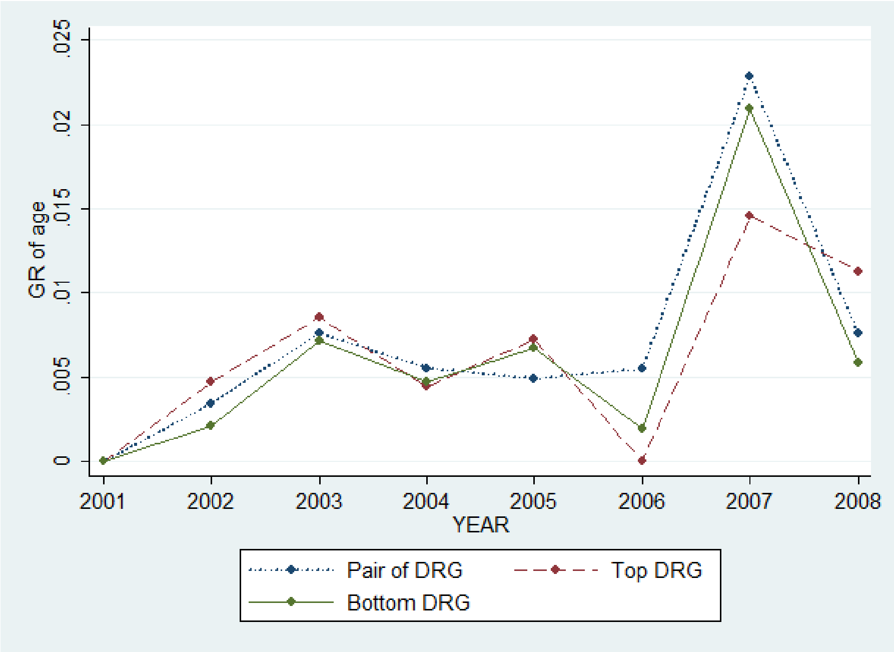


Figure 5: Growth rate of average age



B Tables

Table I: Summary statistics

Unit of observation: pair of DRG					
Variable	Obs	Mean	Std. Dev.	Min	Max
fraction	54593	0.38	29.76	0	100
spreadp	54593	-598.62	902.23	-5374.45	1244.64
m_age_pair	54593	57.66	14.99	0	98
m_age_cc	47348	63.35	14.08	0	101
m_age_sc	51306	54.56	15.75	0	105
m_diagsec_pair	55465	2.14	1.64	0	19
m_diagsec_cc	48187	3.55	1.74	0	19
m_diagsec_sc	52170	1.20	1.02	0	14
p_female_pair	54593	0.48	0.28	0	1
p_female_cc	47348	0.47	0.32	0	1
p_female_sc	51306	0.49	0.30	0	1
m_totdays_pair	54593	8.69	8.03	0	474.85
dp	52672	12869.25	9928.56	441	49482
beds	51930	344	281	10	1551
CMI	50564	1.06	0.31	0.46	2.72
cost	52587	0.0051602	0.0025784	0.0009089	0.0315835

Notes:

(1) *fraction* is multiplied by 10^5;

(2) *cost* is annual individual cost (total cost/dp), divided by 10^6.

Table II: Average age of patients

	(1)	(2)	(3)	(4)
Year	DRG pair	Top DRG	Bottom DRG	Other DRG
2001	56.44	62.06	53.56	41.60
2002	56.64	62.36	53.68	42.17
2003	57.07	62.89	54.06	42.37
2004	57.39	63.17	54.32	43.26
2005	57.67	63.62	54.68	43.26
2006	57.98	63.63	54.79	44.24
2007	59.31	64.55	55.93	50.53
2008	59.76	65.28	56.26	50.98

Notes:
(1) average age of patients in selected DRG pair;
(2) average age of patients in top DRGs of selected DRG pair;
(3) average age of patients in bottom DRGs of selected DRG pair;
(4) average age of patients in all non selected DRG pair.

Table III: Partial estimation results: basic models

	Dependent variable: *fraction*										
Ind. Var.	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
spreadp_post	0.604**	0.523	0.591*	0.643*	0.637*	0.307	0.302	0.290	0.420**	0.679**	0.695**
	(0.294)	(0.320)	(0.327)	(0.335)	(0.335)	(0.241)	(0.240)	(0.243)	(0.185)	(0.267)	(0.267)
m_age_pair				595.9***	596.0***	275.5***	279.2***	272.2***			
				(34.29)	(34.32)	(23.95)	(23.78)	(23.78)			
ageOther					-121.7**	-55.42	-54.49	-50.69	-8.275	-44.67	-44.45
					(49.34)	(48.02)	(47.77)	(47.76)	(32.42)	(37.96)	(37.95)
m_secdiag_pair						9,984***	9,975***	9,491***	9,047***		
						(228.0)	(227.7)	(232.8)	(263.3)		
p_female_pair							-2,049**	-1,892*	-2,357**	-2,832**	
							(1,030)	(1,047)	(1,098)	(1,412)	
totdias_pair								294.3***			
								(48.21)			
m_age_cc									-8.015	66.45***	63.42***
									(12.72)	(16.07)	(16.22)
m_age_sc									65.86***	94.58***	93.82***
									(16.32)	(21.90)	(22.00)
m_secdiag_cc										971.1***	972.2***
										(170.5)	(170.2)
m_secdiag_sc										3,343***	3,339***
										(253.1)	(252.5)
p_female_cc											321.6
											(537.9)
p_female_sc											17.21
											(767.8)
dp	0.0809	0.0811	-0.338***	-0.373***	-0.387***	-0.317***	-0.320***	-0.302***	-0.281***	-0.246**	-0.243**
	(0.0511)	(0.0600)	(0.127)	(0.128)	(0.128)	(0.114)	(0.113)	(0.114)	(0.0967)	(0.116)	(0.116)
beds	-5.756***	-5.744***	-0.677	-1.513	-2.159	-3.004	-2.949	-3.249	-1.341	-0.535	-0.602
	(1.792)	(1.927)	(2.568)	(2.340)	(2.366)	(2.028)	(2.020)	(1.985)	(1.771)	(2.083)	(2.078)
cmi	12,125***	12,133***	2,221	3,431*	4,252**	2,055	2,019	2,422	2,069	2,375	2,428
	(710.3)	(1,122)	(2,072)	(1,997)	(2,003)	(1,774)	(1,764)	(1,757)	(1,329)	(1,613)	(1,613)
lstay	1,141***	1,137***	371.0	316.3	352.3	945.4***	935.6***	773.1***	580.9***	242.0	253.6
	(119.9)	(189.2)	(323.7)	(311.7)	(314.4)	(271.2)	(270.4)	(273.9)	(186.6)	(221.6)	(221.2)
cost	63,479	62,748	-438,117	-535,532*	-520,131*	-295,870	-304,868	-264,520	-211,161	-126,703	-115,800
	(65,479)	(93,820)	(286,404)	(285,172)	(284,913)	(284,029)	(283,010)	(285,705)	(193,413)	(239,953)	(241,697)
yeard4	124.8	128.0	613.7	581.5	663.1	-631.0	-609.8	-529.2	-201.6	409.5	389.2

Continued on next page...

... table III continued

	(498.9)	(473.7)	(498.1)	(483.3)	(484.6)	(462.6)	(463.6)	(469.9)	(328.4)	(383.8)	(385.4)
yeard5	40.70	44.30	716.9	254.9	449.1	-625.8	-599.8	-535.1	-36.85	424.3	407.5
	(485.6)	(489.7)	(561.8)	(544.8)	(564.1)	(539.0)	(538.1)	(543.5)	(323.2)	(408.1)	(409.6)
yeard6	2,339***	2,293***	2,217***	1,610***	1,927***	-92.59	-75.61	12.33	267.9	1,472***	1,467***
	(498.8)	(498.2)	(618.4)	(607.6)	(642.7)	(610.8)	(611.0)	(612.6)	(358.5)	(480.4)	(483.4)
yeard7	2,891***	2,845***	2,579***	1,609***	2,614***	-592.5	-577.4	-384.8	-290.5	1,709***	1,691***
	(514.1)	(545.6)	(629.6)	(581.9)	(800.1)	(795.9)	(797.9)	(797.9)	(480.2)	(586.0)	(588.4)
yeard8	3,198***	3,153***	3,430***	2,098***	3,159***	-1,327	-1,308	-1,087	-1,087**	1,729***	1,696***
	(533.6)	(654.6)	(773.1)	(733.9)	(932.7)	(936.5)	(935.7)	(930.5)	(509.7)	(631.5)	(633.1)
Constant	15,413***	16,146***	51,109***	21,325***	25,938***	7,612	8,648	7,371	6,940	23,366***	21,829***
	(1,739)	(1,234)	(5,737)	(5,896)	(6,232)	(5,657)	(5,741)	(5,740)	(5,387)	(6,826)	(6,847)
Hospital dummies	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	29,747	29,747	29,747	29,747	29,747	29,747	29,747	29,747	23,754	23,754	23,754
R-squared	0.037	0.037	0.104	0.166	0.166	0.400	0.400	0.406	0.417	0.189	0.188
N of pair_drg	112	112	112	112	112	112	112	112	112	112	112

Notes:
(1) robust standard errors in parentheses;
(2) fixed effects at DRG pairs;
(3) *** p<0.01, ** p<0.05, * p<0.1.

Table IV: Principal and secondary diagnoses

	Number of diagnoses		
	(1)	(2)	(2)/(1)
Year	Main diagnosis	Secondary diagnoses	Rate of diagnoses
2001	377,902	681,130	1.802
2002	385,451	745,447	1.934
2003	403,369	811,622	2.012
2004	407,780	837,180	2.053
2005	411,638	871,487	2.117
2006	411,865	906,839	2.202
2007	428,931	976,065	2.276
2008	367,992	876,731	2.382
	3,194,928	6,706,501	2.099

Table V: Upcoding size and cost - the case of the DRG pair 22

Period	T=0	T=1
Average number of cases	24,835	
Marginal effect of *spreadp* $\times$ *post*	0.695	
Average top DRG price (2006)	€1742	
Average bottom DRG price (2006)	€1139	
Spread of price	€602	
Fraction	0.7687	0.7694
Average number of cases in the top DRG	19,091	19,108
Average number of cases in the bottom DRG	5,744	5,727
Upcding (number of cases)	.	17
Average total cost	€39,792,231	€39,802,626
Cost of upcoding	.	€10,395
% of upcoding	.	0,026%

Notes:
(1) mean number of cases is the average over the years;
(2) *fraction* at t=0: 0.7687, the average sample value;
(3) *fraction* at t=1: 0.7694, from $0.7687 + 0.695 \times \frac{10^2}{10^5}$;
(4) €100 (10^2) is the hypothetical increase in spread;
(5) 10^5 is monotonic transformation applied in the regression.

Table VI: Estimation results: age effects models

Dep. Var	Δage_cc	Δage_sc
Ind. Var.	Model I	Model II
2001	0 (omitted)	0 (omitted)
2002	0.0813 (0.139)	-0.124 (0.0877)
2003	-0.134 (0.164)	0.00487 (0.105)
2004	-0.114 (0.190)	0.118 (0.143)
2005	-0.226 (0.204)	0.0451 (0.146)
2006	-0.366* (0.213)	-0.114 (0.170)
2007	-0.586*** (0.218)	0.00391 (0.178)
2008	-0.512** (0.206)	0.0998 (0.188)
Constant	4.415*** (1.139)	-1.532 (1.439)
Obs	38,371	41,803
R-squared	0.032	0.034
N of pair_drg	112	112

Notes:
(1) robust standard errors in parentheses;
(2) *** p<0.01, ** p<0.05, * p<0.1.

Table VII: Long-term impact: estimated coefficients of year dummies

Year	Model 11 - *spreadp_post*	Model 11
2001	0	0
2002	244.4	239.1
2003	261.5	262.7
2004	422.6	419.8
2005	443.9	432.1
2006	947.7	1,507
2007	844.0	1,395
2008	878.3	1,432

Table VIII: Upcoding size and cost - all DRG pairs

Period	T=0	T=1
Average number of cases	384,615	
Marginal effect of *spreadp* $\times$ *post*	0.695	
Average top DRG price (2006)	€3,366	
Average bottom DRG price (2006)	€2,138	
Spread of price	€1,228	
Fraction	0.3797	0.3804
Average number of cases in the top DRG	146,050	146,317
Average number of cases in the bottom DRG	238,565	238,298
Upcding (number of cases)	.	267
Average total cost	€1,001,499,504	€1,001,827,730
Cost of upcoding	.	€328,227
% of upcoding	.	0,033%

Notes:
(1) mean number of cases is the average over the years;
(2) *fraction* at t=0: 0.3797, the average sample value;
(3) *fraction* at t=1: 0.3804, from $0.3797 + 0.695 \times \frac{10^2}{10^5}$;
(4) €100 (10^2) is the hypothetical increase in spread;
(5) 10^5 is monotonic transformation applied in the regression.