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Hospital responses to the refinement of reimbursements by treatment intensity in DRG systems

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Abstract

Many OECD countries have replaced per-diem hospital reimbursement with lump sum payments by diagnosis-related groups. This study analyzes hospital responses to a large-scale refinement of reimbursement practices in Germany on January 1, 2006, in which regulating authorities introduce reimbursements by treatment intensity in the market for stroke disorder. We find that the share of admissions receiving high-intensity treatments jumps by approximately 7 percentage points around the turn of the year. At the same time, a decrease in the average clinical severity of patients receiving these high-intensity treatments reveals that the marginal high-intensity treated patient in 2006 might be less appropriate for high-intensity treatments compared to 2005. We do not find accompanying (short-term) changes in the quality of care, such as decreases in in-hospital mortality.

KEYWORDS

DRGs, hospital reimbursement, hospital supply, clinical pathways

JEL CLASSIFICATION

H51, I11, I18, L51

1 | INTRODUCTION

Since 1984, many of the developed countries around the globe have been following the US model and have replaced per-diem hospital reimbursements with lump sums. Reimbursements based on diagnosis-related groups (DRGs) promise to make hospitals bear the marginal costs of treatments and to reduce health care expenditures (Ellis & McGuire, 1986). With regulating authorities setting reimbursement for each patient group at the (historical) average of market-wide cost, yardstick competition might incentivize hospitals to exert socially optimal cost-reduction efforts (Shleifer, 1985). Indeed, it has been demonstrated that reimbursement based on DRGs is a powerful tool for reducing extra-long hospital stays that originate from medical discretion and information asymmetries among providers, patients and payers (Coulam & Gaumer, 1991; Cutler, 1995; Ellis & McGuire, 1996; Hodgkin & McGuire, 1994).

As has been true under per-diem reimbursement practices, granular modern DRG algorithms extensively reimburse hospitals for the marginal costs of treatments and might thus continue to incentivize hospitals to deviate from the

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clinically optimal treatment intensity and to alter clinical pathways (Ellis, 1998; Ellis & McGuire, 1986; Jena, Prasad, Goldman, & Romley, 2015). Hafsteinsdottir and Siciliani (2010) demonstrate in their theoretical model that hospitals always over-provide medical or surgical treatments when DRG algorithms provide extra reimbursements for these procedures. 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 2003/2004. In line with the theoretical prediction, the empirical findings suggest that hospitals substitute uncemented hip replacements with (clinically similar) cemented hip replacements after the refinement becomes effective. In addition, Gilman (2000) analyzes DRG refinements from 1993 to 1994 that introduce extra reimbursements for surgical procedures to HIV patients under Medicaid. However, the empirical findings contradict the theoretical predictions, as hospitals do not increase the rate of reimbursement-relevant procedures in response to extra reimbursements. One explanation for this might be that the additional surgical procedures analyzed in Gilman (2000) might be harmful for HIV patients. In these circumstances, hospitals might give more weight to patient benefit than profits. The literature remains unclear as to whether there are further observable differences in hospital response in terms of providing financially incentivized procedures that are potentially harmful or in the best case harmless versus financially incentivized procedures that are potentially beneficial.

Moreover, hospitals might non-randomly select the patients that receive the extra treatments in response to extra reimbursements (Dranove, 1987; Kifmann & Siciliani, 2016; Ma, 1994). In some instances, hospitals might increase the treatment intensity for the most seriously ill that might have been previously underpaid. However, hospitals might also increase the treatment intensity for the more mildly ill that likely incur low marginal treatment costs. As a result, the mechanism design inherent to modern DRG algorithms is in the position to both improve and worsen social welfare.

In 2005, the German-DRG (G-DRG) did not make reimbursements contingent on treatment intensity in the market for stroke disorder. In 2006, regulating authorities introduced marginal reimbursements for high-intensity treatments (most notably extensive and early clinical diagnostics as well as early rehabilitative treatments) compared to low-intensity treatments. In cases in which hospitals prescribe high-intensity treatments, they receive, on average, an additional 2200 EUR for each admission. We exploit this plausibly exogenous price shock on January 1, 2006 using an identification strategy based on a sharp regression discontinuity design where time is the running variable (see e.g., Anderson, 2014; Auffhammer & Kellogg, 2011; Gallego, Montero, & Salas, 2013).

In more detail, this study contributes to the previous literature as follows: First, we tailor the model from Hafsteinsdottir and Siciliani (2010) to the German setting and derive predictions for both changes in treatment intensity and in the clinical severity of the treated arising from an exogenous (rather than endogenous) change in marginal reimbursement for treatment intensity. Second, we empirically test our theoretical predictions in a setting with plausibly exogenous increases in marginal reimbursements for high-intensity, but- contrary to Gilman (2000)- harmless or even potentially beneficial treatments in the market for stroke disorder in Germany from 2005 to 2006. Third, we extend the empirical strategy from Chandra and Staiger (2007) and achieve the precise measurement of the admission-specific one-dimensional clinical severity of patients using a supervised machine learning approach. We use this to investigate the patient selection response of hospitals after the introduction of marginal reimbursements. Fourth, unique administrative reimbursement data allows us to achieve admission-specific actual as well as counterfactual changes in reimbursements for the year before and after the German price shock of 2005-2006. The primary data sources are market-wide G-DRG files that cover all (stroke) patients in Germany from 2005 to 2014. Each record includes a rich set of clinical, demographic and administrative information, such as diagnoses, date- and time-stamped procedures (OPS codes) and age.

Our theoretical model demonstrates that hospitals will provide more high-intensity treatments (and less low-intensity treatments) when marginal reimbursements are available. At the same time, the proportion of patients that are less clinically severe increases. The empirical analysis finds that the share of admissions receiving high-intensity treatments jumps by approximately 7 percentage points from 2005 to 2006. A simultaneous decrease in the average clinical severity of patients receiving high-intensity treatments around January 1, 2006 reveals that the marginal high-intensity treated patient in 2006 might be less appropriate for high-intensity treatments compared to 2005. We do not find changes in the (short-term) measures of the quality of care, such as decreases in in-hospital mortality. Extensive robustness tests confirm the validity of the major identification assumptions of the empirical strategy. For example, we show that the observed increase in the documented high-intensity treatments cannot be explained by channels other than real changes to clinical pathways.

The remainder of this study is organized as follows: Section 2 introduces the institutional background of our empirical setting and Section 3 develops the theoretical predictions. Section 4 describes the data and outlines the

empirical strategy. Results are presented in Section 5 and Section 6 discusses the robustness of the findings. Section 7 provides a conclusion.

2 | EMPIRICAL SETTING

Germany introduced lump-sum reimbursements, effective from January 1, 2005, for all publicly and privately insured inpatient services. Since then, the majority of hospital reimbursements have been flat fees by DRG weight. DRG weights are annually computed from 2-year old cost reports of approximately 15% of hospitals. The G-DRG system comprehensively utilizes diagnoses (either directly or via aggregated patient clinical complexity scores) and additional proxies for patient characteristics to adjust admission-specific lump-sum reimbursements for differences in the relative resource intensity.

In an attempt to more appropriately reflect the given conditions in German hospitals, regulating authorities increased the number of DRGs from 845 to 1245 between 2005 and 2018. The steady effort to ensure that DRGs appropriately reflect the given conditions in German hospitals results in various large-scale refinements that are plausibly orthogonal to changes in costs. This study analyzes a large-scale refinement in the market for stroke disorder from 2005 to 2006 in which regulating authorities introduce marginal reimbursements for high-intensity clinical pathways.

A stroke occurs when the blood supply to the brain is interrupted or reduced which can cause a person's brain cells to die (AHA, 2016). Strokes are a clinical emergency that is usually accompanied by a variety of neurological disorders. In Germany, approximately 270,000 patients are admitted to the hospital annually for stroke treatments (in 2016, Destatis, 2017a). Strokes are responsible for approximately 25% of disabilities in adulthood and are a major cause of death in many OECD countries (~7%), particularly in Germany (~8%; Destatis, 2017b; Heuschmann et al., 2010; OECD, 2015). Mortality due to strokes represents approximately 20% of all deaths in these countries.

The medical literature contains convincing evidence that a clearly structured clinical pathway for treating stroke patients improves patient outcomes (see Seenan, Long, and Langhorne (2007) for a systematic review of the literature). For example, extensive and early clinical diagnostics, such as cranial computed tomography (CT) scans, allow the physician to provide treatments tailored to the particular type of stroke, as quickly as possible. In addition, early rehabilitative treatments such as physiotherapy or speech therapy further reduce the incidence of consequential complications and disabilities. In response, medical societies like the American Stroke Association or the German Stroke Society developed clinical guidelines that define and recommend the abovementioned clearly structured, high-intensity clinical pathways.

In 2005, the G-DRG did not make reimbursements contingent on treatment intensity in the market for stroke disorder. Lump-sum reimbursements for patients primarily suffering from strokes typically varied between approximately 1800 EUR (DRG B70C) and approximately 5400 EUR (DRG B70A), depending on patient characteristics such as the specific type of stroke. In 2006, reimbursement for patients that receive high-intensity treatments increased compared to patients that receive low-intensity treatments. Based on voluntary cost reports, regulating authorities argued that uniform reimbursements might not cover the true costs of high-intensity treatments in many circumstances (INEK, 2005).

For hospitals to receive extra reimbursement for high-intensity treatments, they must provide particular services to patients that are mostly based on the mentioned guidelines. For example: Comprehensive and early clinical diagnostics such as cranial CT scans within 60 min (for patients who are likely to receive thrombolysis), early treatments, such as administering thrombolytic drugs—if applicable—to dissolve blood clots within 1 h, extensive monitoring and particularly early rehabilitative treatments such as physiotherapy. For the remainder of this paper, “high-intensity treatments” refers to clinical pathways that meet the high-intensity reimbursement-relevant standards of services. Similarly, “low-intensity treatments” refers to clinical pathways that do not meet the high-intensity reimbursement-relevant standards of services.¹

Appendix Table S1 summarizes the changes in reimbursements for low-intensity treatments and high-intensity treatments on January 1, 2006. While hospitals receive approximately 3700 EUR for the most frequently observed stroke patient in our data in 2005, they receive approximately 3300 EUR in 2006 as long as they provide low-intensity treatments. As soon as hospitals provide high-intensity treatments, they earn approximately 5600 EUR for each admission (+70%). On average, for each case in which high-intensity treatments were prescribed, the hospitals received an additional 2200 EUR.

3 | THEORETICAL MODEL OF TREATMENT DECISIONS IN THE MARKET FOR STROKE DISORDER

Our theoretical considerations are primarily linked to Hafsteinsdottir and Siciliani (2010) and guide our empirical investigation of hospital responses to the introduction of extra reimbursements for high-intensity stroke treatments in Germany. However, we assume that reimbursements are exogenously set by regulating authorities which leads to predictions regarding the behavior of hospitals that differ from Hafsteinsdottir and Siciliani (2010). The assumption we make is common in the literature as DRG weights are annually computed from reports on historical costs from voluntary hospitals (see e.g., Malcomson, 2005; Siciliani, 2006). Thus, changes in DRG weights are plausibly orthogonal to the current treatment costs of an individual hospital. Since we are primarily interested in hospital responses immediately after the introduction of extra reimbursements for high-intensity treatments, the assumption of exogenous changes in reimbursements seems to be particularly important.

Our model consists of two actors: Patients and hospitals. We model the treatment decision-making process from the perspective of the hospital, which faces two treatment options: high-intensity treatments h and low-intensity treatments l . By maximizing their net benefit, hospitals decide whom to offer high-intensity treatments and whom to offer low-intensity treatments with the assumption that all patients must be treated. Hospitals are assumed to be homogeneous and partially benevolent, so they take patient benefits, costs of treatment and reimbursements for treatments into account (Chalkley & Malcomson, 1998).

Our model assumes that patients suffer from the same medical condition-stroke-but vary in their specific clinical characteristics X_i (e.g., presence and severity of symptoms). The index

$$s = X_i \phi \quad (1)$$

represents the patient's clinical severity given her clinical characteristics X_i with $s \in [\underline{s}, \bar{s}]$. To maximize their utility, hospitals decide on the type of treatment by choosing a cutoff level z of the index of clinical severity s .² Hospitals provide low-intensity treatments to patients below the cutoff and high-intensity treatments to patients above the cutoff. Further details on the model assumptions are presented in Appendix S2.

Scenario 1 Regulating authorities do not make reimbursements contingent on treatment intensity

In 2005, hospitals receive a lump sum p_{nr} for each patient, independent of the type of treatment. Hospitals choose the combination of the types of treatment that maximizes their utility by determining the optimal cutoff point z^{nr}

$$\max_z U(z) = \alpha B(z) - C(z) + T(z) \quad (2)$$

where $B(z)$ represents the benefit function, $C(z)$ the cost function, and $T(z)$ the reimbursement function. The first-order condition for an interior solution can be simplified to³

$$\alpha b(z^{nr}, l) - c(z^{nr}, l) + p_{nr} = \alpha b(z^{nr}, h) - c(z^{nr}, h) + p_{nr} \quad (3)$$

The left-hand side of the equation is the hospital's marginal net benefit (altruistic benefit plus marginal revenue minus costs) from providing low-intensity treatments to a patient with z^{nr} . The right-hand side of the equation reflects the marginal net benefit from providing high-intensity treatments. At the optimum utility, both marginal net benefits are equal. Thus, patients who are clinically less severely ill receive low-intensity treatments up to the threshold z^{nr} , while clinically more severely ill patients above this threshold receive high-intensity treatments.⁴

The solid red line in Figure 1 illustrates the hospital's marginal net benefit from providing low-intensity treatments, the solid green line, from providing high-intensity treatments. The net benefit function of low-intensity treatments starts above the net benefit function of high-intensity treatments at \underline{s} and is increasing with s ($b_s(s, l) > 0$, $c_s(s, l) > 0$).⁵

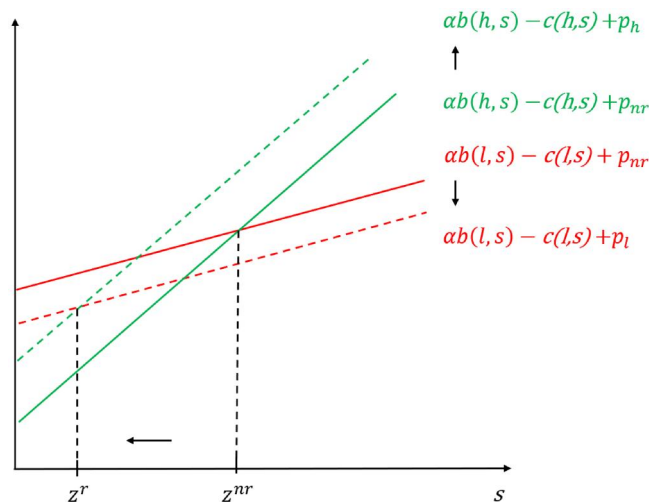


FIGURE 1 Optimal Cutoff. This figure illustrates the change in the optimal cutoff point after regulating authorities introduce extra reimbursements for high-intensity treatments (interior solution). High-intensity treatments are assumed to be net benefit increasing [Colour figure can be viewed at wileyonlinelibrary.com]

Conversely, the net benefit function of high-intensity treatments starts below the net benefit function of high-intensity treatments at \underline{s} , as the net benefit of high-intensity treatments is assumed to be increasing with s . Both net benefit functions intersect at the threshold z^{nr} , meeting the FOC (3). The threshold z^{nr} does not depend on the reimbursement, as it is identical for both types of treatment.

Proposition 1 *As long as regulating authorities do not make reimbursements contingent on treatment intensity, some patients will receive low-intensity treatments and some patients will receive high-intensity treatments. Hospitals will provide low-intensity treatments to the share of patients that are clinically less severely ill and provide high-intensity treatments to the share of patients that are clinically more severely ill.*

Scenario 2 *Regulating authorities introduce extra reimbursements for high-intensity treatments*

In 2006, reimbursement for patients receiving high-intensity treatments p_h increases compared to patients receiving low-intensity treatments p_l with $p_h > p_l$. Again, hospitals choose the optimal cutoff point z^r that maximizes their utility (9). The first-order condition for an interior solution can be written as

$$\alpha b(z^r, l) - c(z^r, l) + p_l = \alpha b(z^r, h) - c(z^r, h) + p_h \tag{4}$$

Similar to Equation (3) above, the left-hand side of the equation is the hospital's marginal net benefit from providing low-intensity treatments to a patient with z^{nr} , the right-hand side of the equation the marginal net benefit from providing high-intensity treatments. However, please note the altered first-order condition in Equation (4) because hospitals now face two alternative reimbursements.

The dotted red line in Figure 1 represents the hospital's marginal net benefit from providing low-intensity treatments as soon as regulating authorities introduce extra reimbursements for high-intensity treatments. The dotted green line indicates the marginal net benefit from providing high-intensity treatments. Contrary to the scenario in which regulating authorities do not make reimbursements conditional on treatment intensity, the net benefit function of low-intensity treatments shifts downward by $p_{nr} - p_l$ and the net benefit function of high-intensity treatments shifts upward by $p_h - p_{nr}$ (please note that $p_h > p_{nr} > p_l$ in our data). As a result, the optimal cutoff point shifts downward to z^r and hospitals provide more high-intensity treatments, meeting the FOC (4).⁶

Proposition 2 *As soon as regulating authorities introduce extra reimbursements for high-intensity treatments, hospitals will provide more high-intensity treatments and less low-intensity treatments. If the difference in reimbursements is sufficiently large, only high-intensity treatments will be provided. Consequently, more patients that are clinically less severely ill receive high-intensity treatments.*

4 | DATA AND EMPIRICAL STRATEGY

4.1 | Data

The primary data sources utilized to analyze hospitals' responses to the introduction of marginal reimbursements for high-intensity treatments are market-wide G-DRG files that cover all inpatient services in Germany from 2005 to 2014 (G-DRG data). Each discharge record tracks, but is not limited to, 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 diagnosis and secondary diagnoses (ICD codes), (date- and time-stamped) procedures (OPS codes) and a hospital identifier. The median admission lists five diagnoses and two procedures.⁷

To compute the differentials in reimbursements and to make admissions comparable across years (to achieve the panel structure), this paper also uses the annual tables of DRG weights as well as Definitions Manuals provided by the regulator (InEK). The Definitions Manuals are applied to map every stroke patient between 2005 and 2014 to her actual and counterfactual DRGs in 2005 and 2006, based on her actual characteristics and for the both variations of treatment intensity. This study thus collects the actual as well as counterfactual own prices and cross prices for the year before and after the price shock of 2005–2006 for both treatment options. This methodology allows for the grouping of admissions between 2005 and 2014 by their identical DRGs that every admission would have been assigned to in 2005 and 2006.⁸

The market of stroke patients, which are affected by the price shock in 2005–2006 as described in Section 2, is defined in accordance with the definition set by regulating authorities in Germany. A list of all relevant ICD-10-GM codes used to define stroke patients based on their primary diagnosis is provided in Table S3 of Appendix S3. High-intensity treatments are measured using procedure codes OPS 8–981.0 and OPS 8–981.1 (OPS codes are the German version of ICD-9 procedure codes for inpatient services).⁹

Table 1 summarizes the market for stroke disorder across approximately 1500 hospitals (85% of hospitals) in Germany between 2005 and 2006 by quarterly and annual totals. In 2005, hospitals admit 207,271 patients suffering from stroke and receive approximately 780 million EUR in reimbursements. In 2006, hospitals receive approximately the same amount of reimbursements for admitting 204,672 patients suffering from stroke. The average age of stroke patients also remains fairly constant over the same period and amounts to 73.17 years in 2005 and 72.93 years in 2006.

The rationale underlying the decision mechanism by which hospitals tailor the intensity of treatment to the patient is not directly observable for the econometrician in the data. In order to reveal this decision mechanism as the foundation for an analysis of changes in the hospitals' selection of patients, this study extends the empirical strategy from Chandra and Staiger (2007) and achieves precise measurement of the admission-specific one-dimensional clinical severity in Germany using a supervised machine learning approach. As the G-DRG does not make reimbursements conditional on treatment intensity in the market for stroke disorder in 2005, it is possible to observe the propensity of hospitals to provide high-intensity treatments in a setting where marginal changes to treatment intensity are independent from extra reimbursements. Based on this, it is possible to apply this rationale for the selection of patients from 2005 to all patients in the market for stroke disorder in 2005 and 2006.

Similar to Chandra and Staiger (2007), we use the admission-specific predicted values from our model showing the propensity of hospitals to provide high-intensity treatments as an empirical measure of the clinical severity. As a result, we obtain an admission-level index that ranks patients based on her clinical characteristics with regard to high-intensity treatments in the market for stroke disorder. This empirical strategy allows the researcher to analyze whether hospitals provided more high-intensity treatments to patients that receive high-intensity treatments in 2006 than they would have provided based on the hospitals' rationale for the selection of patients from 2005.

More formally, it is possible to estimate

$$Pr(\text{High-intensity Treatment}_i) = G(\theta + X_i\phi) \quad (5)$$

where High-intensity Treatment is a binary indicator for high-intensity treatments and X denotes a vast set of patient characteristics for admission i . We use a boosted logistic regression introduced by Friedman, Hastie, and Tibshirani (2000) to achieve high flexibility (and dimensionality) in $G(\cdot)$ for patient characteristics to influence hospital decisions on whether to provide high-intensity, but uncompensated extra treatments to the patient in 2005.¹⁰ The set of patient characteristics X includes stroke-specific symptoms such as the location of the infarction of the cerebral artery or

TABLE 1 Descriptive statistics

Year	Quarter	Count admissions	Total reimbursements	Average Age
2005	1	53,478	202,480,473	73.23
2005	2	51,988	195,387,315	73.13
2005	3	50,253	189,882,342	73.02
2005	4	51,552	192,984,852	73.28
2005	1-4	207,271	780,734,982	73.17
2006	1	52,875	198,554,846	73.03
2006	2	51,476	194,988,756	72.98
2006	3	49,639	188,524,266	72.68
2006	4	50,682	193,593,825	73.03
2006	1-4	204,672	775,661,693	72.93

Notes: This table summarizes the market for stroke disorder in Germany between 2005 and 2006. Column 3 lists the number of admissions. Column 4 provides the sum of reimbursements, normalized using the federal-level base payment rate from 2006 (averages of state-level base payment rates). The federal-level base payment rate is provided by the National Association of Statutory Health Insurance Funds (GKV-Spitzenverband) and is equal to 2804 EUR in 2006. Column 5 reports the average age of patients. The bold values represent the respective annual totals and are of descriptive nature only (that is, no statistical inferences); thus, no statistical significance values exist.

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

language disorders, nonstroke-specific symptoms such as general comorbidities and administrative information such as an emergency indicator.¹¹

The out-of-sample accuracy of correctly predicting the observed, realized treatment intensity of each patient is fairly high (AUC 0.8). Figure S1 of Appendix S3 demonstrates the high accuracy of our estimates for all stroke admissions in 2005 and 2006. It plots the relative frequency of the predicted probability of receiving high-intensity treatments, separately, by the observed, realized treatment intensity (low-intensity treatments and high-intensity treatments). Figure S2 of Appendix S3 the relative importance of the various predictors on the probability of receiving high-intensity treatments.

4.2 | Empirical strategy

Refinements to the mechanism design of the G-DRG generate breaks in reimbursements by date of admission. The G-DRG updates described in Section 2 became effective on January 1, 2006. This empirical setting proposes an identification strategy based on a sharp regression discontinuity design where time is the running variable (see e.g., Anderson, 2014; Auffhammer & Kellogg, 2011; Gallego et al., 2013). The cutoff point t is January 1, 2006 where the price shock occurs. For the main analysis, the admission-level data introduced in Section 4.1 Table 1 is aggregated at the hospital-month level (1456 hospitals between 2005 and 2006). The main analysis additionally presents the results separately for experienced hospitals (i.e., 288 hospitals that did provide high-intensity treatments in 2005) and inexperienced hospitals (i.e., 1168 hospitals that did not provide high-intensity treatments in 2005).

Our basic estimating equations are 1st-order polynomial regressions of the following form:

$$\text{TreatmentIntensity}_{ht} = \beta T + \gamma_1 \tilde{\text{Month}}_t + \gamma_2 T \times \tilde{\text{Month}}_t + \delta_h + \epsilon_{ht} \quad (6)$$

$$\text{ClinicalSeverity}_{ht} = \beta T + \gamma_1 \tilde{\text{Month}}_t + \gamma_2 T \times \tilde{\text{Month}}_t + \delta_h + \epsilon_{ht} \quad (7)$$

$$\text{QualityOutcome}_{ht} = \beta T + \gamma_1 \tilde{\text{Month}}_t + \gamma_2 T \times \tilde{\text{Month}}_t + \delta_h + \epsilon_{ht} \quad (8)$$

where $\text{TreatmentIntensity}_{ht}$ is the share of patients receiving high-intensity treatments in hospital h in the market for stroke disorder in month t between 2005 and 2006. $\text{ClinicalSeverity}_{ht}$ is the average clinical severity in hospital h in month t based on our propensity predictions, estimated separately for patients receiving high-intensity treatments and patients

receiving low-intensity treatments. $QualityOutcome_{ht}$ captures two measures for outcome quality (share of admissions receiving post-discharge rehabilitative care or nursing home care and average in-hospital-mortality) in hospital h in month t . T indicates the period before ($T = 0$) and after ($T = 1$) the price shock and its coefficient β is the treatment effect of interest. The difference in treatment intensity, clinical severity, and the measures of outcome quality at the cutoff point is each equal to the shift in the intercept and is the treatment effect β on T in this regression model. $Month_t$ denotes the month centered at the cutoff point (January 1, 2006) where the price shock occurs. The coefficients γ_1 and γ_2 allow the trends in treatment intensity, clinical severity and the measures of quality to differ before and after the price shock. δ_h is a set of hospital fixed effects, which accounts for time-invariant differences across hospitals. In all cases, we weigh each observation by the number of admissions in the market for stroke disorder. Appendix S3 further discusses the empirical strategy.

5 | RESULTS

5.1 | Treatment intensity and the selection of patients

Figure 2 illustrates the results from the regression discontinuity estimates. In line with our theoretical predictions, hospitals provide high-intensity treatments only to a share of patients before regulating authorities introduce extra reimbursements for high-intensity treatments. Figure 2 documents a remarkable jump in the share of admissions receiving high-intensity treatments: from about 0.18 to 0.25 around the turn of the year. In addition, we observe an upward trend in the share of admissions receiving high-intensity treatments both before and after the introduction of extra reimbursements for high-intensity treatments. The corresponding regression discontinuity estimates show that the share of admissions receiving high-intensity treatments discontinuously increases by 6.8 percentage points from December 2005 to January 2006 (Column 1 in Table 2). This effect is statistically highly significant ($p < 0.001$). The discontinuous increase by 6.8 percentage points is approximately equivalent to a 47% (or approximately 1500 patients) increase in the number of patients receiving high-intensity treatments at the turn of the year. In line with our theoretical predictions, hospitals provide more high-intensity treatments as soon as regulating authorities introduce extra reimbursements for high-intensity treatments in the market for stroke disorder.

These findings are in line with Papanicolas and McGuire (2015), Cutler (1995) and Einav, Finkelstein, and Mahoney (2018), for example, who demonstrate that hospitals respond to changes in marginal reimbursements arising in many DRG systems. Yet, our results are in contrast with Gilman (2000) who finds that hospitals do not respond to marginal reimbursements for high-intensity treatments. One explanation for this might be that financially motivated, marginal changes to clinically similar treatments in Papanicolas and McGuire (2015) or the length of stay in Cutler (1995) and Einav et al. (2018) are most likely not harmful to patients. Hence, hospitals might exercise their discretion. In contrast, financially motivated marginal changes to treatment intensity, and more specifically, the provision of high-intensity treatments such as the specific surgical procedures analyzed in Gilman (2000) are potentially harmful to patients and thus are not excessively provided by hospitals. The high-intensity treatments analyzed in this paper are most likely beneficial rather than harmful for patients. Hence, it seems plausible that hospitals also exercise their discretion under these circumstances.

McClellan (1997) points out in his seminal paper that DRG systems such as MS-DRGs from the United States are frequently not prospective because their various features allow reimbursement to vary with actual treatment decisions during an admission.¹² The author estimates that hospitals received more than 28 cents of additional reimbursement for each additional dollar of reported costs related to treatment decisions in 1990. Additionally, our data indicates that in 2005, treatment decisions in German hospitals resulted in extra reimbursement for 42% of admissions.¹³ For example, regulating authorities frequently allocate patients to DRGs using patient characteristics such as medical or surgical procedures, hours of mechanical ventilation or length of stay, in addition to diagnoses (frequently referred to as risk-adjustment). However, these incentives might hinder the efficiency of health care provision.

Under the assumption that experienced (or specialized) hospitals have a downward shifted cost function for high-intensity treatments compared to inexperienced (or generalized) hospitals, our theoretical model would predict a stronger increase in high-intensity treatments for experienced hospitals compared to inexperienced hospitals. Separate estimates by the experience of hospitals with high-intensity treatments prior to the price shock reveal whether extra reimbursements for high-intensity treatments propels technology-adoption in the market for stroke disorder. The results in Column 2 and Column 3 in Table 2 show that both experienced hospitals and inexperienced hospitals discontinuously increase the share of admissions receiving high-intensity treatments from December 2005 to January

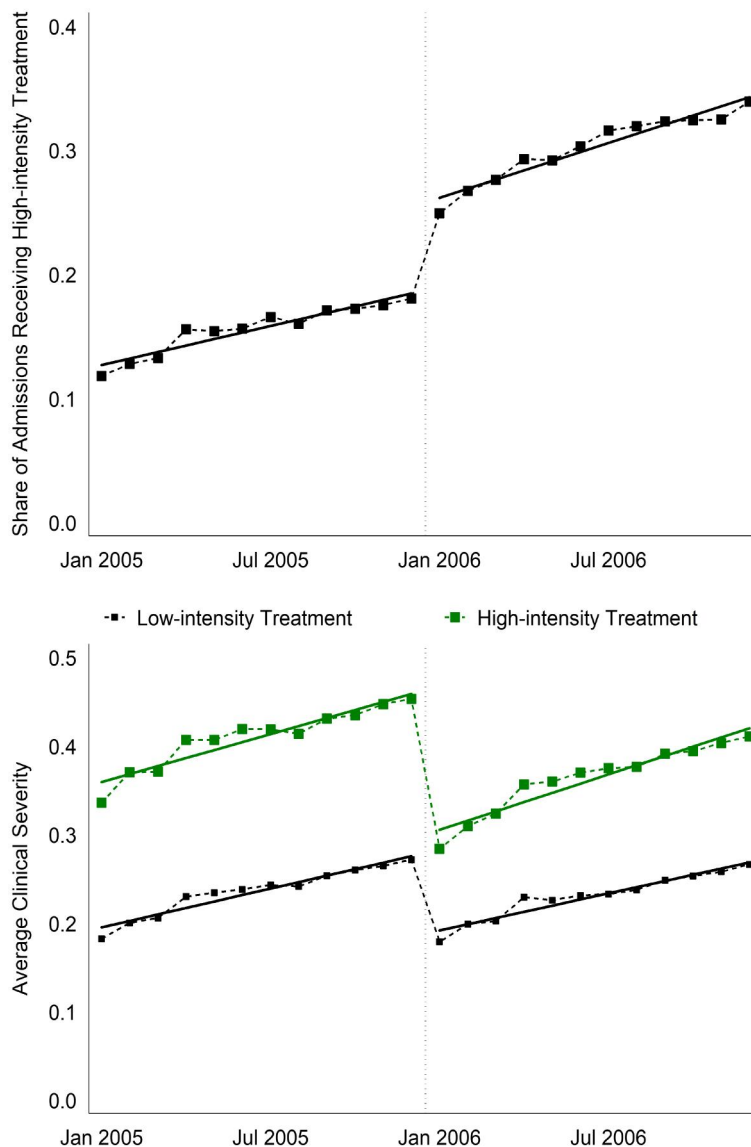


FIGURE 2 Changes in Treatment Intensity and the Selection of Patients. The top panel in this figure presents the monthly share of admissions receiving high-intensity stroke treatments in Germany between 2005 and 2006. The monthly share of admissions receiving high-intensity treatments is illustrated using black squares and connected using a dashed black line. The solid black line depicts the results from the regression discontinuity estimates (please see Section 4.2 for more details). The bottom panel in this figure illustrates the monthly average clinical severity of receiving high-intensity stroke treatments by type of observed, realized treatment (high-intensity treatments and low-intensity treatments). The monthly average clinical severity of patients receiving high-intensity treatments is presented using green squares and connected using a dashed green line. The monthly average clinical severity of patients receiving low-intensity treatments is presented using black squares and connected using a dashed black line. The solid lines depict the results from the regression discontinuity estimates (please see Section 4.2 for more details). Source: G-DRG data is available at the Federal Statistical Office (Data Research Center) [Colour figure can be viewed at wileyonlinelibrary.com]

2006. In addition, the share of admissions receiving high-intensity treatments in inexperienced hospitals further increases gradually by 0.4 percentage points after the price shock of 2005–2006 ($p < 0.001$).

Particularly back in 2005 (and actually until now), the hospital market in Germany is characterized by low levels of specialization. Specialization in the hospital industry was no politically important concept in the hospital market in Germany in the beginning of the G-DRG. Only in later years, regulating authorities designed some financial incentives (mostly in form of minimum requirements for ICU infrastructure). About 85% of hospitals provide treatments in the market for stroke patients. On average, one hospital treats about 138 stroke patients each year which equals one stroke patient every 2.6 days. Our findings in Table 2 Column (2) show that inexperienced hospitals enter the market for high-intensity treatments in the market for stroke disorder. This result suggests that the price shock in the market for stroke

TABLE 2 Changes in treatment intensity and the selection of patients

Dependent variable	(1)	(2)	(3)	(4)	(5)
	Average treatment intensity			Average clinical severity	
Hospital group	All hospitals	Inexperienced hospitals	Experienced hospitals	Experienced hospitals	Experienced hospitals
Patient group	All patients	All patients	All patients	High-intensity treatments	Low-intensity treatments
<i>T</i>	0.068*** (8.18)	0.037*** (4.34)	0.098*** (6.98)	−0.156*** (35.49)	−0.091*** (31.22)
Month	0.005*** (6.08)	0.000** (2.78)	0.010*** (6.52)	0.009*** (17.78)	0.007*** (24.85)
<i>T</i> ×Month	0.002 (1.60)	0.004*** (5.37)	−0.001 (0.42)	0.001 (1.59)	−0.000 (0.81)
Adjusted <i>R</i> ²	0.791	0.538	0.684	0.619	0.503
Hospitals	1456	1168	288	288	288
Observations	30,993	24,368	6625	5076	6602

Notes: This table reports the regression discontinuity results as described in Section 4.2. Average Treatment Intensity is the monthly share of admissions that receive high-intensity stroke treatments between 2005 and 2006. Average Clinical Severity is the monthly average clinical severity by type of observed, realized treatment (high-intensity treatments and low-intensity treatments). *T* denotes a binary indicator for the months following the introduction of extra reimbursements for high-intensity treatments (year 2006). Month denotes the month of admission, centered at the month of the price shock (January, 2006) to ease interpretation. Each column includes hospital fixed effects. T-statistics are calculated based on clustered standard errors at the hospital level and are reported in parentheses below the coefficients.

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

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

disorder incentivized hospitals to rather generalize (hospitals provide more distinct types of treatment) than to specialize (hospitals provide less distinct types of treatment) and that extra reimbursements for high-intensity treatments shape the structure of the market for stroke disorder and probably the organization of the hospital industry more generally.

As proposed by the theoretical model, hospitals provide low-intensity treatments to the share of patients that are clinically less severely ill and provide high-intensity treatments to the share of patients that are clinically more severely ill (Proposition 1). The bottom panel of Figure 2 depicts the average clinical severity (*y*-axis) by year and month (*x*-axis), using green squares for patients receiving high-intensity treatments and black squares for patients receiving low-intensity treatments. This figure demonstrates a steady upward trend in the average clinical severity for both types of treatment (high-intensity treatments and low-intensity treatments), both before and after the introduction of extra reimbursements for high-intensity treatments. This trend might capture the general improvements in tailoring treatments such as the availability of specialized care in stroke units to patients. From December 2005 to January 2006, however, the average clinical severity dramatically decreases from about 0.43 to 0.27 for patients receiving those treatments, and from about 0.28 to 0.18 for patients receiving low-intensity treatments.

More precisely, the average clinical severity of patients receiving high-intensity treatments discontinuously decreases by 15.6 percentage points as soon as regulating authorities introduce extra reimbursements for high-intensity treatments (Column 4 in Table 2). For the average clinical severity of patients receiving high-intensity treatments to decrease in 2006, the marginal patient newly treated with high-intensity treatments has to be clinically less severely ill compared to 2005. This finding empirically confirms the theoretical prediction that more patients that are clinically less severely ill on the index of clinical severity will receive such treatments (Proposition 2). Thus, hospitals do not seem to increase the treatment intensity for the most seriously ill, probably clinically highly appropriate patients that might have been previously underpaid.

Similarly, the average clinical severity of patients receiving low-intensity treatments discontinuously decreases by 9.1 percentage points from December 2005 to January 2006 (Column 5 in Table 2). This result is intuitive because the marginal patient, newly treated with high-intensity treatments, to which hospitals were providing low-intensity treatments in 2005 is clinically less severely ill than patients to which hospitals used to provide high-intensity treatments in 2005.¹⁴ Both effects are statistically highly significant ($p < 0.001$).

Although this study finds that hospitals chose to treat more patients with high-intensity treatments in 2006 than they would have chosen in 2005, the results do not uncover whether hospitals over-provide high-intensity treatments in

2006. Even the more mildly ill, probably less clinically appropriate patients might still profit from and appropriately receive high-intensity treatments. Consequently, whether the mechanism design inherent to modern DRG algorithms is in the position to improve or worsen social welfare depends on potential increases or decreases of patient benefit. The next section addresses this question.

5.2 | Patient outcomes

This section investigates whether the increase in high-intensity stroke treatments benefits patients. The marginal patient newly treated with high-intensity treatments might, for example, receive treatments earlier and benefit from improved patient outcomes even if she used to be clinically less severely ill than patients to which hospitals were already providing high-intensity treatments.

Figure 3 illustrates the results from the regression discontinuity estimates with regard to patient outcomes. This figure does not suggest a discontinuous drop in the share of admissions receiving rehabilitative care or nursing home care directly after discharge from December 2005 to January 2006. Our regression discontinuity estimates confirm that the share of admissions receiving rehabilitative care or nursing home care directly after discharge does not discontinuously change after the introduction of extra reimbursements for high-intensity treatments (Column 1 in Table 3, $p < 0.3$). The bottom panel plots the average in-hospital mortality (y -axis) by year and month (x -axis) using black squares. Fortunately, stroke patients seem to benefit from a steady downward trend in in-hospital mortality. However, this figure does not suggest a change in the average in-hospital mortality from December 2005 to January 2006. Our regression discontinuity estimates confirm that the average in-hospital mortality does not discontinuously change after the introduction of extra reimbursements for high-intensity treatments (Column 4 in Table 3, $p < 0.7$).

Despite the fact that the findings in this study do not suggest that increasing high-intensity treatments improves available short-term measures for the quality of care, high-intensity treatments might still improve long-term measures. For example, disability affects 75% of stroke survivors enough to decrease their employability and 30 to 50 percent of stroke survivors suffer post-stroke depression Coffey (2011) and Senelick (2010). Unfortunately, G-DRG files do not track post-discharge patient health status. Hence, this study might miss these kinds of perceptive medium- and long-term outcomes.

6 | ROBUSTNESS

6.1 | Placebo thresholds

As in the conventional sharp regression discontinuity design, one major identification assumption for the validity of the identification strategy in this study is that, in the absence of the price shock, patients on both sides of the threshold (i.e., patients in December 2005 and patients in January 2006) are, on average, identical. This identifying assumption seems plausible, as clinical practice suggests that seasonally specific trends are absent due to the life-threatening nature of strokes. To further prove the internal validity of the results in this study, this section tests whether the treatment effect is (close to) zero when it should be and whether the jump at the cutoff is contaminated by other factors such as end-of-year specific jumps.

Figure S4 of Appendix S5 summarizes the distribution of the change in differential reimbursement by each turn of the year between 2005 and 2014. It shows that the median of the change in differential reimbursement is the highest for the turn of the year in 2005–2006, and close to zero in the following turns of the year.¹⁵ Thus, the absence of (noticeable) price shocks between 2006 and 2014 allows to test whether the treatment effect is (close to) zero at the various placebo thresholds in the years following the price shock.

Figure 4 illustrates the results from the regression discontinuity estimates for each turn of the year between 2005 and 2014 in all hospitals. The figure plots the estimated coefficients and 99 % confidence intervals (y -axis) by the median price shock (x -axis), using blue circles and vertical red spikes. The share of admissions receiving high-intensity treatments from 2005 to 2006 jumps remarkably-by approximately 7 percentage points ($p < 0.001$)-but remains mainly unchanged and statistically insignificant around the placebo turns of the year between 2006 and 2014. The only exception is the observed discontinuous change in the share of admissions receiving high-intensity treatments from 2006 to 2007. Table S6 of Appendix S5 reports the results from the regression discontinuity estimates. In conclusion, this placebo test supports the key identification assumption of the empirical strategy used in this study.¹⁶

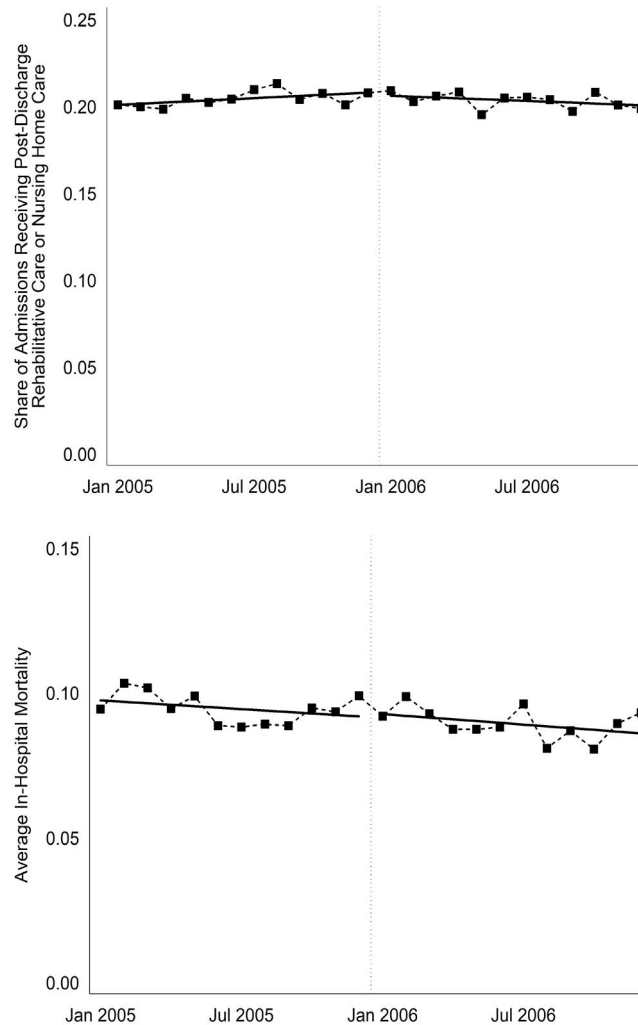


FIGURE 3 Changes in patient outcomes. The top panel in this figure presents the monthly share of admissions receiving rehabilitative care or nursing home care directly after discharge in Germany between 2005 and 2006 using black squares and connected using a dashed black line. The solid black line depicts the results from the regression discontinuity estimates (please see Section 4.2 for more details). The bottom panel in this figure illustrates the monthly average in-hospital mortality using black squares and connected using a dashed black line. The solid line depicts the results from the regression discontinuity estimate (please see Section 4.2 for more details). Source: G-DRG data is available at the Federal Statistical Office (Data Research Center)

6.2 | Placebo outcome

It is important for the validity of the results that the relationship between potential covariates and the treatment is smooth around the threshold (turn of the year). This study uses the number of admissions in the market for stroke disorder as a placebo outcome to test whether admissions are comparable around the cutoff. According to clinical practice, it is unlikely that hospitals are able to specifically attract or reject stroke patients, particularly in the short period after the price shock.

Figure 5 demonstrates that there is no imbalance in the number of admissions around the turn of the year in 2005–2006, where the price shock occurs. The figure plots the number of admissions (y -axis) by month (x -axis) using black squares. The solid lines depict the results from the regression discontinuity estimates. As the estimated treatment effect is statistically insignificant, the number of admissions in the market for stroke disorder do not change discontinuously around the price shock in 2005–2006 (the estimated coefficient yields 845 admissions, the corresponding t -value amounts to 1.34). Again, this placebo test supports the validity of the results.

Furthermore, the regression discontinuity estimates in Figure 5 test, similar to McCrary (2008), whether hospitals “manipulate” the timing of the admissions of stroke patients. The regression results confirm that the frequency of

TABLE 3 Changes in patient outcomes

Dependent variable	(1) (2) (3) Share of admissions receiving rehabilitative or nursing home care			(4) (5) (6) Average in-hospital mortality		
	All hospitals All patients	Inexperienced hospitals All patients	Experienced hospitals All patients	All hospitals All patients	Inexperienced hospitals All patients	Experienced hospitals All patients
<i>T</i>	−0.002 (0.82)	−0.004 (0.95)	−0.001 (0.25)	0.001 (0.78)	0.003 (1.13)	−0.000 (0.20)
Month	0.000 (1,08)	0.000 (1,00)	0.000 (0,54)	−0.000 (1.64)	−0.001* (2.17)	0.000 (0.13)
<i>T</i> ×Month	−0.001 (1.86)	−0.001 (0.85)	−0.001 (1.71)	−0.000 (0.42)	0.000 (0.55)	−0.000 (1.35)
Adjusted <i>R</i> ²	0.506	0.463	0.590	0.181	0.124	0.204
Hospitals	1456	1168	288	1456	1168	288
Observations	30,993	24,368	6625	30,993	24,368	6625

Notes: This table reports the regression discontinuity results as described in Section 4.2. Column 1–Column 3 report the results for the share of admissions receiving post-discharge rehabilitative care or nursing home care, and Column 4 to Column 6 the average in-hospital mortality by month between 2005 and 2006. *T* denotes a binary indicator for the months following the introduction of extra reimbursements for high-intensity treatments (year 2006). Month denotes the month of admission, centered at the month of the price shock (January, 2006) to ease interpretation. Each column includes hospital-fixed effects. T-statistics are calculated based on clustered standard errors at the hospital level and are reported in parentheses below the coefficients.

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

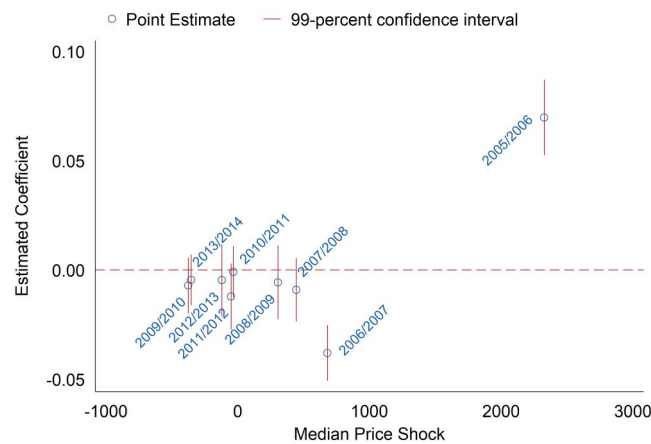


FIGURE 4 Changes in treatment intensity (placebo thresholds). This figure illustrates the results from the regression discontinuity estimates that estimate the share of admissions receiving high-intensity treatments for each turn of the year between 2005 and 2014. The figure plots the estimated coefficients and 99% confidence intervals (y-axis) by the median price shock (x-axis) using blue circles and vertical red spikes. Source: G-DRG data is available at the Federal Statistical Office (Data Research Center) [Colour figure can be viewed at wileyonlinelibrary.com] [Correction added on 2 March 2021, after first online publication: Figure 4 image has been updated for clarity in this version.]

observations does not change in the months around the price shock. This result seems plausible, as clinical practice again suggests that hospitals may not have the discretion to directly control the timing of the admission of life-threatening stroke conditions.

6.3 | Announcement effects and learning effects

Refinements to the incentive structure that would go into effect on January 1, 2006 were already announced by mid-September (specifically on September 13, 2005). The previous literature has shown that hospitals might respond immediately to the expected changes in market conditions (see e.g., Gaynor, Laudicella, & Propper, 2012). Anticipatory changes in hospital behavior before updated reimbursements become effective are unlikely in the empirical setting

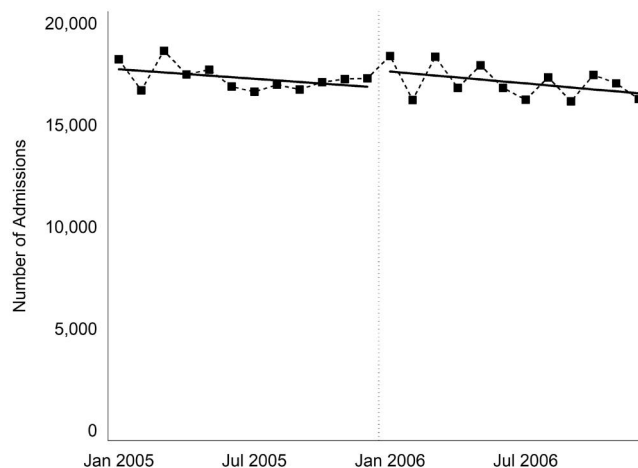


FIGURE 5 Changes in the number of admissions (placebo outcome). This figure presents the monthly number of stroke admissions in Germany between 2005 and 2006. The monthly admissions are illustrated using black squares and connected using a dashed black line. The solid black line depicts the results from the regression discontinuity estimates (please see Section 4.2 for more details). Source: G-DRG data is available at the Federal Statistical Office (Data Research Center)

analyzed in this paper (Farrell & Klemperer, 2007). The reason for this is that efforts and costs to switch to high-intensity stroke treatments are fairly low (e.g., ensure 24-h attendance by a neurologist). Immediate changes in the intensity of treatment would increase present costs and reduce present profits, but without the risk of losing future profits. Similarly, hospitals might require a significant amount of time to adapt to the new regulations (Clemens & Gotlieb, 2014). However, it is expected that hospitals adapt the profit-maximizing intensity of treatment quite rapidly after updated reimbursements become effective on January 1, 2006, as they do not require a significant amount of investment or changes in management. Tables S7 and S8 of Appendix S5 present the results from higher order regression discontinuity models that allow the trend in the treatment intensity or clinical severity to increase as a result of early responses or required learning. Although both the squared and the cubic elements of the trends are sometimes statistically significant, they are economically negligible. In fact, due to overfitting of the data, the coefficients of the squared and cubic elements frequently show the wrong sign. In conclusion, we do not find that hospitals respond to the announcements of the price shock of 2005–2006 nor that they require a significant amount of time to adapt to the new regulations.

6.4 | Coding

Another potential threat to the validity of the results in this study is that the observed increase in the documented high-intensity treatments may be explained by channels other than real changes to clinical pathways. The previous literature demonstrates that hospitals manipulate diagnoses to optimize billing (see Dafny (2005), e.g.). Hospitals might thus manipulate the primary diagnosis and switch a nonstroke primary diagnosis with a stroke secondary diagnosis. Moreover, hospitals might “upgrade” a clinically similar nonstroke primary diagnosis such as transient cerebral ischemic attacks, or an occlusion and stenosis of precerebral arteries that does not result in a cerebral infarction, to a stroke primary diagnosis. In the event that hospitals indeed manipulate the primary diagnosis of admission, and particularly of admissions that would already receive high-intensity treatments, independent from the introduction of extra reimbursements, the results in this paper would overestimate the true effect of the introduction of marginal reimbursements for high-intensity treatments on the use of these treatments.

However, this bias is unlikely as German coding guidelines precisely regulate the order of the diagnoses (i.e., primary diagnosis and secondary diagnoses) for the stroke patients under investigation. Clinical practice suggests that deviations from these guidelines would be easy to detect. Furthermore, the results from Section 6.2 provide evidence that the placebo outcome, that is, the number of admissions with a primary diagnosis of stroke, does not increase in response to the introduction of marginal reimbursements. In the event that hospitals indeed switch a nonstroke primary diagnosis with a stroke secondary diagnosis or “upgrade” a clinically similar nonstroke primary diagnosis to a stroke

primary diagnosis, we would observe an increase in the number of admissions that document a stroke primary diagnosis. Moreover, the results from Section 5 reveal that experienced as well as inexperienced hospitals increase the provision of high-intensity stroke treatments. As the provision of high-intensity treatments demands changes to a hospital's infrastructure and processes, payers would easily detect seemingly technology-adopting hospitals that merely change their coding practices.

In addition to manipulations to diagnosis codes, hospitals might manipulate procedure codes. Hospitals might imitate the provision of high-intensity treatments although they do not, in fact, provide the required procedures. However, clinical practice suggests that this is unlikely. The reason for this is that the required procedures, which include but are not limited to comprehensive and early clinical diagnostics (e.g., cranial CT scans), early treatments (e.g., administering thrombolytic drugs), extensive monitoring, and early rehabilitative treatments (e.g., physiotherapy), are usually scheduled and tracked electronically. Manipulations to reported procedure codes would thus require comprehensive IT manipulations. The findings in Appendix S4 additionally support the conclusion that the results in this paper are not explained by hospitals that manipulate the reporting of high-intensity treatments. The reason for this is that there is no obvious reason for hospitals to “fake” the provision of high-intensity treatments in cases in which the reporting of those treatments is not relevant for reimbursement.

Lastly, some hospitals might merely catch up on reporting their high-intensity treatments after these treatments become relevant for reimbursement. Some inexperienced hospitals might simply not know how to correctly report high-intensity treatments but did, in fact, already provide these treatments in 2005. It is unlikely, however, that this potential catch-up effect of single inadvertently nonreporting hospitals drives the results in this study. Again, the results from Section 5 reveal that experienced hospitals as well as technology-adopting hospitals increase the provision of high-intensity stroke treatments. Hence, technology-adopting, inadvertently nonreporting hospitals cannot explain the jump in the intensity of treatment from 2005 to 2006, at least not for the experienced hospitals.

7 | CONCLUSION

Reimbursements based on DRGs promise to make hospitals bear the marginal costs of treatments. Modern DRG systems in many OECD countries, however, frequently allow hospital reimbursement to vary with actual treatment decisions, and allocate patients to DRGs using patient characteristics such as medical or surgical procedures, hours of mechanical ventilation or length of stay, in addition to diagnoses.

This study addresses the question of whether hospitals respond to the introduction of reimbursements by treatment intensity in the market for stroke disorder in Germany on January 1, 2006. In cases in which hospitals prescribe high-intensity treatments (most notably extensive and early clinical diagnostics as well as early rehabilitative treatments), they receive, on average, an additional 2200 EUR for each admission. We exploit this plausibly exogenous price shock on January 1, 2006 using a sharp regression discontinuity design where time is the running variable.

We find that the share of admissions receiving high-intensity treatments jumps by approximately 7 percentage points from December 2005 to January 2006. A simultaneous decrease in the average clinical severity of patients receiving high-intensity treatments reveals that the marginal, newly high-intensity treated patient in 2006 might be less appropriate for high-intensity treatments compared to 2005. We do not find any changes in the quality of care, such as decreases in the share of admissions receiving rehabilitative care or nursing home care directly after discharge, nor do we find changes in in-hospital mortality.

Our findings might support actions by regulating authorities to financially reward good-practice (or punish bad-practice) clinical pathways within modern DRG systems, or to effectively design pay-for-performance incentives. In addition, authorities might find our results helpful for designing second opinion programs, as our methodology empowers authorities to pinpoint the group of patients that is most likely to receive financially motivated additional but potentially unnecessary treatments.

Further research might find it interesting to investigate to what extent hospitals respond to financially incentivized, but potentially harmful procedures for the variety of clinical settings. In addition, increases in the treatment intensity in the market for stroke disorder might also trigger spillovers to other departments. Potential (positive and negative) externalities of hospital responses to financially incentivized procedures might be important determinants for the industrial organization of hospital markets. This might be particularly true in the medium-run and long-run. Further research might thus find it interesting to investigate empirical settings in which hospitals require higher investment and/or more intensive changes to management compared to the empirical setting under investigation.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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ENDNOTES

- ¹ A full list of the specific set of services defined as high-intensity treatments is provided in Table S2 of Appendix S1.
- ² Hafsteinsdottir and Siciliani (2010) use s as an one-dimensional indicator for clinical severity. For the purpose of this paper, we aggregate the various facets of clinical severity to a single vector. Section 4 introduces the methodology of how we empirically estimate this indicator.
- ³ See Equations (10), (11), and (12) in Appendix S2.
- ⁴ Corner solutions can be ruled out in this scenario. Please see Appendix S2 for more details.
- ⁵ We assume that net benefit is increasing. Whether net benefit is increasing or decreasing depends on the assumptions regarding $b_s(s, l)$ and $c_s(s, l)$. The model results remain the same even in cases in which net benefit decreases.
- ⁶ We can show that a corner solution such as providing only low-intensity treatments can be ruled out. Still, a corner solution such that all patients receive high-intensity treatments is possible if the difference in reimbursements is sufficiently high. This implies that the high-intensity treatments are more lucrative. Please see Appendix S2 for more details.
- ⁷ Appendix S3 provides more details on the G-DRG data.
- ⁸ The previous literature on this topic (see e.g., Dafny, 2005; Jürges & Köberlein, 2015) usually observes the admission-specific actual reimbursement for the year of admission only (repeated cross section) and does not succeed in measuring admission-specific counterfactual reimbursements across years to make admissions comparable across years (panel structure).
- ⁹ We denote patients whose reports document both high-intensity treatments and low-intensity treatments as receiving high-intensity treatments (as required by the Definitions Manuals).
- ¹⁰ Appendix S3 provides more details on this statistical model.
- ¹¹ Appendix A4 provides further details on the included patient characteristics.
- ¹² MS-DRGs refers to the Medicare Severity Diagnosis-Related Groups as defined by the Centers for Medicare and Medicaid Services (CMS).
- ¹³ To achieve these numbers, we analyze whether marginal treatments have been critical for hospital reimbursements in the G-DRG in 2005. More specifically, we compute changes in hospital reimbursements for three potential hospital strategies related to treatment decisions on a 5 percent random sample of all admissions (871,780 observations). The three potential hospital strategies are i. inducing an additional procedure, ii. inducing an additional hour of mechanical ventilation and iii. inducing an additional day of stay in the hospital.
- ¹⁴ Please note that when assessing the introduction of extra reimbursements for high-intensity treatments on the average clinical severity of patients receiving high-intensity treatments, the direction of the estimated effect is more important for interpretation purposes than the magnitude of the estimated effect. The reason for this is that the size of the estimated coefficients depends on the distributional shape of the empirical clinical severity measure in both groups.
- ¹⁵ The distribution of the change in differential reimbursement is calculated based on admissions from all years, regardless of the actual year of admission, and are independent from the observed, realized intensity of treatment. Please see Section 4.1 for more details.
- ¹⁶ Similarly, the results from Appendix S4 also support the validity of the identification strategy in this paper. The reason for this is that the response in treatment intensity is significantly larger for patients captured by the price shock of 2005-2006 than for patients that are not captured by the price shock. Contaminating factors such as end-of-year specific jumps would arguably touch both patient groups equally.

REFERENCES

- AHA. (2016). Heart disease and stroke statistics-2016 update. *Circulation*, 133(4), 38–360.
- Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review*, 104(9), 2763–2796.
- Auffhammer, M., & Kellogg, R. (2011). Clearing the air? The effects of gasoline content regulation on air quality. *American Economic Review*, 101(6), 2687–2722.

- Chalkley, M., & Malcomson, J. M. (1998). Contracting for health services when patient demand does not reflect quality. *Journal of Health Economics*, 17(17), 1–19.
- Chandra, A., & Staiger, D. O. (2007). Productivity spillovers in health care: Evidence from the treatment of heart attacks. *Journal of Political Economy*, 115(1), 103–140.
- Clemens, J., & Gottlieb, J. D. (2014). Do physicians' financial incentives affect medical treatment and patient health? *American Economic Review*, 104(4), 1320–1349.
- Coffey, C. E., & Cummings, J. L. (2011). *The American psychiatric publishing textbook of geriatric neuropsychiatry*. Arlington, MA: American Psychiatric Publishing.
- Coulam, R. F., & Gaumer, G. L. (1991). Medicare's prospective payment system: A critical appraisal. *Health Care Financing Review, Annual Supplement*, 45–77.
- Cutler, D. M. (1995). The incidence of adverse medical outcomes under prospective payment. *Econometrica*, 63, 29–50.
- Dafny, L. S. (2005). How do hospitals respond to price changes? *American Economic Review*, 95(5), 1525–1547.
- Destatis. (2017a). *Krankenhausstatistik 2017*, Wiesbaden, Germany. GENISIS-Online.
- Destatis. (2017b). *Todesursachen in Deutschland. Gesundheit: Fachserie 12 Reihe 4*.
- Dranove, D. (1987). Rate-setting by diagnosis related groups and hospital specialization. *The RAND Journal of Economics*, 18, 417–427.
- Einav, L., Finkelstein, A., & Mahoney, N. (2018). Provider incentives and healthcare costs: Evidence from long-term care hospitals. *Econometrica*, 86(6), 2161–2219.
- Ellis, R. P. (1998). Creaming, skimping and dumping: Provider competition on the intensive and extensive margins. *Journal of Health Economics*, 17(5), 537–555.
- Ellis, R. P., & McGuire, T. G. (1986). Provider behavior under prospective reimbursement. Cost sharing and supply. *Journal of Health Economics*, 5(5), 129–151.
- Ellis, R. P., & McGuire, T. G. (1996). Hospital response to prospective payment: Moral hazard, selection, and practice-style effects. *Journal of Health Economics*, 15(3), 257–277.
- Farrell, J., & Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. *Handbook of Industrial Organization*, 3, 1967–2072.
- Friedman, J., Hastie, T., & Tibshirani, R. (2000). Additive logistic regression: A statistical view of boosting. *The Annals of Statistics*, 28(2), 337–407.
- Gallego, F., Montero, J.-P., & Salas, C. (2013). The effect of transport policies on car use: Evidence from Latin American cities. *Journal of Public Economics*, 107, 47–62.
- Gaynor, M., Laudicella, M., & Propper, C. (2012). Can governments do it better? Merger mania and hospital outcomes in the English NHS. *Journal of Health Economics*, 31(3), 528–543.
- Gilman, B. H. (2000). Hospital response to DRG refinements: The impact of multiple reimbursement incentives on inpatient length of stay. *Health Economics*, 9(4), 277–294.
- Hafsteinsdottir, E. J. G., & Siciliani, L. (2010). DRG prospective payment systems: Refine or not refine? *Health Economics*, 19(10), 1226–1239.
- Heuschmann, P., Busse, O., Wagner, M., Endres, M., Villringer, A., Roether, J., ... Berger, K. (2010). Schlaganfallhäufigkeit und Versorgung von Schlaganfallpatienten in Deutschland. *Aktuelle Neurologie*, 37(7), 333–340.
- Hodgkin, D., & McGuire, T. G. (1994). Payment levels and hospital response to prospective payment. *Journal of Health Economics*, 13(1), 1–29.
- INEK. (2005). *Abschlussbericht. Weiterentwicklung des G-DRG Systems für das Jahr 2006*.
- Jena, A. B., Prasad, V., Goldman, D. P., & Romley, J. (2015). Mortality and treatment patterns among patients hospitalized with acute cardiovascular conditions during dates of national cardiology meetings. *JAMA Internal Medicine*, 175(2), 237.
- Jürges, H., & Köberlein, J. (2015). What explains DRG upcoding in neonatology? The roles of financial incentives and infant health. *Journal of Health Economics*, 43, 13–26.
- Kifmann, M., & Siciliani, L. (2016). Average-cost pricing and dynamic selection incentives in the hospital sector. *Health Economics*, 19, 1226–1239.
- Ma, C. A. (1994). Health care payment systems: Cost and quality incentives. *Journal of Economics & Management Strategy*, 3(1), 93–112.
- Malcomson, J. M. (2005). Supplier discretion over provision: Theory and an application to medical care. *The RAND Journal of Economics*, 36, 412–432.
- McClellan, M. (1997). Hospital reimbursement incentives: An empirical analysis. *Journal of Economics & Management Strategy*, 6(1), 91–128.
- McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2), 698–714.
- OECD. (2015). *Health at a glance 2015: Mortality following stroke*. Paris, France: OECD Publishing.
- Papanicolas, I., & McGuire, A. (2015). Do financial incentives trump clinical guidance? Hip replacement in England and Scotland. *Journal of Health Economics*, 44, 25–36.
- Seenan, P., Long, M., & Langhorne, P. (2007). Stroke units in their natural habitat. Systematic review of observational studies. *Stroke*, 38(6), 1886–1892.
- Senelick, R. C. (2010). *Living with stroke: A guide for patients and families*. Birmingham, UK: HealthSouth Press.
- Shleifer, A. (1985). A theory of yardstick competition. *Rand Journal of Economics*, 16(2), 319–327.
- Siciliani, L. (2006). Selection of treatment under prospective payment systems in the hospital sector. *Journal of Health Economics*, 25, 479–499.

SUPPORTING INFORMATION

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

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