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# How do hospitals respond to cross price incentives inherent in diagnosis-related groups systems? The importance of substitution in the market for sepsis conditions

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## Abstract

This study addresses the question of how hospitals respond to the cross price incentives inherent in reimbursements based on diagnosis-related groups (DRG). Unique market-wide administrative data allow to exploit a natural experiment in Germany in which the relative attractiveness of greatly divergent reimbursements for clinically similar patients changes in the market for sepsis conditions on January 1, 2010. This natural experiment provides—unintentionally—extra reimbursements in cases in which hospitals reorganize transfers for deceasing patients to other facilities, alter the time of death, the choice of the condition being chiefly responsible for the hospital admission (primary diagnosis), or the intensity of mechanical ventilation. The differences-in-differences results demonstrate that hospitals primarily alter the primary diagnosis. As the choice of the primary diagnosis is the backbone of the design of modern DRG systems, the findings suggest that payment contracts between hospitals and payers based on modern DRG algorithms may not necessarily improve patient welfare.

## KEYWORDS

cross price incentives, diagnosis-related groups (DRG), hospital reimbursement, risk-adjustment, sepsis, substitution

## JEL CLASSIFICATION

I11, I18, H51, L51

## 1 | INTRODUCTION

Health care systems in many OECD countries reimburse hospitals based on diagnosis-related groups (DRGs). DRG algorithms categorize admissions into clinically meaningful “products,” which enables payers to set admission-specific prices according to average historical costs. The two most popular DRG algorithms in the United States (Medicare

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Severity DRGs [MS-DRGs] and all patient refined DRGs [APR-DRGs]), as well as the German DRG (G-DRG) algorithm comprehensively utilize diagnoses to adjust admission-specific prices for differences in patient severity. To boost the predictive power of these algorithms, authorities additionally risk-adjust prices based on, for example, age, gender, mechanical ventilation, and procedures.

From a theoretical perspective, it is a priori unclear how much regulating authorities should granulate DRGs (Chalkley & Malcomson, 2002; Hafsteinsdottir & Siciliani, 2010; Siciliani, 2006). Understanding hospital responses to the design of DRG systems is of paramount importance to improve payment contracts between payers and providers. It is surprising that the empirical literature has given relatively little attention to this topic to date.<sup>1</sup> To the best of the author's knowledge, Dafny (2005) pioneers this literature and empirically examines hospital responses to the design of DRG algorithms. Analyses by the regulating authorities in the United States Health Care Finance Administration (HCFA) reveal that the categorization of patients who are over 69 with clinically complex patients is inappropriate for most diagnoses. Consequently, regulating authorities eliminated the age over 69/under 70 criterion beginning in fiscal year 1988. The author demonstrates that hospitals respond to the changes in the incentive structure inherent in DRG systems and upcode patients into more profitable DRGs. Jürges and Köberlein (2015) and Di Giacomo, Piacenza, Siciliani, and Turati (2017) find a similar pattern where hospitals also report higher than justified patient severities. The literature remains unclear as to whether hospitals also alter treatment decisions in response to extra reimbursements. Gilman (2000) analyzes DRG refinements from 1993 to 1994 that introduce extra reimbursements for surgical procedures to HIV patients under Medicaid. As a result, hospitals do not increase the rate of reimbursement-relevant procedures. On the contrary, Papanicolas and McGuire (2015) analyze hospital responses to the introduction of extra reimbursements for uncemented hip replacements compared to (clinically similar) cemented hip replacements in England from 2003 to 2004. The empirical findings suggest that hospitals substitute uncemented hip replacements with (clinically similar) cemented hip replacements after the refinement becomes effective. In addition, Foo, Lee, and Fong (2017) reveal that changes in the relative prices for cesarean versus vaginal deliveries arising from contract renegotiations affect clinical treatment patterns. Douven, Remmerswaal, and Mosca (2015) and Einav, Finkelstein, and Mahoney (2018) analyze hospitals that face nonlinear reimbursements when a patient's stay reaches a threshold number of days. The authors demonstrate that discharges increase substantially after the threshold.

This paper exploits a natural experiment in Germany in which the relative attractiveness of greatly divergent reimbursements for clinically similar patients changes in the market for sepsis conditions (whole-body inflammation caused by an infection and one of the leading causes of death (Martin, Mannino, Eaton, & Moss, 2003) on January 1, 2010. As a result, regulating authorities accidentally incentivize changes to previously unstudied, but far-reaching hospital strategies, namely, to reorganize transfers to other facilities (e.g., hospices), to alter the time of death, the choice of the condition being chiefly responsible for the hospital admission (primary diagnosis), and the intensity of mechanical ventilation. While interferences with the location and the time of death as well as the intensity of mechanical ventilation might be harmful for patients, the discretion to switch the primary diagnosis with a more remunerative secondary diagnosis might undermine the design of modern DRG systems. Its choice affects the reimbursement of about 64% of admissions in the G-DRG in 2014 (latest number currently available). In comparison, treatment decisions (additional medical or surgical procedures; lengthy hospital stays) alter reimbursement for only about 44% of admissions while accelerated patient severities alter reimbursement for only about 6% of admissions.<sup>2</sup>

To the best of the author's knowledge, this is the first study to identify all admission-specific changes in own prices and cross prices that are relevant for hospitals' decision-making (in a given clinical context). This empirical strategy might be promising because it allows for isolation of the most dominant hospital strategies inherent in reimbursements based on DRGs. Because hospitals frequently face a large set of profit-maximizing strategies, ranging from upcoding strategies all the way up to patient selection, the analysis of changes limited to own prices or a truncated subset of cross prices might miss important policy-relevant interactions.

Lastly, this study uses unique administrative reimbursement data (G-DRG data) that links approximately 127 million patient records to 2086 hospitals from 2005 to 2012. The data track the market-wide supply of inpatient services in Germany for both publicly and privately insured patients. This permits to analyze market-wide responses to changes in the design of hospital reimbursement and captures potential market spillovers (see e.g., Baicker, Chernew, and Robbins (2013)).

The differences-in-differences estimates indicate that hospitals primarily alter the choice of the condition being chiefly responsible for the hospital admission (primary diagnosis) in response to the price shock of 2009–2010. The study does not find that hospitals reorganize the transfers for deceasing patients to other facilities, alter the profit-maximizing time of death or alter the intensity of mechanical ventilation. This study compares the difference in the

monthly number of admissions in the 6 months before and after the turn of the year 2009–2010, where the price shock occurs, to the same difference for the turn of the year in 2005–2006, 2006–2007, 2007–2008, and 2008–2009, where no price shocks occur. The counterfactual turn of the year where no price shocks occur allows to control for potential causes for changes in the number of admissions (particularly around the turn of the year) from 2009 to 2010 other than the price shock, such as changes in the incidence of causative diseases. Following the price shock, hospitals fully adapt their profit-maximizing strategies in less than 4 weeks. Hospitals switch the primary diagnosis with the most lucrative secondary diagnosis more aggressively where the change in the size of the differential reimbursement is higher. A variety of robustness tests such as placebo differences-in-differences estimates confirm the validity of the results.

This study is structured as follows. Section 2 introduces the potential hospital strategies emerging from the financial incentives in the market for sepsis conditions. Section 3 characterizes the price shock, the empirical strategy as well as various robustness tests. Section 4 summarizes the data. Section 5 and Section 6 present and discuss the results, while the final section presents the study's conclusions.

## 2 | SEPSIS AND THE MENU OF CROSS PRICES

DRG-based payments to hospital  $j$  for admission  $i$  in year  $t$  are summarized as follows:

$$\text{Hospital Payment}_{j,i,t} = \text{Base Payment Rate}_{j,t} \times \text{DRG weight}_{i,t} \quad (1)$$

where Base Payment Rate is a hospital- or state-specific multiplier and DRG weight reflects the relative resource intensity of admissions in a particular DRG, compared to all other DRGs. DRGs are fixed by patient characteristics such as diagnoses, procedures, and patient demographics. More formally,

$$\text{DRG weight}_{i,t} := (x_{1,i,t}, x_{2,i,t}, \dots, x_{n,i,t}) = P_{i,t} \quad (2)$$

where  $(x_{1,i,t}, x_{2,i,t}, \dots, x_{n,i,t})$  is an  $n$ -tuple of patient characteristics with  $n$  elements  $x_{1,i,t}, x_{2,i,t}, \dots, x_{n,i,t}$  for admission  $i$  in year  $t$ . For brevity, this study denotes DRG weight $_{i,t}$  as  $P_{i,t}$  throughout the rest of this study.

Hospitals usually supply a variety of “products” (DRGs). Patients with a single different reimbursement-relevant element in the  $n$ -tuple of patient characteristics are usually clinically similar, but may yield greatly divergent reimbursements. For example, in cases in which reimbursement for a particular DRG is low (own price), hospitals may find the reimbursement for similar DRGs (cross prices) more attractive and may supply more of these similar DRGs (and vice versa).

The G-DRG categorizes patients in the market for sepsis conditions primarily based on a quadruple of patient characteristics.<sup>3</sup> The four elements are:

- $x_1$  = Discharge reason or transfer status (TRA): For patients suffering from sepsis, the G-DRG differentiates between patients that decease in the hospital and patients that survive or are transferred to another facility (e.g., hospice)
- $x_2$  = Length of stay or time of death (TOD): The G-DRG separates patients that stay in the hospital for more than seven days between 2005 and 2009, and for more than four days between 2010 and 2012. In cases in which patients decease in the hospital, the length of stay equals the time of death
- $x_3$  = Diagnoses (DIA): The G-DRG distinguishes between patients that primarily suffer from sepsis (primary diagnosis) and patients that secondarily suffer from sepsis (secondary diagnosis)
- $x_4$  = Mechanical ventilation (HMV): The G-DRG identifies patients which hospitals mechanically ventilated for more than 95 h

As a consequence, multi-product hospitals may primarily adapt four strategies to maximize their profits: First, hospitals may alter discharge reason or transfer status (“TRA strategy”). The remainder of this study denotes patients that are transferred to another facility as  $x_1 = H$  (high reimbursement) or  $x_1 = L$  (low reimbursement) otherwise. Second, hospitals may alter length of stay or time of death (“TOD strategy”). This study denotes patients that decease

after 8, 9, or 10 days in the hospital as  $x_2 = H$  (high reimbursement) and patients that decrease after 5, 6, and 7 days as  $x_2 = L$  (low reimbursement). Third, hospitals may change position of diagnosis (“DIA strategy”). This study denotes patients that secondarily suffer from sepsis as  $x_3 = H$  (high reimbursement) and patients that primarily suffer from sepsis as  $x_3 = L$  (low reimbursement).<sup>4</sup> Fourth, hospitals may extend mechanical ventilation (“HMV strategy”). This study denotes patients mechanically ventilated for more than or equal to 96 h as  $x_4 = H$  (high reimbursement) and patients mechanically ventilated for less than 96 h as  $x_4 = L$  (low reimbursement).

As the price shock of 2009–2010 in the market for sepsis conditions primarily affects deceasing patients, the analysis in this study focuses on deceasing patients that suffer from sepsis. Patients characterized by the quadruple of patient characteristics ( $L, L, L, L$ ) are denoted as BASE admissions. Patients characterized by the quadruple of patient characteristics ( $H, L, L, L$ ) are denoted as TRA admissions, ( $L, H, L, L$ ) as TOD admissions, ( $L, L, H, L$ ) as DIA admissions, and ( $L, L, L, H$ ) as HMV admissions.

Table 1 illustrates the reimbursement for BASE admissions (own price) and an example set of the most frequently available reimbursements for TRA, TOD, DIA, and HMV admissions (cross prices) offered to hospitals according to the 2009 reimbursement schedule.<sup>5</sup>

### 3 | EMPIRICAL STRATEGY

#### 3.1 | Price shock

Germany introduced fixed prices by DRG, effective from 2005 onwards. Since then, the majority of hospital reimbursements in Germany have been flat fees by DRG weight. The reimbursement schedule allocated patients to 846 DRGs (mainly DRGs mirroring Australian Refined Diagnosis Groups, AR-DRGs) when fixed prices became effective. Since then, responsible authorities have extensively refined and recalibrated the G-DRG on an annual basis, with the defined goal being the adjustment of initial DRGs to more appropriately reflect the given conditions in German hospitals. Hospital admissions are currently mapped to one of about 1149 DRGs.

The persistent effort to have DRGs appropriately reflect the given conditions in German hospitals leads to a rich refinement in the market for sepsis conditions from 2009 to 2010. This unique setting offers a plausibly exogenous market-wide, admission-specific price shock which is similar to the source of variation in prices in Dafny (2005).

Extending upon the previous literature on hospital responses to changes in a DRG algorithm and price changes more generally, the unique administrative reimbursement data allows to calculate admission-specific changes in own prices and changes in the menu of cross prices. To achieve this, this study applies the Definitions Manuals from all years (and particularly from the year before and after the price shock of 2009–2010) to the actual admissions between 2005 and 2012. In addition, this study applies the Definitions Manuals to the simulated counterfactual admissions based on the five variations of the quadruple of reimbursement-relevant patient characteristics for each year between 2005 and 2012. This study thus collects the patients' actual, as well as counterfactual, own prices and cross prices for the year before and after the price shock of 2009–2010. This methodology allows to group admissions between 2005 and 2012 by their identical own prices and cross prices (or changes therein) between 2009 and 2010, defined as:

$$\begin{aligned}
 &P_{BASE,t} \\
 \Delta P_{TRA,t} &= P_{TRA,t} - P_{BASE,t} \\
 \Delta P_{TOD,t} &= P_{TOD,t} - P_{BASE,t} \\
 \Delta P_{DIA,t} &= P_{DIA,t} - P_{BASE,t} \\
 \Delta P_{HMV,t} &= P_{HMV,t} - P_{BASE,t}
 \end{aligned} \tag{3}$$

where  $P_{BASE,t}$  is the reimbursement for BASE admissions (own price),  $P_{TRA,t}$  the reimbursement of TRA admissions (cross price),  $P_{TOD,t}$  the reimbursement of TOD admissions (cross price),  $P_{DIA,t}$  the reimbursement of DIA admissions (cross price), and  $P_{HMV,t}$  the reimbursement of HMV admissions (cross price) in year  $t$ .

From 2009 to 2010, authorities refined the reimbursement relevance of the patient characteristic length of stay (second element of the relevant quadruple of patient characteristics  $x_2$ ) and moved the reimbursement-relevant threshold from seven days to four days to increase  $P_{BASE,t}$ . In so doing,  $P_{TRA,t}$  and  $P_{TOD,t}$  are now identical to  $P_{BASE,t}$ . At

TABLE 1 Example of reimbursements for clinically similar patients suffering from Sepsis conditions in 2009

Patient Group (Quadruple of patient characteristics)									
BASE (L,L,L,L)		TRA (H,L,L,L)		TOD (L,H,L,L)		DIA (L,L,H,L)		HMV (L,L,L,H)	
DRG	$P_{BASE}$	DRG	$P_{TRA}$	DRG	$P_{TOD}$	DRG	$P_{DIA}$	DRG	$P_{HMV}$
T60F	1500	T60C	5300	T60C	5300	L60C	4600	A13F	12,500
		T60E	3000	T60E	3000	F43B	9900	A13G	11,000
		T60A	9600	T60A	9600	F62A	4400	-	-
		T60B	5300	T60B	5300	R61A	10,600	-	-
		T60D	3500	T60D	3500	E64A	3900	-	-

Notes: This table categorizes patients suffering from sepsis into five groups according to their quadruple of patient characteristics. The quadruple of patient characteristics below the name of each patient group lists the values for the four reimbursement-relevant elements in the G-DRG (The element definitions and selection criteria are provided in detail in Section 2). In addition, this table presents the most frequent reimbursements for each patient group in 2009.  $P_{BASE}$  captures the own price for BASE admissions and  $P_{TRA}$ ,  $P_{TOD}$ ,  $P_{DIA}$ , and  $P_{HMV}$  capture the cross prices for BASE admissions available to hospitals when treating (deceasing) patients suffering from sepsis. TRA captures extra reimbursements that result from transferring (deceasing) patients to another facility. TOD indicates extra reimbursements available to hospitals by postponing the time of death. DIA marks achievable reimbursements by switching the primary diagnosis with a secondary diagnosis. HMV captures extra reimbursements that result from inducing extensive mechanical ventilation. The frequency of available reimbursements in 2009 is calculated based on admissions from all years between 2005 and 2012, with the exception of the actual year of admission, and are independent from the observed, realized hospital strategy (please see Section 3 for more details). DRG weights (relative prices) do not include outlier payments and are normalized using the federal-level base rate from 2010 (2, 935.78 EUR) and presented in EUR, rounded to the nearest hundred.

Source: Annual tables of DRG weights, as well as Definitions Manuals, are provided by Institut für das Entgeltsystem; Federal-level base rates are provided by GKV-Spitzenverband.

the same time, the refinement in the market for sepsis conditions drastically cuts the achievable extra reimbursements  $\Delta P_{DIA,t}$  and  $\Delta P_{HMV,t}$ .

The top panel in Figure 1 summarizes the distribution of  $P_{BASE,t}$  for each year between 2005 and 2012. While hospitals receive about 1500 EUR for BASE admissions in 2009, they receive, on average, about 5100 EUR for the identical patients in 2010 (+240%). The bottom panel in Figure 1 illustrates the achievable extra reimbursements for the cross prices  $\Delta P_{TRA,t}$ ,  $\Delta P_{TOD,t}$ ,  $\Delta P_{DIA,t}$  and  $\Delta P_{HMV,t}$  for each of the four available hospital strategies for each year between 2005 and 2012. For example, while the TRA strategy results in an extra 3900 EUR reimbursement in 2009, the median extra reimbursement is reduced to 0 EUR in 2010 (upper left panel).

### 3.2 | Testable predictions

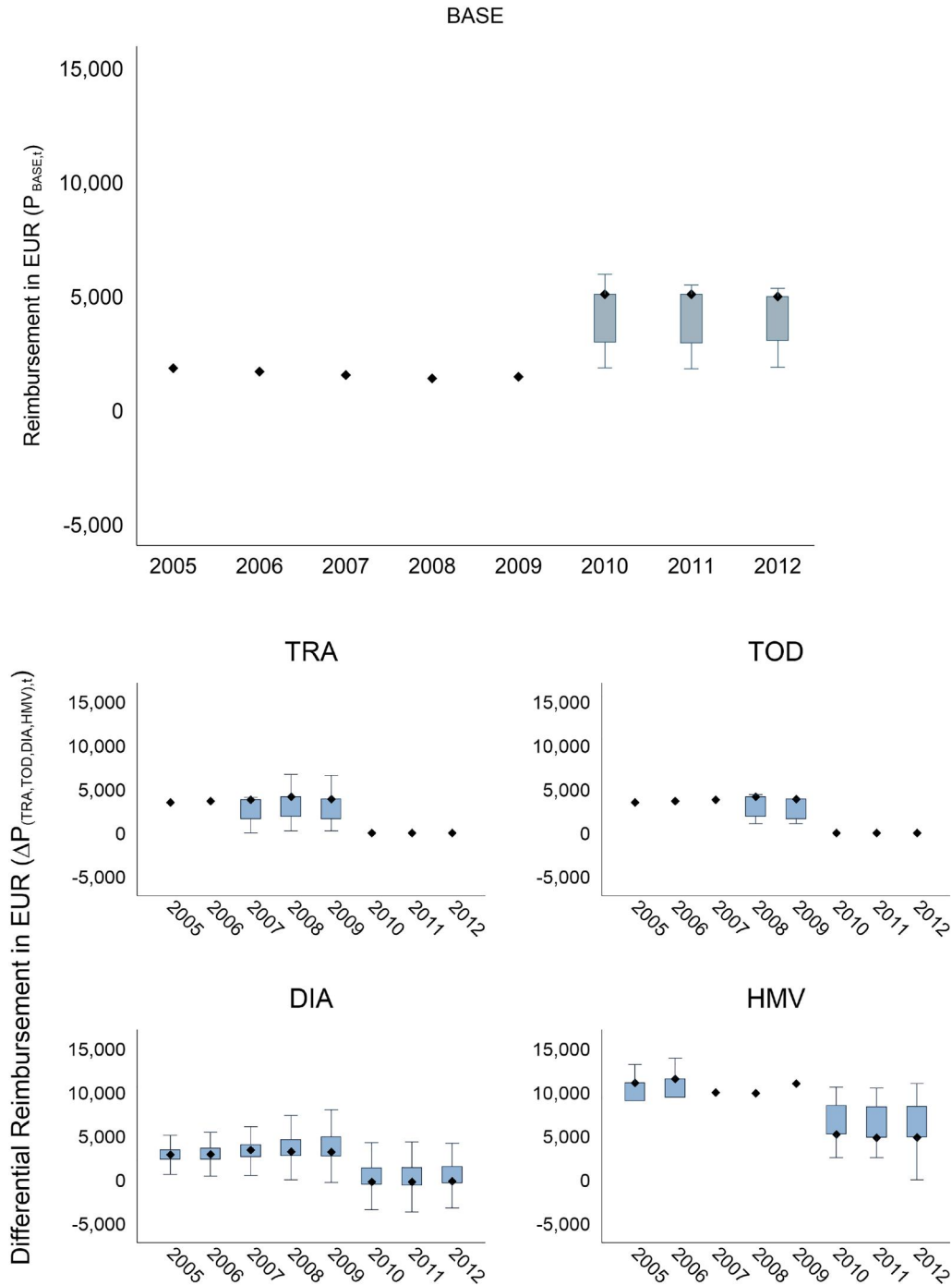
I assume that hospitals maximize utility over profits and patient benefits such as quality (see e.g., Dranove (1987)). At least partially benevolent hospitals trade off utility from profits with disutility from clinically manageable, but potentially harmful, treatment (Chalkley & Malcomson, 1998; Kesternich, Schumacher, & Winter, 2015). The price shock described in Section 3.1 affects the utility from profits, but is orthogonal to the utility from patient benefits. Hospitals thus produce the quantity of BASE admissions only as a function of own prices and cross prices, as expressed by<sup>6</sup>:

$$Q_{BASE,t} = f(P_{BASE,t}, P_{TRA,t}, P_{TOD,t}, P_{DIA,t}, P_{HMV,t}) \quad (4)$$

where  $Q_{BASE,t}$  is the number of BASE admissions,  $P_{BASE,t}$  the reimbursement for BASE admission,  $P_{TRA,t}$  the reimbursement for TRA admissions,  $P_{TOD,t}$  the reimbursement for TOD admissions,  $P_{DIA,t}$  the reimbursement for DIA admissions, and  $P_{HMV,t}$  the reimbursement for HMV admissions in year  $t$ .

Because of the life-threatening nature of sepsis for patients and the acute need for treatment, clinical practice suggests that hospitals may not specifically attract or reject these patients. On the contrary, the discussion in Section A1 of the appendix on the clinical manageability of the four possible strategies that arise from cross prices concludes that hospitals may adapt the TRA, TOD, DIA, and HMV strategy. For example, hospitals in Germany frequently contain





**FIGURE 1** Distribution of (differential) reimbursements for clinically similar patients suffering from sepsis (2005–2012). This illustrates visualizes the distribution of prices for BASE admissions (own price, top panel) as well as the extra reimbursements from prices for transfer status (TRA), time of death (TOD), diagnoses (DIA), and mechanical ventilation (HMV) admissions (cross prices, bottom panel) for each year between 2005 and 2012 (Details on the selection criteria are provided in Section 2). Dark blue diamonds depict the median of the own price for BASE admissions  $P_{BASE,t}$  and the median achievable extra reimbursements for the four cross prices for TRA, TOD, DIA, and HMV admissions  $\Delta P_{TRA,t}$ ,  $\Delta P_{TOD,t}$ ,  $\Delta P_{DIA,t}$ , and  $\Delta P_{HMV,t}$ . The upper hinges of the vertical dark blue boxes indicate the 75th percentile of the distribution and the lower hinges indicate the 25th percentile of the distribution. The distribution of prices is calculated based on admissions from all years, with the exception of the actual year of admission, and are independent from the observed, realized hospital strategy (please see Section 3 for more details). DRG weights (relative prices) include outlier payments. Reimbursements are normalized using the federal-level base rate from 2010 (2, 935.78 EUR) and presented in EUR. Source: Annual tables of DRG weights and Definitions Manuals are provided by Institut für das Entgeltsystem; Federal-level base rates are provided by GKV-Spitzenverband; G-DRG data is available from the Federal Statistical Office (Data Research Center) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

controlling departments and use software (e.g., 3M KODIP Suite) to optimize their billing. Since all major software packages provide simulation results for optimized primary diagnosis and secondary diagnoses combinations, legally or illegally altering coding behavior seems to be a feasible option at almost zero cost.

The five testable predictions about hospital responses to the price shock of 2009–2010 in the market for sepsis conditions are expressed by:

$$\begin{aligned}
 \frac{\partial Q_{BASE,2009/2010}}{\partial P_{BASE,2009/2010}} &= 0 \\
 \frac{\partial Q_{BASE,2009/2010}}{\partial \Delta P_{TRA,2009/2010}} &< 0 \\
 \frac{\partial Q_{BASE,2009/2010}}{\partial \Delta P_{TOD,2009/2010}} &< 0 \\
 \frac{\partial Q_{BASE,2009/2010}}{\partial \Delta P_{DIA,2009/2010}} &< 0 \\
 \frac{\partial Q_{BASE,2009/2010}}{\partial \Delta P_{HMV,2009/2010}} &< 0
 \end{aligned} \tag{5}$$

### 3.3 | Differences-in-differences

For the remainder of this study, this study will denote the turn of year 2009–2010, where the price shock occurs, as the treatment group, and the turn of year in 2005–2006, 2006–2007, 2007–2008, and 2008–2009, where no price shocks occur, as the control groups. The turn of year where no price shocks occur allow to cancel out potential causes for the change in the number of admissions from 2009 to 2010 other than the price shock. For example, the number of admissions in the market for sepsis conditions might generally increase around the turn of the year due to changes in the incidence of causative diseases such as severe consequences of pneumonia, independent from price changes.

I use OLS to compute differences-in-differences estimates. The basic estimating equations are regressions of the following form for each of the five patient groups in the market for sepsis conditions (BASE, TRA, TOD, DIA, and HMV) and in the total market for sepsis conditions (TOTAL):

$$Q_{g,t} = \beta_0 + \beta_1 T_g + \beta_2 Post_t + \beta_3 2009-2010_g \times Post_t + \varepsilon_{g,t} \tag{6}$$

where  $Q_{g,t}$  is the number of admissions for the treatment group or the control groups  $g$  in month  $t$ .  $T_g$  denotes fixed effects for each turn of the year in 2005–2006, 2006–2007, 2007–2008, and 2008–2009, where no price shocks occur, and the turn of the year 2009–2010, where the price shock occurs.  $Post_t$  indicates the 6 months before ( $Post_t = 0$ ) and the 6 months after ( $Post_t = 1$ ) each turn of the year.<sup>7</sup> The coefficient  $\beta_3$  indicates the causal impact of the price shock under the standard identifying assumptions in a differences-in-differences model. Standard errors are clustered at the turn-of-the-year level to account for potential serial correlation problems (Bertrand, Duflo, & Mullainathan, 2004; Brewer, Crossley, & Joyce, 2018; Cameron & Miller, 2015).<sup>8</sup>

The identification strategy used in this study is primarily based on two assumptions. First, it assumes that costs do not change from 2009 to 2010; that is, the price shock in the market for sepsis conditions is orthogonal to changes in costs. This assumption seems plausible, particularly because DRG weights are annually computed from 2-year old cost reports. Even if changes in the reported costs for BASE admissions had dominated the regulator's rationale for the comprehensive refinement in the market for sepsis conditions, changes in present costs from 2009 to 2010 only affect changes in future prices from year 2011 to year 2012, for example. Second, the identification strategy assumes that the demand for sepsis admissions does not change around January 1, 2010. Again, this assumption seems plausible because of the emergency nature of the disease.



Observed changes in hospital behavior from 2009 to 2010 might also result from changes specific to the turn of the year 2009–2010, other than the price shock that arises from the rich refinement in the market for sepsis conditions.<sup>9</sup> As changes specific to the turn of the year 2009–2010 are not captured by the preceding turns of the year, statistical inferences from the main specification might be biased. However, a peculiarity of the empirical setting under investigation allows me to investigate this potential threat in Section 5.3. The rich refinement in the market for sepsis conditions from 2009 to 2010 results in heterogeneous price shocks *within* each of the four patient groups TRA, TOD, DIA, and HMV. These heterogeneous price shocks allow to analyze whether the number of admissions also changes from 2009 to 2010 for admissions that are not (or only little) affected by the price shock of 2009–2010. If the observed changes in the number of admissions result from changes specific to the turn of the year 2009–2010 other than the price shock, heterogeneous price shocks would not lead to heterogeneous hospital responses.

For simplicity, the empirical strategy focuses on hospital responses to first-order financial incentives. However, hospitals might also respond to second-order financial incentives because they might, for example, not only delay the time of death or switch one of the various secondary diagnoses with the primary diagnosis, but might also pursue both strategies at once. In consequence, decreases in admissions for patient groups other than TRA, TOD, DIA, and HMV admissions might explain potential increases in the number of admissions in the overall market for sepsis conditions (TOTAL).

### 3.4 | Robustness

Section D of the appendix assesses the robustness of the conclusions. First, placebo differences-in-differences estimates reveal that the monthly number of admissions does not change in response to a “fake” price shock on January 1, 2011 where in fact no price shock occurs. Second, the findings are robust against potential seasonality-specific patterns in the number of admissions in the market for sepsis conditions. Third, the conclusions in this paper do not change for alternative pre- and postperiods or compositions of the counterfactual turns of the year. For example, this study compares the difference in the monthly number of admissions one year after and one year before the turn of the year 2009–2010, where the price shock occurs, to the same difference for the turn of the year in 2005–2006 and 2007–2008, where no price shock occurs. Fourth, this study uses the empirical fact that refinements to the incentive structure generate breaks in reimbursements by date of admission as annually updated reimbursements become effective on January 1. This empirical setting proposes an appropriate alternative identification strategy that is similar to a sharp regression discontinuity design in which the cutoff point  $t$  is January 1, 2010 where the price shock occurs (Lee, Lemieux, Heckman, Imbens, & Deaton, 2010). The results do not change.

## 4 | DATA

I use market-wide administrative reimbursement data (G-DRG data) to test the predictions about hospital responses to the price shock of 2009–2010. G-DRG data is collected to compute reimbursement owed to hospitals and to analyze refinements (§ 301 SGB V, § 21 KHEntgG). This data covers both publicly and privately billed inpatient hospital care in Germany and links about 127 million patient records to 2086 hospitals from 2005 to 2012. The data are available from the Federal Statistical Office (Data Research Center).

Each discharge record tracks demographic information (e.g., age, gender, and zip code), date and time of each admission and discharge by hospital department, admission source, admission cause, and discharge reason codes, primary and secondary diagnoses (up to 90 ICD codes), date- and time-stamped procedures (up to 100 OPS codes, the German version of ICD-9 procedure codes for inpatient services or CPT/HCPCS codes for outpatient services), and a hospital identifier. The median admission lists five diagnoses and two procedures.

I also use the annual tables of DRG weights as well as Definitions Manuals provided by the regulator (Institut für das Entgeltsystem). Federal-level base rates are provided by the National Association of Statutory Health Insurance Funds (GKV-Spitzenverband).

I collect the patient population data based on the quadruple of patient characteristics used to categorize patients that suffer from sepsis, as described in Section 2. As a result, this study obtains a panel of the relevant patient groups in the market for sepsis conditions (BASE, TRA, TOD, DIA, and HMV) and the overall market for sepsis conditions (TOTAL).

Statistics are computed by the date of admission throughout the paper, as this is the relevant point in time for the reimbursement schedule.

Table 2 summarizes the data. The number of admissions for the overall market for deceasing patients that suffer from sepsis (TOTAL) increases from 5405 in 2005 to 8167 in 2012 (+51%). The revenue paid to hospitals increases from about 25 million EUR to about 45 million EUR over the same period (+78%). The number of admissions for the group of patients affected by the increase in own prices (BASE) from 2009 to 2010 over-proportionally increases from 1053 to 2186 (+108%). Even more dramatically, revenues jump from about 2 million EUR to about 11 million EUR from 2005 to 2012 (+477%). These increases in admissions and revenues might not only be due to increases in BASE admissions, but may also be propelled by changes in the substitution of TRA, TOD, DIA or HMV admissions with BASE admissions. Over the same period, the average age of patients increases slightly by about 2.2% in the overall market for sepsis conditions (TOTAL) and 1.2% for BASE admissions. The interested reader will find the distribution of the number of admissions for BASE admissions plotted by the time of death and the years before (2005–2009) and after (2010–2012) the price shock in Section B of the appendix, Figure S1.

## 5 | RESULTS

### 5.1 | Dominant hospital strategies in the market for sepsis

The increase in the own price for BASE admissions from 2009 to 2010 discounts the relative attractiveness of the available cross prices for TRA, TOD, DIA, and HMV admissions. This price shock predicts increases in the number of BASE admissions and substitutive decreases in the number of TRA, TOD, DIA, and HMV admissions. The statistical and economic significance of the change in the number of admissions identifies which of the four available hospital strategies are the most dominant in response to the price shock of 2009–2010 in the market for sepsis conditions.

Figure 2 illustrates the results from the differences-in-differences estimates. The graphical evidence suggests that hospitals primarily switch one of the various secondary diagnoses with the primary diagnosis in response to changes in the incentive structure in the market for sepsis conditions from 2009 to 2010.

Table 3 reports the differences-in-differences point estimates. Column (1) documents that the monthly number of BASE admissions jumps in the treatment group from 2009 to 2010 by 79 admissions, while the monthly number of BASE admissions does not change in the control groups. The coefficient on 2009–2010  $\times$  Post is statistically highly significant ( $p < 0.001$ ). This estimated effect is also economically highly significant. The estimated increase of 79 admissions from 2009 to 2010 equals about 14% of the overall market for sepsis conditions observed in December, 2009 (571 admissions).

Column (4) demonstrates a drop in monthly DIA admissions in the treatment group from 2009 to 2010 by approximately 62 admissions and suggests that the drop in DIA admissions might completely offset the observed jump in BASE admissions ( $p < 0.001$ ). The number of TRA admissions in Column (2), the number of TOD admissions in Column (3), and the number of HMV admissions in Column (5) does (individually) not decrease in response to discounts in the relative attractiveness of available cross prices for TRA, TOD, and HMV admissions from 2009 to 2010 ( $p = 0.301$ ,  $p = 0.560$ , and  $p = 0.168$ ). As a result, changes in each TRA, TOD, and HMV strategy do probably not contribute to the substitutive increase in the number of BASE admissions. It is important to note, however, that the empirical setting under investigation does unfortunately not allow a more precise estimate of the change in TRA, TOD, and HMV admissions in response to the price shock of 2009–2010. At the 95% confidence level, the estimated change in admissions ranges between  $-7$  and  $22$  for the TRA strategy, between  $-12$  and  $21$  for the TOD strategy, and between  $-2$  and  $9$  for the HMV strategy. In consequence, it might be possible that hospitals do adapt the TRA, TOD, and HMV strategy in response to the price shock of 2009–2010 but at economic significance levels that are too small to identify in the empirical setting under investigation.

The previous literature already identified two particular hospital strategies for how hospitals upcode patients into more profitable DRGs: Hospitals report high patient severities by manipulating the existence of complicating diagnoses (Dafny, 2005; Di Giacomo et al., 2017) or by manipulating birth weights (Jürges & Köberlein, 2015). The results of this study extend the previous literature and identify a previously unrevealed mechanism to upcode patients into more profitable DRGs: switching the primary diagnosis with a more remunerative secondary diagnosis.

The results in Column (6) statistically support the assumption that hospitals do not specifically attract new, deceasing patients suffering from sepsis, as the monthly number of admissions in the overall market for sepsis

TABLE 2 Descriptive statistics

Patient Group		TOTAL			BASE		
Year	Hospitals	Count	Age	Revenue	Count	Age	Revenue
2005	1171	5405	74.1	25,316,485	1053	76.9	1,918,612
2006	1148	5890	74.8	27,628,009	1146	77.9	1,917,722
2007	1163	5959	74.7	29,171,492	1025	77.5	1,572,192
2008	1143	5970	74.9	28,686,628	943	78.1	1,310,849
2009	1146	6353	75.3	31,848,980	977	77.6	1,421,199
2010	1157	7142	75.4	39,425,991	1985	77.2	9,960,808
2011	1172	7288	75.0	40,814,074	2015	77.0	10,483,300
2012	1160	8167	75.7	45,042,516	2186	77.8	11,076,736

Notes: This table summarizes the data for (deceasing) patients in the overall market for sepsis conditions (TOTAL) between 2005 and 2012 (Details on the selection criteria are provided in Section 2). TOTAL admissions include admissions from BASE, TRA, TOD, DIA, and HMV. Hospitals denotes the number of hospitals that admit (deceasing) patients in the overall market for sepsis conditions (TOTAL). Count denotes the number of admissions, and age denotes the average age of patients. Revenues include outlier payments and are the annual normalized sum of DRG weights (relative prices), presented in EUR. The normalization is based on the federal-level base rate from 2010 (2, 935.78 EUR).

Source: Annual tables of DRG weights, as well as Definitions Manuals, are provided by Institut für das Entgeltsystem; Federal-level base rates are provided by GKV-Spitzenverband; G-DRG data is available from the Federal Statistical Office (Data Research Center).

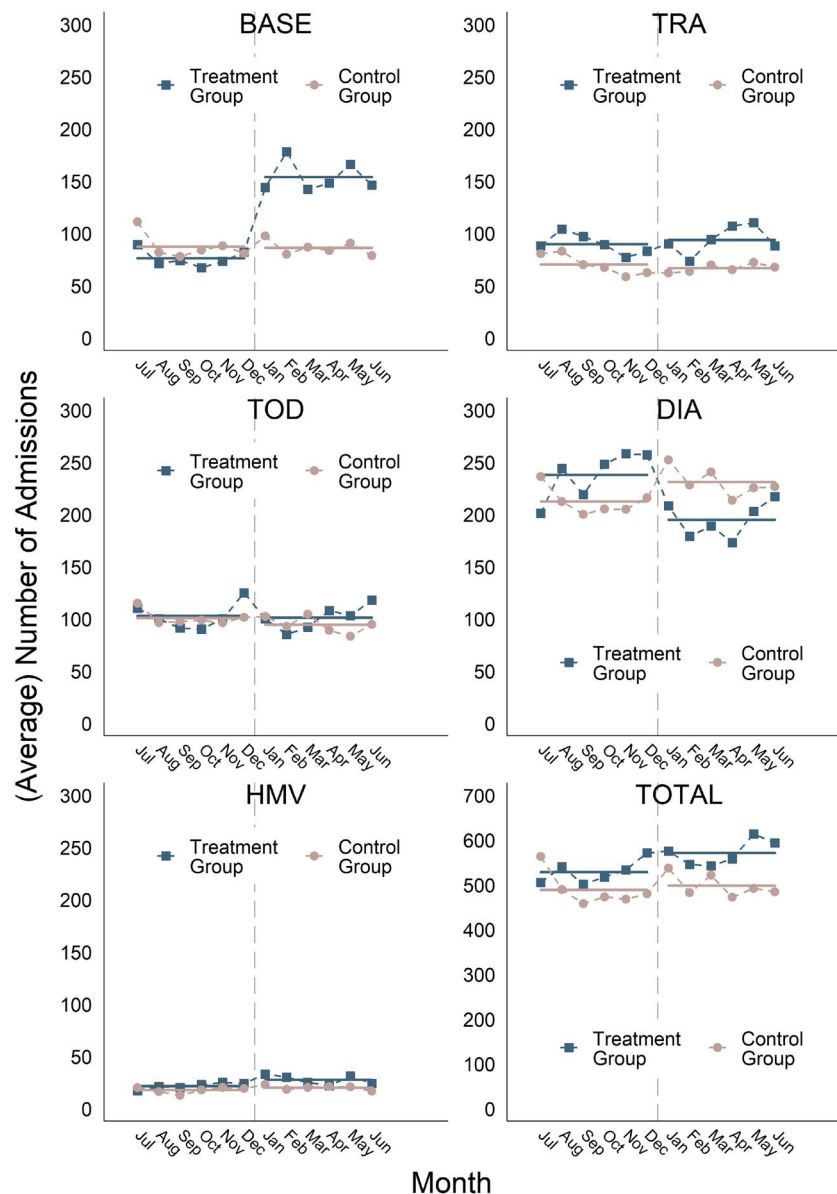
conditions (TOTAL) does not change from 2009 to 2010 ( $p = 0.102$ ). Moreover, the statistically insignificant coefficient on  $2009-2010 \times Post$  for TOTAL admissions proposes the conclusion that hospitals respond only to first-order financial incentives and that higher-order financial incentives might be impractical to exploit. Similarly, the results in Column (6) suggest the irrelevance of the theoretical hospital strategy that hospitals directly manipulate patients' survival or discharge (to home) deceasing patients close to death.

The 95% confidence interval for the estimated coefficient on  $2009-2010 \times Post$  for BASE admissions in Column (1) ranges from 63 to 95 while the confidence interval for the estimated coefficient on  $2009 - 2010 \times Post$  for DIA admissions in Column (4) ranges from  $-87$  to  $-36$ . The large overlap of the confidence intervals substantiates the conclusion that hospitals primarily switch one of the various secondary diagnoses with the primary diagnosis in response to changes in the incentive structure in the market for sepsis conditions from 2009 to 2010.

## 5.2 | Timing and speed of changes in hospital behavior

Authorities announce refinements to the incentive structure toward the end of October and the annually updated reimbursements become effective on January 1. The previous literature has shown that hospitals might already respond immediately to expected changes in market conditions (see e.g., Gaynor, Laudicella, & Propper, 2012). As a consequence, the conventional differences-in-differences design would underestimate the magnitude of the true response. However, anticipatory changes in hospital behavior before updated reimbursements become effective are highly unlikely in the empirical setting analyzed in this study. The reason for this is that switching efforts for the four hospitals strategies TRA, TOD, DIA, and HMV are fairly low. Immediate changes in hospital behavior such as switching the primary diagnosis with a—in the future—more remunerative secondary diagnosis would reduce present profits without the risk of losing future profits. In this setting, economic theory predicts that hospitals will change their behavior only after updated reimbursements become effective in the market for sepsis conditions (Farrell & Klemperer, 2007).

Hospitals might require a significant amount of time to adapt to the new regulations (Clemens & Gottlieb, 2014). In the event that hospitals may require more than 6 months to adapt to the price shock of 2009–2010, the differences-in-differences estimates from the main specification would underestimate the magnitude of the true response and miss potential long-term consequences. However, it is expected that hospitals adapt the profit-maximizing strategies TRA,



**FIGURE 2** Dominant Hospital Strategies in the Market for Sepsis Conditions. This figure presents the monthly number of admissions (y-axis) by month (x-axis) for each patient group (BASE, TRA, TOD, DIA, and HMV), as well as for the overall market for sepsis conditions (TOTAL; details on the selection criteria are provided in Section 2). The number of admissions 6 months before and after the turn of the year 2009–2010, where the price shock occurs, are presented as dark blue squares and denoted as “Treatment Group.” The average monthly number of admissions 6 months before and after the turns of the year in 2005–2006, 2006–2007, 2007–2008, and 2008–2009, where no price shocks occur, are depicted as light red circles and denoted as “Control Group.” Vertical dashed gray lines mark the turns of the year. Horizontal dark blue lines indicate the predictions of the monthly number of admissions from the differences-in-differences estimates for the treatment group, and horizontal light red lines, the predictions of the monthly number of admissions for the control group, as described in Section 3.3. Source: G-DRG data is available from the Federal Statistical Office (Data Research Center) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

TOD, DIA, and HMV quite rapidly after updated reimbursements become effective on January 1, as they do not require a significant amount of investments or change management.

Figure 3 sheds some light on the timing and the speed of changes in hospital responses to price changes. More specifically, it illustrates how quickly hospitals alter their coding behavior after the price shock of 2009–2010. Figure 3 uncovers an immediate and complete change in hospitals' coding behavior. The number of admissions immediately jumps from December 2009 to January 2010. It does not evolve steadily throughout 2010, the 6 months after the price

TABLE 3 Differences-in-differences estimates

Q	Patient group					
	(1) BASE	(2) TRA	(3) TOD	(4) DIA	(5) HMV	(6) TOTAL
2009 – 2010 × Post	79*** (9.82)	8 (1.04)	5 (0.59)	–62*** (–4.77)	4 (1.40)	33 (1.66)
Post	–1 (–0.24)	–4 (–1.18)	–6 (–1.51)	19** (3.05)	2 (1.63)	10 (0.73)
Adjusted R <sup>2</sup>	0.661	0.565	–0.022	0.360	0.296	0.317
Observations	60	60	60	60	60	60

Notes: This table reports the differences-in-differences estimates for each patient group (BASE, TRA, TOD, DIA, and HMV) in Column (1) through Column (5), as well as the differences-in-differences estimates for the overall market for sepsis conditions (TOTAL) in Column (6), as described in Section 3 (Details on the selection criteria are provided in Section 2). The dependent variable Q is the monthly number of admissions between July 2005 and June 2010 (6 months before and after each of the included five turns of the year amount to 12 months × 5 years = 60 observations). 2009–2010 × Post is the variable of interest and indicates whether admissions are affected by the price shock of 2009–2010. Post indicates the 6 months following the turns of the year. Each regression accounts for turn of the year-fixed effects and is not reported. T-statistics are calculated based on robust standard errors clustered at the turn-of-the-year level and reported in parentheses below the coefficients.

Source: G-DRG data is available from the Federal Statistical Office (Data Research Center).

Significance levels are indicated as follows: \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .

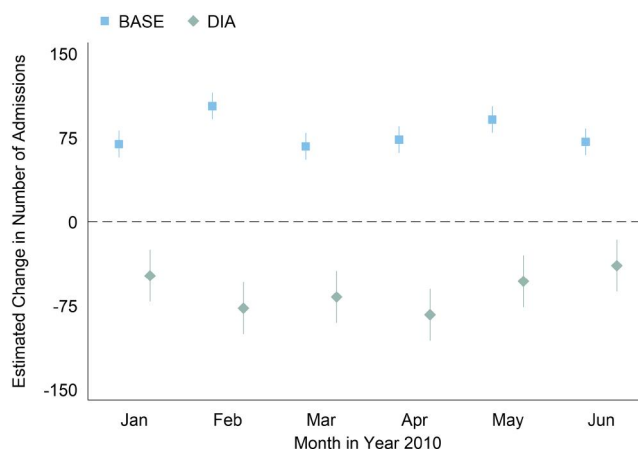


FIGURE 3 Timing and speed of changes in hospital behavior. This figure depicts the point estimates for the change in the monthly number of BASE admissions using light blue squares, and in the monthly number of DIA admissions, using light green diamonds (Details on the selection criteria are provided in Section 2). 95% confidence intervals are marked as horizontal bars next to each point estimate. The estimated change in the monthly number of admissions comes from an extension to the main estimating equations presented in Section 3.3, which splits the single treatment indicator 2009–2010 × Post into six treatment indicators based on the month of treatment in 2010. The horizontal dashed gray line illustrates the estimated change in the monthly number of admissions under the null hypothesis. Source: G-DRG data is available from the Federal Statistical Office (Data Research Center) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

shock. The estimated change in the monthly number of admissions comes from a modification of the main specification presented in Section 3.3 and splits the post-period in the variable of interest 2009–2010 × Post into monthly subperiods 2009–2010 × January for January through 2009–2010 × June for June. Section C1 of the appendix, Table S2 reports the corresponding differences-in-differences point estimates.

The findings reveal that the 6-month window used in the main specification does not underestimate the magnitude of the true response and does not miss potential long-term consequences. To optimize the choice of the primary diagnosis, hospitals might either alter the position of the sepsis diagnosis (primary or secondary) based on already available diagnoses codes or increase the set of available diagnosis codes by improving documentation. The results suggest that hospitals predominantly optimize the choice of the primary diagnosis based on already available secondary diagnoses. Sacarny (2018) observes that improving documentation is rapid but incomplete and the adoption of the relevant diagnoses codes steadily increases after an initial jump. The author points out that clinical documentation is frequently tempered by significant frictions due to agency problems between a hospital and its doctors.



### 5.3 | Hospital responses and the size of financial incentives

As a reminder from Section 2, individual patient characteristics, such as a status post organ transplantation potentially scale reimbursement for patients *within* each of the four patient groups TRA, TOD, DIA, and HMV in the market for sepsis conditions. As the unique administrative reimbursement data allows to link the changes in own prices and cross prices directly to admissions, this section utilizes this additional source of variation to investigate whether hospitals upcode more aggressively in cases in which differential reimbursements are higher.

Large extra profits paired with low probabilities of conviction and (near) zero punishments per offense might result in a large number of offenses. Authorities in Germany do not consider upcoding to be either a criminal offense or a petty offense; hence hospitals do not face punishments in the event that chart reviews identify upcoding activities. The only consequence is that hospitals must return the extra reimbursements that resulted from upcoding. Under the assumption that the monetary costs of upcoding are independent from the size of the differential reimbursements, hospitals might upcode admissions more aggressively in cases in which differential reimbursements are higher.

In addition, heterogeneous price shocks allow to analyze whether the number of admissions also changes from 2009 to 2010 for admissions that are not (or only little) affected by the price shock of 2009–2010. If the observed changes in the number of admissions result from changes specific to the turn of the year 2009–2010 other than the price shock, heterogeneous price shocks would not lead to heterogeneous hospital responses.

Figure 4 plots the monthly number of BASE admissions (top panel) and DIA admissions (bottom panel) in the year before and after the price shock of 2009–2010, subdivided into three groups according to the size of the price shock of 2009–2010  $\partial\Delta P_{DIA, 2009/2010}$ .<sup>10</sup> Section C2 of the appendix, Table S3 reports the corresponding differences-in-differences point estimates.

The increase in the monthly number of admissions for BASE admissions and the corresponding decrease in the number of DIA admissions is most pronounced for admissions with the highest reimbursement differential. The monthly number of BASE admissions (DIA admissions) quite discontinuously increases (decreases) by about 16 (–18) admissions for admissions with the highest reimbursement differential (>5, 000 EUR). This increase in the number of BASE admissions equals approximately 267% relative to the average monthly number of BASE admissions in 2009 (9 admissions). Similarly, the monthly number of BASE admissions (DIA admissions) starkly increases (decreases) by about 52 (–30) admissions for admissions with a medium reimbursement differential (from 2, 500 EUR to 5, 000 EUR). This increase in the number of BASE admissions equals approximately 121% relative to the average monthly number of BASE admissions in 2009 (43 admissions). In contrast, the estimated increase (decrease) of 10 BASE admissions (–14 DIA admissions) for admissions with the lowest reimbursement differential (<2, 500 EUR) is only marginally statistically significant and amounts to about 33% relative to the average monthly number of BASE admissions in 2009 (30 admissions).

These findings are in line with the previous literature. For example, Dafny (2005) show that hospitals quite sophisticatedly upcode patients into more profitable DRGs, and more extensively upcode patients, the higher the financial incentive.

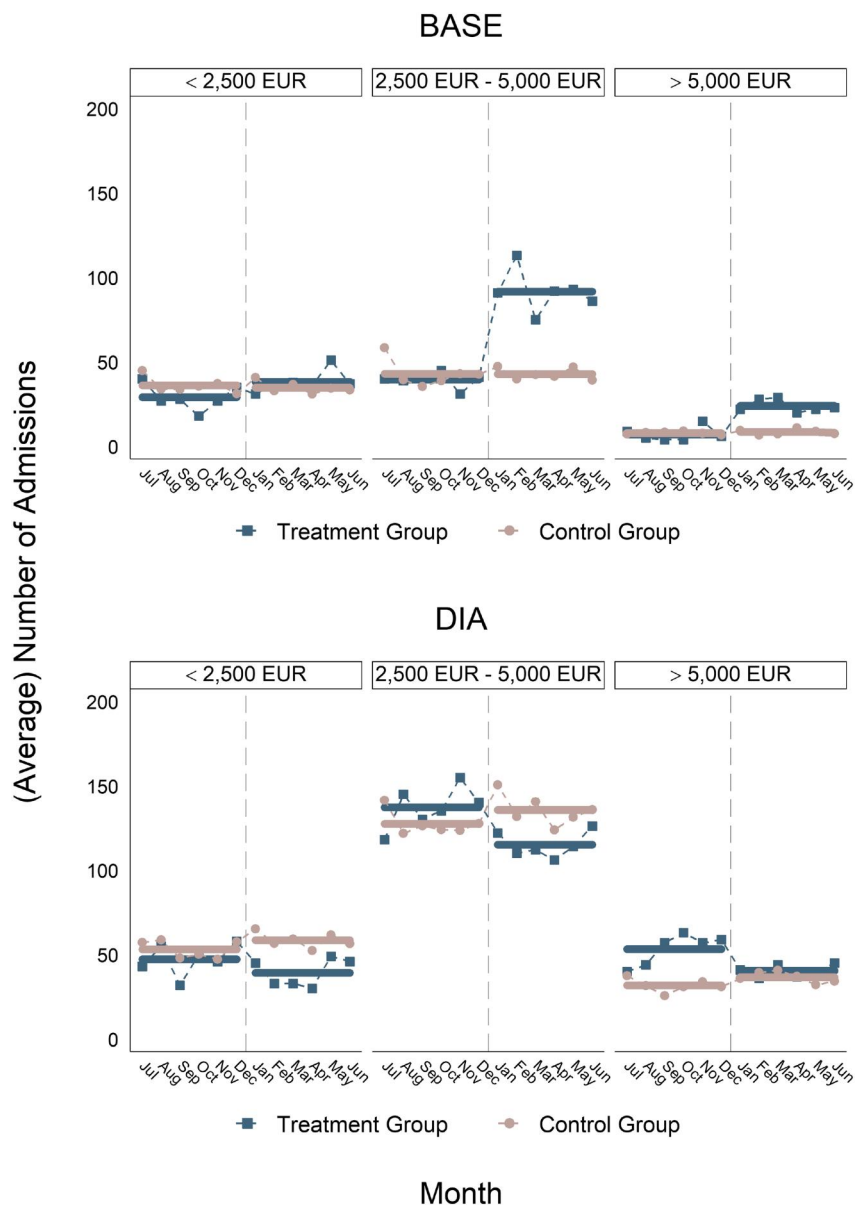
These findings also support the conclusion that the results from Section 5.1 are not biased by changes specific to the turn of the year 2009–2010 other than the price shock.

## 6 | DISCUSSION

I relate the estimated annual sum of increasable reimbursements to the size of the overall market revenue to assess the potential effects of manipulating the primary diagnosis on competition.<sup>11</sup> A back-of-the-envelope calculation shows that hospitals might annually exploit extra reimbursements of about 8%–10% from primary diagnosis manipulations in the market for sepsis conditions. Given the low average operating margins or returns on sales (between 0.2% and 7.1% in the German hospital industry), this result suggests that upcoding activities might be vital for hospitals to survive competition (Penter, 2013).

Given that patient characteristics are never perfectly observed by the payer, any payment system will probably have measurement error. To yet increase fairness in competition, regulators might be able to eliminate the position of the diagnosis (primary or secondary) from the mechanism of setting prices. The modern statistical machinery might allow regulators to achieve a similar (or even superior) accuracy in predicting differences in costs based on the full set of





**FIGURE 4** Hospital responses and the size of financial incentives. This figure plots the monthly number of admissions (y-axis) by month (x-axis) for BASE admissions (top panel) and DIA admissions (bottom panel) by the size of the price shock of 2009–2010  $\partial\Delta P_{DIA, 2009/2010}$  (left, middle, and right panel; Details on the selection criteria and the computation of  $\partial\Delta P_{DIA, 2009/2010}$  are provided in Section 2 and Section 4, respectively). The number of admissions 6 months before and after the turn of the year 2009–2010, where the price shock occurs, are presented as dark blue squares and denoted as “Treatment Group.” The average monthly number of admissions 6 months before and after the turns of the year in 2005–2006, 2006–2007, 2007–2008, and 2008–2009, where no price shocks occur, are depicted as light red circles and denoted as “Control Group.” Vertical dashed gray lines mark the turns of the year. Horizontal dark blue lines illustrate the predictions of the monthly number of admissions from the differences-in-differences estimates for the treatment group, and horizontal light red lines, the predictions of the monthly number of admissions for the control group, respectively, as described in Section 3.3. Source: G-DRG data is available from the Federal Statistical Office (Data Research Center) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

diagnoses without differentiating between their primary and secondary position. At least, it might be worth increasing the effort to further improve coding guidelines to reduce hospitals' discretion to choose the most lucrative condition chiefly responsible for the hospital admission. The incentives arising from the choice of the primary diagnosis might affect the behavior of a large variety of hospitals and distort the efficiency (and distributional aspects) of health care policy.

The results also suggest that hospitals care about patient benefit. For example, patients that would naturally die on the seventh day after admission might suffer from additional pain when hospitals postpone death for a couple of hours (or even days). Similarly, extensive mechanical ventilation frequently results in infectious diseases. Although the discounts in the relative attractiveness of available cross prices for TOD admissions and HMV admissions are considerable, this study does not find evidence that hospitals produce more TOD admissions or HMV admissions after the price shock of 2009–2010. Disutility from clinically manageable but potentially harmful treatment might outweigh the utility from profits.

Alternatively, adjustments to treatment intensity might also be hard to implement in clinical practice. The daily routine in hospitals might not allow for day-to-day coding and reimbursement simulations. Since the changes in the nonlinear reimbursements to prolong lives affect only BASE admissions (which might be a small share of all admissions at the hospital or department level), physicians and nurses might not know about (or remember) these extra reimbursements. However, the G-DRG offers nonlinear reimbursements for extensive mechanical ventilation for almost all admissions in a hospital, so physicians and nurses are most likely aware of these incentives.

The findings imply that coding behavior (or changes therein) may lead to a potential endogeneity bias in econometric analyses based on administrative data such as MedPAR files. The previous literature usually assumes that identical patients are equivalently documented across time and regions, hospitals and physicians. Both the economic and medical literature find it appealing to sample patients based on their primary diagnosis to test statistical hypotheses. However, this study might invalidate this assumption, as the primary diagnosis of identical patients is dissimilarly documented, at least across time, in response to (changes in) the financial incentives to do so.

Similarly, the findings might also challenge the effectiveness of pay-for-performance incentives based on administrative data which frequently assume an exogenous choice of the primary diagnosis. For example, the postoperative sepsis rate (CAHRA PSI 13) eliminates patients with sepsis being the primary diagnosis. Based in my findings, hospitals may have the discretion to improve their quality rankings and pretend to treat a deceasing patient with sepsis being the primary diagnosis instead of a secondary diagnosis.

## 7 | CONCLUSIONS

This study investigates whether the design of hospital financing affects the supply of health services. Many OECD countries finance hospitals based on lump-sum payments by DRGs. DRG algorithms categorize admissions and frequently create—at times probably unintentionally—a myriad of nonlinear admission-specific cross prices. As hospitals might respond to these nonlinear cross prices, the design of modern DRG systems might hinder the efficiency, as well as negatively impact the distributional aspects of hospital financing.

This study exploits a natural experiment in Germany in which a rich set of previously unstudied own prices and cross prices in the German DRG system (G-DRG) change. Authorities refined the incentive structure inherent in the G-DRG in the market for sepsis conditions from 2009 to 2010. As a result, authorities provide extra reimbursements in cases in which hospitals reorganize transfers to other facilities, alter the time of death, the choice of the condition being chiefly responsible for the hospital admission (primary diagnosis), or the intensity of mechanical ventilation. This study uses market-wide administrative reimbursement data that allows to pioneer the identification of admission-specific changes in own prices and cross prices. The statistical analysis is based on a differences-in-differences design, computed using OLS, to reveal the most dominant hospital strategies in the market for sepsis conditions after the price shock of 2009–2010.

The findings demonstrate that hospitals primarily alter the choice of the condition being chiefly responsible for the hospital admission (primary diagnosis) in response to the price shock. Hospitals immediately adapt the new upcoding strategies (within less than 1 month after the price shock). Moreover, hospitals switch the primary diagnosis with the most lucrative secondary diagnosis more aggressively where the size of the differential reimbursement is higher.

These results might motivate economists and regulating authorities to effectively improve contracts between payers and providers that are based on modern DRG algorithms. An alternative design of hospital financing that eliminates the position of the diagnosis (primary or secondary) for setting prices, while holding constant the accuracy in predicting differences in costs using the modern statistical machinery, may alleviate potential adverse effects on payers (and patients).

Given that the previous literature has paid relatively little attention to the design of modern DRG systems, it still remains largely unknown how hospitals respond to the myriad available cross prices to exploit profits. For example, do hospitals alter their treatment intensity, such as potentially harmful extensive mechanical ventilation, only in cases where no alternative upcoding strategies are available? In the event that they do, do hospitals induce treatment intensity to the most appropriate patients or independent from clinical appropriateness?

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## CONFLICT OF INTEREST

The author declares that he has no conflict of interest.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the Federal Statistical Office (Data Research Center).

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## ENDNOTES

- <sup>1</sup> For a more comprehensive discussion on the more general effects of (financial) incentives on hospital supply, please see Chandra, Cutler, and Song (2011).
- <sup>2</sup> To obtain these numbers, this study simulates the relevant hospital strategies on a 5% random sample of all admissions in Germany in 2014 (871,780 observations). More specifically, this study computes whether hospital reimbursement changes for an admission in response to the choice of the primary diagnosis, the treatment decision (medical and surgical procedures or length of stay), or the level of patient severity (clinical complexity scores or absence of particular secondary diagnoses).
- <sup>3</sup> Technically, the G-DRG also uses a particular set of surgeries and procedures, such as intestinal surgeries (e.g., OPS code 5–469.\*) to categorize patients that suffer from sepsis. This study assumes that hospitals do not induce these types of surgeries and procedures in life-threatening, likely already inoperable patients. The G-DRG further isolates reimbursement for patients with HIV/AIDS, newborns, and patients receiving transplants that suffer from sepsis, and bases payments on an alternative set of patient characteristics. This study thus also excludes these types of admissions from the analysis. The results in Section 5.1 confirm the validity of these assumptions.
- <sup>4</sup> Section A2 of the appendix, Table S1 lists the ICD-10-GM diagnosis codes that the regulator uses to define sepsis.
- <sup>5</sup> Additional individual patient characteristics can further scale reimbursement for patients in the market for sepsis conditions *within* each of the four patient groups TRA, TOD, DIA, and HMV. For example, reimbursement for TOD admissions is higher in cases in which a patient reports a status post organ transplantation (DRG T60A) compared to a patient that does not report a status post organ transplantation (DRG T60E). However, potential manipulations to these additional individual patient characteristics do not shift patients *across* each of the five types of admissions BASE, TRA, TOD, DIA, and HMV.
- <sup>6</sup> I assume that the incentives for hospital physicians in Germany correlate with the (financial) incentives of the department or hospitals. The reason for this is that while salaries for more junior physicians are frequently based on collective labor agreements, salaries for department heads and more senior physicians frequently include financial bonuses based on financial performance. Hospital physicians are usually employed by the hospital.
- <sup>7</sup> This study computes the differences-in-differences estimates at the turn-of-the-year month level to account for the potential correlation of shocks within each turn-of-the-year month cell (Wooldridge, 2003). For example, clinical shocks might affect all admissions for a given turn of the year on a monthly basis.
- <sup>8</sup> The literature demonstrates that the degrees of freedom (df) used in computing the cluster-robust estimate of the variance matrix should be adjusted, particularly in cases in which differences-in-differences estimates are based on a small number of groups (Cameron & Miller, 2015). The number of groups, that is, the turns of the year, in the analysis, equals  $G = 5$ . According to the literature, this study computes the df as follows:  $df = G/(G-1)$ . Alternatively, this study collapses the time series information into a pre- and postperiod which explicitly takes into account the effective sample size (Bertrand et al., 2004). Conclusions do not change and are not reported.
- <sup>9</sup> For example, the financing of public health insurances in Germany is based on medical conditions of insurees (“Morbi-RSA”). As sepsis conditions are one of the medical conditions that trigger higher financing, public health insurances might try to incentivize hospitals to upcode their insurees accordingly (Bauhoff, Fischer, Göppfarth, & Wuppermann, 2017). However, even in the event that public health

insurances provided hospitals with coding instructions, the compensation for sepsis conditions, and hence the incentives for hospitals to upcode insruces, did not change around the turn of the year 2009–2010. The Morbi-RSA defines sepsis conditions based on the same 32 ICD-10-GM diagnosis codes in both years (BAS, 2009, 2010); out of the 58 ICD-10-GM diagnosis codes that define sepsis conditions in the G-DRG, see Section A2 of the appendix, Table S1). As a result, incentives arising from the financing of public health insurances are unlikely to affect the results of this paper.

<sup>10</sup> Section C2 of the appendix, Figure S2 plots the distribution of the change in differential reimbursements for DIA admissions  $\partial P_{DIA, 2009/2010}$  from 2009 to 2010 and highlights the two reimbursement thresholds 2, 500 EUR and 5, 000 EUR used to categorize admissions for this sub-analysis.

<sup>11</sup> I calculate the annual sum of increasable reimbursements based on the annualized estimated change in monthly BASE admissions  $\partial Q_{BASE, 2009/2010}$  from 2009 to 2010 from Table 3 (and monthly DIA admissions  $\partial Q_{DIA, 2009/2010}$ , respectively) weighted by the median size of the achievable extra reimbursement for DIA admissions  $\Delta P_{DIA, 009}$  in 2009 from Figure 1. As a remainder, the estimated change in monthly BASE admissions is 79, or  $79 \times 12 = 948$  annually. The estimated change in monthly DIA admissions is 62, or  $62 \times 12 = 744$  annually. The average difference in the reimbursement differential for admissions is 3191 EUR. As a result, the estimated sum of annual increasable reimbursements in 2009 is between  $744 \times 3, 191 \text{ EUR} = 2, 374, 104 \text{ EUR}$  and  $948 \times 3, 191 \text{ EUR} = 3, 025, 068 \text{ EUR}$ , or between 7.5% and 9.5% of the annual revenue for TOTAL admissions of 31, 848, 980 EUR in the overall market for sepsis conditions in 2009 from Table 2.

<sup>12</sup> I do not use all available turns of the year when using the 12-month window before and after the turn of the year in the alternative specification (vs. the baseline specification) because the outcome variable number of admissions would be - by mechanics - highly serially correlated in case all the turns of the year in 2005–2006, 2006–2007, 2007–2008, and 2008–2009 would be included using 12-months windows in the control group. The number of admissions after a given turn of the year (e.g., admissions in 2006 for 2005–2006) are identical to the number of admissions before the following turn of the year (e.g., admissions in 2006 for 2006–2007). This mechanically induced serial correlation complicates the computation of confidence intervals and standard OLS estimates might severely understate the standard deviation of the estimator (Bertrand et al., 2004).

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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