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ABSTRACT

Do Hospitals Respond to Increasing Prices by Supplying Fewer Services?*

Medical providers often have a significant influence on treatment decisions which they can use in their own financial interest. Classical models of supplier-induced demand predict that medical providers will supply fewer services if they face increasing prices. We test this prediction based on a reform of hospital financing in Germany. Uniquely, this reform changed the overall level of reimbursement – with increasing prices for some hospitals and decreasing prices for others – without affecting the relative prices for different types of patients. Based on administrative data, we find that hospitals do indeed react to increasing prices by reducing service supply.

JEL Classification: I11, L10, L21

Keywords: physician-induced demand, hospital care, prospective payment

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1. Introduction

Asymmetric information can have severe effects on how markets function. This is particularly relevant for healthcare markets, where medical providers often have more information about the necessary treatments than either patients or health insurers and treatment decisions often follow physicians' recommendations (Arrow 1963). Rapidly increasing healthcare expenditure in many countries is raising the importance of the question whether and to what degree healthcare providers use their superior knowledge to their own economic advantage, e.g. by inducing demand for their own services. According to a classical model of supplier-induced demand (Evans 1974, McGuire 2000) medical providers weigh the benefits of adhering to ethical and medical standards against the benefits of higher revenues. This model leads to the counterintuitive prediction that medical providers will supply fewer services if they face higher prices.

Credible empirical evidence on supplier-induced demand is scarce. Whether medical providers induce demand – and to what extent – is a controversial question in health economics, and previous studies have often been criticized for their failure to overcome methodological challenges (see discussions by Fuchs 1996, McGuire 2000, Sloan and Hsieh 2012). Previous studies tend to follow two alternative empirical approaches. The first focuses on the relationship between the regional concentration of healthcare providers and regional volumes of medical care (Fuchs 1978, Dranove and Wehner 1994, Gruber and Owings 1996, Douven et al. 2015). The fundamental challenge with this approach is that healthcare providers' location decisions also follow market demand.

A second approach is to examine the effect of price changes on treatment volumes directly (Price 1983, Yip 1998, Heaton and Helland 2009, Clemens and Gottlieb

2014, Shigeoka and Fushimi 2014). Prices in the medical sector are often set by public or semi-public agencies, such that changes in regulated prices are often plausibly unrelated to changes in demand for medical services. One important challenge in this literature is that previously examined price changes affect only a subset of patients, such as Medicare beneficiaries (Price 1983, Yip 1998, Clemens and Gottlieb 2014), automobile accident victims (Heaton and Helland 2009), and at-risk newborns (Shigeoka and Fushimi 2014), while leaving prices for other patients unaffected. The effect of price changes is then a combination of two effects: 1. the effect of a change in relative prices between groups of patients, and 2. the effect of a change in the overall price level. When models of supplier-induced demand predict that higher prices will lead to the supply of fewer services, this refers to the second effect, which is typically referred to as the "income effect" in the literature (McGuire 2000). Isolating the income effect from the effect of a change in relative prices is very difficult in settings where price changes affect just a subset of patients.

In our study, we exploit a unique setting that makes it possible to estimate the income effect directly and without having to disentangle the income effect from the effect of changes in relative prices. We estimate the effect of changes in reimbursement prices on the volume of hospital care based on a reform in hospital financing in Germany, which provides an exogenous variation in prices. Several aspects of the German reform set it apart from the price changes examined in previous studies: 1) the reform changed prices across the board for (almost) all patients and types of care[1]; 2) this price variation shifted prices proportionally and did not alter relative prices for different types of care or groups of patients; and

[1] Exceptions are discussed in Section 2.

3) price changes affected hospitals differentially and ranged from substantial across-the-board decreases in prices for some hospitals to substantial across-the-board increases for other hospitals.

In 2004, Germany adopted a system of hospital payment based on diagnosis-related groups (DRGs), in which payment for a hospital admission is based on the patient's main diagnosis. A particular aspect of the German reform that sets it apart from similar reforms in other countries is that payment changes were introduced gradually. In the beginning, reimbursement prices varied widely between hospitals according to hospital-specific base rate factors (*Basisfallwerte*). In 2004, base rate factors were around 36 percent higher for hospitals in the 90^{th} percentile of the distribution of base rate factors than for hospitals in the 10^{th} percentile. Between 2004 and 2009, base rate factors gradually converged towards the average base rate factor at the state level. Thus, base rate factors increased for some hospitals and decreased for others.

In our empirical approach we exploit this variation in reimbursement prices by using administrative data provided by the German Statistical Office. Specifically, we estimate the effect of changes in prices between 2004 and 2009 on changes in hospital care volumes. Our empirical approach is similar to a differences-in-differences estimation approach. However, instead of looking at a binary treatment variable, we examine the effect of a change in prices, which is a continuous treatment variable.

We find an elasticity of prices on the number of hospital admissions of -0.14 and an elasticity of prices on the case-mix index – a measure of the average payment per patient admitted – of -0.29 over a five-year period. Thus, hospitals respond to increasing prices by reducing service supply, as the theory of supplier-induced demand predicts. The variation in initial prices makes it possible to estimate how the effect of price changes on care volume differs across the distribution of prices. We find stronger effects at lower prices.

Our empirical results are robust to controlling for changes in the average base rate factors of competing hospitals as well as for regional demographic and economic trends. In robustness checks, we find that our results cannot be explained by pre-existing trends in volume growth. They can also not be explained by mergers or changes in ownership type, by deviations from the adjustment schedule, or by differences in initial capacity utilization. Furthermore, our results cannot be explained by demand-side reactions to price changes, since prices faced by patients are not affected by changes in base rate factors.

Our findings for Germany are roughly in line with the assumption of the federal budgeting process in the United States, i.e. that medical providers will respond to a one-percent decrease in Medicare reimbursement prices by increasing treatment volume by around 0.3–0.5 percent (Congressional Budget Office 2007). Our findings are also in line with other recent empirical studies that find that lower reimbursement prices increase treatment intensity for automobile accident victims in the United States (Heaton and Helland 2009) and newborns in Japan (Shigeoka and Fushimi 2014). By contrast, Clemens and Gottlieb (2014) show that higher Medicare reimbursement prices for outpatient care increase the volume of care. One possible explanation for this difference could be that we examine the effect of price changes for inpatient care instead of outpatient care.[2] Clemens and

[2] Inpatient care is characterized by relatively high fixed costs compared to outpatient care as well as by relatively low marginal costs for additional treatment. The sign of the effect of price changes on volume of care depends on the relative size of the reimbursement prices and marginal costs (see our model in Section 3).

Gottlieb's results could also be attributed to a change in relative prices rather than to an income effect if higher Medicare reimbursement prices lead to more treatment for Medicare patients compared to patients with other types of health insurance.

The adaption of a DRG-type reimbursement system in Germany has coincided with an uptick in growth rates in volumes of hospital care. This has attracted a lot of attention among economists and healthcare professionals (Felder et al. 2012, Klauber et al. 2013, Kumar and Schönstein 2013, Schreyögg et al. 2014). Other countries with DRG-type hospital reimbursement systems, such as Australia, Japan, and United States (in the Medicare sector), have also experienced a rapid growth in volumes of hospital care in recent decades (Chernew and Newhouse 2012). Provider incentives could be one of the underlying causes of increasing care volumes in DRG-type reimbursement systems.

Our findings have important policy implications. Supplier-induced demand can lead to market failure such that price signals in medical markets do not lead to efficient outcomes. Supplier-induced demand is an important theoretical justification for policies that impose quantity restrictions on medical providers. This may be achieved, for example, through Health Maintenance Organizations or Accountable Care Organizations, which give medical providers financial incentives to limit volume growth.

Our study continues as follows. Section 2 describes the institutional background of hospital financing in Germany. Section 3 presents a stylized model of supplier-induced demand. Section 4 discusses the empirical strategy. The data are described in Section 5, and our results are presented in Section 6. Section 7 concludes.

2. Institutional background

Hospital financing in Germany comes from several sources. By far the most important sources are sickness funds and private health insurers, which cover around 88.5 percent of all hospital expenditure (Simon 2010).[3] Funding from these sources is largely used to cover hospitals' operating costs, including payments for physicians' services. In Germany, physicians are usually employees of the hospital where they work, and they receive a salary from the hospital. Importantly, payment rates for hospital care do not differ between publicly and privately insured patients.[4] The remaining hospital revenues are derived mainly from state governments, which are responsible for long-term infrastructure investments. Patient co-payments in Germany are small relative to hospital costs. Patients have to pay a fixed charge of €10 per night of their hospital stay as a contribution towards room and board, and there are surcharges for additional services such as a single room or treatment by the hospital director. (For surveys of hospital financing in Germany, see Quentin et al. 2010 and Simon 2010).

Before 2004, hospital payment for operating costs was based mainly on negotiated budgets with per-diem charges as the unit of account. In 2004, Germany switched to a system of hospital financing in which hospitals are reimbursed according to patients' diagnosis-related groups (DRGs). The aim of this reform was to make hospital payment more transparent and promote efficiency and competition. The German reform mirrors similar reforms in hospital payment

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[3] The remaining 11.5 percent is covered by private households (2.3 percent), employers (3.4 percent), public accident insurance (1.2 percent) and the federal states (4.6 percent). All numbers refer to 2007 and are provided by Simon (2010).

[4] By contrast, payment rates for outpatient care differ between privately and publicly insured patients.

in other countries that have switched to DRG-type systems, starting from the early 1980s. A particular aspect of the German reform that sets it apart from similar reforms in other countries is that payment changes were introduced gradually. During a first "budget-neutral phase" in 2004, hospitals were reimbursed according to DRGs but prices were adjusted with hospital-specific base rate factors in such a way that hospitals could still achieve their historical budgets. During the "convergence phase," which lasted from 2005 until 2009, hospital-specific prices gradually converged towards average prices at the state level.

Under the German DRG system, payment for a hospital admission is based on the following formula: [5]

$$payment_{i,h,t} = drg_{i,t} * baserate_{h,t} \qquad (1)$$

Payment is the product of two factors: $drg_{i,t}$ is the cost-weight factor for DRG *i* in year *t*, while $baserate_{h,t}$ refers to a hospital-specific base rate factor for hospital *h* in year *t*. All discharged hospital patients are assigned to a DRG. This assignment is based mainly on diagnoses but in some instances is also based on procedures and patient characteristics such as age, sex, and weight (for newborns). The German DRG system was modeled on the Australian DRG system and initially had 664 DRGs. DRG cost-weight factors are the same for all hospitals. They are set at the national level jointly by representatives from health insurers and hospitals, and they are adjusted annually based on detailed patient-level cost data from a sample of hospitals. The cost-weight factors are normalized such that the average

[5] This description abstracts from adjustment factors for teaching hospitals etc. During our study period, DRG payment covered most but not all treatments, and psychiatric treatments were the main exception.

cost-weight factor is set to one. Cost- weight factors are much higher than one for cost-intensive DRGs such as a liver transplant, and they are lower than one for less cost-intensive DRGs such as an ordinary hand fracture.

Hospital-specific base rate factors reflect historical budgets before the introduction of DRG payment. During the budget-neutral phase of the reform, hospital-specific base rate factors were computed by dividing pre-reform budgets by the sum of the cost-weight factors hospitals would have earned for their pre-reform services based on post-reform cost-weight factors. Using hospital-specific base rate factors ensured that hospitals could still achieve their historical budgets under DRG payments in the early stage of the reform as long as they continued to provide the same volume and type of services.

During the 2005–2009 convergence phase, hospital-specific base rate factors gradually converged towards state averages. Base rate factors gradually decreased for hospitals with above-average base rate factors, and they increased for hospitals with below-average base rate factors. The convergence process is illustrated in Figure 1. From 2009, hospitals in the same state received the same base rate factor. In order to protect hospitals from excessive budget cuts, annual reductions in total hospital budgets were limited; for example, to not more than 2.5 percent in 2008.

The distribution of hospital-specific base rate factors is shown in Table 1. The initial variation in base rate factors was substantial. In 2004, the difference between the 10th and 90th percentiles of base rate factors was around 36 percent. In 2009, base rate factors were equalized at the state level. Remaining differences at this stage reflected differences in base rate factors between states. The convergence of base rate factors implied substantial increases in across-the-board reimbursement prices for some hospitals and substantial reductions for others. Base rate factors at the 10^{th} percentile increased by 15.4 percent in real terms between 2004 and 2009, while those at the 90^{th} percentile decreased by 11.8 percent.

The German DRG rules make provisions to protect against induced demand. Hospitals may keep only 35 percent of additional revenues if they exceed the number of target admissions. Additional revenues that are generated by up-coding, i.e. charging a more expensive DRG for the same treatment, are meant to be reclaimed fully by health insurers (Tuschen et al. 2005). However, these provisions are not applied consistently in practice. Hospitals routinely delay budget negotiations until late in the year, and they then negotiate target numbers of admissions that are close to the actual number of admissions (Kumar and Schoenstein 2013). Furthermore, increases in the case-mix index, which is the average cost-weight factor for patients in a hospital, can be reimbursed if the hospital can provide good medical reasons for more intensive treatment.

3. Supplier-induced demand

According to the theory of supplier-induced demand, medical providers can influence demand for their services due to their superior knowledge about patients' healthcare needs. Providers weigh the benefits of adhering to ethical and medical standards against higher revenues. Modifying the McGuire (2000) model, a medical provider's utility function can be characterized as:[6]

$$\max U = U(\mathrm{Y}, I) \tag{2}$$

where $Y = (P - MC)X(\mathrm{I})$

A medical provider has utility *U*, which is an additively separable function of net income *Y* and the demand inducement she conducts *I*. $U_Y > 0; U_I < 0; U_{YY} < 0$; $U_{II} < 0$. Quantity of treatment *X* is affected by the amount of demand inducement *I*. $X' > 0$; $X'' < 0$. *P* is the price the provider receives for a unit of treatment and *MC* is the marginal cost for a unit of treatment.

The provider chooses the level of demand inducement *I* to maximize utility. For this maximization problem we distinguish between two cases. For the case $P > MC$ the first order condition is given by:

$$(P - MC)X' = -U_I / U_Y \tag{3}$$

From this equation follows the counterintuitive result that $dX / dP < 0$. Thus, the medical provider reduces the quantity of treatment as a reaction to increasing reimbursement prices. This relationship reflects that at the optimum the marginal utility from extra income must be equal to the marginal disutility from inducing additional demand. In the case of high prices the marginal utility from additional income is low. Hence, there will be little demand inducement. By contrast, for the

[6] McGuire's model allows for two different prices for the same service for different groups of patients. Since prices in Germany don't vary between patients we simplify the model to the case of one price.

case of lower prices the marginal utility from additional income is higher, and the agent will therefore induce more demand.

In the case $P < MC$ the hospital will provide no services.[7] Thus, it is also possible that lower prices result in the provision of fewer services. Whether higher prices lead to more or fewer hospital services then becomes an empirical question that we aim to answer in this study.

The above model of supplier-induced demand treats hospitals as a single decision-making unit. This reflects the fact that in Germany physicians who work at hospitals are typically salaried employees who report to the hospital management. They share in the success of a hospital through bonuses and better working conditions.

How can hospitals increase the demand for their services? One of the most important driving factors behind patients' hospital choices is recommendations from outpatient physicians (Salfeld et al. 2009). Thus, it is important for hospitals to cultivate good relationships with outpatient physicians who are able to refer patients to the hospital. For example, hospital directors can visit outpatient physicians and inform them about new treatment techniques available at the hospital. Reportedly, many hospitals also pay outpatient physicians for patient referrals (GKV-Spitzenverband 2012).

In addition to increasing the number of patient admissions, hospitals can also aim to increase payments per patient admitted.[8] As a measure of the average payment

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[7] For the case $P = MC$ the optimal level of X is not defined.

[8] For evidence of up-coding by hospitals see, for example, Dafny 2005 and Juerges and Koeberlein 2013.

per admitted patient we use the case-mix index, which is the average cost-weight factor per admitted patient for a hospital in a given year.

4. Empirical approach

Our aim is to estimate the effect of changes in reimbursement prices on changes in care volumes. Specifically, we want to test the hypothesis that this effect has a negative sign such that hospitals respond to increasing prices by supplying fewer services and, correspondingly, that they respond to decreasing prices by supplying more services. We use base rate factors as a measure for reimbursement prices. During our study period, base rate factors increased for some hospitals and decreased for others. This provides a source of variation that we exploit in our empirical strategy by examining how changes in base rate factors relate to changes in treatment volumes.

Our empirical approach is based on linear regression models with two periods and hospital-specific fixed effects:

$$vol_{it} = \beta baserate_{it} + \gamma baserate\_comp_{it} + X_{it}'\delta + \mu_t + \alpha_i + \varepsilon_{it} \tag{4}$$

where vol_{it} is the treatment volume for hospital $i \in (1 \ldots N)$ in year $t \in (2004, 2009)$, $baserate_{it}$ is the base rate factor, $baserate\_comp_{it}$ is the average base rate factor for competing hospitals[9], X_{it} includes regional

[9] We define competing hospitals as hospitals that attract patients from the same geographical area. In Section 5 we describe how the variable for the average base rate factor for competing hospitals is constructed.

demographic and economic characteristics, μ_t are year indicators, α_i are unobserved hospital fixed effects, and ε_{it} represents unobserved time-varying hospital characteristics. β and γ are parameters, and δ is a vector of parameters. β is the parameter of interest and represents the effect of changes in reimbursement prices on changes in hospital volumes.

Fixed effects models with two periods are equivalent to long-difference regression models. The model in equation (4) can be written as:

$$\Delta vol_{it_{2004},t_{2009}} = \beta\Delta baserate_{it_{2004},t_{2009}} + \gamma\Delta baserate\_comp_{it_{2004},t_{2009}}$$

$$+\Delta X_{it_{2004},t_{2009}}{}'\delta + \Delta\mu_{t_{2004},t_{2009}} + \Delta\varepsilon_{it_{2004},t_{2009}} \qquad (5)$$

where $\Delta vol_{it_{2004},t_{2009}}$ is the change in treatment volume for hospital *i* between 2004 and 2009. Equivalently, $\Delta baserate_{it_{2004},t_{2009}}$, $\Delta baserate\_comp_{it_{2004},t_{2009}}$, and $\Delta X_{it_{2004},t_{2009}}$ are changes in the base rate factor, the average base rate factor for competing hospitals, and regional and economic characteristics. These changes refer to hospital *i* and the period 2004–2009. $\Delta\mu_{t_{2004},t_{2009}}$ is the constant in the regression equation above and accounts for time trends in hospital volume, and $\Delta\varepsilon_{it_{2004},t_{2009}}$ are changes in time-varying unobserved determinants of treatment volume.

The covariates $\Delta baserate\_comp_{it_{2004},t_{2009}}$ and $\Delta X_{it_{2004},t_{2009}}$ control for factors that could shift demand for a hospital's services. For example, if changing reimbursement prices are a reason for hospitals to compete for patients more vigorously, then this may have a negative effect on demand for competing hospitals' services. $\Delta baserate\_comp_{it_{2004},t_{2009}}$ controls for changes in the average base rate factors of hospitals that attract patients from the same geographical area. $\Delta X_{it_{2004},t_{2009}}$ controls for regional demographic and economic trends. Changes in population size and the health of the local population influence the demand for hospital services. In our empirical approach we control for regional changes in the average age of men and women as well as in population density and unemployment rates.

We estimate long-difference regression models that refer to the total effect of changes in base rate factors on changes in volumes of care over 2004–2009. One advantage of long-difference regression models compared to standard fixed effects regression models with multiple periods is that they account not only for immediate effects that take place in the same year but also for lagged effects that take place later in the five-year period. We also estimate alternative models for the periods 2004–2008, 2004–2007, 2004–2006, and 2004–2005. In this way, we estimate both the short-term and medium-term effects of changing prices.

Regression equation (5) provides a consistent estimator of β if the following exogeneity assumption holds:

$$E[\Delta\varepsilon_{it_{2004}t_{2009}} \mid \Delta baserate_{it_{2004}t_{2009}}, \Delta baserate\_comp_{it_{2004}t_{2009}}, \Delta X_{it_{2004}t_{2009}}, \Delta\mu_{t_{2004}t_{2009}}] = 0 \qquad (6)$$

Note that the equation above does not contain any assumptions about time-invariant unobserved characteristics α_i. The exogeneity assumption is not violated if time-invariant unobserved characteristics α_i are related to changes in base rate factors. Changes in base rate factors depend on a hospital's pre-reform cost base, which is related to its size and location as well as unobserved hospital characteristics. This does not violate the exogeneity assumption per se as long as changes in base rate factors are not related to changes in time-varying unobserved hospital characteristics $\Delta\varepsilon_{it_{2004}t_{2009}}$.

Our empirical approach is similar to a differences-in-differences regression approach. However, instead of looking at a binary treatment variable, we examine the effect of a change in prices, which is a continuous treatment variable. Thus, we compare not just two groups with different treatments, i.e. one treatment group and one control group, but we look at a continuous range of treatments and compare different treatments with each other.

The exogeneity assumption in equation (6) is similar to the common trend assumption in a differences-in-differences estimation framework. The exogeneity assumption may be violated if there are unobserved time-varying hospital characteristics that are related to changes in both base rate factors and hospital volumes. In the following paragraphs we discuss whether the exogeneity assumption is plausible in the context of our study. Specifically, we discuss potential violations of the exogeneity assumption and how we can test for these violations.

A first potential violation of the exogeneity assumption may arise if changes in base rate factors are correlated with unobserved underlying trends in hospital volumes. We can test for this violation by examining whether trends in hospital volumes before the introduction of the DRG system are related to subsequent changes in base rate factors. As a proxy variable for subsequent changes in the base rate factor we can use the initial base rate factor in 2004. This test is equivalent to the classical test of the common trend assumption based on pre-trends within a differences-in-differences framework. Our test is based on the following linear regression model:

$$\Delta vol_{h,2000-2003} = \beta_0 + baserate_{h,2004}\beta_1 + u_h \tag{7}$$

where $\Delta vol_{h,2000-2003}$ is the change in hospital volume between 2000 and 2003, β_0 and β_1 are parameters, and u_h is an error term. Under the null hypothesis that the exogeneity assumption holds, parameter β_1 should be zero. In alternative specifications we replace $\Delta vol_{h,2000-2003}$ with $\Delta vol_{h,2001-2003}$ and $\Delta vol_{h,2002-2003}$.

A second potential violation of the exogeneity assumption may be caused by mergers during 2004–2009. Mergers may be related to changes in volumes, but they may also be related to changes in base rate factors. We can test directly whether mergers are correlated with changes in base rate factors by regressing an indicator variable, which takes the value one if a hospital was party to a merger over 2004–2009, on the initial base rate factor in 2004. If there is no correlation between the initial base rate in 2004 and subsequent mergers, we can maintain the null hypothesis that the exogeneity assumption holds.

A third potential violation of the exogeneity assumption may arise if hospitals are able to influence base rate factors. This could be the case over 2005–2008, as base rate factors did not always follow the adjustment schedule shown in Figure 1 but were instead negotiated annually between sickness funds and hospitals. It is possible that deviations from the adjustment schedule in Figure 1 can be related to hospital volume. This concern does not apply to 2009, when base rate factors were equalized at the state level. In order to address this potential violation of the exogeneity assumption we use an instrumental variables estimation approach. As an instrumental variable for $baserate_{it}$ we use $baserate_{it_{2004}} * \mu_t$, which is the initial base rate factor for a hospital in 2004 interacted with a year indicator for year *t*. The first-stage regression equation is then given by:[10]

$$baserate_{it} = \pi_1 baserate_{it_{2004}} \mu_t + \pi_2 baserate\_comp_{it} + X_{it}'\pi_3 + \mu_t + \alpha_i + \varepsilon_{it} \quad (8)$$

The idea behind this instrumental variables approach is that we can use initial base rate factors in 2004 in order to predict base rate factors in subsequent years. With this approach we obtain predicted base rate factors that follow an average adjustment schedule similar to the adjustment schedule shown in Figure 1.

An alternative explanation for a negative β could be constraints on capacity utilization, meaning that hospitals with high initial capacity utilization are capacity constrained and that they cannot increase volumes further. If high initial capacity utilization is correlated with increasing base rate factors, this could provide an alternative explanation for a negative β. We can test for this alternative explanation by examining the relationship between initial capacity utilization and initial base rate factors.

5. Data

Our main source of data is hospital statistics from the German Statistical Office for the period 2000–2009. These hospital statistics combine information about hospital characteristics such as ownership type and size with patient-level

[10] The second stage is given by the linear regression model in equation (4).

information on admissions, such as the main diagnosis and county of residence for each patient. These data are merged with county-level regional indicators from the German Statistical Office and with information on base rate factors provided by AOK, a group of health insurers.

Our study is based on a 70 percent random sample of all German hospitals. Our data include 1,159 hospitals with information on the number of admissions and base rate factors in the year 2004. Of those, 165 were excluded from the sample because they are not open year-round or are day clinics or psychiatric hospitals. A further 185 hospitals were excluded because they could not be tracked up to 2009. While hospital closures were very rare during our study period, mergers were quite common.[11] Our baseline estimation sample consists of 801 hospitals.

Outcome variables are the natural logarithm of the total number of annual hospital admissions, the natural logarithm of the total number of annual hospital admissions for specific diagnoses classified according to ICD 9 codes, or the casemix index (the average cost-weight factors of patients admitted to a hospital in a given year). The main explanatory variable of interest is the natural logarithm of base rate factors (*vereinbarte Basisfallwerte*).

We compute a variable for the natural logarithm of the average base rate factors for competing hospitals that attract patients from the same geographical area. This calculation consists of two steps: 1) We first compute the average base rate factor for competing hospitals in each county. This calculation is based on hospital market shares for residents of each county. 2) We then compute the average base

[11] While over 2004–2009 only 19 hospitals were closed, about 20 percent of all German hospitals were involved in mergers. These numbers are based on the RWI Krankenhauspanel, an alternative data source with detailed information on the full sample of German hospitals but no information on volume of care.

rate factors for competing hospitals for each hospital. This calculation is based on the county shares of patients for each hospital, e.g. what share of a hospital's patients comes from a specific county.[12] Since our data come from a 70 percent random sample of German hospitals, this calculation will lead to a slightly noisy but unbiased measure of average base rate factors for hospitals that attract patients from the same geographical area.

We further compute variables on demographic and economic indicators for hospital catchment areas. For this calculation we weight county-level indicators for the average age of men, average age of women, population density, and unemployment rate based on the county shares of patients in each hospital.

Summary statistics for the hospitals in our data set are shown in Table 2. Between 2004 and 2009 the average number of admissions per hospital increased from 10,940 to 11,878. The average values of the case-mix index were very close to one. Between 2004 and 2009, public hospitals as a share of the total decreased slightly from 40.8 percent to 39.1 percent, while the share of not-for-profit hospitals fell from 45.1 percent to 44.2 percent. The remaining hospitals are private. The Herfindahl index for market concentration increased somewhat over the study period. Regional indicators showed a decline in unemployment rates and an increase in the average age of men and women. Average population density did not change much.

[12] Both hospital market shares for county residents and county shares for hospital patients are computed based on shares in 2004 and kept constant across years.

6. Results

Baseline specification

Table 3 shows estimation results for the effect of changes in base rate factors on the number of admissions over alternative time periods. For the period 2004–2009, a one percent increase in base rate factors led to a decrease in hospital admissions of 0.14 percent. Correspondingly, a decrease in base rate factors caused the number of admissions to increase. This effect is significantly different from zero at the five-percent level. Since the prices faced by patients were not affected by changes in the base rate factors, this effect reflects a supply-side response. This result shows that hospitals respond to higher reimbursement prices by providing fewer services, as predicted by models of supplier-induced demand.

The effect of base rate factors on the number of admissions tends to be even larger for shorter time periods. A one-percent increase in prices reduces the number of admissions by 0.32 percent for the period 2004–2008, 0.36 percent for the period 2004–2007, 0.25 percent for the period 2004–2006 period, and 0.13 percent for the period 2004–2005. These coefficients are all statistically significant at the one-percent level. These results suggest that the effect of higher prices on volume of care may be stronger in the short term than in the medium term. This can be explained if hospital costs tend to be fixed in the short run but are more variable in the medium and long run. According to our model in Section 3, the financial incentives for inducing demand depend on the difference between the price and marginal costs of additional treatment. If this difference becomes smaller for longer time periods, then we would expect the effect of prices on the number of admissions to become weaker over longer time periods.

Robustness checks

Estimation results in Table 4 show how trends in hospital volumes before the introduction of DRG payment are related to initial base rate factors. Initial base rate factors predict future price changes. Specifically, we examine whether changes in the number of hospital admissions for the periods 2000–2003, 2001–2003, and 2002–2003 are related to the initial base rate factor in 2004. We include specifications with and without controlling for regional characteristics such as the average base rate factor of competing hospitals as well as the mean age of men and women, population density, and unemployment rate. The coefficients for base rate factors are never statistically significant, and they vary in sign. Compared with the coefficients for prices shown in Table 3, the magnitude of the coefficients for pre-trends is also much smaller. This suggests that our results cannot be explained by differences in underlying trends.

In Table 5 we show estimation results that relate initial base rate factors in 2004 to an indicator for subsequent mergers in the period 2004–2009. This estimation is based on a different data set in which we combined data on base rate factors with information on mergers. The estimation results indicate that there is no correlation between these two variables. The estimation coefficient is 0.000, and it is precisely estimated. Thus, we can rule out that merger activity leads to a violation of the exogeneity assumption. In additional analyses we also show that the estimation results in Table 3 are essentially unchanged if we restrict the sample to hospitals that do not change ownership type during the estimation period.[13]

[13] Results are available from the authors upon request

Table 6 shows the results of instrumental variables estimation. Actual base rate factors for the period 2005–2008 were subject to negotiations and may deviate somewhat from the scheme illustrated in Figure 1.[14] If these deviations were related to care volume, this would violate the strict exogeneity assumption in equation (5). In order to address this concern, we use an instrumental variables estimation approach. Column (2) shows the specification for the period 2004–2008. As an instrumental variable for $baserate_{it_{2008}}$ we use $baserate_{it_{2004}} * \mu_{t_{2008}}$, the initial base rate factor for the hospital in 2004 interacted with an indicator variable for 2008. The estimation coefficient for the instrumental variable can be interpreted as an adjustment factor that predicts to what extend the difference between the initial base rate factor in 2004 and the average base rate factor is reduced over 2004–2008. The first-stage coefficient for the instrumental variable is -0.799. This coefficient implies that the initial differences in base rate factors in 2004 were reduced by 79.9 percent over 2004–2008. The first-stage F-statistics of the instrumental variable show that the instrumental variable is strong, with values far above 10. This instrumental variable approach is also valid, as this adjustment factor is determined by an exogenous variation in base rate factors introduced by the German hospital payment reform. We use an equivalent approach to account for deviations in base rate factors from the adjustment schedule in Figure 2 in the years 2005, 2006, and 2007. The corresponding regression results are shown in Columns (3) to (5) of Table 6.

The estimation results in Table 6 for the main regressions indicate that higher prices lead to decreases in treatment volume. A one-percent increase in prices

[14] This concern does not apply to the year 2009 when base rate factors were equalized at the state level.

reduced treatment volume by 0.195 percent for the period 2004–2008, by a similar amount for the period 2004–2007, and by a slightly smaller amount for the period 2004–2006. These coefficients are statistically significant at conventional levels and are smaller than the corresponding OLS regression coefficients in Table 3. However, as for the OLS regression, they are larger than the effect of prices on volume for the period 2004–2009. For the period 2004–2005, however, the coefficient for price is smaller in absolute value and not statistically significant.

Table 7 shows the results of how capacity utilization before the reform is related with initial base rate factors in 2004. Pre-reform capacity utilization is measured using bed occupancy rates in 2003. Hospitals with higher initial base rate factors had significantly higher capacity utilization than hospitals with lower initial base rate factors. Thus, hospitals that started with higher capacity utilization before the reform also saw larger post-reform increases in the number of admissions. Subsequent increases in admission numbers cannot be explained by low initial capacity utilization.

Heterogeneous effects

In Table 8 we show how the effect of base rate factors on the number of admissions varies according to hospital characteristics such as ownership status, size, and the competiveness of the local market environment. Ownership status may be public, not-for-profit or private. Size is captured by indicators that show whether a hospital's total number of admissions is above or below the median. The competitiveness of the environment is captured by indicators that show whether the Herfindahl index is above or below the median. We find no evidence of the heterogeneous effects of base rate factors on the number of hospital admissions. In additional analyses we restrict the sample to hospitals that did not switch categories, e.g. their ownership status stayed the same over 2004–2009. The results are very similar.[15]

Non-linear effects of prices on the number of admissions

Figure 2 shows non-linear effects of base rate factors on care volumes. We divide the sample of hospitals into four quartiles according to the total change in base rate factors over 2004–2009, and we estimate the effect of price changes on the number of admissions separately for each of the quartiles. The x-axis in Figure 2 shows the average base rate factors for each of the four groups at the beginning of the reform. The y-axis shows the estimation coefficients for the base rate factors for each of the four groups. These coefficients are connected by a solid line and the 95-percent confidence intervals of these coefficients are connected by dotted lines. The effect of price changes on the number of admissions tends to be larger for hospitals with low initial base rate factors. For hospitals with higher initial base rate factors, the effect of price changes is not significantly different from zero. This suggests that the income effect of changing prices depends on the level of reimbursement prices: Hospitals respond more strongly to price changes when they receive lower payment for their services.

Effects of prices on the number of admissions for specific diagnoses

In Table 9 we show estimation results for the effect of prices on the number of admissions for specific diagnoses. We focus on diagnoses with large regional variation in treatment according to a report published by Organization for Economic Cooperation and Development (OECD) (Kumar and Schoenstein 2013).

[15] Results are available from the authors on request.

Diagnoses with a large amount of regional variation may be particularly susceptible to demand inducement. Specifically, we look at cataracts (three-digit ICD 9 code H25), chronic tonsillitis (three-digit ICD 9 code J35), cesarean sections (three-digit ICD 9 code O82), prostate cancer (three-digit ICD 9 code C61), and breast cancer (three-digit ICD 9 code C50). We restrict the sample to hospitals that had at least 30 admissions with the relevant diagnosis in a given year. We find that for the period 2004–2009, a one-percent increase in prices reduced the number of admissions for cataracts by 1.07 percent and for tonsillitis, by 0.6 percent. For cesarean sections, the coefficient for price is negative and similar in magnitude to the effect for all admissions in Table 3. However, the coefficient is not statistically significant. For prostate cancer and breast cancer the coefficients are positive and insignificant. One limitation of our data is that we only know patients' diagnosis codes and not their treatment codes. By using ICD 9 diagnosis codes we cannot distinguish whether, for example, a cancer patient underwent surgery.

Effects of prices on the intensity of treatment

Table 10 shows estimation results for the effect of changes in base rate factors on the case-mix index over different time periods. For the period 2004–2009, a one-percent increase in prices led to a decrease in the case-mix index by 0.29 percentage points. This coefficient is statistically significant at the one-percent level. The results for shorter time periods tend to be even stronger, with the exception of the period 2004–2005. This last result may be explained by a smaller sample size: In 2005, a large number of hospitals had missing information on case-mix indices.

These results suggest that higher prices lead to a substantial decrease in the average charges for hospital patients. There are two possible explanations for this.

Firstly, it is possible that higher prices lead to a reduction in up-coding, i.e. hospitals are less likely to classify services into higher-paying DRGs (see, for example, Dafny 2005, Juerges and Koeberlein 2013). Secondly, it is also possible that hospitals respond to higher prices by adjusting the intensity of treatment (see, for example, Cutler 1995).

DRG cost-weight factors for diagnoses were not constant during our study period. DRG weights are adjusted annually. Therefore, it is possible that the case-mix index in hospitals where prices fell increased not only because of up-coding or more intensive treatment plans but also because of higher DRG weights for the services these hospitals offered.

7. Conclusions

We examine the effect of hospital payment on care volumes based on a reform of hospital financing in Germany. In 2004, hospital payment for patients in Germany was transformed to a system where reimbursement is based on diagnosis related groups (DRGs). At the start of the reform, payment rates for the same diagnosis varied widely between hospitals according to historical costs, but over 2004–2009 payment rates were gradually equalized across hospitals. Thus, payment rates increased for some hospitals and decreased for others.

We find that a one-percent increase in payment rates for the period 2004–2009 led to a decrease in the number of hospital admissions by 0.14 percent and to a decrease in the case- mix index – a measure of the average charges per patient – of 0.29 percentage points. Our empirical results are robust to controlling for the average prices of competing hospitals as well as for regional demographic and economic trends. Through robustness checks we find that our results cannot be explained by pre-existing trends in volume growth, mergers or changes in ownership type, deviations from the adjustment schedule, or differences in initial capacity utilization.

Thus, our results suggest that hospitals respond to increasing prices by providing fewer services, as predicted by models of supplier-induced demand. These findings have important policy conclusions. In a world where supplier-induced demand plays an important role, price signals in medical markets will not lead to efficient outcomes. Supplier-induced demand is an important theoretical justification for imposing quantity restrictions on healthcare providers. Our findings also suggest that existing mechanisms for containing induced demand in Germany are not very effective.

In this study we provide evidence of income effects: Hospitals provide services in greater volumes and more intensively if they are under financial pressure. While this behavior is likely to raise healthcare expenditure, our study provides no evidence that increased treatment is harmful to patients. It is quite possible that patient health benefits from the additional treatment patients receive due to induced demand. How induced demand affects patient health is an interesting topic for future research.

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Table 1: Distribution of base rate factors (*Basisfallwerte*)

Base rate factor	Year 2004	Year 2009*
10th percentile	2238.12	2581.80
25th percentile	2426.92	2609.77
50th percentile	2611.24	2626.05
75th percentile	2818.19	2690.40
90th percentile	3050.17	2690.40

* Deflated with the harmonized consumer price index to prices in 2004.

Table 2: Descriptive statistics

	Year 2004		Year 2009	
	Mean	Standard dev.	Mean	Standard dev.
Number of admissions	10940.590	10452.560	11878.680	11289.700
Case mix index (CMI)	1.001	0.264	1.012	0.407
Public hospitals	0.408	0.492	0.391	0.488
Not-for-profit hospitals	0.451	0.498	0.442	0.497
Herfindahl index (HHI)	0.189	0.131	0.198	0.139
Unemployment rate	9.935	4.144	7.726	3.007
Average age men	36.950	1.006	37.889	0.889
Average age women	40.093	1.433	40.628	1.298
Population density	0.678	0.722	0.681	0.735
Number of hospitals	801		801	

Table 3: Effects of price changes on number of admissions

			Log volume		
	2004–2009	2004–2008	2004–2007	2004–2006	2004–2005
	(1)	(2)	(3)	(4)	(5)
Log price	-0.136**	-0.316***	-0.357***	-0.245***	-0.126***
	(0.055)	(0.066)	(0.071)	(0.063)	(0.047)
Log avg. price	0.135	0.059	0.041	-0.013	0.126
competitors	(0.139)	(0.150)	(0.142)	(0.158)	(0.157)
Regional indicators	Yes	Yes	Yes	Yes	Yes
N (Hospitals)	801	797	801	801	796

Parentheses show robust standard errors, clustered at the hospital level.
Regional indicators include average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area. The estimation equation also includes year indicators.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Robustness check for different trends before the introduction of DRG payment

	Change in log volume					
	2000–2003	2000–2003	2001–2003	2001–2003	2002–2003	2002–2003
	(1)	(2)	(3)	(4)	(5)	(6)
Log price 2004	0.030	0.023	0.014	0.015	-0.039	-0.046
	(0.044)	(0.043)	(0.037)	(0.038)	(0.030)	(0.032)
Regional indicators 2004	No	Yes	No	Yes	No	Yes
N (Hospitals)	789	789	794	794	792	792

Parentheses show robust standard errors, clustered at the hospital level.
Regional indicators include average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area.
* significant at 10%; ** significant at 5%; *** significan

Table 5: Robustness check – Relationship between initial base rate factor and subsequent mergers

	Mergers (2004–2009)	Mergers (2004–2009)
	(1)	(2)
Log Price 2004	0.000	0.000
	(0.002)	(0.018)
Regional indicators 2004	No	Yes
N (hospitals)	1568	1568

Parentheses show robust standard errors, clustered at the hospital level.
Regional indicators include average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Robustness check – instrumental variables estimation

	Log volume				
	years 2004 and 2009	years 2004 and 2008	years 2004 and 2007	years 2004 and 2006	years 2004 and 2005
	(1)	(2)	(3)	(4)	(5)
Main regression					
Log price	-0.149***	-0.195***	-0.197***	-0.156**	-0.025
	(0.045)	(0.051)	(0.053)	(0.063)	(0.086)
Log avg. price	0.137	0.043	0.024	-0.025	0.089
competitors	(0.140)	(0.153)	(0.152)	(0.157)	(0.184)
Regional indicators	Yes	Yes	Yes	Yes	Yes
First stage					
Log price 2004	-0.992***	-0.791***	-0.664***	-0.502***	-0.319***
* year indicator	(0.005)	(0.012)	(0.016)	(0.014)	(0.013)
Log avg. price	0.051***	0.001	0.049	0.109	0.320
competitors	(0.015)	(0.048)	(0.067)	(0.070)	(0.083)
Regional indicators	Yes	Yes	Yes	Yes	Yes
First stage F-statistic	42807.61	3797.02	1811.35	1244.67	646.68
N (hospitals)	801	797	801	801	796

Parentheses show robust standard errors, clustered at the hospital level.
Regional indicators include average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Alternative explanation – different capacity utilization before the reform

	Capacity utilization 2003	Capacity utilization 2003
	(1)	(2)
Log price 2004	0.099***	0.102***
	(0.029)	(0.029)
Regional indicators 2004	No	Yes
N (hospitals)	800	800

Parentheses show robust standard errors, clustered at hospital level.
Regional indicators include log average price of competitors, average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Heterogeneous effects of price changes on number of admissions

	Log Volume		
	years 2004 and 2009	years 2004 and 2009	years 2004 and 2009
	(1)	(2)	(3)
Log price *	-0.132**		
Public	(0.056)		
Log price *	-0.130**		
Not-for-profit	(0.056)		
Log price *	-0.136*		
Private	(0.055)		
Log price *		-0.094*	
Large volume		(0.053)	
Log price *		-0.123**	
Small volume		(0.053)	
Log price *			-0.130**
High HHI			(0.056)
Log price *			-0.134**
Low HHI			(0.055)
Log avg. price	0.123	0.102	0.146
Competitors	(0.140)	(0.137)	(0.139)
Regional indicators	Yes	Yes	Yes
N (hospitals)	801	801	801

Parentheses show robust standard errors, clustered at hospital level.
Regional indicators include average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area. The estimation equation also includes year indicators.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Effect of price changes on volume of treatment for specific diagnoses

	Log volume				
	Cataracts years 2004 and 2009	Tonsillitis years 2004 and 2009	C-section years 2004 and 2009	prostate cancer years 2004 and 2009	breast cancer years 2004 and 2009
	(1)	(2)	(3)	(4)	(5)
Log price	-1.071**	-0.592***	-0.267	0.045	0.103
	(0.462)	(0.181)	(0.647)	(0.256)	(0.263)
Log avg. price	-0.163	1.248**	3.315**	0.861	0.560
competitors	(1.302)	(0.553)	(1.512)	(0.674)	(0.640)
Regional indicators	Yes	Yes	Yes	Yes	Yes
N (hospitals)	114	335	87	268	387

Parentheses show robust standard errors, clustered at hospital level.
Regional indicators include average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area. The estimation equation also includes year indicators.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: Effects of price changes on case-mix Index

	CMI				
	years 2004 and 2009	years 2004 and 2008	years 2004 and 2007	years 2004 and 2006	years 2004 and 2005
	(1)	(2)	(3)	(4)	(5)
Log price	-0.285***	-0.382***	-0.377***	-0.279***	-0.007
	(0.082)	(0.080)	(0.082)	(0.056)	(0.011)
Log avg. price	-0.082	-0.000	-0.001	0.110	0.149
competitors	(0.176)	(0.139)	(0.132)	(0.094)	(0.097)
Regional indicators	Yes	Yes	Yes	Yes	Yes
N (hospitals)	743	747	753	753	333

Parentheses show robust standard errors, clustered at hospital level.
Regional indicators include average age of men, average age of women, population density, and unemployment rate in a hospital's catchment area. The estimation equation also includes year indicators.
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1: Convergence of base rate factors

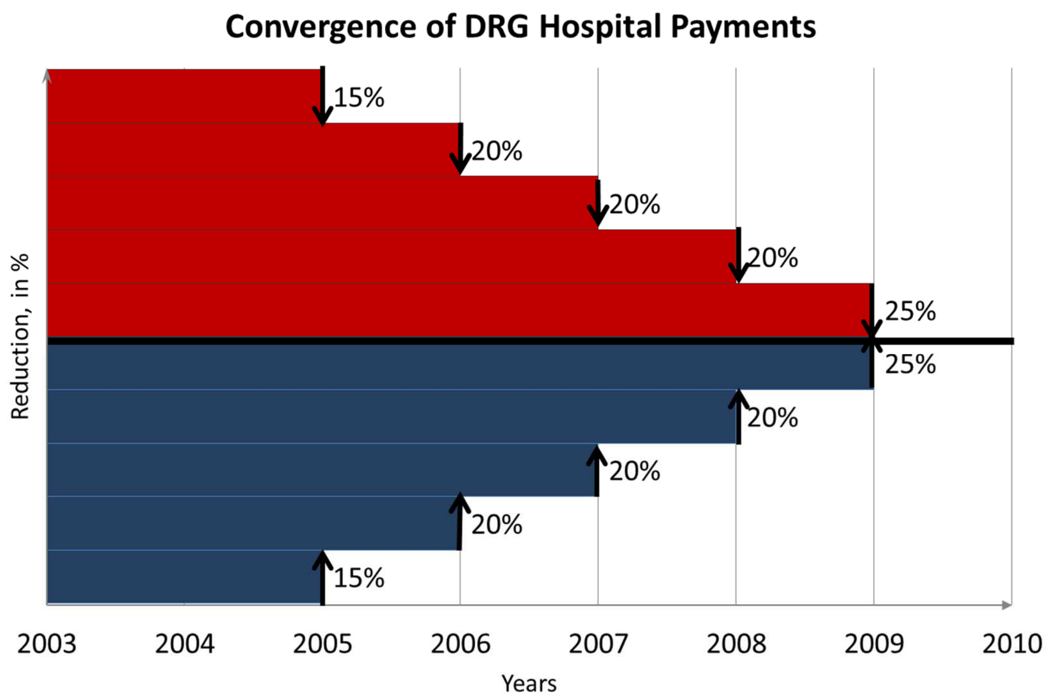

Figure 2: Non-linear effects of base rate factors on number of admissions