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Abstract

Many OECD countries have replaced per-diem hospital reimbursement with lump sum payments by diagnosis-related groups (DRGs). However, modern DRG systems still allow hospitals to pass on actual treatment costs to payers, which might hinder the efficiency of health care provision. This paper 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 treatment jumps by approximately 7 percentage points around the turn of the year. At the same time, a decrease in the average clinical appropriateness for patients receiving this high-intensity treatment reveals that the marginal high-intensity treated patient in 2006 is less appropriate for high-intensity treatment compared to 2005. We do not find accompanying (short-term) changes in the quality of care, such as decreases in in-hospital mortality. Thus, regulating authorities may improve efficiency by reducing the importance of extra reimbursements for marginal treatments in modern DRG systems.

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1 Introduction

Since 1984, many of the developed countries around the globe have been following the U.S. 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 treatment and to reduce health care expenditures (Ellis and 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 and Gaumer, 1991; Hodgkin and McGuire, 1994; Cutler, 1995; Ellis and McGuire, 1996).

However, McClellan (1997) points out in his very important paper that DRG systems such as MS-DRGs from the U.S. are frequently not prospective because their various features allow reimbursement to vary with actual treatment decisions during an admission. 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 percent of admissions.[1] 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). The reason for this is that these proxies for actual treatment costs more accurately explain observed (historical) costs, with the result that modern DRG algorithms are more likely to successfully direct more funding to hospitals treating seriously ill patients that require high-intensity treatment than to those treating mildly ill patients.[2] As a result, regulating authorities might prevent hospitals from avoiding the seriously ill, but underpaid patients, or from lowering quality below acceptable levels.

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 clinically optimal treatment intensity and to alter clinical pathways (Ellis and McGuire, 1986; Ellis, 1998; Jena et al., 2015). Hafsteinsdottir and Siciliani (2010) demonstrate in their theoretical model that hospitals

[1] 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.

[2] In 2005, MS-DRGs explain almost 40 percent of the variance in costs (Wynn et al., 2007).

always overprovide 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.[3] 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 vs. 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; Ma, 1994; Kifmann and Siciliani, 2016). In some instances, hospitals might increase the treatment intensity for the most seriously ill and clinically highly appropriate patients that might have been previously underpaid. However, hospitals might also increase the treatment intensity for the more mildly ill, probably less clinically appropriate patients 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 order to give further insights on the question how hospitals respond to reimbursements by treatment intensity in a (presumably lump sum) DRG system, we exploit a large scale refinement of reimbursement practice in Germany. In 2005, the German-DRG (G-DRG) does not make reimbursements contingent on treatment intensity in the market for stroke disorder. In 2006, regulating authorities introduce marginal reimbursements for high-intensity treatment (most notably extensive and early clinical diagnostics as well as early rehabilitative treatments) compared to low-intensity treatment. In cases in which hospitals prescribe high-intensity treatment, they receive, on average, and additional 2,200 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 Auffhammer and Kellogg (2011); Gallego et al. (2013); Anderson (2014), for example).

[3]Even healthy patients face unavoidable risks, such as adverse reactions to anesthesia, infections or even death, during or immediately after surgery. Among many others, Noordzij et al. (2010) estimate an overall rate of postoperative mortality of 1.85 percent in hospitals in the Netherlands between 1991 and 2005.

In more detail, this paper 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 appropriateness 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 treatment 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 clinical appropriateness for receiving high-intensity stroke treatment in Germany using an supervised machine learning approach. We use this to render transparent 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.[4] 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 treatment (and less low-intensity treatment) when marginal reimbursements are available. At the same time, the proportion of patients that are less clinically appropriate for high-intensity treatment increases. The empirical analysis finds that the share of admissions receiving high-intensity treatment jumps by approximately 7 percentage points from 2005 to 2006. A simultaneous decrease in the average clinical appropriateness for patients receiving high-intensity treatment around January 1, 2006 reveals that the marginal high-intensity treated patient in 2006 is less appropriate for high-intensity treatment 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. Lastly, our findings indicate that the introduction of extra reimbursements for high-intensity treatment in the market for stroke disorder does not only initiate the adoption of high-intensity treatment in patients that are directly affected by the price shock but also in clinically similar patients that are unaffected by the price shock. Extensive robustness tests confirm the validity of the major identification assumptions of the empirical strategy.

Our results suggest that regulating authorities may foster potentially beneficial treatments by introducing extra reimbursements for desired treatments or clinical pathways. Thus, it might be possible to incorporate payment models based on pay-for-performance

[4] The previous literature on this topic (see Dafny (2005); Jürges and Köberlein (2015), for example) 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).

within modern DRG systems. However, our results also suggest that extra reimbursements that are not directly tied to outcomes might not improve the quality of the outcomes, at least for the targeted patients. Money does not appear to be allocated as directed but might be spent on other patients. In addition, regulating authorities may improve efficiency by reducing the importance of extra reimbursements for marginal treatments in modern DRG systems. Although extra reimbursements may boost beneficial clinical pathways, hospitals might select patients for high-intensity treatment that do not profit from these treatments (at least in the short-run). Given that regulating authorities in Germany steadily increased the importance of treatment type in allocating funds to hospitals, excessive extra reimbursements for high-intensity treatment in Germany might explain the high-level use of surgical procedures in Germany compared to the many other OECD countries (OECD, 2018).

The remainder of this paper 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.[5] Since then, the majority of hospital reimbursements have been flat fees by DRG weight. Reimbursements for admission i to hospital j in year t are summarized as follows:

$$Reimbursement_{i,j,t} = DRG\,weight_{i,t} \times Base\,Payment\,Rate_{j,t} \tag{1}$$

where $DRG\,weight$ reflects the relative resource intensity of admissions. Popular DRG algorithms such as MS-DRGs and APR-DRGs from the U.S. or G-DRGs from Germany, comprehensively utilize diagnoses (either directly or via aggregated patient clinical complexity scores) and additional proxies for patient severities, such as age, gender and mechanical ventilation as well as procedures to adjust admission-specific lump-sum reimbursements for differences in the relative resource intensity. In Germany, DRG weights are annually computed from 2-year old cost reports of approximately 15 percent of hospitals. $Base\,Payment\,Rate$ is a state-specific amount.

In 2005, when lump-sum reimbursements become effective (mainly DRGs mirroring Australian Refined Diagnosis Groups, AR-DRGs), the reimbursement schedule allocates patients to 845 DRGs. Since 2005, regulating authorities have extensively refined and

[5] The majority of patients in Germany are publicly insured (about 87 percent (vdek, 2018)). Publicly insured patients represent about 95 percent of admissions in our data.

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. In 2018, hospital admissions are mapped to one of 1,245 G-DRGs. 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 paper 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. The acute underprovision of blood to the brain is a result of either an ischemic infarction (~ 87 percent of strokes) or a hemorrhage (~ 13 percent of strokes) of the cerebral vessels and 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. Symptoms may include sudden numbness or weakness in the face, arm or leg (especially on one side of the body), confusion, trouble speaking, trouble seeing, trouble walking and lack of coordination. In Germany, approximately 270,000 patients are admitted to the hospital annually for stroke treatment (in 2016, Destatis (2017a)). Strokes are responsible for approximately 25 percent of disabilities in adulthood and are a major cause of death in many OECD countries (~ 7 percent), particularly in Germany (~ 8 percent) (Heuschmann et al., 2010; OECD, 2015; Destatis, 2017b). Mortality due to strokes represents approximately 20 percent 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 et al. (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 does not make reimbursements contingent on treatment intensity in the market for stroke disorder. Lump-sum reimbursements for patients primarily suffering from strokes typically vary between approximately 1,800 EUR (DRG B70C) and approximately 5,400 EUR (DRG B70A), depending on patient characteristics such as the specific type of stroke. In 2006, reimbursement for patients that receive high-intensity treatment increases compared to patients that receive low-intensity treatment. Based on voluntary cost reports, regulating authorities argued that uniform reimbursements might not cover the true costs of high-intensity treatment in many circumstances (INEK, 2005).

For hospitals to receive extra reimbursement for high-intensity treatment, 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 computed tomography (CT) scans within 60 minutes (for patients who are likely to receive thrombolysis), early treatment, such as administering thrombolytic drugs - if applicable - to dissolve blood clots within 1 hour, extensive monitoring and particularly early rehabilitative treatments such as physiotherapy. For the remainder of this paper, "high-intensity treatment" refers to clinical pathways that meet the high-intensity reimbursement-relevant standards of services. Similarly, "low-intensity treatment" refers to clinical pathways that do not meet the high-intensity reimbursement-relevant standards of services.[6]

Table 1 summarizes the changes in reimbursements for low-intensity treatment and high-intensity treatment on January 1, 2006. While hospitals receive for the most frequently observed stroke patient in our data approximately 3,700 EUR in 2005, they receive approximately 3,300 EUR in 2006 as long as they provide low-intensity treatment. As soon as hospitals provide high-intensity treatment, they earn approximately 5,600 EUR for each admission. These changes in reimbursements introduce marginal reimbursements for high-intensity treatment of approximately +70 percent. On average, for each case in which high-intensity treatment was prescribed, the hospitals received an additional 2,200 EUR.[7]

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 treatment as described in the previous section, the assumption of exogenous changes in reimbursements seems to be particularly important.

[6] A full list of the specific set of services defined as high-intensity treatment is provided in Table A.1 of appendix Section A.1.

[7] The average price shock is calculated by using observed, realized quantities from 2005, the year prior to the price shock, as weights.

Table 1: Extra Reimbursement for High-intensity Treatment

DRG 2005		DRG 2006	Description	Price Differential in 2006
		B70E 1.175 ~3,300 EUR	Apoplexy with low-intensity treatment (without intracranial hemorrhage; more than one day length of stay)	
B70B 1.305 ~3,700 EUR	↗ ↘			+70%
		B70B 2.205 ~5,600 EUR	Apoplexy with high-intensity treatment (without intracranial hemorrhage; more than one day length of stay)	
		B70C 1.681 ~4,700 EUR	Apoplexy with low-intensity treatment (with intracranial hemorrhage; more than one day length of stay)	
B70A 1.912 ~5,400 EUR	↗ ↘			+57%
		B70A 2.635 ~7,400 EUR	Apoplexy with high-intensity treatment (with intracranial hemorrhage; more than one day length of stay)	
		B70G 0.596 ~1,700 EUR	Apoplexy with low-intensity treatment (and deceased within four days after admission)	
B70C 0.639 ~1,800 EUR	↗ ↘			+20%
		B70F 0.727 ~2,000 EUR	Apoplexy with high-intensity treatment (and deceased within four days after admission)	

Note: This table presents the reimbursements in 2005 (column DRG 2005) and the differential reimbursements for low-intensity treatment and high-intensity treatment effective from January 1, 2006 (column DRG 2006) in the market for stroke disorder. Reimbursements in EUR are presented below each DRG weight and are computed using the base payment rate from 2006, rounded at the nearest hundred.
Source: Institut für das Entgeltsystem (InEK).

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 treatment h and low-intensity treatment l. By maximizing their net benefit, hospitals decide whom to offer high-intensity treatment and whom to leave with low-intensity treatment 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 treatment into account (Chalkley and 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

$$s = X_i \phi \tag{2}$$

represents this heterogeneity of patients and ranks patients on how appropriate a given patient is for receiving high-intensity treatment given her clinical characteristics X_i with $s \in [\underline{s}, \overline{s}]$. The distribution of this index is described by the density function $f(s)$ and the cumulative distribution function $F(s)$.[8] For high-intensity treatment, the patient's benefit is $b(s,h)$ and increases with the appropriateness for high-intensity treatment $b_s(s,h) > 0$. The patient's benefit from low-intensity treatment is $b(s,l)$ and decreases with the appropriateness for high-intensity treatment $b_s(s,l) < 0$. In addition, we assume that the benefit of high-intensity treatment is always higher or equal for patients with the same level of appropriateness s than for patients receiving low-intensity treatment $b(s,h) \geq b(s,l)$ for all possible s.

Treatment costs also depend on the index of appropriateness s. We introduce the cost function $c(s,h)$ for high-intensity treatment and the cost function $c(s,l)$ for low-intensity treatment. Treatment costs increase with s for both types of treatment ($c_s(s,h) > 0$, $c_s(s,l) > 0$). Costs for high-intensity treatment are always higher than costs for low-intensity treatment $c(s,h) > c(s,l)$ for all s. Furthermore, increases in treatment costs with s are higher for low-intensity treatment than for high-intensity treatment ($c_s(s,l) > c_s(s,h)$).[9] We also assume that low-intensity treatment is cost-efficient for patients with the lowest index of appropriateness s such that $b(\underline{s},l) - c(\underline{s},l) > b(\underline{s},h) - c(\underline{s},h)$. For patients with the highest index of appropriateness s, high-intensity treatment is cost-efficient such

[8] We model patient benefits arising from high-intensity treatment and low-intensity treatment based on an index of appropriateness for high-intensity treatment. This feature of the model implies that a higher appropriateness for high-intensity treatment implies a lower appropriateness for low-intensity treatment. Hafsteinsdottir and Siciliani (2010) use s as an indicator for patient severity. Similarly, for the purpose of our empirical strategy, we map the various facets of patient severity (e.g., clinical symptoms, demographics) to a single vector. Section 4 introduces the methodology of how we succeed in measuring this clinical appropriateness of receiving high-intensity stroke treatments.

[9] Patients that are more appropriate for high-intensity treatment, but are assigned to low-intensity treatment, may develop complications that are observed only after the low-intensity treatment has completed. Hence, incorrect initial assignment likely results in higher subsequent efforts and costs.

that $(b(\overline{s}, h) - c(\overline{s}, h) > b(\overline{s}, l) - c(\overline{s}, l)$.

Reimbursement is denoted as p_{nr} for admissions receiving either treatment, as long as regulating authorities do not make reimbursements contingent on treatment intensity in the market for stroke disorder. As soon as regulating authorities introduce extra reimbursements for high-intensity treatment, reimbursements are denoted p_h for admissions receiving high-intensity treatment and p_l for admissions receiving low-intensity treatment.

To maximize their utility, hospitals decide on the type of treatment by choosing a cutoff level z of the index of appropriateness s. Hospitals provide low-intensity treatment to patients below the cutoff and high-intensity treatment to patients above the cutoff. The number of low-intensity treatment is $\underline{n} = \int_{\underline{s}}^{z} f(s)ds = F(z)$ and the number of high-intensity treatment is $\overline{n} = \int_{z}^{\overline{s}} f(s)ds = 1 - F(z)$. The total number of patients treated by a hospital is $n = \underline{n} + \overline{n}$, which is normalized to one.

A hospital's utility function is expressed as

$$U(z) = \alpha B(z) - C(z) + T(z) \tag{3}$$

where α reflects the altruism parameter with $\alpha \in]0, 1]$. The total benefit function is given by

$$B(z) = \int_{\underline{s}}^{z} b(s, l)f(s)ds + \int_{z}^{\overline{s}} b(s, h)f(s)ds \tag{4}$$

Similar to the total benefit function, the total cost function is described by

$$C(z) = \int_{\underline{s}}^{z} c(s, l)f(s)ds + \int_{z}^{\overline{s}} c(s, h)f(s)ds \tag{5}$$

As long as regulating authorities do not make reimbursements contingent on treatment intensity, reimbursement is given by p_{nr} and the reimbursement function can be written as

$$T_{nr}(z) = \int_{\underline{s}}^{\overline{s}} p_{nr} f(s)ds \tag{6}$$

As soon as regulating authorities introduce extra reimbursements for high-intensity treatment, we obtain

$$T_r(z) = \int_{\underline{s}}^{z} p_l f(s)ds + \int_{z}^{\overline{s}} p_h f(s)ds \tag{7}$$

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}

$$\max_{z} U(z) = \alpha B(z) - C(z) + T(z) \tag{8}$$

Using (4), (5) and (6), the first-order condition for an interior solution can be simplified to

$$\alpha b(z^{nr}, l) - c(z^{nr}, l) + p_{nr} = \alpha b(z^{nr}, h) - c(z^{nr}, h) + p_{nr} \tag{9}$$

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 treatment to a patient with z^{nr}. The right-hand side of the equation reflects the marginal net benefit from providing high-intensity treatment. At the optimum utility, both marginal net benefits are equal. Thus, patients who are clinically less appropriate for high-intensity treatment receive low-intensity treatment up to the threshold z^{nr}, while more appropriate patients above this threshold receive high-intensity treatment.[10]

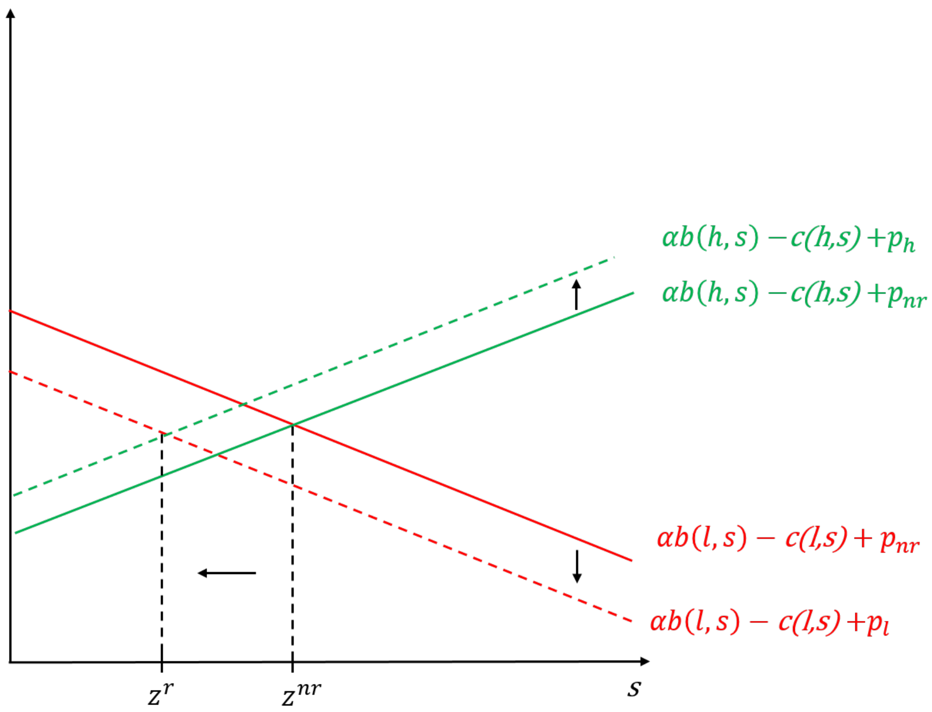
The solid red line in Figure 1 illustrates the hospital's marginal net benefit from providing low-intensity treatment, the solid green line, from providing high-intensity treatment. The net benefit function of low-intensity treatment starts above the net benefit function of high-intensity treatment at $\underline{s}$ and is decreasing with s ($b_s(s, l) < 0$, $c_s(s, l) > 0$). The reason for this is that we assume cost-efficiency for low-intensity treatment for patients with the lowest appropriateness of receiving high-intensity treatment and a decreasing net benefit.

Conversely, the net benefit function of high-intensity treatment starts below the net benefit function of high-intensity treatment at $\underline{s}$, as the net benefit of high-intensity treatment is assumed to be increasing with s. As we assume cost-efficiency for high-intensity treatment for patients with the highest appropriateness of receiving high-intensity treatment, both net benefit functions intersect at the threshold z^{nr}, meeting the FOC (9). 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 treatment and some patients will receive high-intensity treatment. Hospitals will provide low-intensity treatment to the share of patients that are clinically less appropriate for receiving high-intensity treatment and provide high-intensity treatment to the share of patients that are more appropriate for high-intensity treatment.*

[10] Corner solutions can be ruled out in this scenario. Please see Section A.2 of the appendix for more details.

Figure 1: Optimal Cutoff



Note: This figure illustrates the change in the optimal cutoff point after regulating authorities introduce extra reimbursements for high-intensity treatment (interior solution). High-intensity treatment is assumed to be net benefit increasing. The same result holds for decreasing net benefit (please see appendix Section A.2 for more details).

Scenario 2: Regulating Authorities Introduce Extra Reimbursements for High-intensity Treatment

In 2006, reimbursement for patients receiving high-intensity treatment p_h increases compared to patients receiving low-intensity treatment p_l with $p_h > p_l$. Again, hospitals choose the optimal cutoff point z^r that maximizes their utility (3). Using (4), (5) and(7), the following first-order condition for an interior solution can be written as

$$\alpha b(z^r, l) - c(z^r, l) + p_l = \alpha b(z^r, h) - c(z^r, h) + p_h \tag{10}$$

Similar to equation (9) above, the left-hand side of the equation is the hospital's marginal net benefit from providing low-intensity treatment to a patient with z^{nr}, the right-hand side of the equation the marginal net benefit from providing high-intensity treatment. However, please note the altered first-order condition in equation (10) 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 treatment as soon as regulating authorities introduce extra reimbursements for high-intensity treatment. The dotted green line indicates the marginal net benefit from providing high-intensity treatment. Contrary to the scenario in which regulating authorities do not make reimbursements conditional on treatment intensity, the net benefit function of low-intensity treatment shifts downward by $p_{nr} - p_l$ and the net benefit function of high-intensity treatment 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 treatment, meeting the FOC (10).[11]

Proposition 2 *As soon as regulating authorities introduce extra reimbursements for high-intensity treatment, hospitals will provide more high-intensity treatment and less low-intensity treatment. If the difference in reimbursements is sufficiently large, only high-intensity treatment will be provided. Consequently, more patients that are clinically less appropriate on the index of clinical appropriateness for high-intensity treatment will receive such treatment.*

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 treatment 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, all information that is relevant to compute reimbursements. This includes 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. The regulating authority (Institut für das Entgeltsystem, InEK (German DRG Institute)) collects the reimbursement data from hospitals each year, primarily to recalibrate the G-DRG and to compute reimbursements (§21 KHEntgG). The G-DRG data is adjusted by the regulating authorities and is available at the Federal Statistical Office (Data Research Center).[12]

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 patients' actual as well as counterfactual own prices and cross prices for the year before and after the price

[11] We can show that a corner solution such as providing only low-intensity treatments can be ruled out, as the high-intensity treatment is cost-efficient for highly appropriate patients. Still, a corner solution such that all patients receive high-intensity treatment is possible if the difference in reimbursements is sufficiently high. This implies that the high-intensity treatment is more lucrative. Please see Section A.2 of the appendix for more details.

[12] Section A.3 of the appendix provides more details on the G-DRG data.

shock of 2005-2006 for both treatment options, i.e., low-intensity treatment and high-intensity treatment. 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. 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 A.2 of appendix Section A.3.[13] High-intensity treatment is 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).[14]

Table 2 summarizes the market for stroke disorder across approximately 1,500 hospitals (85 percent 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.

As discussed in Section 3, stroke patients are heterogeneous and vary in clinical characteristics such as the presence and severity of clinical symptoms. Based on these clinical characteristics, hospitals decide whether to provide high-intensity treatment to the patient (please see Equation 2). However, 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 paper extends the empirical strategy from Chandra and Staiger (2007) and achieves precise measurement of the admission-specific clinical appropriateness for high-intensity stroke treatments 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 treatment 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.

[13]The G-DRG (as well as many other DRG algorithms) defines the primary diagnosis as the "condition established after study to be chiefly responsible for occasioning the admission of the patient to the hospital for care" (Deutsche Kodierrichtlinien (German Coding Guidelines). This paper drops newborns as well as patients with incomplete information, such as missing diagnoses, for which we cannot compute reimbursements. In addition, we limit our analysis to inpatient admissions that do not receive organ transplants or pacemaker implantations. As the year of admission determines the relevant reimbursement schedules, which become effective on January 1 each year, throughout the paper, we aggregate our data by the year of admission.

[14]We denote patients whose reports document both high-intensity treatment and low-intensity treatment as receiving high-intensity treatment (as required by the Definitions Manuals).

Table 2: 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**

Note: 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 2,804 EUR in 2006. Column 5 reports the average age of patients.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

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 treatment as an empirical measure of the clinical appropriateness for high-intensity stroke treatment. As a result, we obtain an admission-level index that ranks patients based on how appropriate the patient is for receiving high-intensity treatment given her clinical characteristics. This empirical strategy allows the researcher to analyze whether hospitals provided more high-intensity treatment to patients that receive high-intensity treatment 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

$$Pr(High - intensity\,Treatment_i) = G(\theta + X_i\phi) \tag{11}$$

where $High - intensity\,Treatment$ is a binary indicator for high-intensity treatment and X denotes a vast set of patient characteristics for admission i. We use a boosted logistic regression introduced by Friedman et al. (2000) to achieve high flexibility (and dimensionality) in $G()$ for patient characteristics to influence hospital decisions on whether to provide high-intensity, but uncompensated extra treatment to the patient in 2005.[15] The set of patient characteristics X includes stroke-specific symptoms such as the location of the infarction of the cerebral artery or language disorders, non stroke-specific symptoms such

[15]Boosted regressions combine the strengths of two algorithms: Regression trees (models that relate a response to their predictors by recursive binary splits) and boosting (an adaptive method for combining many simple models to improve predictive performance). Section A.3 of the appendix provides more details on this statistical model.

as general comorbidities and administrative information such as an emergency indicator.[16]

Figure A.2 of appendix Section A.3 presents the relative influence of the various predictors on the probability of receiving high-intensity treatment.[17] For example, the location of the infarction of the cerebral artery (cerebral infarction) is a very important patient characteristic used by hospitals to decide whether to provide high-intensity treatment, as it explains more than 10 percent of the decision. The out-of-sample accuracy of correctly predicting the observed, realized treatment intensity of each patient is fairly high (AUC 0.8). Figure 2 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 treatment, separately, by the observed, realized treatment intensity (low-intensity treatment and high-intensity treatment). Green bars denote patients with observed, realized low-intensity treatment and white bars denote patients with observed, realized high-intensity treatment. In both years, the figure reveals two disparate distributions of the empirical measure of appropriateness: The average (median) predicted probability of receiving high-intensity treatment is considerably higher for patients that indeed receive a high-intensity treatment (0.36) compared to patients that receive a low-intensity treatment (0.21). Thus, our model succeeds in accurately separating stroke patients by their appropriateness for receiving high-intensity treatment according to their clinical characteristics.

4.2 Empirical Strategy

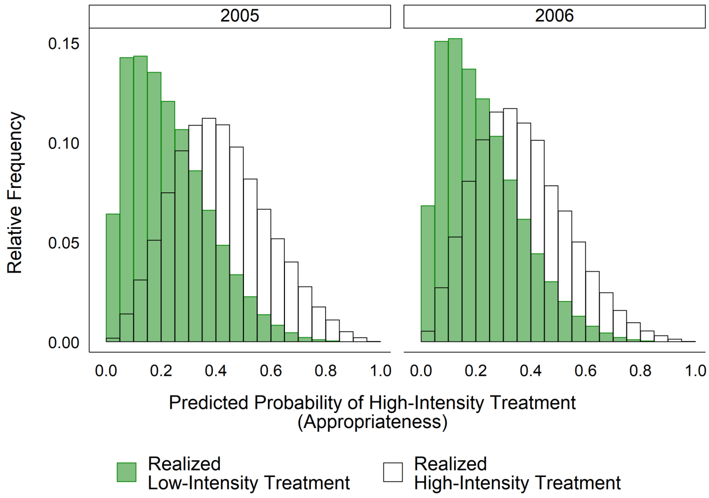
This section describes the empirical strategy used to investigate hospital responses to the introduction of extra reimbursements for high-intensity treatment in the market for stroke disorder on January 1, 2006. Refinements to the mechanism design of the G-DRG generate breaks in reimbursements by date 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 Auffhammer and Kellogg (2011); Gallego et al. (2013); Anderson (2014), for example).[18] 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 2 is aggregated at

[16] The G-DRG data provide a vast set of information as foundation for the prediction. For example, for stroke patients, each stroke-related symptom must be coded as a single secondary diagnosis. Table A.3 of appendix Section A.3 provides further details on the included patient characteristics.

[17] Similar to coefficients in conventional regressions, the relative influence quantifies the importance of the predictors. The more the predictor enters the model and the more its use improves the model performance, the higher the relative influence of the predictor.

[18] Hausman and Rapson (2018) comprehensively discuss the identification strategy based on the regression discontinuity in time (RDiT) framework as well as its empirical applications. The identification of causal effects using this method - as in the conventional regression discontinuity framework - hinges on the assumption that there is a sharp cutoff, around which there is a discontinuity in the probability of assignment from 0 to 1. The cutoff in reimbursements is strictly implemented and hospitals cannot exercise discretion on the reimbursement schedule.

Figure 2: Empirical Measure of Appropriateness



Note: This figure plots the relative frequency of the predicted probability of receiving high-intensity treatment (appropriateness) by the observed, realized treatment intensity for all stroke admissions in 2005 and 2006. Appropriateness is the propensity of hospitals to provide high-intensity treatment. The empirical measure of appropriateness comes from a boosted logistic regression that explains the observed, realized treatment intensity using a set of patient characteristics based on observations from the year 2005, i.e., a setting where marginal changes to treatment intensity are independent from extra reimbursements.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

the hospital-month level (1,456 hospitals between 2005 and 2006).[19] The main analysis additionally presents the results separately for experienced hospitals (i.e., 288 hospitals that did provide high-intensity treatment in 2005) and inexperienced hospitals (i.e., 1,168 hospitals that did not provide high-intensity treatment in 2005).

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

$$Treatment\ Intensity_{ht} = \beta T + \gamma_1 \tilde{Month}_t + \gamma_2 T \times \tilde{Month}_t + \delta_h + \varepsilon_{ht} \quad (12)$$

$$Treatment\ Appropriateness_{ht} = \beta T + \gamma_1 \tilde{Month}_t + \gamma_2 T \times \tilde{Month}_t + \delta_h + \varepsilon_{ht} \quad (13)$$

$$Quality\ Outcome_{ht} = \beta T + \gamma_1 \tilde{Month}_t + \gamma_2 T \times \tilde{Month}_t + \delta_h + \varepsilon_{ht} \quad (14)$$

[19] Some hospitals do not provide services to stroke patients in each period, particularly rural hospitals because of the emergency nature of the stroke disorder. Thus, the panel is unbalanced. Under the assumptions that the potential selection is independent of idiosyncratic shocks and that the correlation between the selection and the hospital fixed effects is arbitrary, the estimates in this paper are unbiased and consistent. The results throughout the paper do not change when we restrict the analyses to a fully balanced panel of hospitals. This robustness test demonstrates the validity of the abovementioned assumptions.

where $TreatmentIntensity_{ht}$ is the share of patients receiving high-intensity treatment in hospital h in the market for stroke disorder in month t between 2005 and 2006. $TreatmentAppropriateness_{ht}$ is the average appropriateness in hospital h in month t based on our propensity predictions, estimated separately for patients receiving high-intensity treatment and patients receiving low-intensity treatment. $QualityOutcome_{ht}$ 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, treatment appropriateness, 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. $\tilde{Month}_t$ 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, treatment appropriateness 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 weight each observation by the number of admissions in the market for stroke disorder. Unweighted regressions generate qualitatively similar results. We calculate cluster-robust standard errors at the hospital level to test the hypotheses (see Abadie et al. (2017), for example). These are robust to the potential serial correlation of the error term within hospitals over time.

When applying the theoretical considerations from Section 3 to the empirical setting, as described in Section 2, we expect that the analysis of the intensity of treatment will find a statistically significant, positive coefficient β (Equation 12) for all hospitals, both experienced hospitals as well as inexperienced hospitals. This result would indicate that hospitals indeed produce more high-intensity treatment as soon as regulating authorities introduce extra reimbursements for this high-intensity treatment. β represents the monthly change in the share of patients that receive high-intensity treatment from 2005 to 2006 (in percentage points). In addition, we expect a statistically significant, negative coefficient β in the analysis of treatment appropriateness, which would connote that, after the price shock of 2005-2006, experienced hospitals provide additional high-intensity treatment to patients that are less clinically appropriate for those treatments (Equation 13).[20] Finally, we either expect a statistically significant, negative coefficient β or a statistically insignificant effect in the analysis of patient outcomes (Equation 14). A negative coefficient β would indicate an improvement in the respective outcome measure and represents the change in the respective outcome measure in percentage points.

[20] We restrict this analysis to experienced hospitals as the change in the appropriateness for receiving high-intensity treatment is undefined for inexperienced hospitals which did not provide high-intensity treatment in 2005. Please note that for interpretation purposes, the direction of the estimated β coefficient is more important than the magnitude of the estimated coefficient. The reason for this is that the size of the estimated coefficient depends on the level and distributional shape of the empirical measure of appropriateness.

The major identification assumptions of the empirical strategy described in this section are identical to the identification assumptions in conventional sharp regression discontinuity designs (Imbens and Lemieux, 2008). Section 6 presents a vast set of robustness tests that confirm the validity of these identification assumptions. First, Section 6.1 tests whether the relationship between the forcing variable, $\tilde{Month}_t$, and the outcome variables, such as $Treatment\ Intensity_{ht}$, may be fundamentally discontinuous, and the jump at the cutoff point is contaminated by other factors such as seasonality. Second, Section 6.2 test whether stroke patients are comparable around the cutoff using the number of admissions as a placebo outcome. Third, Section 6.3 tests the robustness of the 1st-order polynomial estimating equations. Fourth, Section 6.4 discusses whether alternative channels such as changes in coding behavior might explain the results in this paper.

In addition, this paper assumes that costs do not change discontinuously around January 1, 2006; that is, the price shock in the market for stroke disorder is orthogonal to changes in costs. This assumption seems plausible particularly because refinements to the G-DRG and DRG weights are annually computed from 2-year old cost reports. Even if changes in the reported costs for high-intensity treatment had dominated the regulator's rationale for the comprehensive refinement in the market for stroke disorder, changes in present costs from year 2005 to year 2006 only affect changes in future prices from year 2007 to year 2008, for example.[21] Furthermore, this paper assumes that the demand for high-intensity treatment does not change discontinuously around January 1, 2006. This assumption seems plausible because of the emergency nature of the stroke condition.

5 Results

5.1 Treatment Intensity and the Selection of Patients

A large-scale refinement in the market for stroke disorder on January 1, 2006 introduces marginal reimbursements for high-intensity treatment. Our theoretical model, developed in Section 3, predicts that under these circumstances, hospitals will provide more high-intensity treatment and fewer low-intensity treatment. At the same time, more patients that are clinically less appropriate for receiving high-intensity treatment will receive these treatments (Proposition 2).

The statistical and economic significance of the discontinuous change in the share of

[21] Reported costs come from 2-year old cost reports of about 15 percent of hospitals. As cost reporting is voluntary, the count and composition of reporting hospitals shifts. For example while cost data from 148 hospitals were used to compute refinements and DRG weights in 2005, cost data from 247 hospitals were used in 2014. Similarly, about 22 percent of all cost reporting hospitals were private in 2005. In 2012, about 8 percent of all cost reporting hospitals were private. In addition, cost reporting practices change over the years. For example, German authorities demand major improvements in the allocation of costs to a particular admission in 2009. More specifically, authorities harmonized cost center accounting regulations across hospitals and introduced specific internal cost allocation reference values. Thus, it seems unlikely that reported changes in costs are highly correlated with actual changes in costs.

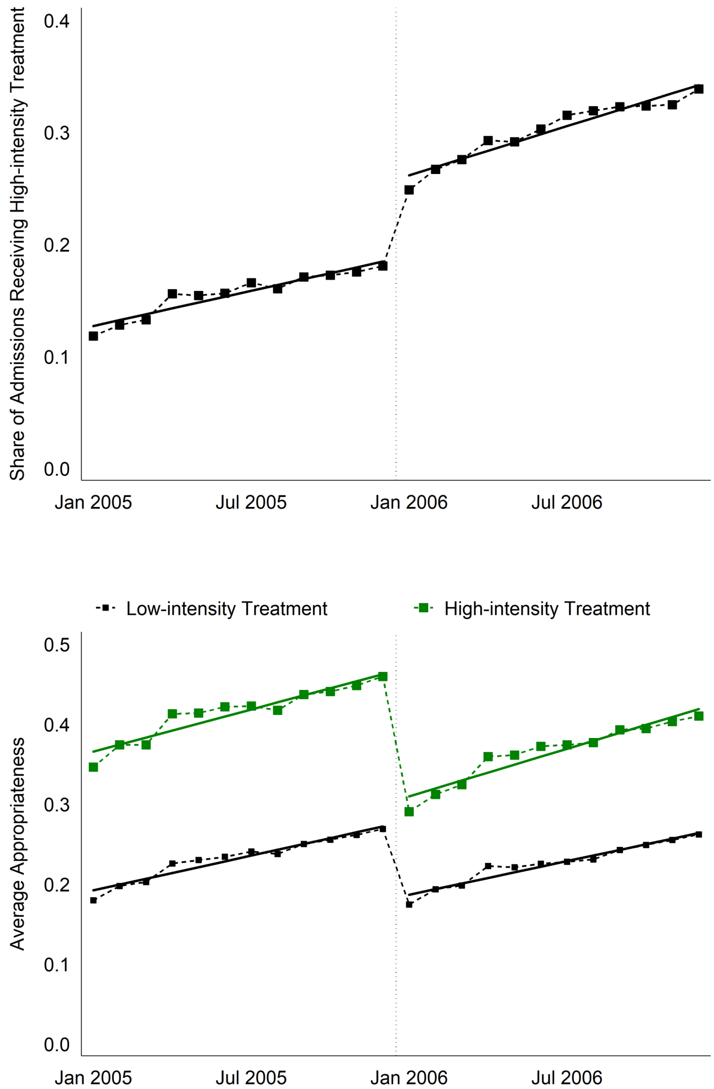
admissions receiving high-intensity treatment and the average appropriateness for receiving high-intensity treatment on January 1, 2006 identify whether hospitals respond to the introduction of extra reimbursements for high-intensity treatment in the market for stroke disorder. Figure 3 illustrates the results from the regression discontinuity estimates. The top panel plots the share of admissions receiving high-intensity treatment (y-axis) in all hospitals by year and month (x-axis) using black squares. In line with our theoretical predictions, hospitals provide high-intensity treatment only to a share of patients before regulating authorities introduce extra reimbursements for high-intensity treatment. Figure 3 documents a remarkable jump in the share of admissions receiving high-intensity treatment: 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 treatment both before and after the introduction of extra reimbursements for high-intensity treatment. The corresponding regression discontinuity estimates show that the share of admissions receiving high-intensity treatment discontinuously increases by 6.8 percentage points from December 2005 to January 2006 (Column 1 in Table 3). This effect is statistically highly significant ($p < 0.001$). The discontinuous increase by 6.8 percentage points is approximately equivalent to a 47 percent (or approximately 1,500 patients) increase in the number of patients receiving high-intensity treatment at the turn of the year. In line with our theoretical predictions, hospitals provide more high-intensity treatment as soon as regulating authorities introduce extra reimbursements for high-intensity treatment in the market for stroke disorder.

These findings are in line with Papanicolas and McGuire (2015), Cutler (1995) and Einav et al. (2017), for example, who demonstrate that hospitals respond to changes in marginal reimbursements arising in many DRG systems.[22] Yet, our results are in contrast with Gilman (2000) who finds that hospitals do not respond to marginal reimbursements for high-intensity treatment. 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. (2017) 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 treatment 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 treatment 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.

Separate estimates by the experience of hospitals with high-intensity treatment prior to

[22] Cutler (1995) is the first to present that reductions in marginal reimbursements for an additional length of stay reduce lengthy hospital stays in Medicare hospitals. Most recently, Einav et al. (2017) analyze Medicare hospitals that receive extra reimbursements when a patient's stay reaches a threshold number of days. The authors show that the number of discharges increases substantially after this threshold.

Figure 3: Changes in Treatment Intensity and the Selection of Patients



Note: 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 treatment 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 appropriateness of receiving high-intensity stroke treatment by type of observed, realized treatment (high-intensity treatment and low-intensity treatment). The monthly average appropriateness of receiving high-intensity treatment for patients receiving those treatments is presented using green squares and connected using a dashed green line. The monthly average appropriateness of receiving high-intensity treatment for patients receiving low-intensity treatment 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).

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 3 show that both experienced hospitals (i.e., hospitals that did provide high-intensity treatment in 2005) and inexperienced hospitals (i.e., hospitals that did not provide high-intensity treatment in 2005) discontinuously increase the share of admissions receiving high-intensity treatment from December 2005 to January 2006. In addition, the share of admissions receiving high-intensity treatment in inexperienced hospitals further increases gradually by 0.4 percentage points after the price shock of 2005-2006 ($p < 0.001$). These results suggest 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 treatment to the share of patients that are clinically less appropriate for receiving high-intensity treatment and provide high-intensity treatment to the share of patients that are more appropriate for high-intensity treatment (Proposition 1). The bottom panel of Figure 3 depicts the average appropriateness of receiving high-intensity treatment (y-axis) by year and month (x-axis), using green squares for patients receiving high-intensity treatment and black squares for patients receiving low-intensity treatment. This figure demonstrates a steady upward trend in the average appropriateness of receiving high-intensity treatment for both types of treatment (high-intensity treatment and low-intensity treatment), both before and after the introduction of extra reimbursements for high-intensity treatment. This trend might capture the general improvements in tailoring treatment such as the availability of specialized care in stroke units to patients. From December 2005 to January 2006, however, the average appropriateness of receiving high-intensity treatment 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 treatment.

More precisely, the average appropriateness of receiving high-intensity treatment for patients receiving those treatments discontinuously decreases by 15.6 percentage points as soon as regulating authorities introduce extra reimbursements for high-intensity treatment (Column 4 in Table 3).[23] For the average appropriateness for patients that receive high-intensity treatment to decrease in 2006, the marginal patient newly treated with high-intensity treatment has to be clinically less appropriate compared to 2005. This finding empirically confirms the theoretical prediction that more patients that are clinically less appropriate on the index of clinical appropriateness for high-intensity treatment will receive such treatment (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.

[23] As a reminder, we restrict this analysis to experienced hospitals to test this hypothesis as the change in the appropriateness for receiving high-intensity treatment is undefined for inexperienced hospitals which did not provide high-intensity treatment in 2005.

Table 3: Changes in Treatment Intensity and the Selection of Patients

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Average Treatment Intensity			Average Appropriateness	
Hospital Group	All Hospitals	Inexperienced Hospitals	Experienced Hospitals	Experienced Hospitals	Experienced Hospitals
Patient Group	All Patients	All Patients	All Patients	High-intensity Treatment	Low-intensity Treatment
T	0.068***	0.037***	0.098***	-0.156***	-0.091***
	(8.18)	(4.34)	(6.98)	(35.49)	(31.22)
$\tilde{Month}$	0.005***	0.000**	0.010***	0.009***	0.007***
	(6.08)	(2.78)	(6.52)	(17.78)	(24.85)
$T\times\tilde{Month}$	0.002	0.004***	-0.001	0.001	-0.000
	(1.60)	(5.37)	(0.42)	(1.59)	(0.81)
Adjusted R^2	0.791	0.538	0.684	0.619	0.503
Hospitals	1,456	1,168	288	288	288
Observations	30,993	24,368	6,625	5,076	6,602

Note: 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 Appropriateness is the monthly average appropriateness of receiving high-intensity stroke treatments by type of observed, realized treatment (high-intensity treatment and low-intensity treatment). T denotes a binary indicator for the months following the introduction of extra reimbursements for high-intensity treatment (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: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

Similarly, the average appropriateness of receiving high-intensity treatment for patients receiving low-intensity treatment discontinuously decreases by 9.1 percentage points from December 2005 to January 2006 (Column 5 in Table 3). This result is intuitive because the marginal patient, newly treated with high-intensity treatment, to which hospitals were providing low-intensity treatment in 2005 is clinically less appropriate than patients to which hospitals used to provide high-intensity treatment in 2005.[24] Both effects are statistically highly significant ($p < 0.001$).

Although this paper finds that hospitals chose to treat more patients with high-intensity treatment in 2006 than they would have chosen in 2005, the results do not uncover whether hospitals over-provide high-intensity treatment in 2006. Even the more mildly ill, probably less clinically appropriate patients might still profit from and appropriately receive high-intensity treatment. 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.

[24] Please note that when assessing the introduction of extra reimbursements for high-intensity treatment on the average appropriateness of receiving those 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 appropriateness measure in both groups.

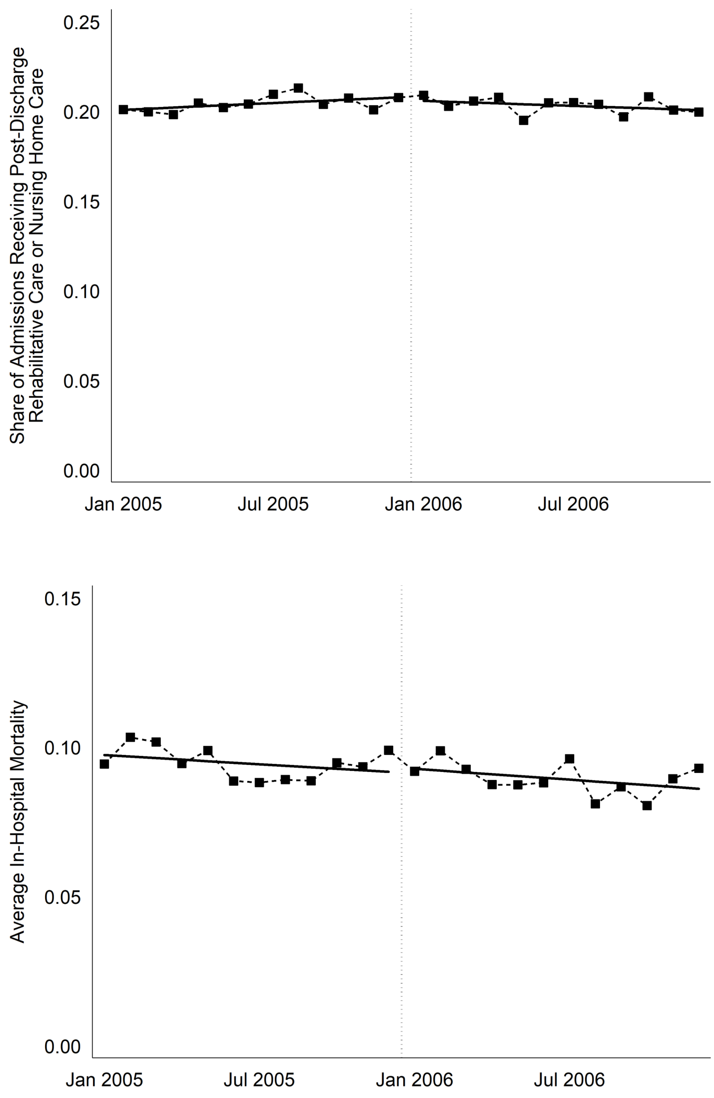
5.2 Patient Outcomes

This section investigates whether the increase in high-intensity stroke treatments (in response to the introduction of extra reimbursements for high-intensity treatment) benefits patients. As a reminder, hospitals have to provide, for example, comprehensive and early clinical diagnostics such as cranial computed tomography (CT) scans within 60 minutes (for patients who are likely to receive thrombolysis), early treatment such as administering thrombolytic drugs - if applicable - to dissolve blood clots within one hour, extensive monitoring or particularly early rehabilitative treatments such as physiotherapy to receive extra reimbursement for high-intensity treatment. Thus, the marginal patient newly treated with high-intensity treatment might, for example, receive treatment earlier and benefit from improved patient outcomes even if she used to be clinically less appropriate than patients to which hospitals were already providing high-intensity treatment.

Figure 4 illustrates the results from the regression discontinuity estimates with regard to patient outcomes. The top panel plots the share of admissions receiving rehabilitative care or nursing home care directly after discharge in all hospitals (y-axis), by year and month (x-axis), using black squares. 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 treatment (Column 1 in Table 4, $p < 0.3$). The bottom panel plots the average in-hospital mortality (y-axis) by year and month (x-axis) using black squares. Happily, 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 treatment (Column 4 in Table 4, $p < 0.7$).

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

Figure 4: Changes in Patient Outcomes



Note: 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).

Table 4: Changes in Patient Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Share of admissions receiving rehabilitative or nursing home care			Average In-Hospital Mortality		
Hospital Group	All Hospitals	Inexperienced Hospitals	Experienced Hospitals	All Hospitals	Inexperienced Hospitals	Experienced Hospitals
Patient Group	All Patients	All Patients	All Patients	All Patients	All Patients	All Patients
T	-0.002	-0.004	-0.001	0.001	0.003	-0.000
	(0.82)	(0.95)	(0.25)	(0.78)	(1.13)	(0.20)
$\tilde{Month}$	0.000	0.000	0.000	-0.000	-0.001*	0.000
	(1,08)	(1,00)	(0,54)	(1.64)	(2.17)	(0.13)
$T \times \tilde{Month}$	-0.001	-0.001	-0.001	-0.000	0.000	-0.000
	(1.86)	(0.85)	(1.71)	(0.42)	(0.55)	(1.35)
Adjusted R^2	0.506	0.463	0.590	0.181	0.124	0.204
Hospitals	1,456	1,168	288	1,456	1,168	288
Observations	30,993	24,368	6,625	30,993	24,368	6,625

Note: This table reports the regression discontinuity results as described in Section 4.2. Column 1 to 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 treatment (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: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

5.3 Spillover Effects

The previous empirical literature emphasizes the importance of input mix and technology choices (i.e., clinical pathways) for externalities in regulated industries (Baicker and Staiger, 2005; Acemoglu and Finkelstein, 2008). In fact, our theoretical model from Section 3 also suggests externalities in cases in which (negative) cost shocks are considered equivalent to (positive) reimbursement shocks. In Figure 1, it is easy to see that a downward shift in the cost curve has the same equilibrium effects as an upward shift in the reimbursement curve.

As a reminder from Section 2, hospitals must provide particular services, such as comprehensive and early clinical diagnostics, as well as early rehabilitative treatments to profit from extra reimbursements. The observed financially-motivated increase in the use of high-intensity treatment probably also causes a decrease in the (marginal) costs of high-intensity treatment for patients that are clinically similar, but not affected by the introduction of extra reimbursements. The introduction of extra reimbursements in the market for stroke disorder may thus initiate the adoption of high-intensity treatment in other clinical areas as well.

To test this hypothesis, we investigate the share of admissions receiving high-intensity treatment and the average appropriateness of receiving high-intensity treatment in an area that is clinically very similar to the market of stroke treatments as defined in the analysis above. More specifically, regulating authorities exclude a very specific group of patients from the introduction of extra reimbursements in 2005-2006. Regulating authorities exclude patients that suffer from a stroke and experience complex complications, such as a cerebral edema or an increased benign intracranial hypertension (which frequently requires an immediate craniotomy (surgical opening of the skull to access the brain), after admission).

Figure 5 illustrates the share of admissions receiving high-intensity treatment in all hospitals (y-axis), by year and month (x-axis), using black squares for the specific group of patients for which hospitals do not receive extra reimbursements after the price shock of 2005-2006. The top panel suggests a jump in the share of admissions receiving high-intensity treatment: from about 0.12 to 0.14 around the turn of the year. The corresponding regression discontinuity estimates illustrate that the share of admissions receiving high-intensity treatment discontinuously increases by 3.9 percentage points from December 2005 to January 2006 (Column 1 in appendix Section A.4 Table A.4). This effect is statistically highly significant ($p < 0.001$).

The bottom panel depicts the average appropriateness of receiving high-intensity treatment (y-axis) by year and month (x-axis) for the very specific group of patients for which hospitals do not receive extra reimbursements after the price shock of 2005-2006. Patients receiving high-intensity treatment are presented using green squares and patients receiving low-intensity treatment, using black squares. From December 2005 to January 2006, the average appropriateness of receiving high-intensity treatment decreases from 0.50 to 0.30 for patients receiving those treatments, and decreases from about 0.18 to 0.13 for patients receiving low-intensity treatment. More precisely, the average appropriateness of receiving high-intensity treatment for patients receiving those treatments discontinuously decreases by 17.7 percentage points, although regulating authorities did not directly introduce extra reimbursements for high-intensity treatment for this particular group of patients (Column 2 in appendix Section A.4 Table A.4). Again, for the average appropriateness for patients that receive high-intensity treatment to decrease, the marginal patient newly treated with high-intensity treatment has to be clinically less appropriate in 2006 compared to 2005.

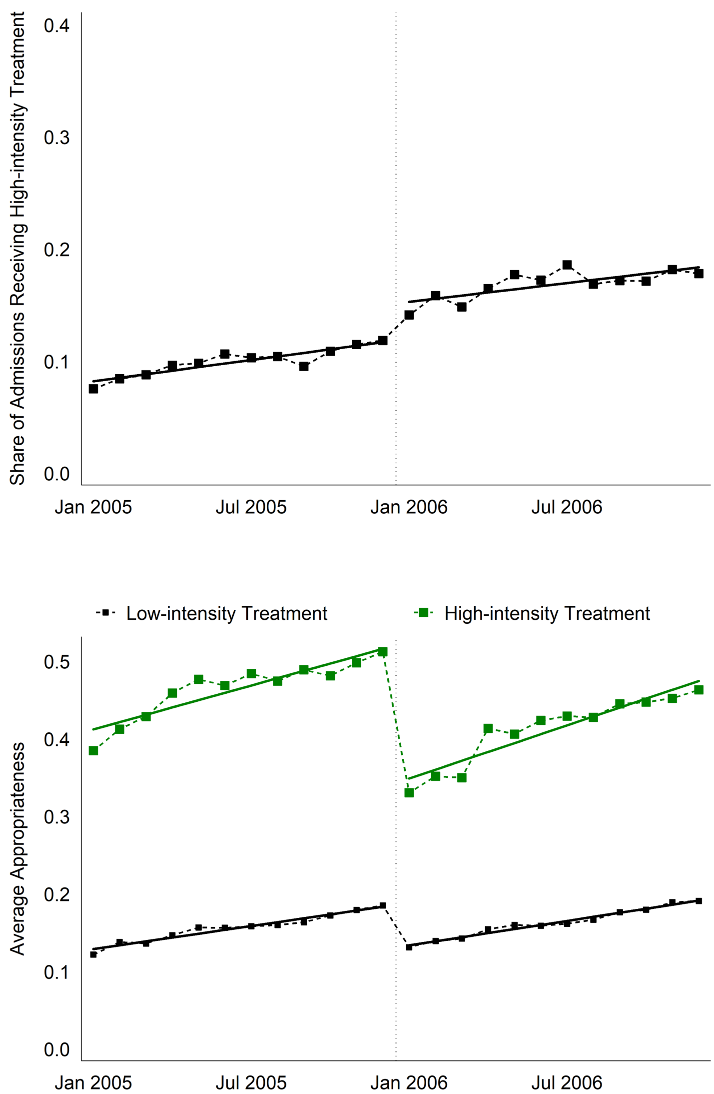
The findings in this section suggest that the introduction of extra reimbursements for high-intensity treatment does not only initiate an extensive adoption of high-intensity treatment for patients directly affected by the price shock, but also for clinically similar patients that are unaffected by the price shock. Thus, the widespread determination of reimbursements by treatment intensity inherent to DRG systems in many OECD countries might have long-lasting effects on the market-wide organization of the hospital industry.

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 paper is that, in the absence of the price shock, patients on both sides of the threshold (i.e., patients in December 2005

Figure 5: Spillover Effects



Note: The top panel in this figure presents the monthly share of admissions receiving high-intensity stroke treatments in Germany for our specific group of stroke patients between 2005 and 2006. The monthly share of admissions receiving high-intensity treatment 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 appropriateness of receiving high-intensity stroke treatment by type of realized treatment (high-intensity treatment and low-intensity treatment). The monthly average appropriateness of receiving high-intensity treatment for patients receiving those treatments is presented using green squares and connected using a dashed green line. The monthly average appropriateness of receiving high-intensity treatment for patients receiving low-intensity treatment 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).

and patients in January 2006) are, on average, identical. In other words, the share of patients receiving high-intensity treatment in the market for stroke disorder in December 2005 and January 2006 would be the same in absence of the price shock of 2005-2006. 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 paper, 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 A.3 of appendix Section A.5 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.[25] 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 6 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-percent 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 treatment 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 treatment from 2006 to 2007. Table A.5 of appendix Section A.5 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 paper.[26]

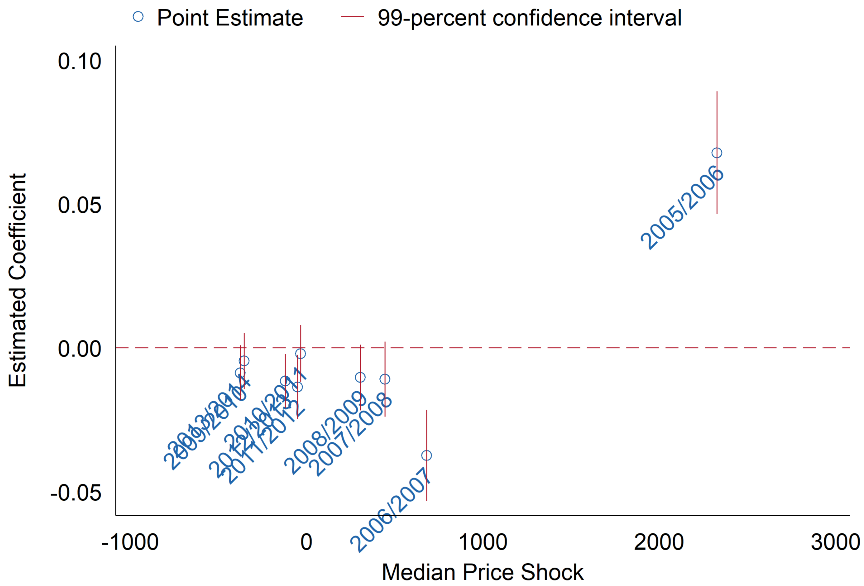
6.2 Placebo Outcome

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 paper 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

[25] 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.

[26] Similarly, the results from Section 5.3 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, that is, independent from the size of the price shock of 2005-2006. As a result, contaminating factors cannot explain these findings.

Figure 6: Changes in Treatment Intensity (Placebo Thresholds)



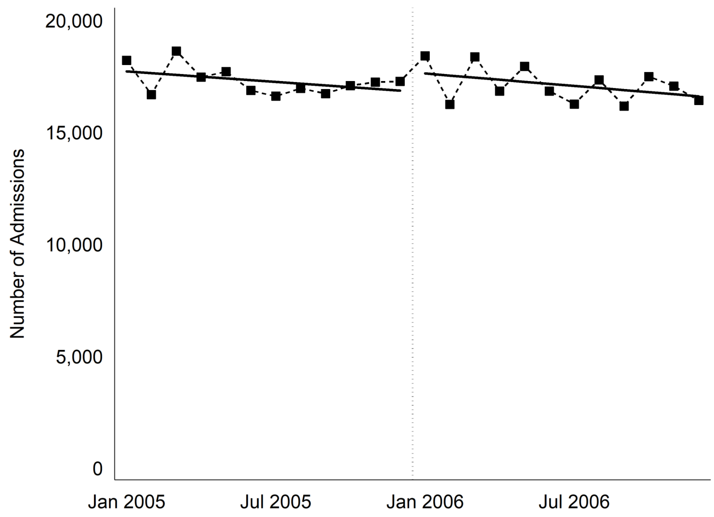
Note: This figure illustrates the results from the regression discontinuity estimates that estimate the share of admissions receiving high intensity treatment for each turn of the year between 2005 and 2014. The figure plots the estimated coefficients and 99-percent confidence intervals (y-axis) by the 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).

unlikely that hospitals are able to specifically attract or reject stroke patients, particularly in the short period after the price shock.

Figure 7 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 line 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 7 test, similar to McCrary (2008), whether hospitals "manipulate" admissions of stroke patients around the time of the price shock. Hospitals might not specifically attract or reject stroke patients in response to the price shock but rather "manipulate" the timing of the admission. The regression results confirm that the frequency of 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.

Figure 7: Changes in the Number of Admissions (Placebo Outcome)



Note: 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).

6.3 Announcement Effects and Learning Effects

This paper chooses a linear functional form primarily because there is no a priori reason to assume that the trends in treatment intensity, treatment appropriateness and the measures of quality are sensitive to a parametric linear functional form. Scanning the results in Section 5 Figure 3 and Figure 4 supports this assumption. Nonetheless, hospitals may have already responded to the announcements of changes in prices. 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 Gaynor et al. (2012), for example). Similarly, hospitals might require a significant amount of time to adapt to the new regulations (Clemens and Gottlieb, 2014). Given this, the results in this paper would underestimate the true effect of the price shock of 2005-2006 because the increase in treatment intensity in January 2006 would not capture the full effect if hospitals already altered treatment patterns prior to the price shock or if they require time to adapt to the new regulations.

However, anticipatory changes in hospital behavior before updated reimbursements become effective are unlikely in the empirical setting analyzed in this paper. The reason for this is that efforts and costs to switch to high-intensity stroke treatments are fairly low (e.g., ensure 24-hr 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. Economic theory predicts that, under these circumstances, hospitals will change their behavior only after updated reimbursements become effective (Farrell and Klemperer, 2007). Similarly, 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 needed investment or changes in management.

Table A.6 of appendix Section A.5 presents the results from higher order regression discontinuity models that allow the trend in the treatment intensity or treatment appropriateness to increase as a result of early responses or required learning.[27] Additionally, in order to even detect highly-granular, non-linear changes in treatment intensity and treatment appropriateness, Table A.7 and Table A.8 of the appendix Section A.5 increase the granularity of resolution and investigates weekly observations. 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.[28] 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 paper is that the observed increase in the documented high-intensity treatment 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), for example). As a reminder, regulating authorities introduce extra reimbursements for high-intensity treatment in the market for stroke disorder exclusively for admissions that report stroke as the primary diagnosis.[29] Hospitals might thus manipulate the primary diagnosis and switch a non-stroke primary diagnosis with a stroke secondary diagnosis. Moreover, hospitals might "upgrade" a clinically similar non-stroke primary diagnosis such as transient cerebral ischaemic 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

[27]We use parametric non-linear estimates such as polynomial regressions to test the robustness of the main results, as parametric estimates offer greater precision than potential nonparametric estimates such as local linear regressions.

[28]In addition, the main results presented in Section 5.1 suggest that changes in the trends of treatment intensity and treatment appropriateness from the period before to the period after the price shock are economically of minor importance. For example, the share of admissions receiving high-intensity treatment discontinuously increases by 6.8 percentage points at the time of the price shock, while the trend in the share of admissions receiving high-intensity treatment increases by approximately 0.2 percentage points each month after the price shock. In the event that the change in the trend in treatment intensity is indeed due to learning effects, the true effect of the introduction of marginal reimbursements in the market for stroke disorder would increase by about 35 percent within the first year after the price shock ($\frac{0.002\times12}{0.068} = 0.35$).

[29]Please see Section 4.1 for further details.

primary diagnosis of admission, and particularly of admissions that would already receive high-intensity treatment, 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 treatment 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.[30] 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, i.e., 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 non-stroke primary diagnosis with a stroke secondary diagnosis or "upgrade" a clinically-similar non-stroke 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 hospitals (i.e., hospitals that did provide high-intensity treatment in 2005) as well as inexperienced hospitals (i.e., hospitals that did not provide high-intensity treatment in 2005) increase the provision of high-intensity stroke treatments. As the provision of high-intensity treatment 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 treatment 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 computed tomography (CT) scans), early treatment (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 Section 5.3 additionally support the conclusion that the results in this paper are not explained by hospitals that manipulate the reporting of high-intensity treatment. The reason for this is that there is no obvious reason for hospitals to "fake" the provision of high-intensity treatment 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 treatment but did, in fact, already provide this treatment in 2005. It is unlikely, however, that this potential catch-up effect of single inadvertently non-reporting hospitals drives the results in this paper. Again, the results from Section 5 reveal that experienced hospitals (i.e., hospitals that

[30] Please see Section 4.1 for further details.

did provide high-intensity treatment in 2005) as well as technology-adopting hospitals (i.e., hospitals that did not provide high-intensity treatment in 2005) increase the provision of high-intensity stroke treatments. Hence, technology-adopting, inadvertently non-reporting 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 diagnosis-related groups (DRGs) promise to make hospitals bear the marginal costs of treatment. 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 paper 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 treatment (most notably extensive and early clinical diagnostics as well as early rehabilitative treatments), they receive, on average, an additional 2,200 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 treatment jumps by approximately 7 percentage points from December 2005 to January 2006. A simultaneous decrease in the average clinical appropriateness for patients receiving high-intensity treatment reveals that the marginal, newly high-intensity treated patient in 2006 is less appropriate for high-intensity treatment 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 (P4P) 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-incentivised procedures might be important determinants for the industrial organization of hospital markets.

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A Appendix

A.1 Appendix Empirical Setting

Minimum Requirements for High-intensity Treatment

Table A.1: Minimum Requirements for High-intensity Treatment

-	Treatment in a specialized stroke unit with a multidisciplinary team
-	24-hr attendance by a neurologist
-	24-hr monitoring of blood pressure, heart rate, respiration, oxygen saturation, body temperature, intracranial pressure and electroencephalography
-	Monitoring and documentation of neurological status every six hrs to detect progression or recurrence of stroke or other complications early
-	Cranial computed tomography within 6 hrs of admission or within 60 minutes after admission for patients who are likely to receive thrombolysis
-	Neurosonography/transcranial doppler sonography
-	Etiological and differential diagnosis via transesophageal echocardiography, hemostaseology, etc., within the hospital
-	24-hr availability of cerebral angiography
-	24-hr availability of thrombolysis
-	Immediate beginning of physiotherapy, ergotherapy, neuropsychiatric treatment, logopedics or other rehabilitative treatments, if necessary, at least once a day
-	Providing treatment for at least 24 hrs

Note: This table presents the full list of the specific services defined as high-intensity treatment that hospitals must provide to receive extra reimbursement for high-intensity treatment.
Source: German Institute for Medical Documentation and Information (DIMDI); Institut für das Entgeltsystem (InEK).

A.2 Appendix Theoretical Model

Corner Solution in Theoretical Model

Section 3 introduces a simple model of the stroke treatment decision in cases in which regulating authorities do not make reimbursements contingent on treatment intensity, as well as in those in which regulating authorities introduce extra reimbursements for high-intensity treatment. For the former, corner solutions are ruled out completely. For the latter, however, we demonstrate that where extra reimbursements are sufficiently large, a corner solution $z^r = \underline{s}$ in which hospitals provide high-intensity treatment to all patients is possible. The following paragraphs provide the formal proof for these results.

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

One corner solution in which hospitals only provide low-intensity treatment ($z = \overline{s}$) emerges if

$$\alpha b(\overline{s}, l) - c(\overline{s}, l) > \alpha b(\overline{s}, h) - c(\overline{s}, h) \tag{15}$$

Given the two assumptions that hospitals are sufficiently altruistic and that providing high-intensity treatment for the most appropriate patients $\overline{s}$ is cost efficient, the corner solution does not arise because the hospital's net benefit of high-intensity treatment is always higher than the hospital's net benefit of low-intensity treatment ($\alpha b(\overline{s}, l) - c(\overline{s}, l) < \alpha b(\overline{s}, h) - c(\overline{s}, h)$) when treating highly appropriate patients.

Another corner solution in which hospitals only provide high-intensity treatment ($z = \underline{s}$) emerges if

$$\alpha b(\underline{s}, l) - c(\underline{s}, l) < \alpha b(\underline{s}, h) - c(\underline{s}, h) \tag{16}$$

Given the two assumptions that hospitals are sufficiently altruistic and that providing high-intensity treatment for the least appropriate patients $\underline{s}$ is cost efficient, the corner solution does not arise because the hospital's net benefit of low-intensity treatment is always higher than the hospital's net benefit of high-intensity treatment ($\alpha b(\underline{s}, l) - c(\underline{s}, l) > \alpha b(\underline{s}, h) - c(\underline{s}, h)$) when treating low appropriate patients. This result would also be valid in the case of no altruism because $c(\underline{s}, h) > c(\underline{s}, l)$.

Scenario 2: Regulating authorities introduce extra reimbursements for high-intensity treatment

As reimbursements differ for high-intensity and low-intensity treatment, a corner solution in which hospitals only provide low-intensity treatment ($z = \overline{s}$) emerges if

$$\alpha b(\overline{s}, l) + p_l - c(\overline{s}, l) > \alpha b(\overline{s}, h) + p_h - c(\overline{s}, h) \tag{17}$$

As we assume that hospitals are sufficiently altruistic and that providing high-intensity treatment for highest appropriate patients $\overline{s}$ is cost efficient, the corner solution does not arise because the hospital's net benefit of high-intensity treatment is always higher than the hospital's net benefit of low-intensity treatment $\alpha b(\overline{s}, l) + p_l - c(\overline{s}, l) < \alpha b(\overline{s}, h) + p_h - c(\overline{s}, h)$ when treating highly appropriate patients. This result would also be valid in the case of no altruism if the reimbursement differentials are sufficiently high.

The corner solution in which hospitals provide only high-intensity treatment ($z = \underline{s}$) emerges if

$$\alpha b(\underline{s}, l) + p_l - c(\underline{s}, l) < \alpha b(\underline{s}, h) + p_h - c(\underline{s}, h) \quad (18)$$

With the assumption of altruism, if reimbursement differentials are sufficiently high, it is possible that the hospital's net benefit of high-intensity treatment is higher than the hospital's net benefit of low-intensity treatment for patients with the lowest appropriateness for high-intensity treatment. A corner solution in which hospitals only provide high-intensity treatment ($z^r = \underline{s}$) is therefore possible.

Decreasing Net Benefit

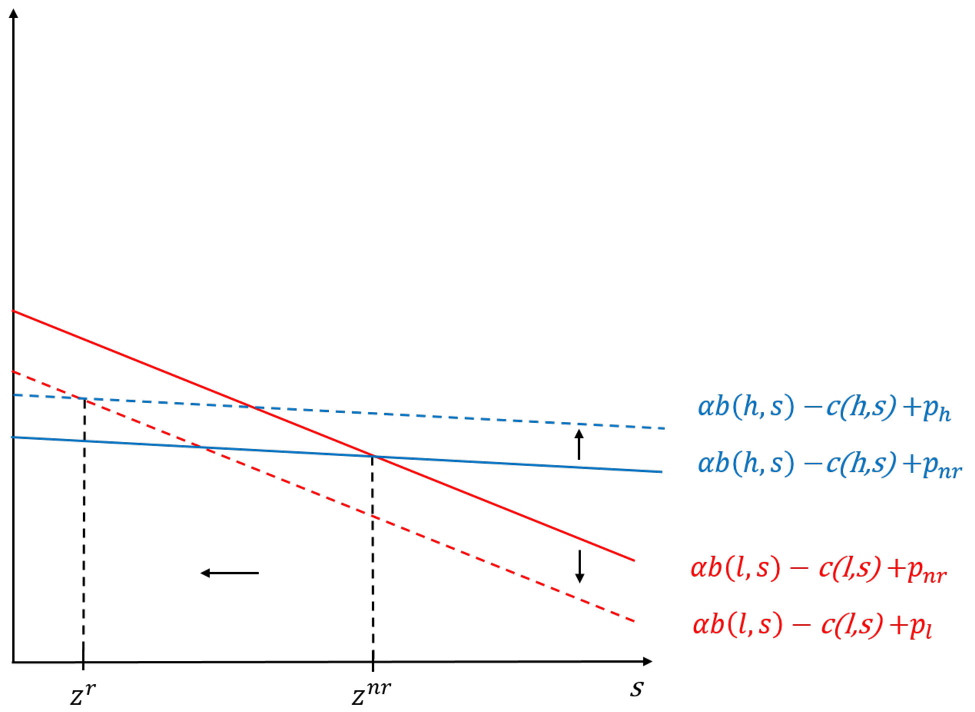
In section 3, Figure 1 assumes an increasing net benefit for hospitals. In contrast, Figure A.1 visualizes the scenario in which high-intensity treatment is net benefit decreasing. Similar to Figure 1, the solid red line and the dotted red line represent the decreasing net benefit function of low-intensity treatment in cases in which regulating authorities do or do not introduce extra reimbursements for high-intensity treatment. The solid blue line represents the decreasing net benefit function for high-intensity treatment in cases in which regulating authorities introduce extra reimbursements for high-intensity treatment, and the dotted blue line in cases in which regulating authorities do not introduce extra reimbursements for high-intensity treatment. The decreasing net benefit function of high-intensity treatment again begins below the net benefit function of low-intensity treatment because we assume cost-efficiency of low-intensity treatment for those cases with the lowest appropriateness for high-intensity treatment. As soon as regulating authorities introduce extra reimbursements for high-intensity treatment, the net benefit function of low-intensity treatment again shifts downwards by $p_{nr} - p_l$ and the net benefit function of high-intensity treatment shifts upwards by $p_h - p_{nr}$. This yields a downward shift of the cutoff point to z^r, meeting the FOC (10) or a corner solution in which hospitals only provide high-intensity treatment, even in the case of a net benefit decreasing high-intensity treatment.

A.3 Appendix Data

G-DRG Data (Extension)

G-DRG data cover all inpatient services in Germany. Only inpatient services in prison and military hospitals that do not treat civilians are excluded from G-DRG files. In Germany, hospital physicians are typically employed by the hospital. A small percentage of admissions, however, are treated by (often part-time) independent specialists that frequently run their own outpatient practices. Hospitals receive DRGs specifically calculated for treatments supplied by independent specialists, which only cover costs occurred by the hospital, not the independent billing specialist, and the independent specialist receives his or her reimbursement from the outpatient payment schedule. We constrain our analysis to

Figure A.1: Optimal Cutoff based on Net Decreasing Benefit



Note: This figure illustrates the change in the optimal cutoff point after regulating authorities introduce extra reimbursements for high-intensity treatment (interior solution). High-intensity treatment is assumed to be net-benefit decreasing.

admissions that are not treated by independent physicians.

List of ICD-10-GM Codes for Stroke

Table A.2: List of ICD-10 GM Codes for Stroke

G93.4	I60.6	I61.4	I62.09	I63.5	I66.4
G96.8	I60.7	I61.5	I62.1	I63.6	I66.8
I60.0	I60.8	I61.6	I62.9	I63.8	I66.9
I60.1	I60.9	I61.8	I63.0	I63.9	I67.0
I60.2	I61.0	I61.9	I63.1	I64	I67.10
I60.3	I61.1	I62.00	I63.2	I66.0	I67.11
I60.4	I61.2	I62.01	I63.3	I66.1	
I60.5	I61.3	I62.02	I63.4	I66.2	

Note: This table lists the ICD-10-GM codes used to define the market for stroke disorder.
Source: Institut für das Entgeltsystem (InEK).

Empirical Measure of Appropriateness

The estimation of the appropriateness to receive high-intensity treatment is based on three set of information: stroke specific symptoms non stroke-specific symptoms and administrative information. The German Stroke Society nicely summarizes stroke-specific symptoms in their guidelines (Schilling et al., 2008). The interested reader will find a list of all relevant ICD-10-GM codes used to measure stroke-specific symptoms in Table A.2. Non stroke-specific symptoms are measured using Elixhauser comorbidity groups as well as all other remaining 3-digit ICD-10-GM codes, based on the patients' primary diagnosis and secondary diagnoses (Elixhauser et al., 1998; van Walraven et al., 2009). Administrative information includes demographics such as the age and sex of patients, emergency indicators such as the reason, weekday and hour of admission and (seasonal) trends such as the week of the year of admission.

To train our model, we exclude admissions from inexperienced hospitals, that is, hospitals which have not yet adopted high-intensity treatment in 2005. We train our model based on a randomly-selected 90-percent training sample and 10-fold cross-validate our model (i.e., compute the out-of-sample estimates of the loss function) based on the remaining 10-percent test sample. The maximum depth of variable interactions is 10 and implies a model with up to 10-way interactions. The learning rate (or step-size reduction) is equal to 0.005. The fraction of the training set observations randomly selected to propose the next tree in the expansion is 0.5.

Stroke-Specific Symptoms

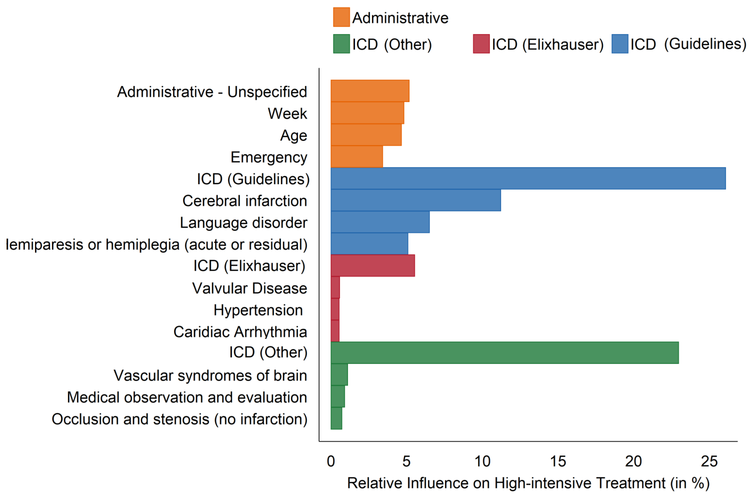
Table A.3: Stroke-specific Symptoms

Hemiparesis/hemiplegia	G81.0, G81.1, G81.9
Paraparesis/paraplegia and/or tetraparesis/tetraplegia	G82.00-G82.03, G82.09, G82.10- G82.13, G82.19, G82.20-G82.23, G82.29, G82.30-G82.33, G82.39, G82.40- G82.43, G82.49-G82.53, G82.59-G82.67, G82.69
Symptoms of the spinal cord	G83.0-G83.3, G83.40, G83.41, G83.49, G83.80, G83.88, G83.9, G95.83, G95.85, G95.88
Disorders with respect to consciousness, orientation, memory	R40.0-R40.2, R41.0-R41.3, R41.8, R55
Sensibility disorders	R20.0-R20.3, R20.8
Disorders related to walking, coordination and/or movement	R25.0-R25.3, R25.8, R26.0-R26.2, R26.8, R27.0, R27.8
Urinary incontinence/fecal incontinence	N31.0-N31.2, N39.40- N39.42, R33, R15
Swallowing disorders	R13.0, R13.1, R13.9
Decreased perception of odors and/or taste	R43.0-R43.2, R43.8
Perception disorder	R44.0-R44.3, R44.8, R29.5
Communication disorder/aphasia	R47.0, R47.1, R47.8, R49.0-R49.2, R49.8, R48.0- R48.2, R48.8
Impaired vision/blindness	H53.0, H53.2, H53.4, H54.4, H54.7, H58.1
Disorders with respect to motor abilities	U50.*
Cognitive disorders	U51.*
Focal epilepsy	G40.1, G40.2
Hypertension	I10.00, I10.01, I10.10, I10.11
Atrial flutter/atrial fibrillation	I48.00, I48.01, I48.10, I48.11
Peripheral arterial disease	I70.0, I70.20-I70.25, I70.8, I70.9
Diabetes mellitus	E10.*, E11.*
Obesity and related diseases	E66.0, E66.1, E66.8 , E78.0,E78.1, E78.2, E78.8, E79.0
Other diseases of the brain/nervous system	G93.4, G96.8
Infarction of precerebral or cerebral arteries	I63.0-I63.9, I64, I66.0, I66.1, I66.2, I66.4, I66.8, I66.9
Diseases or dissection of brain-supplying vessels	I67.0, I67.10, I67.11
Brain hemorrhage	I60.0-I60.9, I61.0- I61.9, I62.00-I62.02, I62.09, I62.1, I62.9

Note: This table provides a list of all relevant ICD-10-GM GM codes used to measure stroke-specific symptoms as summarized by the German Stroke Society in their guidelines (Schilling et al., 2008).
Source: German Stroke Society.

Relative Influence of Predictors

Figure A.2: Relative Influence of Predictors



Note: This figure presents the relative influence of predictors used to achieve the empirical measure of appropriateness. Estimates come from a boosted logistic regression that explains the observed, actual treatment intensity using a set of patient characteristics based on observations from the year 2005, i.e., a setting where extra reimbursements are independent from marginal changes to treatment intensity.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

A.4 Appendix Results

Spillover Effects

Table A.4: Spillover Effects

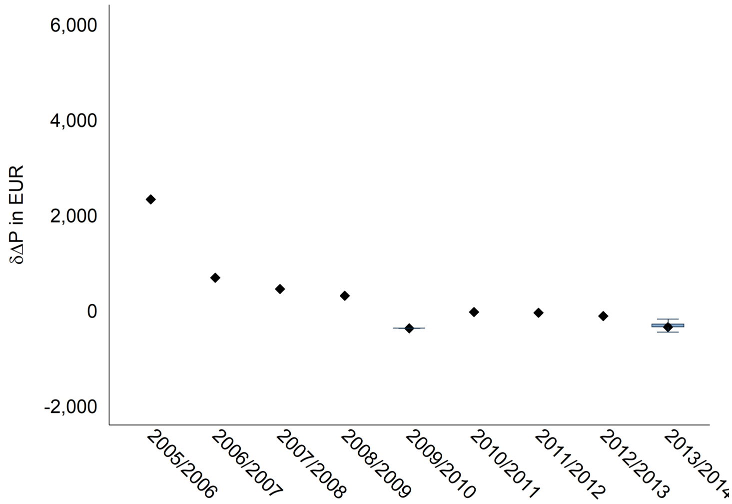
	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Average Treatment Intensity			Average Appropriateness	
Hospital Group	All Hospitals	Inexperienced Hospitals	Experienced Hospitals	Experienced Hospitals	Experienced Hospitals
Patient Group	All Patients	All Patients	All Patients	High-intensity Treatment	Low-intensity Treatment
T	0.039***	0.019***	0.056***	-0.177***	-0.048***
	(6.54)	(4.26)	(5.44)	(20.60)	(13.40)
$\tilde{Month}$	0.003***	0.000	0.006***	0.009***	0.004***
	(4.92)	(0.96)	(4.88)	(8.41)	(11.00)
$T \times \tilde{Month}$	-0.001	0.002***	-0.003	0.004***	-0.001
	(0.90)	(3.34)	(1.73)	(3.53)	(1.16)
Adjusted R^2	0.683	0.464	0.575	0.417	0.466
Hospitals	1,456	1,168	288	288	288
Observations	22,393	16,214	6,179	3,897	5,966

Note: This table reports the regression discontinuity results as described in Section 4.2 for our specific group of stroke patients. Average Treatment Intensity is the monthly share of admissions that receive high-intensity stroke treatments between 2005 and 2006. Average Appropriateness is the monthly average appropriateness of receiving high-intensity stroke treatments by type of observed, realized treatment (high-intensity treatment and low-intensity treatment). T denotes a binary indicator for the months following the introduction of extra reimbursements for high-intensity treatment (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: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

A.5 Appendix Robustness

Placebo Thresholds

Figure A.3: Distribution of Change in Differential Reimbursement by Turn of Year (in EUR)



Note: This figure summarizes, by the turn of year, the distribution of the change in differential reimbursement. Dark blue diamonds depict the median of the change in differential reimbursement $\delta\Delta P$. 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 (if applicable). 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). DRG weights (relative prices) include outlier payments. Reimbursements are normalized using the federal-level base rate from 2006 ($2,804.09$ EUR) and presented in EUR.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

Table A.5: Regression Discontinuity Results (Placebo Thresholds)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	Average Treatment Intensity								
Patient Group	2005/ 2006	2006/ 2007	2007/ 2008	2008/ 2009	2009/ 2010	2010/ 2011	2011/ 2012	2012/ 2013	2013/ 2014
T	0.068***	-0.037***	-0.011*	-0.010*	-0.009*	-0.002	-0.014**	-0.012**	-0.005
	(8.18)	(6.08)	(2.17)	(2.34)	(2.36)	(0.53)	(3.16)	(3.19)	(1.22)
$\tilde{Month}$	0.005***	0.006***	0.005***	0.004***	0.002***	0.002***	0.001	0.002***	0.002***
	(6.08)	(8.78)***	(6.49)	(6.53)	(6.13)	(4.50)	(1.83)	(3.79)	(4.40)
$T \times \tilde{Month}$	0.002	-0.001	-0.000	-0.001	-0.000	-0.001	0.001	0.001	-0.002*
	(1.60)	(0.98)	(0,43)	(1.86)	(0.87)	(1.53)	(1.38)	(1.06)	(2.40)
Adjusted R^2	0.801	0.888	0.910	0.933	0.953	0.955	0.953	0.952	0.947
Hospitals	1,456	1,420	1,389	1,376	1,356	1,355	1,342	1,367	1,404
Observations	30,993	30,368	29,645	29,060	28,382	27,737	27,109	26,385	26,184

Note: This table reports the regression discontinuity results as described in Section 4.2 for each turn of the year between 2005 and 2014. Average Treatment Intensity is the monthly share of admissions that receive high-intensity stroke treatments. T denotes a binary indicator for the months following the turn of each year. Month denotes the month of admission, centered at the month at the turn of the year 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: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

Announcement Effects and Learning Effects

Table A.6: Higher-order Regression Discontinuity (Monthly)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Average Treatment Intensity		Average Appropriateness			
Hospital Group	All Hospitals		Experienced Hospitals		Experienced Hospitals	
Patient Group	All Patients		High-intensity Treatment		Low-intensity Treatment	
T	0.060***	0.050***	-0.171***	-0.201***	-0.093***	-0.114***
	(7.05)	(5.67)	(30.68)	(29.06)	(42.49)	(36.87)
$\widetilde{Month}$	0.001	0.006*	0.003	0.015***	0.002***	0.010***
	(0.73)	(2.21)	(1.56)	(4.59)	(4.20)	(8.95)
$\widetilde{Month}^2$	-0.000	0.001	-0.001***	0.002***	-0.000**	0.001***
	(1.94)	(1.37)	(4.59)	(3.37)	(11.31)	(6.04)
$\widetilde{Month}^3$		0.000		0.000***		0.000**
		(1.84)		(4.32)		(8.54)
$T \times \widetilde{Month}$	0.011***	0.011*	0.019***	0.023***	0.009***	0.013***
	(3.99)	(2.07)	(9.89)	(5.01)	(11.88)	(6.37)
$T \times \widetilde{Month}^2$	-0.000	-0.002*	-0.000	-0.006***	0.000	-0.004***
	(0.62)	(2.28)	(1.31)	(7.23)	(1.58)	(9.42)
$T \times \widetilde{Month}^3$		-0.000		-0.000	0.000	
		(0.39)		(0.55)		(0.16)
Adjusted R^2	0.792	0.792	0.631	0.634	0.582	0.584
Hospitals	1,456	1,456	288	288	288	288
Observations	30,993	30,993	5,076	5,076	6,602	6,602

Note: This table presents the results from regression discontinuity estimates that allow the trend in the treatment intensity or treatment appropriateness to increase as a result of the announcement or required learning. T denotes a binary indicator for the months following the introduction of extra reimbursements for high-intensity treatment (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: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

Table A.7: Regression Discontinuity (weekly)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable		Average Treatment Intensity		Average Appropriateness	
Hospital Group	All Hospitals	Inexperienced Hospitals	Experienced Hospitals	Experienced Hospitals	Experienced Hospitals
Patient Group	All Patients	All Patients	All Patients	High-intensity Treatment	Low-intensity Treatment
T	0.067***	0.038***	0.096***	-0.157***	-0.093***
	(8.15)	(4.48)	(6.83)	(35.87)	(-31.92)
$\tilde{Week}$	0.001***	0.000**	0.002***	0.002***	0.002***
	(6.26)	(2.77)	(6.70)	(18.05)	(24.85)
$T \times \tilde{Week}$	0.000	0.001***	-0.000	0.000*	-0.000
	(1.61)	(5.45)	(0.44)	(2.12)	(0.47)
Adjusted R^2	0.712	0.498	0.553	0.418	0.251
Hospitals	1,456	1,168	288	288	288
Observations	106,183	77,572	28,274	19,789	26,265

Note: This table reports the regression discontinuity results as described in Section 4.2 on a weekly basis instead of aggregating the data on the month level. Average Treatment Intensity is the weekly share of admissions that receive high-intensity stroke treatments between 2005 and 2006, Average Appropriateness is the weekly average appropriateness of receiving high-intensity stroke treatments by type of observed, realized treatment (high-intensity Treatment and low-intensity Treatment). T denotes a binary indicator for the weeks following the introduction of extra reimbursements for high-intensity treatment (year 2006). $\tilde{Week}$ denotes the week of admission, centered at the week of the price shock (first week 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: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

Table A.8: Higher-order Regression Discontinuity (weekly)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Average Treatment Intensity		Average Appropriateness			
Hospital Group	All Hospitals		Experienced Hospitals		Experienced Hospitals	
Patient Group	All Patients		High-intensity Treatment		Low-intensity Treatment	
T	0.061***	0.048***	-0.170***	-0.206***	-0.092***	-0.118***
	(7.24)	(5.64)	(31.48)	(33.57)	(42.41)	(40.86)
$\tilde{Week}$	0.000	0.002*	0.001	0.004***	0.000**	0.003***
	(0.49)	(2.64)	(1.73)	(5.84)	(3.02)	(9.97)
$\tilde{Week}^2$	-0.000*	0.000*	-0.000***	0.000***	-0.000***	0.000***
	(2.14)	(1.97)	(4.38)	(4.28)	(11.74)	(7.72)
$\tilde{Week}^3$		0.000*		0.000***	0.000***	
		(2.45)		(5.14)		(10.22)
$T\times\tilde{Week}$	0.003***	0.002*	0.004***	0.006***	0.002***	0.003***
	(4.23)	(1.97)	(10.01)	(6.32)	(12.86)	(6.72)
$T\times\tilde{Week}^2$	-0.000	-0.000**	-0.000*	-0.000***	0.000*	-0.000***
	(0.62)	(2.97)	(2.06)	(9.66)	(1.97)	(12.14)
$T\times\tilde{Week}^3$		0.000		-0.000	0.000	
		(0.59)		(0.34)		(0.68)
Adjusted R^2	0.712	0.712	0.427	0.430	0.325	0.327
Hospitals	1,456	1,456	288	288	288	288
Observations	106,183	106,183	19,789	19,789	26,265	26,265

Note: This table presents the results from regression discontinuity estimates that allow the trend in the treatment intensity or treatment appropriateness to increase as a result of the announcement or required learning. The outcome variables are aggregated at the week level instead of the month level. T denotes a binary indicator for the weeks following the introduction of extra reimbursements for high-intensity treatment (year 2006). Week denotes the week of admission, centered at the week of the price shock (first week 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: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.
Source: G-DRG data is available at the Federal Statistical Office (Data Research Center).

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