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ABSTRACT

Hospital Resources: Persistent Reallocation under Price Changes

Changes in medical expenses may force hospitals to reallocate their resources, which potentially come at the detriment of healthcare quality. Using data on the universe of German hospitals, I investigate resource reallocations between capital stock, human resources, services and the organizational structure in case of reform-induced treatment price shocks at the hospital level. To identify a causal effect, I develop a unique identification strategy where I exploit hospitals' exposure to snowfall. A particularity of the reform led to exogenous treatment price shocks at hospital level in response to weather-induced excess of patients. The results show that higher prices induce hospitals to hire more physicians and nurses and encourage fewer mergers and privatization and less closures while not affecting the capital stock. In addition, hospitals become less specialized and reduce their treatment volume. These effects persist long after the treatment price shocks have vanished.

JEL Classification: I11, L10, L21

Keywords: hospital care, DRG, management

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1 Introduction

In the past decades, healthcare spending in OECD countries has increased massively and reached 4,069 $ per capita in 2017, exceeding spending on education by 70 percent. Hospitals have become the main providers of healthcare services (OECD, 2018). At the same time, large-scale reallocation processes of hospital resources have been observed. The number of cases and treatments increases dramatically, while the number of input factors such as nursing staff remains relatively constant. Understanding the effect of changes in healthcare spending on the reallocation of hospital resources is important because hospital resources are crucial for the quality of healthcare (Needleman et al., 2002). However, the impact of healthcare spending on hospital resources has been debated in a so far inconclusive literature (Sloan and Hsieh, 2017).

If hospital healthcare spending changes, hospitals can adjust along three resource dimensions. First, they can adjust input factors such as nurses or physicians to save costs or increase productivity. Second, hospitals can adjust output factors such as the variety or volume of treatments, thereby realizing economies of scale or turnover increases. Third, hospitals could change their ownership structure by merging or privatizing to minimize transaction costs. In the worst case, they have to be closed (Guterman and Dobson, 1986).

In this paper, I show how hospitals reallocated resources between 2006 and 2016 due to exogenous general treatment price shocks between 2005 and 2010. The analysis is based on panel data from the universe of German hospitals, which offers a unique abundance of hospital resource information. For identification, I use the introduction of the German Diagnosis Related Groups (G-DRG-System). Diagnosis Related Groups have been implemented worldwide (Busse and Quentin, 2011). The G-DRG-Reform led to general idiosyncratic treatment price shocks for hospitals, but did not alter relative treatment prices for different types of care or groups of patients. This is an advantage to reforms used in most of the literature, which are based on relative treatment price shocks (see, for example, Dafny (2005); Acemoglu and Finkelstein (2008); Clemens and Gottlieb (2014)). Furthermore, I rely on plausible exogenous variation in treatment prices, which is ensured by a novel identification strategy. I exploit days of snow in hospitals catchment areas, which led to exogenous treatment price shocks at hospital level in response to weather-induced excess of patients due to a particularity of the G-DRG-Reform. I focus on the reallocation of human resources, capital stock as well as changes in services offered and the organizational structure. This allows me to simultaneously analyze underlying hospital preferences for input and output factors under general treatment price shocks.

The implementation of the G-DRG-System in 2004 caused continuous idiosyncratic treatment price shocks at the hospital level between 2005 and 2010. Starting with hospital individual prices in 2004, prices converged to the federal state average until 2010. Some hospitals were exposed to price increases, while others experienced price reductions. The variation in price shocks was large. Due to strong price decreases, many hospitals encountered economic difficulties and an increasing risk of economic default, especially those in public ownership (Klauber et al., 2018).

From 2010 onwards, treatment price shocks only varied at the federal state level, enabling a novel study of long-term effects of price shocks after price shocks vanish. The G-DRG-Reform enhanced treatment price decreases and mitigated treatment price increases between 2005 and 2010 for individual hospitals if its number of in-patient[1] cases in 2004 was higher and more severe than in 2003 compared with other hospitals in a federal state.

Treatment price rice shocks of the G-DRG-Reform are endogenous to the allocation of hospital resources, for several reasons. First, they reflect historic cost structures, which might correlate with resource allocations after the G-DRG-Reform. Second, hospitals were able to manipulate treatment price shocks in 2004 by shifting in-patient cases. In order to avoid that the results are driven by unobserved heterogeneity, I instrument treatment price shocks by exploiting idiosyncratic changes of weather conditions between 2003 and 2004 in hospital catchment areas. This approach is based on unique high-resolution satellite data of population-weighted exposure to the number of yearly days of snow and road network data, which I link to the hospital location. Unlike other datasets, the hospital panel data in this study has information about the exact hospital location. Days of snow have a strong positive impact on the number of cost-intensive hospital admissions, easily doubling the number of related admissions in winter months (Franklin et al., 1995). I focus on general hospitals, which usually treat snow related admissions. Germany is an interesting case for this novel identification strategy due to its changeable weather conditions, which makes it difficult for people to avoid accidents by adjusting their behavior. First-stage results reveal a strong correlation between changes in the number of days of snow and hospital individual treatment prices, driven by snow-related admissions.

The results of the paper show that treatment price shocks significantly affect hospital resources. Effects of price shocks are linear, which is why the G-DRG-Reform leads to a polarization of health-care. Treatment volumes are negatively and ranges of treatments are positively associated with price shocks. Hospitals significantly reallocate their resources towards smaller treatment volumes and an extended range of treatments if prices increase, which indicates supplier-induced demand. However, as the G-DRG-Reform reduced treatment prices for a large share of hospitals, supplier-induced demand counteracts saving affords and negatively affects public health. The correlation between treatment price shocks and the number of employed nurses and physicians is positive. Treatment price reductions decrease the nurse to patient ratio and the physician to patient ratio, possibly to the detriment of patients' health (Aiken et al., 2002). The stock of capital is unaffected by treatment price shocks. These effects tend to be persistent, even if idiosyncratic treatment price shocks vanish after 2010. Structural differences in pre-treatment characteristics lead to heterogeneous effects. For instance, private and small hospitals are more strongly affected. Furthermore, treatment price shocks affect the organizational structure of a hospital by being negatively associated with the probability of mergers, privatization and closures. IV estimates show that OLS results are biased towards zero in almost all dimensions, indicating endogenous price shocks.

[1] Treatments that require at least one overnight stay

This paper adds to several strands of the literature. By analyzing the effect of universal treatment price shocks on input factors, it adds to the literature of Finkelstein (2007), Acemoglu and Finkelstein (2008) and Clemens and Gottlieb (2014), finding responses to medical investment decisions for capital and human resources based on relative price shocks. Furthermore, by focusing on the range of treatments and the treatment volume, this paper adds to the literature showing a clear link between relative price shocks and the range and volume of treatments (Rice, 1983; Yip, 1998; Dafny, 2005; Clemens and Gottlieb, 2014). By exploting the G-DRG-Reform as well, Salm and Wübker (2015, 2018) show that general treatment price shocks affected the number of treatments and input factors, while not affecting the quality of care. By examining changes in organizational structures, I complement the work of Krishnan (2001) and Gowrisankaran et al. (2015), who show a clear positive relationship between relative price increases and the probability of changes in the organizational structure of hospitals. Compared to these studies, I simultaneously focus on input and output factors and on the organizational structure while relying on plausibly exogenous variation in general treatment prices. Further, I analyze persistent patterns in the reallocation of hospital resources even when treatment price shocks vanish.

The remainder of this paper is structured as follows. In section 3.2, I provide background information about the G-DGR-Reform and the datasets. Section 3.3 describes the empirical strategy, followed by the empirical analysis in section 3.4 Section 3.5 concludes.

2 Institutional Background and Data

2.1 The German Diagnosis Related Groups Reform

The implementation of the G-DRG-System caused massive changes in the way hospitals set their treatment prices. Like in many countries, German hospitals set their treatment prices based on the full costs of services in a fee-for-service payment system (FFS) with few restrictions. Whereas in DRG-Systems prices are fixed for given diagnoses, prices in FFS are not fixed and depend on the treatments a patient received. In the German FFS, at the end of each year, hospitals negotiated with relevant health insurance companies[2] about their next year's treatment prices, considering the present cost structure and the hospitals' supply mandate for the following year. In the following year, hospitals could deviate from the agreed service quantity. Additional costs were compensated if medically justified.

In contrast to other countries, the G-DRG-System was planned as a universal price system. The healthcare reform[3] in 2000 asked the relevant self-governing bodies at the federal level to implement an extensive DRG-System for hospitals until January 1, 2003. In 2003, hospitals optionally chose between the old FFS and the new DRG-System. From 2004 onwards, the new system was mandatory and it remains in place until today. However, the DRG-System in 2003 and 2004 was

[2]With those health insurance companies that covered >= 5 percent of the cases in a hospital in the previous year.

[3]GKV-Gesundheitsreformgesetz

"budget-neutral" as the new and old systems co-existed, giving hospitals the possibility to become familiar with the new accounting procedures. The budget was still negotiated as before, although costs were accounted according to the new system. The G-DRG-System applies to almost all patients, regardless of whether or not they are members of the statutory health insurance system, private health insurance, or self-paying patients. It further applies to all hospitals including all clinical departments with the exception of institutions or facilities providing psychiatric, psychosomatic medicine or psychotherapy services (Fürstenberg et al., 2013). After the reform, more than 95 percent of the hospital budget was reimbursed according to the G-DRG-System (Klauber et al., 2011).

Treatment prices in the G-DRG-System are set as in other DRG-Systems. Since 2004, treatment prices under the G-DRG-System have been based on the following formula

$$price_{iht} = drg_{it} \times baserate_{ht}, \tag{1}$$

where drg_{it} (G-DRG) is the cost-weight factor for a diagnose i in year t, while $baserate_{ht}$ refers to the base rate for a hospital h in year t, which acts as a baseline. The Institute for the Hospital Remuneration System calculates levels for each G-DRG, representing the average estimated costs for given diagnoses at national level. G-DRGs are meant to cover the medical treatment, the provision of pharmaceuticals and therapeutic appliances, nursing care, food and accommodation. In contrast to other countries, G-DRGs do not cover capital costs. Officially, federal states should pay for investments (Herr et al., 2011).

The base rate in the G-DRG-System is set in a unique way. The aim of the reform was to equalize treatment prices within federal states. Usually, DRG-Systems in other countries account for structural hospital differences by hospital specific base rates, which equal yearly average treatment costs per case for each hospital (Schreyögg et al., 2006). Hospital specific base rates were only temporarily implemented in Germany and since 2010 only vary at the federal state level. Hospital-specific base rates were calculated by dividing the hospital's 2004 budget – which was negotiated at the end of 2003 based on the old accounting system – by the 2004 case mix.[4] The case mix is part of the new accounting system, reflecting the yearly number of in-patient cases weighted by their severeness. In 2004, hospital base rates considerably varied, ranging from less than 1,000 € to more than 10,000 €, reflecting huge differences in hospital cost structures. Hospitals with different structures than the average in a federal state might not be able to replicate average treatment costs. In order to mitigate reform effects, a convergence phase was implemented from 2005 until 2010, in which hospital-specific base rates of 2004 converged to the average hospital base rate of the federal state (Figure 1a). The federal state-specific base rate was calculated for each year starting in 2004, based on the accumulated budgets of all hospitals in a federal state divided by their accumulated case mixes. Hospital base rates were then gradually reduced or increased to the federal base rate.[5] Thus, the G-DRG-Reform enhanced treatment price decreases and mitigated treatment price

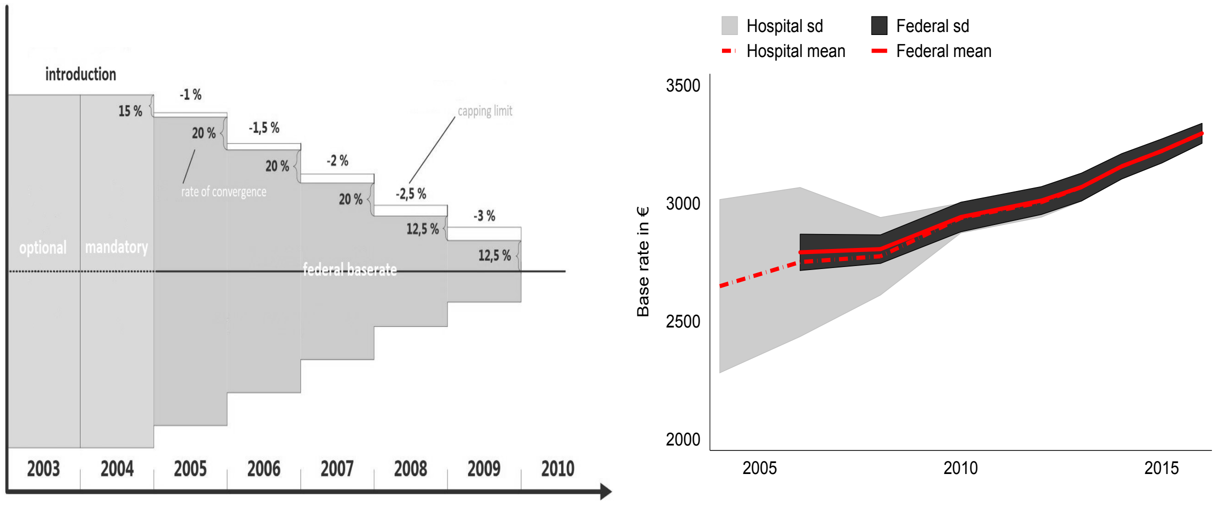
[4]case mix = in-patient cases $\times$ case mix index. The case mix index is a hospital specific weighting factor for the average severeness of yearly admissions

[5]A capping limit between one and three percent of the hospitals' budget was implemented for those hospitals with

increases between 2005 and 2010 for an individual hospital if the number of inpatient cases in 2004 was higher an more severe than in 2003 compared with other hospitals in a federal state. Originally, the convergence phase should have ended in 2009 but was prolonged until 2010 as many hospitals faced financial difficulties. The development of the actual federal and hospital base rate is shown in Figure1b, indicating the effectiveness of the reform. From 2010 onwards, base rates only varied at the federal state level.

However, treatment price shocks in the G-DRG-System are potentially endogenous. The convergence phase was intended to allow hospitals to adjust structures over time. Thus, price shocks reflect historic resource allocations. For example, Figure 6 in Appendix A shows a strong correlation between the number of beds as well as the number of physicians with the hospital base rate of 2004. Lower base rates in 2004 are a signal of efficiency. However, more efficient hospitals might adjust hospital resources more strongly to treatment price shocks in the convergence period if they are more flexible than inefficient hospitals. This would bias the results towards zero. Furthermore, hospitals had an incentive in reducing the case mix of 2004 to increase their base rate, or in other words to improve their starting position of the convergence phase, regardless of whether they were above or below the federal base rate. In fact, Figure 7 in Appendix A shows a strong decline in in-patient cases in 2004 – which reduced the case mix – followed by an immediate recovery. Hospitals that adjust the number of in-patient cases more strongly in 2004, might be those hospitals that adjust hospital resources stronger in the convergence phase. Estimates would be upward biased. Ex ante, it is unclear whether the results are upward biased by the adjustment of in-patient cases in 2004 or biased towards zero by correlations between previous resource allocation and resource reallocations in the convergence phase.

decreasing base rates. Base rate harmonization could only lead to yearly reductions in hospital budgets within these capping limits. Such capping limits were not in place for hospitals whose base rates increased. This increased the overall hospital budged and the federal baserate (Fürstenberg et al., 2013).



(a) Convergence phase (b) Actual base rate

Figure 1: Base rate development over time

Notes: These graphs display (1a) the planned convergence of hospital base rates in the federal state and (1b) the actual convergence of hospital base rates cross Germany. Source: AOK

2.2 Mechanisms

This section highlights relevant hospital resources that are prone to external treatment price shocks. The selection of relevant resources is based on the assumption that hospitals try to maximize profits by adjusting input and output factors and the organizational structure to realize the efficient use of resources, higher intensity and improvements in productivity (Hodgkin and McGuire, 1994; Epstein and Mason, 2006; Sánchez-Martínez et al., 2006).

Input factors. The provision of hospital treatment involves utilizing a variety of different inputs during the production process, especially human resources and stock of capital. The most important input factor in a hospital is human resources, especially the number of physicians and nurses, with strong positive implications for hospitals productivity (Needleman et al., 2002; Unruh, 2003). However, labor is the most important cost factor, characterized by high variation between staff categories (Saltman and Figueras, 1998). This makes it very likely that human resources are positively associated with treatment price shocks. The same also applies to the stock of capital. Substantial capital investments hold increasing interest for medical suppliers (Levin et al., 2008) due to their strong positive impact on productivity. Capital-intensive investments like MRI scanners are likely to be amplified by treatment price shocks as they come with negligible marginal costs. (Clemens and Gottlieb, 2014).

Output factors. While input factors are major leverages, hospitals could try to increase their efficiency by portfolio adjustments towards higher treatment volumes and narrower treatment ranges to realize economies of scale (Farsi and Filippini, 2008). Medical providers can indirectly drive the quantity of their patients' healthcare due to the consumers' lack of information about treatment options (Arrow, 1978). The benefits of adhering to ethical and medical standards are weighted against the benefits of higher revenues, leading to the counter-intuitive prediction that medical providers will supply a reduced treatment volume and a narrower treatment range if treatment prices increase (Evans, 1974; McGuire, 2000). Especially, if health insurance diminishes or eliminates price sensitivity (Feldstein, 1973). As health insurance is statutory in Germany and fully covers hospital stays, it is reasonable that treatment price shocks do not directly affect demand but rather indirectly via supplier-induced demand.

Organizational structure. The hospital ownership is an important characteristic in the context of treatment price shocks, especially in Germany where many hospitals have been privatized in the last two decades. Public hospitals finance around 50 percent of their investments themselves. Officially federal states are responsible for such investments, although they are unable to comply with the duty due to financial distress. Moreover, many municipalities – which are typically the owners of public hospitals – are financially constrained (Augurzky et al., 2010). Hospitals can change the organizational structure as response to treatment price shocks to realize cost savings through mergers or privatization (Chalkley and Malcomson, 2000; Kristensen et al., 2010; Herr et al., 2011). If hospital produce at above average costs and do not realize cost savings or revenue increases, hospitals have to close (Klauber et al., 2018). This makes it likely that privatizations, mergers and closures are negatively associated with treatment price shocks.

2.3 Data and Descriptive Statistics

For the analysis of treatment price shocks on resource allocation, I link panel data of the universe of hospitals in Germany with high-resolution satellite data and routing data. In this section, I describe the construction of the dataset and present descriptive statistics. Most of the hospital dataset equals the dataset used in Pestel and Wozny (2019). Thus, I limit the construction of the dataset to the parts that differ from Pestel and Wozny (2019).

Hospital quality report data comprise hospital characteristics like the number of beds and ownership structure as well as detailed information about services offered, the stock of employees and special equipment between 2006 and 2016. A detailed explanation of the dataset can be found in Pestel and Wozny (2019). I restrict the dataset to general hospitals with at least a unit for internal medicine and a surgery unit which are plausibly affected by snow induced demand shocks. Thus, I exclude special hospitals like hospices, wellness clinics, rehabilitation centers etc. resulting in around 1,100 hospitals per year (see Figure 5 in Appendix A). I will use special hospitals for the robustness check. Furthermore, I can only use hospitals which already existed in 2004, resulting in 8,626 hospital-year observations. I supplement the quality reports with the German Hospital Directory[6] to have information about hospital locations and basic hospital characteristics before 2006, provided by the Federal Statistical Office. Having data about hospital locations before 2006 is essential for the IV, as it is based on hospital catchment areas in 2003 and 2004.

Base rate deviation. Information about hospital and federal base rates is provided by the Federal Association of the AOK, a representative of the interests of many local health insurance companies in Germany. The main regressor of interest $(br_{ft_{2004}} - br_{it_{2004}})$ is the deviation between the federal base rate in 2004 $(br_{ft_{2004}})$ and the hospital base rate in 2004 $(br_{it_{2004}})$, which determines treatment price shocks in the following years.

Hospital catchment areas are assigned based on hospitals' locations since the hospital quality report data does not provide information on the residence of patients. Catchment areas are based on driving time and calculated as in Pestel and Wozny (2019) where a detailed explanation of the catchment area calculation can be found.

Snow data. Hospitals' exposure to days of snow is assigned by overlaying snow fall grids with the hospital catchment areas and the GEOSTAT population grid dataset. The snowfall data is part of the Global Snow Pack dataset and is provided by the German Aerospace Center. Since 2000, it has measured the daily existence of snow on the ground at a 500 $\times$ 500 meter resolution based on satellite imaging (Dietz et al., 2015). Figure 9a in Appendix B shows a strong variation in days of snow over time, which is also true between consecutive years within catchment areas across Germany (Figure 9b in Appendix B). The GEOSTAT population grid dataset is provided by EUROSTAT and measures the population density at a 1,000 $\times$ 1,000 meter resolution based on satellite imaging in 2006 and 2011.

To have an intuition on how the instrument is constructed, Figure 10 in Appendix B shows the assignment procedure for the city of Bonn. Using snow grids, average days of snow are calculated for each hospital catchment area. Grids are weighted by their share that is within a catchment area, assuming that the distribution within a grid is constant. In order to account for heterogeneity in catchment areas, grids are additionally weighted by the population density shown in Figure 11 in Appendix B. The population weighting factor is a continuous variable that equals zero if the population is zero and one in case of population maximum. The resulting average of those weighted grids within a catchment area is used as the yearly hospital's yearly exposure to days of snow.

Descriptive statistics. Table 1 displays the descriptive statistics for the main variables used in the regression. Panel A shows substantial variation in the characteristics of hospitals. The number of

[6] Verzeichnis der Krankenhäuser und Vorsorge- oder Rehabilitationseinrichtungen in Deutschland

beds ranges from 4 to 3,001 and the number of in-patient cases from 77 to 198,452, revealing that the definition of a hospital is independent of its size but rather a legal concept based on permanent availability and equipment. Non-profit and public hospitals account for 43 and 40 percent in the data set. About 17 percent of the general hospitals in the data set are private. However, private hospitals in Germany are obliged to provide the same health services to the same conditions as non-private ones.[7] Between 2006 and 2016, 9 percent of the hospitals were involved in mergers but only 2 percent closed. Panel A in Figure 8 in Appendix A shows a constant increase in the share of private, merged and closed hospitals over time.

Panel B in Table 1 lists indicators related to the quantity of human resources and special equipment such as CT or MRT scanners. The annual full-time equivalent staff of physicians and nurses is around 64 and 170, respectively. The average number of special equipments is around 80. This reflects the structure of the German hospital sector, characterized by a large number of relatively small hospitals. Panel C shows hospital output factors. The average number of yearly medical treatment volume is 15,434, ranging from 84 to 197,987. The treatment range – expressed by the number of different medical services categories such as transplantations – is 87 on average. Panels B and C in Figure 8 in Appendix A show that input and output factors increase over time. However, increases in output factors are much stronger.

Panel D in Table 1 shows a substantial variation in the base rate deviation between federal and hospital base rates in 2004, ranging from -3,534 € to 1,666 €. This is unsurprising given the strong variation in hospital characteristics, which makes it more difficult for hospitals to replicate average costs. Strong variation also applies to the instrument in Panel E, ranging between -32 and 82 population weighed days of snow, whereby the mean is around 24 days. It reveals a sizable change in exposure to days of snow across hospitals, which can be attributed to the mild and changeable weather conditions in Germany (see Panel E) and the heterogeneous distribution of hospitals.

Municipality characteristics of hospital locations in Panel F are provided by the Federal statistical Office, confirming the heterogeneous distribution of hospitals across Germany. For example, while the smallest municipality has 4,000 inhabitants, the largest has 3.5 million inhabitants.

[7] Three types of hospital ownership are defined by German Law: public, owned by the state a federal state or a municipality; non-profit, owned by non-profit associations like the Red Cross or institutions of the church and private hospitals, which primarily aim to make profit by individuals or legal entities (Wissenschaftliche Dienste, 2014)

Table 1: Descriptive statistics of hospital characteristics

	Mean	SD	min	max	N
A. Hospital structure					
Non-profit	0.43	0.50	0	1	8626
Public	0.40	0.49	0	1	8628
Private	0.17	0.38	0	1	8626
Merged	0.09	0.15	0	1	8626
Closed	0.02	0.05	0	1	8626
Number of Beds	375.46	312.68	4	2917	8626
Inpatients	15666.47	14257.88	77	198452	8626
Base rate in € in 2004	2674.98	362.121	871	7238	1123
B. Human capital and equipment					
Physicians	63.55	135.49	5	3952	8626
Nurses	170.25	287.96	4	4395	8626
Special equipment	80.41	92.90	1	221	8626
C. Services					
Treatment range	87.47	88.72	5	232	8626
Treatment volume/100	154.63	144.38	84	197.98	8626
D. Base rate deviation					
$(br_{ft_{2004}} - br_{it_{2004}})$	21.29	382.56	-3533.97	1666.29	1123
E. Instrument					
$(\Delta snow_{ft_{2003},t_{2004}} - \Delta snow_{it_{2003},t_{2004}})$	23.84	30.34	-32.01	81.68	1123
F. Municipality characteristics					
Inhabitants/1000	256.98	628.47	0.40	3574.83	8626
Employed/1000	112.28	250.20	0.00	1367.68	8626
Share male < 30 years	0.32	0.03	0.23	0.41	8626
Share male 30 - 64 years	0.50	0.02	0.43	0.55	8626
Share male > 64 years	0.18	0.02	0.13	0.27	8626
Share female < 30 years	0.29	0.03	0.20	0.39	8626
Share female 30 - 64 years	0.47	0.02	0.41	0.53	8626
Share female > 64 years	0.23	0.03	0.16	0.34	8626
E. Weather characteristics					
Mean temperature (°C)	9.53	1.41	-5.07	12.34	8626
Mean precipitation in mm/m^2	2.15	0.51	0.78	5.81	8626
Mean Wind speed (m/ss)	3.32	0.93	1.12	11.09	8626

Notes:This table displays the descriptive statistics for the most important variables. Observation in Panels D and E are based on the number of general hospitals in 2004. The data underlying the statistics in Panel E is calculated for hospital catchment areas based on driving time. Panel F is based on the municipality in which a hospital is located in.

3 Empirical Strategy

In this section, it is presented the empirical model and the identifying assumption that are necessary to interpret the estimated relationship as causal. I present two alternative identification strategies: first, I apply a selection-on-observable strategy; and second, I apply an instrumental variable approach that exploits idiosyncratic days of snow in a critical time window. For the instrument, I focus on the population weighted deviation in the change in the number of days of snow between 2003 and 2004 between single hospital catchment areas and the remaining catchment areas in a federal state.

3.1 Basic model

The staggered convergence phase of the base rate from 2005 until 2010 motivates a continuous treatment setting with the following empirical model, which I apply to general hospitals in Germany over the 2006-2016 period.

The basic model reads:

$$y_{ict} = \alpha + \beta \left(br_{ft_{2004}} - br_{it_{2004}}\right) \times \delta_t + \boldsymbol{X'_{ict}}\gamma + \delta_c + \tau_t + \varepsilon_{ict}, \tag{2}$$

where y_{ict} indicates the outcome in year t measured at hospital i located in city c. The main term of interest $(br_{ft_{2004}} - br_{it_{2004}}) \times \delta_t$ is the deviation of the base rate $br_{it_{2004}}$ of a hospital i in 2004 from the base rate $br_{ft_{2004}}$ of a federal state f in 2004 multiplied by the year indicators δ_t. I include the year indicators δ_t to mimic the step-wise harmonization of the base rate, expecting increasing effect sizes over time. Thus, β reveals the average year-specific changes in a hospital's resources between 2006 and 2016 if the hospital base rate deviates from the federal base rate in 2004. In comparison to a long-difference regression with only two observation periods, this model allows me to flexible compare the results with the related literature, even if observation periods differ. The vector $\boldsymbol{X'_{ict}}\gamma$ controls for a number of time-varying characteristics at the level of hospitals and for city population characteristics including population size, employment as well as the city population's composition by age groups and gender. Additionally, I include a set of weather controls measured at the closest weather monitor to the hospital (see Table 1 for details). In order to capture time-varying characteristics across municipalities and federal states, I also include municipality and federal state-specific linear time trends. Finally, municipality fixed effects δ_c capture any time-invariant municipality characteristics while year fixed effects τ_t control for any time-specific effects that are uniform across all hospitals. The error term ε_{ict} summarizes all determinants of the proportion of outcomes not captured by the regression. Standard errors are clustered at the county level.

Non-linearity. Given that treatment prices increase for some hospitals and decrease for others, non-linear effects of price changes are plausible if the effects of price increases and decreases are asymmetric. I test this by comparing the effects on outcomes for different ranges of price shocks using a spline regression.

Variation over time. As the base rate convergence fades out in 2010 while the observation period lasts until 2016, I provide evidence on the heterogeneous effect over time. For this purpose, I estimate a difference-in-difference specification whereby I interact eight mutually exclusive year dummies between 2006 and 2016 with the base rate deviation from 2004.[8]

$$y_{ict} = \sum_{t=1}^{8} \delta_t \times (br_{ft_{2004}} - br_{it_{2004}}) + \boldsymbol{X'_{ict}}\gamma + \delta_c + \tau_t + \varepsilon_{ict}. \tag{3}$$

The coefficient δ_t measures the effect of an increase in the difference between the hospital and federal base rate in 2004 on hospital resources for the eight year dummies $t = 1, \ldots, 8$, controlling for the same characteristics as before. In this analysis, I do not focus on the organizational structure because hospitals do not demerge or re-open.

3.2 Instrument Variable Strategy

Hospital base rates are potentially endogenous in 2004 if they are correlated with structural hospital characteristics, which would bias results towards zero. I exploit external variation in hospital base rates by increases in treatments using idiosyncratic deviations in weather conditions to which hospitals are exposed. In the economic literature, precipitation has been established as a valid instrument (e.g. Almond et al. (2009), Maccini and Yang (2009)). Days of snow are found in the epidemiological literature to have a strong positive impact on the number of cost intensive hospital admissions. Especially for fractures and other types of injuries caused by falling on slippery ground (Ralis, 1981; Björnstig et al., 1997) as well as cardiovascular events due to physically-demanding activities like snow shoveling, which increases blood pressure in a situation where cold temperatures narrow blood vessels (Franklin et al., 1995; Auger et al., 2017). The fact that Germany is located in a moderate climate amplifies the effect of snowfall on hospital admissions. Due to a high variation of weather conditions, it is difficult for individuals to avoid accidents by adjusting behavior (Eisenberg and Warner, 2005). Therefore, I use the deviation in the change between 2003 and 2004 in the population weighted number of days of snow between single hospitals catchment areas and the remaining catchment areas in the same federal state to instrument hospital base rates.

The idea behind this instrument is motivated by a peculiarity of the G-DRG-System convergence phase. It started in 2004 with a budget-neutral year in which hospitals negotiated their budget with health insurance companies based on the old system at the end of 2003. Higher levels of days of snow in 2003 improved hospitals' bargaining position as it enabled them to draw attention to the increasing need for treatments. The negotiated budget was then divided by the case mix of 2004, which is the number of in-patient cases per year weighted by their severeness. This was undertaken

[8] Hospital Quality reports were not reported in 2007, 2008 and 2011

to calculate a hospital-specific base rate, representing the starting point of the convergence phase in 2005. However, if hospitals were exposed to higher levels of snow in 2004 compared with 2003, case mixes increased due to increasingly more severe admissions. As a result, hospital base rates decreased. Furthermore, federal base rates were calculated based on the accumulated hospital budgets in a federal state and divided by the accumulated case mixes in a federal state. Thus, deviations in days of snow between 2003 and 2004 affected the federal state base rate similar to hospital base rates. A single hospital would face lower treatment prices over the convergence period if days of snow in its own catchment area in 2004 occurred more frequently than in 2003 or if days of snow in the remaining catchment areas in the federal state occurred more frequently than in 2004. I capture this mechanism with the following approach.

The first stage regresses the deviation of the hospital from the federal base rate in 2004 on the instrument, namely the population-weighted deviation of changes in days of snow between 2003 and 2004 conditional on the average days of snow.

$$(br_{ft_{2004}} - br_{it_{2004}}) = \lambda_0 + \lambda_1(\Delta snow_{ft_{2003},t_{2004}} - \Delta snow_{it_{2003},t_{2004}}) + \boldsymbol{X'_{ict_{2004}}}\boldsymbol{\kappa} + \delta_c + \varepsilon_{ic}, \quad (4)$$

I measure the instrument $\lambda_1(\Delta snow_{ft_{2003},t_{2004}} - \Delta snow_{it_{2003},t_{2004}})$ as the deviation of the change in the number of days of snow between 2003 and 2004 $(\Delta snow_{it_{2003},t_{2004}})$ in a catchment area of hospital i from the change of days of snow between 2003 and 2004 in the remaining catchment areas $(\Delta snow_{ft_{2003},t_{2004}})$ in a federal state f, additionally controlling for hospital and municipality characteristics in 2004 and city fixed effects δ_c[9]. Furthermore, I control for average days of snow in hospital catchment areas before 2003. The instrument predicts a hospital's base rate deviation from the federal base rate based on the abnormal change in the number of days of snow between 2003 and 2004 between a hospital's catchment area and the remaining catchment areas in a federal state.

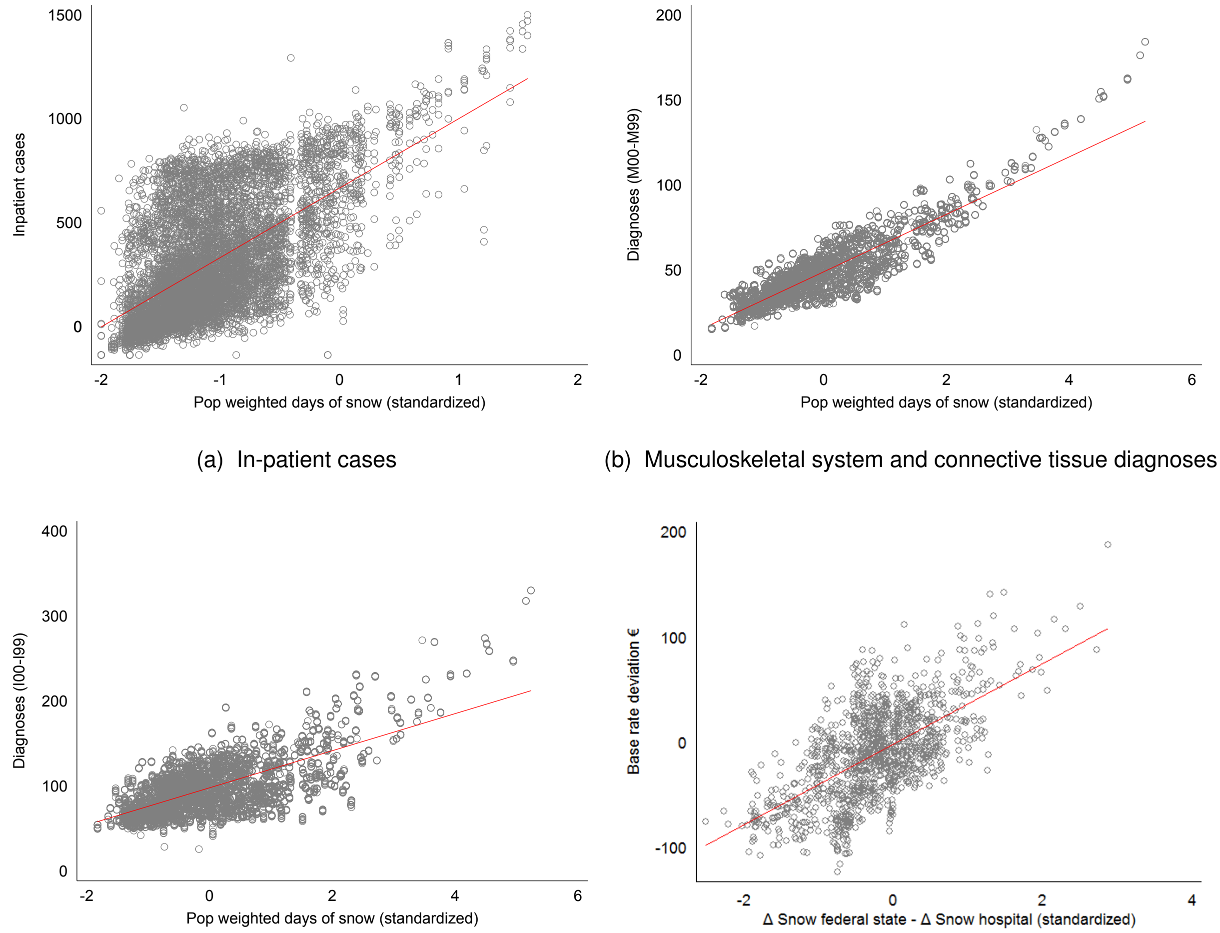
In order to demonstrate the relevance of the instrument, I show the effect of population-weighted days of snow in hospital catchment areas on in-patient cases in general and for cases that should be especially affected by days of snow. Panel A in Figure 2 displays the correlation between the instrument and in-patient cases between 2006 and 2016 after controlling for hospital and municipality characteristics and municipality and year fixed effects. As I do not have data on diagnoses as prior to 2006, I assume that days of snow affect in-patient cases after 2006 in the same manner as before 2006. A one-standard-deviation increase in population-weighted days of snow increases the number of in-patient cases by around 400 cases or 2.5 percent at the mean. Using the same specification, the same picture is true for diagnoses regarding the musculoskeletal system, connective tissue (Panel B) and the circulatory system (Panel C), which should be most sensitive to snow.

[9]Figure 12 in Appendix B shows that days of snow in 2003 and 2004 are strongly correlated with the size of the hospital. However, these differences disappear when adding municipality fixed effects.

For example, a one-standard-deviation increase in population-weighted days of snow increases the number of musculoskeletal system and connective tissue diagnoses by around 6 percent at the mean. Thus, days of snow in hospital catchment areas have a direct impact on the number of in-patient cases and should affect hospitals' base rate.

Panel D in Figure 2 shows the first-stage correlation of Equation 4. The correlation is strong and has the expected positive sign, resulting from an increase in the difference in the change of exposure to days of snow between the single hospital catchment area and the remaining catchment areas in a federal state between 2003 and 2004. A one-standard-deviation increase in the instrument increases the base rate deviation by around 10 percent of a standard deviation. Detailed information about the F-statistic and the first stage results is shown in Table 3.

As a robustness check, I replicate the IV approach with non-exclusive catchment areas based on 10 minutes driving time around a hospital location. Table 5 in Appendix C shows similar first-stage results and comparable F-statistics compared to Table 3.



(a) In-patient cases

(b) Musculoskeletal system and connective tissue diagnoses

(c) Diseases of the circulatory system

(d) Hospital base rate

Figure 2: First-stage correlation

Notes: Panels A-C) display the correlation between hospital admissions and days of snow in hospital catchment areas between 2006 and 2016, conditional on hospital and municipality characteristics, municipality and year fixed effects and average snowfall between 2000 and 2003. Panel D) displays the first-stage correlation between the standardized instrument $(\Delta snow_{ft_{2003},t_{2004}} - \Delta snow_{it_{2003},t_{2004}})$ *and the base rate deviation in 2004 by controlling for the hospital and municipality characteristics, municipality and year fixed effects and average snowfall between 2000 and 2003.*

Exclusion restriction. To represent a valid IV, days of snow have to satisfy the exclusion restriction that changes between 2003 and 2004 in the deviation of days between a hospital's catchment area and the remaining catchment areas in a federal state – conditional on the yearly mean of days of snow and other controls – only affects hospital resources through its effect on base rates. Variation in days of snow could simultaneously affect the base rate and resources allocations; for example, if small hospitals sort into places with more days of snow. However, this would not violate the exclusion restriction because I control for average days of snow in catchment areas and municipality fixed effects.

In order to confirm the exclusion restriction, I perform balancing and falsification tests. In a balancing test, I regress the number of hospital beds in 2004 on the instrument. A significant coefficient would indicate that the instrument is invalid due to its correlation with the error term of Equation 2. Figure 12 in Appendix B shows that once controlling for municipality fixed effects, the instrument does not predict the number of beds. This finding is consistent with the assumption that the instrument is as good as randomly assigned. I further perform falsification tests by using the same instrument as in Equation 4 but now based on the change of days of snow between 2004 and 2005 as well as 2005 and 2006 to test the validity of the instrument. Finding high F-statistics after 2004 would indicate that the instrument picks up snow patterns that are correlated with hospital resources, thus violating the exclusion restriction. Column (1) in Table 6 in Appendix C replicates the F-statistic of Table 3 and Columns (2) and (3) show the F-statistics of the falsification tests. The F-statistics in Columns (2) and (3) of Table 6 in Appendix C are weak. Based on the same idea, I perform a falsification test in Table 7 in Appendix C where I focus on special hospitals that treat snow-related admissions less often. Column (1) replicates the F-statistic of Table 3, whereas Column (2) shows the F-statistic for the sample of special hospitals. As expected, the F-statistic in Column (2) is weak. This is again consistent with random sampling variation around the true effect of zero.

Thus, the exclusion restriction would only be violated if changes in the number of days of snow between 2003 and 2004 affected hospital resources through a channel other than the base rate. I assume that this is implausible because variation in days of snow between 2003 and 2004 should not trigger strategic management decisions that affect resources in the following years.

4 Results

In this section, I present the estimation results for the effect of treatment price shocks on hospital resource reallocation. I first show OLS estimates to compare the results with the existing literature and discuss extensions such as non-linear effects and the variation of effect sizes over time. In order to address concerns about endogeneity, I show IV estimates.

4.1 OLS Results

Table 2 displays the OLS results. Each coefficient is the result of a separate regression of the outcome listed on the left on the treatment price shocks and the controls listed at the bottom. The outcomes in Panels A and B are standardized to a mean of zero and a standard deviation of one. As the results in Panel C represent percentages based on binary indicators, I do not standardize these outcomes. A coefficient of $\hat{\beta}$ = 0.01 in Panel A and B means that an increase in prices by 1 € over the convergence phase – which equals a 1 € deviation between the federal and the hospital base rate in 2004 – is associated with an increase in the respective hospital resources by 1 percent of a standard deviation per year between 2006 and 2016. I discuss the effect size relative to an increase in prices by one standard deviation (sd(€) = 382,56), to facilitate the interpretation. In Panel C, the base rate deviation is multiplied by 100.

Column (1) reports the OLS estimates from binary regressions without controls. All coefficients are small and weakly significant. After controlling for year and municipality fixed effects in Column (2), the point estimates become larger in absolute terms. I include municipality fixed effects to reduce the potential bias from residential sorting. As shown in Figure 6 in Appendix A, larger hospitals have higher base rates, although they are more frequently located in urban areas. Thus, controlling for municipality fixed effects captures confounding differences between hospitals with different sizes. Year fixed effects capture general trends in the hospital sector like demographic or technical changes. Controlling for hospital characteristics in Column (3) increases point estimates while controlling for weather characteristics in Column (4) leave the results rather unchanged. The coefficients between Columns (4) and (5) become larger again when controlling for linear municipality and federal state time trends. Linear municipality time trends capture the urbanization of hospital supply, which is driven by migration towards cities and the political will to relocate more medical services to the city. However, the hospitals that face an increase in demand due to urbanization are those that experience base rate increases less often due to their larger size. This confounding effect is captured by linear municipality time trends.

If I include the full set of controls in Panel A, a one-standard-deviation increase in treatment prices is associated with a yearly increase in the number of physicians by 0.6 percent[10] and the number of nurses by 0.7 percent of a standard deviation. Investments in special equipment are unaffected. This can be explained by the fact that G-DRGs do not cover capital investments because hospitals receive additional funds for investments from municipalities or federal states. Panel B shows an increase in the treatment range if treatment prices increase. A one-standard-deviation increase in treatment prices is associated with a yearly increase in the range of treatments by 1.2 percent of a standard deviation. The treatment volume decreases by 1.1 percent of a standard deviation per year. Panel C shows that an increase in the treatment prices by 100 € reduces the probability of privatization by 0.3 percentage points per year and the probability of being merged by 0.2 percentage points per year. The effect sizes on closures are relatively large. However, this is based on a very small sample as only 2 percent of all hospitals were closed in the observation period. Table 8 in Appendix C displays the adjusted R^2 for the OLS regressions in Table 2.

[10]For example, in Column (5) of Table 2 an increase in the base rate deviation of one standard deviation ($= 383$) translates into an effect size for a standard deviation of physicians ($= 135$) of $0.002 \times 383/135 = 0.006$, i.e., 0.6 percent.

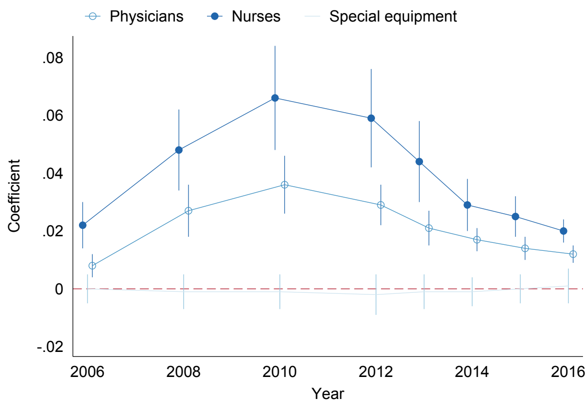
Table 2: OLS results: the effect of treatment prices on hospital resources

	(1)	(2)	(3)	(4)	(5)
A. Input					
Physicians	0.001*	0.002**	0.002*	0.002**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Nurses	0.001	0.002**	0.004**	0.004**	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Special equipment	-0.000	-0.001	-0.002	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
B. Output					
Treatment range	0.001*	0.002**	0.002***	0.002***	0.003***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Treatment volume	-0.001	-0.002**	-0.003***	-0.003***	-0.004***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
C. Structure					
Private	0.000	-0.002**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Merged	-0.001	-0.001**	-0.001**	-0.002**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Closed	-0.000	-0.001*	-0.001*	-0.001*	-0.001*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
N	8626	8626	8626	8626	8626
Controls:					
Year FE	No	Yes	Yes	Yes	Yes
Municipality FE	No	Yes	Yes	Yes	Yes
Hospital characteristics	No	No	Yes	Yes	Yes
Weather characteristics	No	No	No	Yes	Yes
Municipality characteristics	No	No	No	No	Yes
Linear time trends	No	No	No	No	Yes

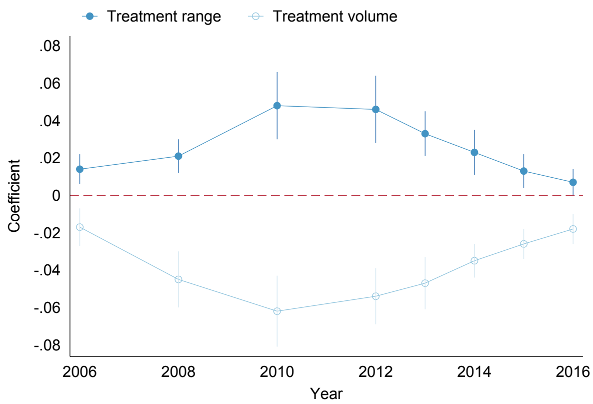
Notes: This table displays the OLS results. Each coefficient is the result of a separate OLS regression of the outcome listed on the left on the base rate in €, controlling for the variables indicated below. In Columns (1)-(5) of panel A and B, the hospital resources have been standardized. In Panel C, outcomes have not been standardized. However, the base rate deviation is multiplied by 100. Standard errors are displayed in parentheses and clustered at the county level. Significance level: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Non-linear Effects. In Table 9 in Appendix C, I test for a non-linear relationship. Based on spline regression of hospitals above and below the average federal base rate in 2004, I find no evidence of non-linear effects. Thus, the transition from a base rate decrease to an increase seems to be linear. Put differently, an increase in the base rate deviation between hospitals and federal base rates in 2004 has the same effect for hospitals above and below the federal base rate. This leads to a polarization of resources between hospitals that faced treatment price increases and hospitals that faced treatment price reductions.

Variation over time - OLS. Figure 3 plots the year-specific effects of treatment price increases on input (Panel A) and output factors (Panel B). From 2006 onwards, treatment price shocks already affect input and output factors. Until 2010, hospitals gradually adjust their resources. If the treatment price increase, the number of physicians, nurses and the treatment range increases, whereas the amount of special equipment remains rather constant and the treatment volume decreases. In all resource dimensions, the peak seems to be reached by the end of the convergence phase in 2010. For example, in 2010 the number of physicians and nurses are 10.2 percent and 8.8 percent of a standard deviation higher for a one-standard-deviation increase in treatment prices. Correspondingly, the treatment range in 2010 is 19.3 percent of a standard deviation higher while the treatment volume is 16 percent of a standard deviation lower. Input and output factors tend to converge to the pre-reform levels after 2010. However, differences still remain until 2016, indicating a persistent pattern of treatment price shocks.



(a) Input



(b) Output

Figure 3: Variation over time - OLS

Notes: These graphs plot the estimated OLS coefficients and the 95 percent confidence intervals for the year-specific effect of the base rate deviation in 2004 on hospital resources. The estimates are based on Equation 3. Standard errors are clustered at the county level.

4.2 IV Results

In Table 3, I present the instrumental variable estimates from regressions with all controls and year and municipality fixed effects and linear time trends. Column (1) reproduces the OLS results from

Column (5) in Table 2. Column (3) report the first-stage coefficients and F-statistics of the IV estimation based on 1,123 observations in 2006. The reduced-form estimates in Column (2) have the expected signs. A higher deviation of days of snow between a single hospital catchment area and the remaining hospital catchment areas within a federal state means a higher deviation between the federal and the hospital base rate, which has a positive effect on the number of physicians, nurses and the diversity of treatments, and a negative impact on treatments, privatization, mergers and closures. Seven out of eight coefficients are statistically significant at the 5 percent-level. While the magnitude of the reduced-form coefficient is not straightforward to interpret, the statistical significance is important for the interpretation of the second-stage results. It rules out the possibility that the second-stage results in Column (3) are a statistical artifact stemming from sampling variation in the first stage.

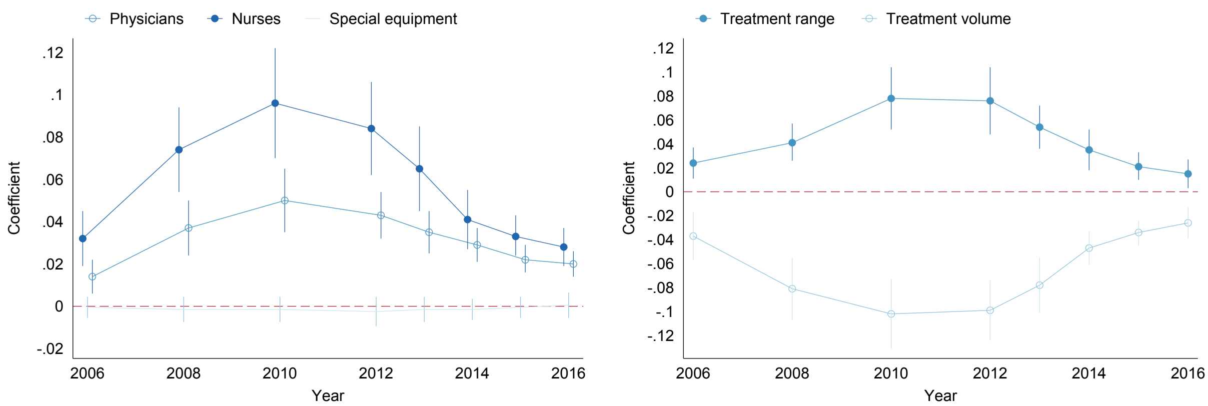
The second-stage results are larger than the OLS results. A one-standard-deviation increase in treatment prices is associated with a yearly increase in the number of physicians by 1.1 percent and the number of nurses increases by 0.9 percent of a standard deviation. Panel B shows also stronger magnitudes of second-stage results compared with the OLS results. A one-standard-deviation increase in treatment prices is associated with a yearly increase in the treatment range by 2.5 percent of a standard deviation, while the treatment volume decreases by 2.4 percent of a standard deviation. Panel C shows that an increase in treatment prices of 100 € reduces the probability of privatization by 0.7 percentage points per year and the probability of being merged by 0.4 percentage points per year.

Table 3: IV results: the effect of treatment prices on hospital resources

	OLS (1)	Reduced form (2)	IV-2SLS (3)
A. Input			
Physicians	0.002***	0.150***	0.004**
	(0.000)	(0.035)	(0.002)
Nurses	0.005***	0.200**	0.007**
	(0.001)	(0.081)	(0.003)
Special equipment	-0.001	-0.180	-0.002
	(0.000)	(0.130)	(0.002)
B. Output			
Treatment range	0.003***	0.130***	0.006***
	(0.001)	(0.035)	(0.002)
Treatment volume	-0.004***	-0.101***	-0.009***
	(0.001)	(0.031)	(0.003)
C. Structure			
Private	-0.003**	-0.219***	-0.007*
	(0.001)	(0.049)	(0.004)
Merged	-0.002**	-0.199***	-0.004*
	(0.001)	(0.053)	(0.002)
Closed	-0.001*	-0.143**	-0.001
	(0.000)	(0.051)	(0.000)
First-stage:			
Snow instrument			50.922***
			(10.006)
F-statistic			47.238
N	8626	8626	
Controls:			
Year FE	Yes	Yes	
Municipality FE	Yes	Yes	
Hospital characteristics	Yes	Yes	
Weather characteristics	Yes	Yes	
Municipality characteristics	Yes	Yes	
Linear time trends	Yes	Yes	

Notes: This table displays the IV results. Column (1) reproduces the OLS results from Column (5) in Table 2. Column (2) reports the reduced-form coefficients of separate regressions of the outcomes on the instrument and controls. The main IV results are displayed in Column (3). Column (3) additionally reports the first-stage coefficients of the base rate regressed on the instrument and all controls mentioned in section 2.4 and the corresponding F-statistics. Standard errors are displayed in parentheses and clustered at the county level. Significance level: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Variation over time - IV. Figure 4 plots the year-specific effects of treatment price increases on input (Panel A) and output factors (Panel B), based on split sample 2SLS per year. The magnitudes are larger than in Figure 3, while the general picture remains rather constant. From 2006 onwards, treatment price shocks already affect input and output factors. Until 2010, hospitals gradually adjust their resources. The peak seems to be reached by the end of the convergence phase in 2010. For example, in 2010 the number of physicians and nurses are 12 percent and 12.8 percent of a standard deviation higher for a one-standard-deviation increase in treatment prices. Correspondingly, the treatment range in 2010 is 35 percent of a standard deviation higher, while the treatment volume is 27 percent of a standard deviation lower. Subsequently, input and output factors tend to converge to the pre-reform levels. As in the case of the previous OLS results, differences remain until 2016, confirming a persistent pattern of treatment price shocks.



(a) Input

(b) Output

Figure 4: Variation over time - IV

Notes:Notes: These graphs plot the estimated IV-coefficients and the 95 percent confidence intervals for the year-specific effect of the base rate deviation in 2004 on hospital resources. The estimate is based on Equation 3. Standard errors are clustered at the county level.

Interpretation of IV estimator. There are three potential reasons why the IV estimator – given that the instrument is valid and strong – produces different results from an OLS estimator. First, the difference can be explained by heterogeneous treatment effects. If treatment effects are not constant across hospitals, the IV estimator identifies a local average treatment effect (LATE). With a continuous instrument, this means that the estimator places a stronger weight on hospitals with increasing treatment prices, which are typically small hospitals. In Figures 13a and 13b in Appendix C, I explore potential sources of heterogeneous treatment effects. I do not find a stronger first-stage relationship for hospitals that experience decreases compared with increases in treatment prices or differences between large and small hospitals. Thus, there is no identification of a LATE. A second reason could be measurement error of the treatment prices. Given that I use official data of hospital base rates, this is rather unlikely. This suggests that OLS estimates are confounded due to unobserved heterogeneity that is not absorbed by controls and fixed effects. The true effect is biased towards zero, which indicates that resource allocations before 2004 correlate with resource allocations in the convergence phase, as described in section 2.1.

4.3 Discussion of the main results

The estimates presented in sections 3.1 and 3.2 show that treatment price shocks induced reallocations of hospital resources. These price shocks can be substantial. For an average hospital, a one standard deviation increase in prices translates into a budget increase of 5.9 million Euros between 2005 and 2010.[11] I show that treatment price shocks can have persistent effects on hospital resource reallocations even when treatment price shocks vanish after 2010. Persistent pattern in price shocks have been observed for several sectors where firms pass on price increases to consumers faster than decreases (Peltzman, 2000). This is the first paper to show persistent pattern in the reallocation of hospital resources if prices change.

To assess the magnitude of the results, it is useful to compare them with results obtained in other studies exploiting treatment price shocks in hospitals. The effect sizes and even the sign of the magnitude vary across studies. According to the estimates of the federal budgeting for medical reimbursement in the United States, a one-percent decrease in treatment prices increases the treatment volume by around 0.3-0.5 percent. By contrast, Clemens and Gottlieb (2014) show that higher treatment prices increase the treatment volume, whereas Dafny (2005) finds no effect. Using the G-DRG-Reform, Salm and Wübker (2015, 2018) find results that are smaller compared to the results in this paper but they do find linear effects as well. For example, a one-percent increase in treatment prices decreases the treatment volume by 0.14 percent until 2009, the number of nurses by 0.4 percent and the number of physicians by around 0.2 percent until 2010. OLS estimations in this paper, which include the post convergence period after 2010 – thus representing a lower-bound estimate – show that an increase in treatment prices by one percent of the mean (mean(€) = 27) decreases the treatment volume by 0.23 percent[12] until 2009, the number of physician by 0.34 percent and the number of nurses by 0.38 percent until 2010. Results are even larger in this paper for 2010 when interacting mutually exclusive year dummies with the base rate deviation from 2004, thereby analyzing heterogeneous effects over time. Furthermore, estimations in this paper, which rely on plausibly exogenous variation in treatment price shocks confirm larger effect sizes. IV results – which include the post convergence period after 2010 – show that the number of physicians actually increased by 0.85 percent, the number of nurses by 0.7 percent and the treatment volume by 0.62 percent on average per year. Again, effect sizes in 2010 are much larger when analyzing

[11] One standard deviation in the deviation between the federal and the hospital base rate in 2004 equals around 383 €. The average treatment volume of a hospital is around 15,400 cases per year.

[12] For example, in Column (5) of Table 2 an increase in the base rate deviation of one percent of the mean ($= 27$) translates into an effect size for the mean of treatments ($= 144.38$) from 2006 to 2009 of $0.004 \times 27/144.38 \times 3 = 0.0025$, i.e., 0.25 percent.

heterogeneous effects over time.

4.4 Heterogeneous Effects

In Table 4, I test whether the impact of treatment price shocks differs between major hospital characteristics, by focusing on pre-treatment ownership, hospital size and urban or rural locations in 2004. The selection of pre-treatment characteristics is based on the information available in the German Hospital Directory. However, the hospital ownership and size are good proxies for the efficiency of a hospitals. Furthermore, hospitals in rural and urban areas have experienced different trends. Hospital supply has been reallocated to cities due to the inefficiency of rural hospitals. In case of treatment price shocks, inefficiency should lead to heterogeneous effects.

For each set of groups, I estimate split sample 2SLS. In all regressions, I control for the same characteristics as in Column (5) of Table 2. Comparing Columns (1) and (2) shows different treatment effects between hospitals that were public or non-public in 2004. With the exception of special equipment, input and output factors of non-public hospitals are more strongly affected compared with public hospitals. This means that public hospitals react less to treatment price decreases given the finding of linearity in price changes in Table 9 in Appendix C. In case of input factors, this finding is in line with more flexible employment in the non-public sector. Smaller impacts on the treatment range and the treatment volume in Panel B could indicate more supplier-induced demand among private hospitals. Finding stronger effects for non-public hospitals could also be explained by the fact that municipalities – which are the owners of public hospitals – might subsidize their hospitals.

In Columns (3) and (4), I compare hospitals with above- and below-median numbers of beds[13] in 2004. Again, a rather general effect occurs, whereby larger hospitals tend to react more strongly to treatment price shocks compared with smaller hospitals. One potential explanation is the general financial pressure among large hospitals. They faced difficulties in replicating the average treatment costs of a federal state expressed by higher base rates in 2004 shown in Figure 6 in Appendix A. Furthermore, larger hospitals can reduce resources more easily due to economies of scale. Interestingly, smaller hospitals merge sightly less often than larger hospitals if treatment prices increase. One explanation could be that it is much easier for smaller hospitals to merge.

Finally, in Columns (5) and (6), I assess if the effects differ between hospital, which were located in urban versus rural areas[14] in 2004. I find no difference in estimates for input factors between rural and urban areas and some minor differences for output factors. The range and the volume of treatments are stronger affected in case of rural hospitals. Rural hospitals might compensate higher inefficiency with more supplier-induced demand. More importantly, the hospital structure in Panel C seems to play a major role between urban and rural areas. A treatment price increase decreases the probability of mergers much stronger in rural areas. This is in line with policies that favor the consolidation of hospital supply, especially in rural areas.

[13] Median number of beds = 325

[14] Municipalities with less than 50,000 inhabitants

Table 4: Heterogeneous Effects

	Public (1)	Non-public (2)	(Large) (3)	(Small) (4)	(Urban) (5)	(Rural) (6)
A. Input						
Physicians	0.003*	0.006*	0.006*	0.002*	0.004**	0.004**
	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Nurses	0.005**	0.009**	0.010**	0.005**	0.008**	0.007**
	(0.002)	(0.004)	(0.005)	(0.002)	(0.004)	(0.003)
Special equipment	-0.002	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
B. Output						
Treatment range	0.004**	0.007***	0.008**	0.004***	0.004**	0.007***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
Treatment volume	-0.007***	-0.011***	-0.012***	-0.006***	-0.008***	-0.010***
	(0.002)	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)
C. Structure						
Merged	-0.002*	-0.005**	-0.004**	-0.003*	-0.002*	-0.006**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Closed	-0.001	-0.001	-0.001	-0.002*	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	3431	5197	4315	4313	5434	3192
Controls:						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Weather characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Municipality characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trends	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each cell represents the effect of the base rate instrument on the outcome listed in the Column and the sample described at the top, from an IV specification that includes our baseline set of controls. Robust standard errors clustered at the county level.

5 Conclusion

In this paper, I have examined the causal effect of general treatment price shocks on hospital resource reallocations in Germany. Starting in 2005, hospital payment for patients was transformed to the G-DRG-System, which led to general idiosyncratic treatment price shocks for individual hospitals until 2010. Some hospitals were exposed to price increases, while others experienced price reductions. However, thus far there is little evidence of the impact of general price shocks on the reallocation of hospital resources.

The results of the paper show that treatment price shocks significantly affected hospital resources. By exploiting data from the universe of German hospitals for the 2006-2016 period, I find that price shocks are positively associated with number nursing staff and physicians and the range of treatments but negatively with the treatment volume. The probability of hospital mergers, closures and privatization is negatively associated with price shocks. Effects are stronger for private and larger hospitals. I show that treatment price shocks can have persistent effects on hospital resource reallocations even when treatment price shocks vanish. Using unique high-resolution satellite data, I implement an novel instrument variable strategy that exploits the exogenous variation in the number of days of snow in hospital catchment areas. A peculiarity of the reform allowed deviations in weather condition at the time of the reform implementation to have an effect on treatment prices in the next five years. IV estimates show that OLS results are biased towards zero for almost all dimensions. Thus, simple OLS regressions would underestimate the true effect due to correlations between structural hospital characteristics and the reallocation of resources after price shocks.

These findings have implications for research and policy. Most research explore reforms where treatment prices change only for a sub-group of patients. This is why there is little evidence about the impact of general treatment price shocks on hospital resources. By exploiting the G-DRG-Reform, I show that hospital reallocate resources due to general treatment price shocks. As this is the first paper showing a persistent pattern in the reallocation of hospital resources if prices change, further research on this topic is necessary. However, this requires well-founded identification strategies. Finding results that are biased towards zero for input and output factors and the organizational structure also points to the importance of unobserved heterogeneity in the context of healthcare policy evaluation.

For policy-makers, these results are important for several reasons. The G-DRG-Reform led to a persistent polarization of hospital resources, as some hospitals were exposed to treatment price increases, while others experienced treatment price reductions. If hospitals increase the treatment volume as a response to price decreases by offering unnecessary therapies, it has a negative impact on population well-being and public spending. On the other hand, results show a decrease in the range of treatments if prices decrease. Hospitals might specialize more, thus attracting more patients. From a policy perspective, it is important to evaluate weather such changes in the treatment range jeopardize an adequate nationwide provision of treatments. Furthermore, the results reveal a decrease in the number of nurses and physicians if treatment prices decrease. This could partly explain the nursing shortage in German hospitals. However, since hospitals specialize more they might be able to realize efficiency gains, which justify decreases in input factors without losses of productivity. Another important aspect are changes in the organizational structure, given that many public hospitals became privatized or merged with other hospitals. The findings show that this is at least partly driven by the G-DRG-Reform. However, this can again lead to a lack of services offered in some regions if merged hospitals specialize or if hospitals are taken over by ecclesiastical organizations that do not provide all services due to moral conviction (Filistrucchi and Prüfer, 2018). To have a complete picture, further research is needed on the direct impact of treatment price shocks on healthcare quality.

Appendices

A Hospital data

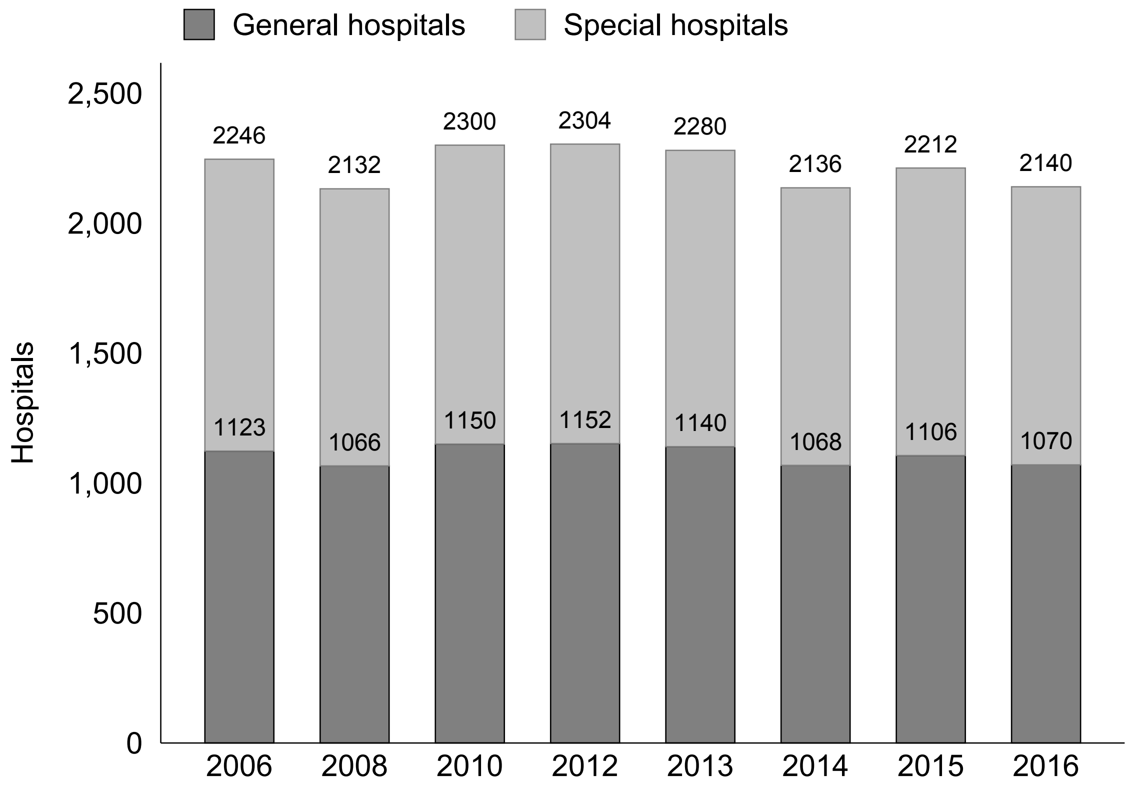
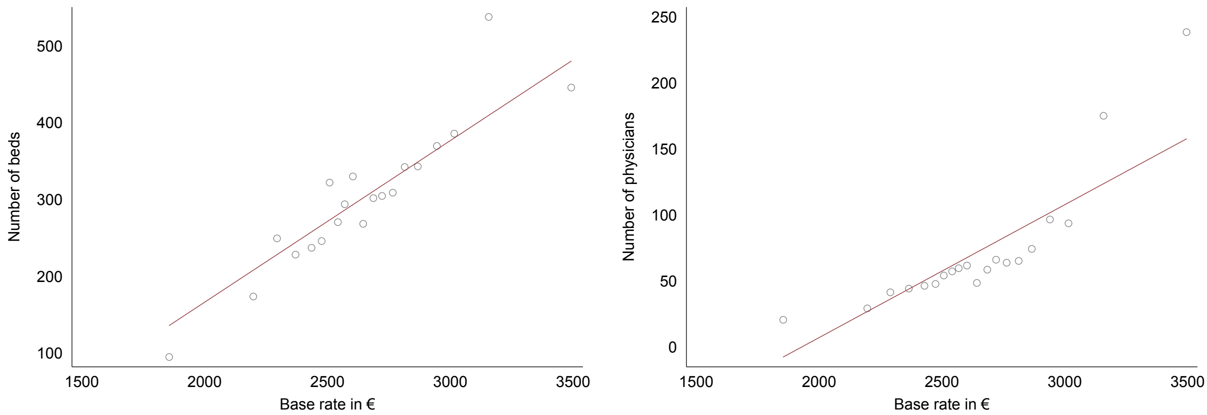


Figure 5: Number of hospital locations

Notes: This figure shows the number of all German hospital locations separated by general and special hospitals



(a) Number of beds and hospital base rate (b) Number of physicians and hospital base rate

Figure 6: Hospital resources and base rate

Notes: Panel (a) shows a binscatters of the raw correlation between the hospital base rate and the number of beds in 2004. Panel (b) shows the binscatter for the raw correlation between the hospital base rate in 2004 and the number of physicians in 2006 because detailed data of hospital input factors is only available since 2006. Source: Hospital Quality Reports, German Hospital Directory.

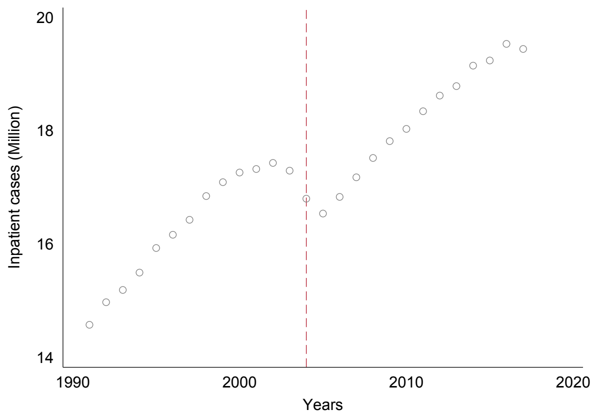
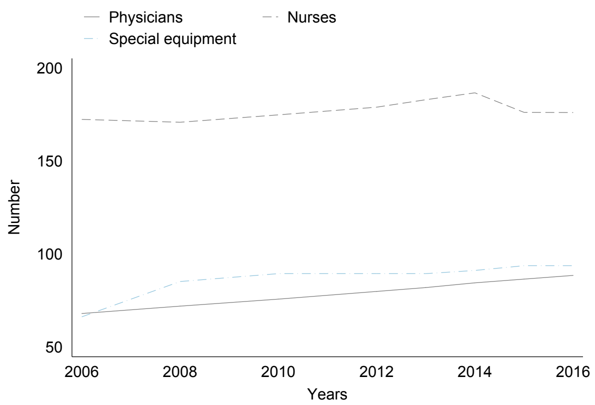
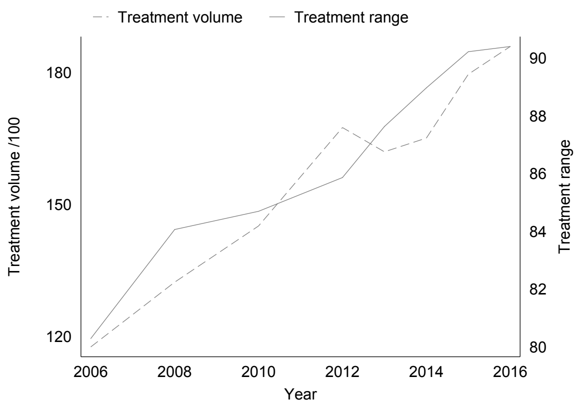


Figure 7: In-patient cases over time

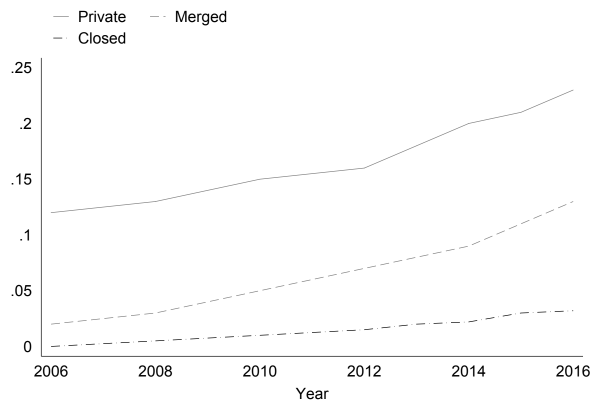
Notes: This figure shows the number of in-patient cases over time. Source: Federal statistical Office.



(a) Input



(b) Output

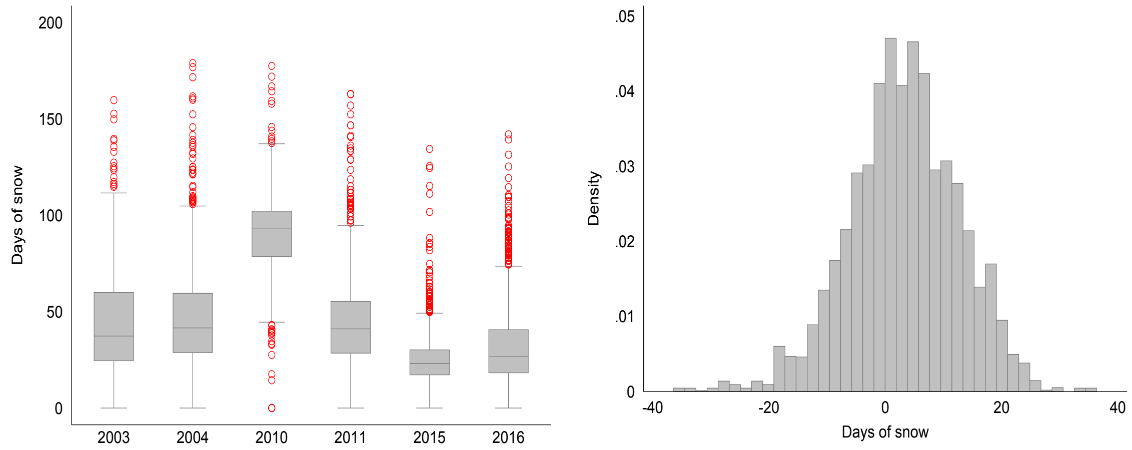


(c) Structure

Figure 8: Input, output and structure over time

Notes: Panel (a) shows the average number of hospital input factors over time. Panel (a) shows the average number of hospital output factors over time. Panel (c) shows the share of private, closed and merged hospitals over time. Source: Hospital Quality Reports.

B Catchment areas and days of snow



(a) Days of snow per year

(b) Deviation in days of snow between 2003 and 2004

Figure 9: Days of snow

Notes: This graph displays the variation in days of snow over time. Panel (a) displays the variation in days of snow between 2003 and 2004 for 500 $\times$ 500 meter grids across Germany. Panel (b) displays the distribution of days across Germany over time for 500 $\times$ 500 meter grids. Source: Global Snow Pack dataset.

Figure 10: Days of snow and catchment areas in Bonn

Notes: This graph displays the variation in days of snow between 2003 and 2004 for 500 × 500 meter grids in hospital catchment areas in the city of Bonn. Source: Global Snow Pack dataset.

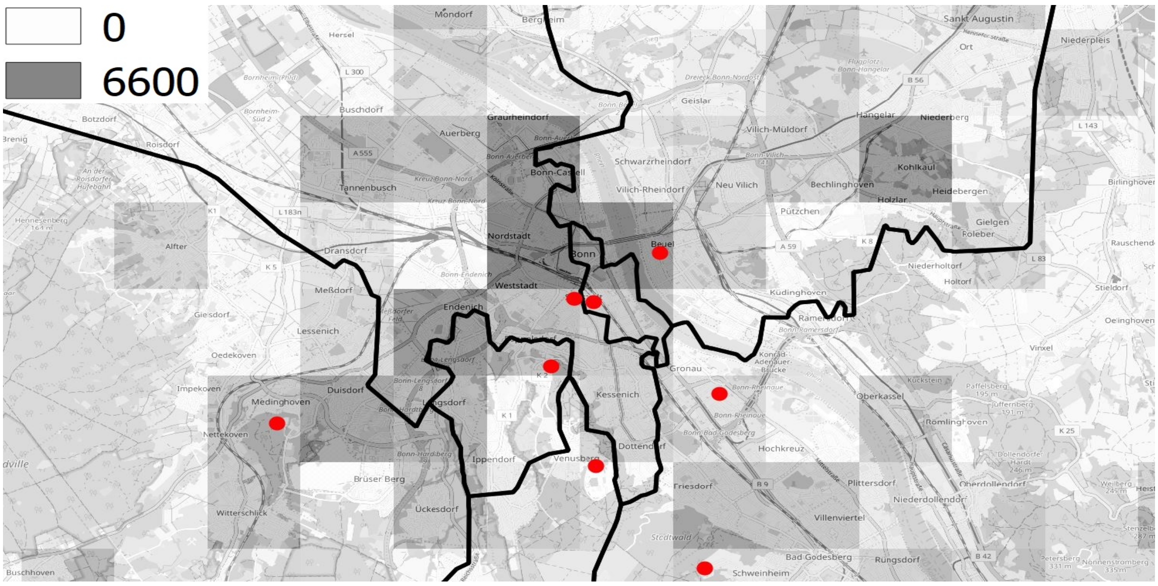
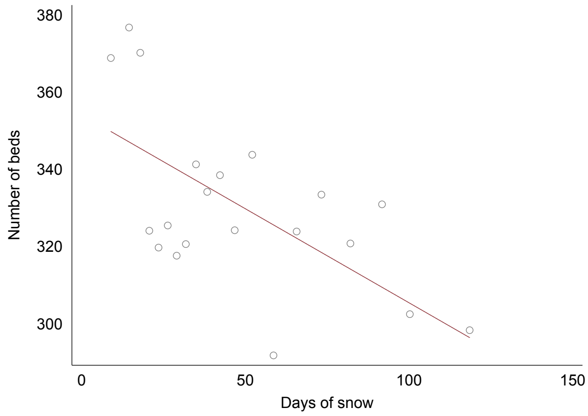
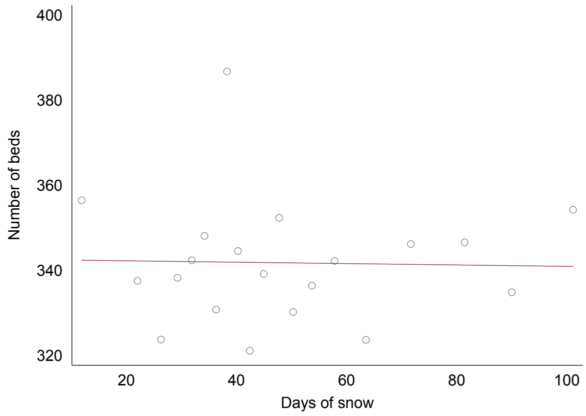


Figure 11: Population density and catchment areas in Bonn

Notes: This graph displays the variation in the population density in hospital catchment areas in the city of Bonn in 2006 based on 1,000 × 1,000 meter grids. Source: GEOSTAT.



(a) Raw correlation



(b) Correlation with municipality fixed effects

Figure 12: Hospital resources and days of snow

Notes: Panel (a) shows a binscatters of the raw correlation between the number of beds and the number and days of snow in 2004. In Panel (b), I control for municipality fixed effects.

C Additional Results

Table 5: Alternative IV results: The effect of treatment prices on input and output

	OLS (1)	Reduced form (2)	IV-2SLS (3)
A. Input			
Physicians	-0.002***	-0.143**	-0.004**
	(0.000)	(0.050)	(0.002)
Nurses	-0.005***	-0.185**	-0.007**
	(0.002)	(0.071)	(0.003)
Special equipment	-0.001	-0.175	-0.001
	(0.000)	(0.099)	(0.001)
B. Output			
Treatment range	0.003***	-0.126***	-0.006***
	(0.001)	(0.035)	(0.002)
Treatment volume	0.004***	0.101***	0.009**
	(0.001)	(0.031)	(0.004)
C. Structure			
Private	-0.003**	-0.197**	-0.006*
	(0.001)	(0.089)	(0.003)
Mergers	-0.002**	-0.323***	-0.005*
	(0.001)	(0.061)	(0.002)
Closed	-0.001*	-0.287***	-0.001
	(0.000)	(0.043)	(0.000)
First-stage:			
Snow instrument			44.422***
			(9.467)
F-statistic			43.737
N	8626	8626	
Controls:			
Year FE	Yes	Yes	
Municipality FE	Yes	Yes	
Hospital characteristics	Yes	Yes	
Weather characteristics	Yes	Yes	
Municipality characteristics	Yes	Yes	
Linear time trends	Yes	Yes	

Notes: This table displays the IV results based on the alternative catchment area definition. Column (1) reproduces OLS results from Column (5) in Table 2. Column (2) reports the reduced-form coefficients of separate regressions of the outcomes on the instrument and controls. The main IV results are displayed in Column (3). Column (3) additionally reports the first-stage coefficients of the base rate regressed on the instrument and all controls mentioned in section 2.4 and the corresponding F-statistics. Standard errors are displayed in parentheses and clustered at the county level. Significance level: $***: p < 0.01, **: p < 0.05, *: p < 0.1$.

Table 6: Placebo test: F-statistic for different years

	2004	2005	2006
	(1)	(2)	(3)
F-statistic	47.238	4.201	2.236
N	8626	8626	8626
Controls:			
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Hospital characteristics	Yes	Yes	Yes
Weather characteristics	Yes	Yes	Yes
Municipality characteristics	Yes	Yes	Yes
Linear time trends	Yes	Yes	Yes

Notes: This table displays the F-statistic of different instruments. In each Column, I construct the instrument base on the deviation of snowfall between the year listed at the top and its corresponding previous year. Column (1) reproduces the F-statistic of Table 3. Standard errors are displayed in parentheses and clustered at the county level. Significance level: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Table 7: Placebo test: F-statistic for different hospital samples

	General (1)	Special (2)
F-statistic	47.238	12.201
N	8626	8626
Controls:		
Year FE	Yes	Yes
Municipality FE	Yes	Yes
Hospital characteristics	Yes	Yes
Weather characteristics	Yes	Yes
Municipality characteristics	Yes	Yes
Linear time trends	Yes	Yes

Notes: This table displays the F-statistic of different instruments. Column (1) reproduces the F-statistic of Table 3. In Column (2), I use the sample of the excluded special hospitals. Standard errors are displayed in parentheses and clustered at the county level. Significance level: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Table 8: Adjusted R^2 for OLS Results.

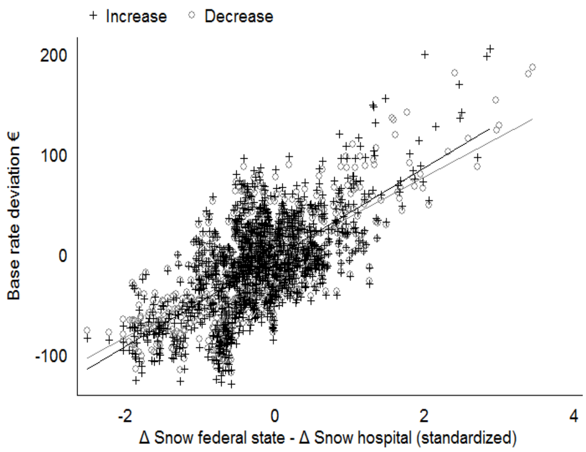
	(1)	(2)	(3)	(4)	(5)
A. Input					
Physicians	0.02	0.20	0.25	0.26	0.29
Nurses	0.01	0.18	0.21	0.21	0.24
Special equipment	0.02	0.19	0.20	0.21	0.23
B. Output					
Treatment range	0.03	0.17	0.19	0.22	0.27
Treatment volume	0.03	0.21	0.22	0.24	0.28
C. Structure					
Private	0.02	0.15	0.15	0.16	0.19
Merged	0.02	0.18	0.18	0.19	0.22
Closed	0.11	0.12	0.11	0.13	0.14
N	8626	8626	8626	8626	8626
Controls:					
Year FE	No	Yes	Yes	Yes	Yes
Municipality FE	No	Yes	Yes	Yes	Yes
Hospital characteristics	No	No	Yes	Yes	Yes
Weather characteristics	No	No	No	Yes	Yes
Municipality characteristics	No	No	No	No	Yes
Linear time trends	No	No	No	No	Yes

Notes: This table displays the adjusted R^2 for the baseline results presented in Columns (1)-(5) in Table 2

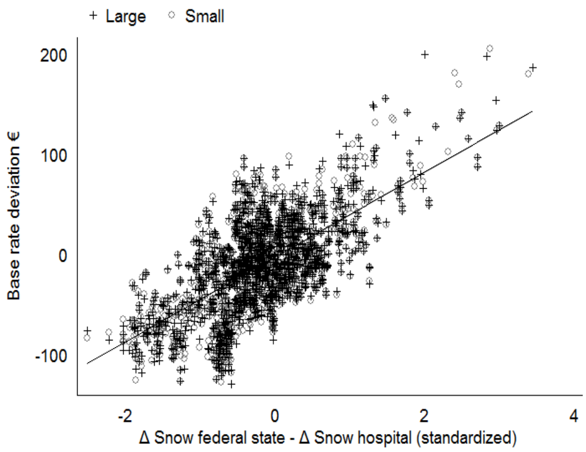
Table 9: OLS Results: The effect of treatment prices on input and output for different base rate stages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Input								
Physicians								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase	0.02*							
	(0.000)							
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease	0.002*							
	(0.000)							
Nurses								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase		0.005**						
		(0.002)						
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease		0.005**						
		(0.002)						
Special equipment								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase			-0.001					
			(0.001)					
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease			-0.001					
			(0.001)					
B. Output								
Treatment range								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase				0.003**				
				(0.001)				
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease				0.003***				
				(0.001)				
Treatment volume								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase					-0.004***			
					(0.001)			
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease					-0.005***			
					(0.001)			
C. Structure								
Private								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase						-0.003**		
						(0.001)		
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease						-0.003**		
						(0.001)		
Merged								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase							-0.002**	
							(0.001)	
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease							-0.002*	
							(0.001)	
Closed								
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price increase								-0.001
								(0.001)
$(br_{i_{2004}} - br_{ft_{2004}}) \times$ price decrease								-0.001
								(0.001)
N	8626	8626	8626	8626	8626	8626	8626	8626
Adj R^2	0.29	0.24	0.23	0.27	0.28	0.19	0.22	0.14
Controls:								
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays the estimates from OLS regressions of input and output factors on a treatment price increase that is interacted with an indicator that equals unity if a hospital base rate in 2004 was above the federal hospital base rate. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $*** : p < 0.01$, $** : p < 0.05$, $* : p < 0.1$.



(a) By treatment price change



(b) By hospital size

Figure 13: First-stage correlation by sub-group

Notes: Notes: This figure displays the scatter plots of first-stage regressions split between hospitals with increasing and decreasing treatment prices or large and small hospitals.

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