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Spending the night? Provider incentives, capacity constraints and patient outcomes

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Abstract:
Healthcare providers' response to payment incentives may have consequences for both fiscal spending and patient health. This paper studies the effects of a change in the payment scheme for hospitals in Norway. In 2010, payments for patients discharged on the day of admission were substantially decreased, while payments for stays lasting longer than one day were increased. This gave hospitals incentives to shift patients from one-day stays to two-day stays, or to decrease the admission of one-day stays. I study hospital responses by exploiting the variable size of price changes across diagnoses in a difference-in-differences framework. I find no evidence that hospitals respond to price changes, and capacity constraints do not appear to explain this finding. Results imply that the current payment policy yields little scope for policymakers to affect the healthcare spending and treatment choices.

Keywords: Provider incentives, hospital reimbursement, price response, capacity constraints

JEL classification: H51, H75, I11, I18

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Sammendrag

Denne artikkelen studerer effektene av en endring i finansieringssystemet for norske sykehus. I 2010 ble sykehusenes kompensasjon for dagbehandling drastisk redusert, mens kompensasjonen for døgnbehandling ble økt. Dette ga sykehusene insentiver til å flytte pasienter fra dagbehandling til døgnbehandling, eller til å redusere antall dagbehandlinger. Slike tilpasninger til økonomiske insentiver kan ha konsekvenser både for offentlige finanser og for pasienters helse. Artikkelen utnytter variasjon mellom diagnosegrupper i størrelsen på marginalgevinsten av å legge inn pasienten for å undersøke om sykehus responderer på insentivendringene. Resultatene viser at sykehus ikke responderer på endringene i insentiver, og det ser ikke ut til at mangel på ledige sengeplasser forklarer hvorfor pasienter ikke flyttes fra dagbehandling til døgnbehandling. Disse funnene indikerer at dagens finansieringsmodell gir lite rom for at økonomiske insentiver kan påvirke behandlingsvalg og ressursbruk i helsetjenesten.

1 Introduction

Escalating healthcare spending constitutes one of the largest fiscal challenges facing governments in developed countries, and supply side factors have gained increased attention as the main driver (see, e.g. Anthony et al., 2009; Skinner, 2012; Chandra et al., 2012; Finkelstein et al., 2016).[1] As choice of payment policy might have consequences for both spending and patient health, it is a pressing empirical task to study how healthcare providers' incentives influence the care they provide.

Healthcare providers have private information about a patient's need for treatment and the quality thereof. The payer, either an insurer or the patient herself, needs to formulate incentives for providers to supply high-quality care at minimum costs. Healthcare systems around the world, from Medicare in the U.S. to national health services in England and Norway, often employ partially prospective payment schedules in which prices are set as the average costs across all patients admitted for a certain diagnosis (i.e. DRG prices). Though such contracts may stimulate both efficiency and quality, distortion effects may arise from the wedge between hospital payment and actual costs.

This paper examines how hospitals respond to price changes. An important challenge when studying price responses is that prices are typically adjusted to reflect changes in treatment costs. Hence, any observed changes in prices likely reflect a reverse causality between care intensity and prices. To address such endogeneity concerns, I rely on two features of the reimbursement scheme for hospitals in Norway. First, as payments are calculated based on costs from 2-3 years back, price changes are unlikely to reflect concurrent changes in treatment costs. Second, I exploit variation from a policy change in 2010 which substantially affected the payments, but did not reflect changing costs. Before the policy change, payment was independent of the subsequent length of stay. After the policy change, providers are paid a considerably lower amount for stays wherein the patient is discharged on the day of admission. At the second day after admission there is a large, approximately \$2000 on average, increase in payments for keeping a patient an additional day, but no payments for any days beyond it.[2] The size of the marginal payment for the second day varies significantly across diagnosis groups; one standard deviation amounts to about \$1200. The new payment scheme thus creates incentives for hospitals to decrease the admission of one-day stays (extensive margin), or to shift patients from one-day stays to two-day stays, provided that the marginal revenue exceeds the marginal cost of the additional day (intensive margin). In addition, hospitals may be inclined to prioritize the more profitable patient groups.

I start out by examining whether patients are, on average, more likely to stay longer than one day following the policy change. This has the intuitive appeal that hospitals may

[1] Over the period 2000 to 2016, health spending has risen from 12.5 percent of GDP to more than 17 percent in the U.S (OECD, 2017). Many European countries have experienced equally striking increases in health spending: from 6 percent to 9.7 percent in the U.K. and from 7.7 percent to 10.5 percent in Norway.

[2] Prices are measured in 2012-levels. Throughout the paper I assume a currency rate NOK/USD=8. Numbers are calculated in the estimation sample.

respond to the new payment scheme without considering the magnitude of the marginal payments. Next, I investigate whether hospitals respond differently by the size of the marginal payments. To this end, I employ a difference-in-differences model to compare admissions within diagnoses subject to large price changes to admissions within diagnoses subject to small price changes. Any response to the payment scheme may depend on whether the hospital is facing capacity constraints. I therefore additionally investigate whether hospitals with a lower bed occupancy rate are more likely to respond.

The Norwegian healthcare system provides an attractive context for this study for several reasons. A first advantage of the Norwegian context is the publicly financed healthcare system, which is reflective of the systems in place throughout Europe, as well as in Canada. In light of marked differences across institutional settings, in terms of hospital ownership and physician remuneration, one might expect to see different effects of similar changes in financial incentives. Reliable causal estimates of price changes are, however, somewhat sparse, and among the notable exceptions, many are set in the U.S. Nonetheless, this literature finds mixed evidence for effects on volume and medical care intensity, including the length of a hospital stay, but generally finds small or no effects on patient outcomes (see, e.g. Dafny, 2005; Clemens and Gottlieb, 2014; Allen et al., 2016; Verzulli et al., 2017; Brekke et al., 2017; Einav et al., 2018).[3]

A second advantage of the Norwegian context is the availability of high quality data. The paper draws on data from administrative registers which include all visits financed by the Norwegian public healthcare system. The unusually rich data comprise complete patient level observations of diagnoses, procedures, admission and discharge times. This allows me to construct detailed patient outcomes, as well as measures of hospitals' capacity constraints. The measure of capacity leverages variation across hospitals in the bed occupancy rate, emerging from the combination of bed capacity and patient congestion.

An important contribution of this paper is to account for the marginal costs arising from capacity constraints. Studies of hospital behavior under capacity constraints are rarely seen within the literature despite the possibility that capacity may be binding and hence affect the price response.[4] If the marginal costs of more treatment are non-negligible, estimated price effects will resemble responses to changes in revenue and not changes in profits. These alternatives may have different policy implications. For example, small or absent price responses could be due to hospitals' ethical concerns or preferences for patient welfare, but lack of responses could also be explained by insufficient monetary payoff.

I concentrate on patients admitted for any orthopedic surgery. These admissions are subject to sharp variation in provider incentives, and they account for about one third of

[3] Clemens and Gottlieb (2014); Allen et al. (2016); Einav et al. (2018) find positive effects of price changes on medical care intensity, while Dafny (2005); Verzulli et al. (2017) find no evidence. Clemens and Gottlieb (2014) and Dafny (2005) find no or little impact on volume, while Januleviciute et al. (2016); Verzulli et al. (2017); Brekke et al. (2017); Liang (2015) find positive volume effects. Of these papers, Allen et al. (2016); Januleviciute et al. (2016); Verzulli et al. (2017); Brekke et al. (2017) study a European setting.

[4] Verzulli et al. (2017) is one exception. They study price changes in Italy, and find smaller price effects for hospitals with lower excess capacity.

all surgeries in Norway. The focus on one specialty at the hospital allows me to study admissions that are likely subject to the same personnel and bed constraints. In addition, orthopedic patients are often relatively healthy and have fewer multiconditions, which make them more likely to be on the length of stay margin affected by the payment scheme changes.

The main findings of this paper may be summarized along the following lines. I do not find any evidence that the 2010-policy change increased the overall probability of patients staying longer than one day. One explanation for the absent response may be that the average masks differential responses across patient groups. For example, patients in less profitable diagnosis groups may be discharged, or not admitted, to free up beds or personnel for patients in more profitable diagnosis groups. Nonetheless, when comparing diagnosis groups subject to large price changes to groups subject to low price changes, I find no discernible differences in the volume of admitted patients. The absence of extensive margin effects through volume and hence patient composition allow me to interpret the estimated probability to stay longer than one day as an intensive margin effect. However, I find no evidence that hospitals are more likely to shift patients from one-day stays to two-day stays within diagnosis groups for which the marginal revenue of the second day is the highest. Capacity constraints may be flagged as one potential explanation for the absence of any price response, as a substantial share of the hospital beds in Norway are filled at any given day, and wait times are generally high (OECD, 2015).[5] However, when comparing hospitals with high pre reform bed occupancy rates to hospitals with lower bed occupancy rates, the results lend no support to the hypothesis that capacity constraints impede hospitals' shifting of patients into longer stays. Finally, given the absence of response on the length of stay, it is unsurprising that I find no evidence that price changes affect patient health.

I conclude that, within the context studied, hospitals are notably insensitive to prices. Effects are precisely estimated, allowing me to discard effect sizes of any economic importance. These findings suggest less concern for perverse incentives and crowding-out of hospitals' motivation, at least within healthcare systems similar to that of Norway. Nonetheless, the results imply that the current payment policy yields little scope for policymakers to affect the healthcare spending and treatment choices.

The remainder of this paper proceeds as follows. Section 2 describes the institutional setting, and explains the payment system and the policy change. Section 3 lays out the empirical strategy. Data, sample and descriptive statistics are presented in Section 4. Sections 5 and 6 present and discusses the results.

[5]According to OECD, 90% of hospitals bed in Norway are filled on any given day. In comparison, the average share of beds filled in the OECD is 80% (OECD, 2015). Another signal of capacity constraints is the long wait times, for example, average wait time for hip replacement was 152 days in 2014 (Godøy et al., 2017)

2 Institutional setting and policy change

2.1 Institution and payment scheme

Norway has a universal, single-payer healthcare system, in which specialist care is primarily funded by a compulsory national insurance scheme.[6] The reimbursement scheme from the national level to regional health authorities entails a fixed part and an activity-based part.[7] Provided that certain financial criteria are met, the regional health authorities are free to further allocate funding to the health trusts and contract specialists within their region. There are no clear guidelines for distribution of funding to lower levels (NOU, 2008), but in practice activity-based financing trickles down to the hospital level, and even to the departmental level within hospitals (Helsedirektoratet, 2007; Riksrevisjonen, 2014).

Physicians at hospitals are paid by a fixed salary, which is not directly connected to hospital reimbursement rates. A salaried physician may nevertheless have a motivation to internalize hospital incentives if it pays back indirectly, for instance by increasing the physician's bargaining power, by improving future job prospects, or by allowing for more comfortable working conditions.[8] Several physicians have expressed concern over the perverse incentives implied by the hospital payment scheme, as illustrated by an op-ed by Lieng et al. (2013) published in the Journal of the Norwegian Medical Association. This may suggest that hospital incentives are at least partially embedded in the decision-making process of the clinicians.

Activity-based financing using diagnosis-related groups (DRGs) is a central feature of the reimbursement scheme for hospitals in Norway. Patients discharged at a somatic hospital are assigned a diagnosis group, where groups comprise patients who are homogeneous in medical criteria and costs of treatment. Each diagnosis group is assigned a cost weight which reflects the average costs of treating a patient within that group, relative to all other patients. Hospitals are reimbursed based on this cost weight regardless of the actual costs incurred in treating the patient. More specifically, the hospital receives the diagnosis-specific weight (w_{jt}) multiplied by the average costs of treating any patient at a somatic hospital ($\bar{c}_{t-2}$) and the share of activity based financing (ABF_t): $p_{jt} = w_{jt} \times \bar{c}_{t-2} \times ABF_t$. Cost estimations are based on average costs of a sample of hospitals. National average treatment costs are revised regularly, and there is a time lag of two to three years for

[6] Some services, such as outpatient admissions and visits to primary care physicians are subject to small co-payment rates. In 2015, the out-of-pocket payment rate for an outpatient procedure was approximately 40USD. However, once a patient's yearly total out-of-pocket healthcare expenditures exceed about 260USD all further expenses within that calendar year are reimbursed.

Since 2001, patients who are referred to specialist health care have had the right to choose the hospital at which they want to receive treatment. Patients may choose to be treated at hospitals outside of their catchment area; either at another health trust within their region or in another region, but the latter is infrequently observed.

[7] The activity-based part has been varying since its introduction, starting at 30 percent in 1997 and oscillating between 40 and 60 in the mid-2000s to finally stabilize at 40 percent in 2006. Activity-based part in percent by year: 1997: 30, 2003: 60, 2004: 40, 2005: 60, 2006-2014: 40, 2015: 50. Investments and geographic and demographic differences between regions are covered by a capitation adjusted block grant.

[8] These arguments are confirmed in informal discussions with hospital physicians and health personnel.

changes in costs to be reflected in price changes.[9]

2.2 2010-Policy change

Diagnosis-specific reimbursement rates were initially independent of the length of a patient's hospital stay. In 2010, the reimbursement rates for each surgical diagnosis group were split into pairs, yielding one rate for stays lasting longer than one day, and one rate for stays lasting one day only. The intention was to make the diagnosis groups more homogeneous in costs, and to remove financial incentives to discharge patients too early (SAMDATA, 2012). In the calculation of new rates, the total set of diagnosis-specific prices was recalibrated so that the total sum of diagnosis group weights produced in 2010 would correspond to that of 2009, given the activity level (and behavior) in 2009 (Helsedirektoratet, 2010, 2011a).[10]

At the outset, note that the change in *average* payments per diagnosis group is minor; the reform was budget neutral, and primarily affected the *marginal* payments within each group. Figure 1 illustrates the payment schemes before and after the policy change. Before the policy change, payment was prospective given the patient diagnosis and hospitals were reimbursed by a fixed price per admission (approximately p = \$3200 on average), independent of the length of stay or the treatment intensity. After the policy change, hospitals receive on average $\underline{p}$ = \$1500 upon admission. On the second day since the day of admission, the payment scheme exhibits a threshold, at which point there is a large (approximately \$2000 on average, or $\overline{p} - \underline{p}$) increase in payments for keeping a patient for one additional day, but no payments for any subsequent days beyond the threshold. Figure 1 describes the average change in the marginal revenue ($\overline{p}-\underline{p}$) caused by the reform. There is also substantial variation between diagnosis groups; this variation will be taken to the data. In Section A3 I formalize the price incentives along the intensive margin, and discuss implications of heterogeneous marginal costs.

3 Empirical strategy

This section describes the empirical methods used to examine the response to the new payment scheme. When payments upon admission decrease while the marginal revenue at the second day increases, hospitals may respond by shifting patients from one-day stays to two-day stays (intensive margin) or by lowering the volume of one-day stays (extensive margin). Both responses will lead to an increase in the estimated probability of patients staying longer than one day.[11] I therefore start out by exploring the policy induced change in the overall probability of staying longer than one day. This has the intuitive appeal that hospitals may respond to the new payment scheme without considering the size of

[9] Prices in 2012 were based on costs from 2010; prices in 2011 from cost data in 2009; 2010 (2007); 2009 (2007) and 2008 (2006). Weights are also updated annually if grouping structure etc has changed.

[10] See Section A1 for more details on how the new weights were calibrated.

[11] Intuitively, any extensive margin response will affect the probability of staying longer than one day by entering through the denominator.

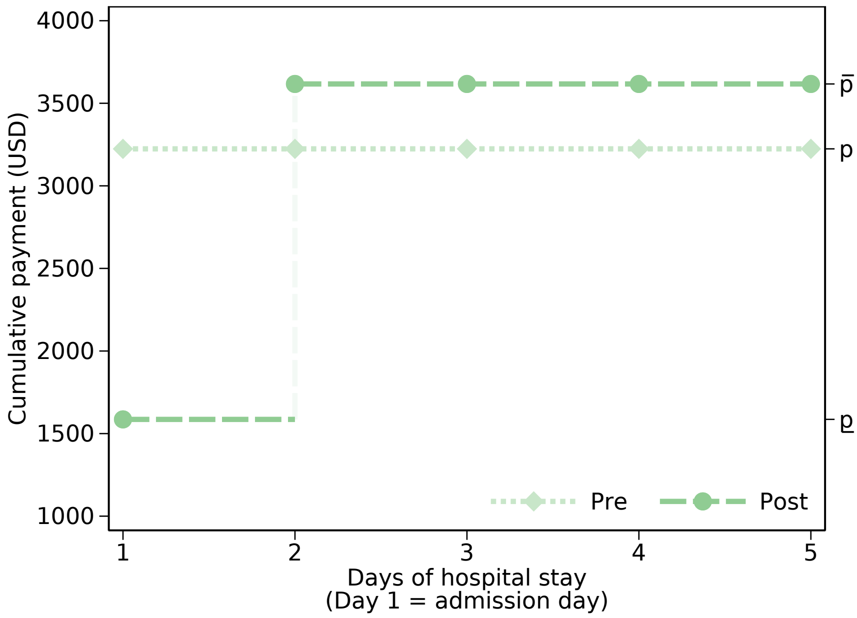


Figure 1: Incentives before and after policy change.
Light dotted line illustrates the hospitals payment scheme before the policy change; darker long-dashed line represents the payment scheme after the policy change. Before the policy change, cumulative payment per patient is not a function of days at the hospital, and payment is fixed at p. After the policy change, cumulative payment is $\underline{p}$ upon admission, and changes discretely, to $\overline{p}$, on the second day since the day of admission. Prices are weighted by the number of admissions in pre-policy year 2009.

the marginal payment. Hospital managers may find it difficult to communicate incentives to the physicians, and perhaps in particular if physicians do not earn the exact size of the marginal payment. Managers may therefore prefer to send a simpler message to their physicians to increase the length of stay by one day across all diagnosis groups.

I next test whether the decision makers consider the size of the marginal payment. To this end, I formulate a difference-in-differences model and compare patients in diagnosis groups subject to large price changes with groups subject to smaller price changes.

3.1 Average response to policy change

Studying average responses to the policy reform is challenging since everyone is affected by the price change, rendering no single control group. Instead, I compare the pre and post policy outcomes in a simple model:

$$y_{ijkt} = \alpha post_t + \beta year_t + \gamma_{jk} + \varepsilon_{ijkt}, \tag{3.1}$$

where y_{ijkt} is either a binary variable equal to one if the patient stays longer than one day at the hospital, or the log number of admissions.[12] The indicator $post_t$ is equal to

[12]When estimating volume effects, the data are collapsed to cells of hospital-diagnosis-year

one in all years ≥2010, and $year_t$ is either a linear or quadratic time trend.[13] Hospital by diagnosis fixed effects (γ_{jk}) control for time invariant characteristics in diagnosis groups within hospitals, and flexibly allow for heterogeneity in the case-mix offered at different hospitals. If the probability of staying longer than one day increases following the policy change, I expect $\alpha > 0$. If hospitals respond by decreasing the number of one-day stays, this would yield a negative impact on the total volume.

3.2 Response by magnitude of marginal payments

I next study whether the payment change differentially affected the probability of one-day stays in diagnosis groups that were subject to large price changes compared to diagnosis groups subject to smaller price changes. Any potential effect on staying longer than one day may be a result of both extensive and intensive margin responses. I therefore additionally estimate the effect on the number of admitted patients. Absent effects along the extensive margin may indicate that any potential effect on staying longer than one day is driven by the intensive margin.

To study effects of price changes, I estimate the following regression model:

$$y_{ijkt} = \alpha HighPrice_j \times post_t + \delta_t + \gamma_{jk} + \varepsilon_{ijkt}, \tag{3.2}$$

where $HighPrice_j$ is a binary variable taking the value one when the change in the marginal revenue at the second day is above the median ($\overline{p} - \underline{p}$ in Section 2.2). If patients admitted in high price groups are more likely to spend longer than one day at the hospital, we would expect $\alpha > 0$.[14]

All unobserved characteristics that may influence the outcome variable are captured by the idiosyncratic error term ε_{ijkt}, and this error term is assumed uncorrelated with the explanatory variables. Standard errors are clustered at the diagnosis group level. To avoid overstating the significance of the findings due to few clusters (20 in total), I calculate p-values and 95% confidence intervals using the wild bootstrap (Cameron and Miller, 2015; Roodman, 2015).[15]

The main assumption in any difference-in-differences model is that, absent the policy change, trends in outcomes would evolve similarly across groups. This can be investigated directly in an event-study model where the $post_t$ indicator is replaced by separate year

[13] This model bears close similarities to a regression discontinuity (RD) design, which yields similar results. The main reason for not using RD as the main approach is that RD may be less ideal if effects occur with some lags, e.g. if it takes time for the hospitals to learn about the new incentives.

[14] Note that the year fixed effects effectively purge out any average impact of the payment change. Instead, the model offers insights into whether providers respond differently according to the amount to be gained. If providers respond to the incentive but do so independently of size of the marginal payments across diagnosis groups, this will not be picked up in the models. However, such overall responses will be captured in the aforementioned model of Equation (3.1).

[15] I cluster at the diagnosis group level because this is the "assignment" level for the price variation. When not exploiting the heterogeneity in price incentives, as in Equations (3.1) and (3.3), I cluster at the hospital level. However, results are similar when clustering at diagnosis level, hospital level, or when clustering two-ways, i.e. taking into account the correlation between hospitals and diagnosis groups.

dummies and the treatment indicator is estimated for each year (relative to pre-reform year 2009).

3.3 Capacity constraints

The final model is motivated by the notion that hospitals often operate at high capacity. Hospitals can only induce longer stays if they have spare capacity to accommodate the patient. To test the hypothesis that capacity constraints may be binding, I group hospitals by their pre policy change bed occupancy rate and formulate an alternative difference-in-differences model:

$$y_{ijkt} = \alpha ExcessCapacity_k \times post_t + \delta_t + \gamma_{jk} + \varepsilon_{ijkt}, \tag{3.3}$$

where $ExcessCapacity_k$ is a binary variable equal to one if the orthopedic unit at hospital k operated below the median bed occupancy rate prior to the payment change.

If hospitals with spare capacity are more likely to respond to the policy change, we expect $\alpha > 0$. Standard errors are clustered at the hospital level.

4 Data, sample and descriptives

The empirical analysis is based on data obtained from the Norwegian Patient Registry (NPR). The registry contains complete patient level observations from all public hospitals as well as private providers contracting with regional health authorities in Norway.[16] From 2008 onwards, records contain patient identifiers that can be linked to administrative data of the entire resident population in Norway. The patient data include information on primary and secondary diagnoses (ICD10), surgical/medical procedures (NCSP/NCMP), exact time, date and place of admissions and discharges, diagnosis-related groups and cost weights.

The estimation sample includes all surgical orthopedic admissions in the NPR data over the period 2008 to 2012.[17,18] Orthopedics is by far the largest branch of surgery, comprising about one third of all surgical admissions, both in terms of volume and revenue.[19] I include both elective and emergency admissions, as they are both subject to the new payment scheme.[20] Some diagnosis groups are aggregated to avoid compositional

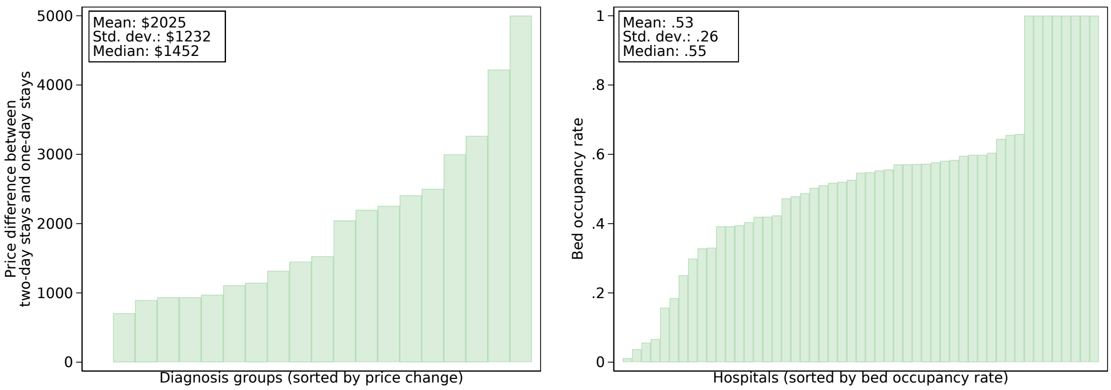
[16] Very few providers operate as for-profit institutions without any contract with public health authorities. The volume of such activity is not known, but is thought to be extremely low.

[17] I use orthopedics as shorthand for the Major Diagnostic Category (MDC) 8 “Diseases and Disorders of the Musculoskeletal System And Connective Tissue”. MDCs are formed by dividing all DRGs into 30 mutually exclusive diagnosis areas that each correspond to a single organ system.

[18] Following a report by the Norwegian Directorate of Health (Helsedirektoratet, 2012), I discard admissions to the emergency departments in Bergen and Oslo due to missing or wrong reporting to the NPR. This does not appreciably affect the results.

[19] Calculation of revenue is based on data from 2009 (pre-reform). In comparison, the second biggest MDC, Diseases in the Circulatory system, generated 14% of the surgical revenue in the same year.

[20] Results from a sample of elective surgeries only yields the same conclusion as for the full sample (see Appendix Tables A4.6 and A4.7).



(a) Price variation by diagnosis groups

(b) Bed occupancy rate by hospitals

Figure 2: Variation in price changes and bed occupancy rate.
Panel (a) shows the variation across diagnosis groups in marginal revenue at the second day. Panel (b) shows the variation across hospitals in the pre-reform bed occupancy rate (patients/beds). Higher bed occupancy rates represent lower excess capacity.

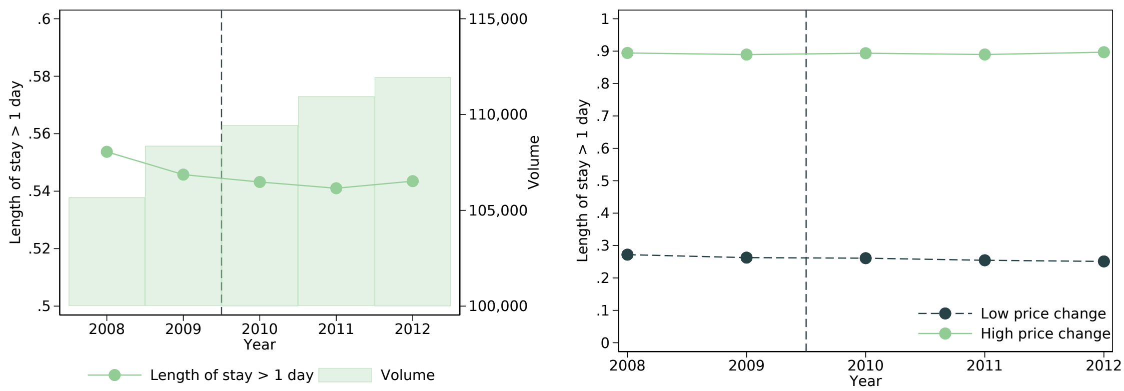
changes over the study period - I use the phrase 'diagnosis groups' as shorthand for these aggregated groups despite the slight imprecision.[21]

The main explanatory variable is an indicator based on the marginal payment at the second day. This marginal payment is defined as the difference in payments between two-day stays and one-day stays ($\overline{p} - \underline{p}$). The variation across diagnosis groups is illustrated in Figure 2a. The sample mean marginal revenue of shifting a patient from one-day stays to two-day stays is \$2025, and the standard deviation is \$1232. Median is \$1452.

When examining whether the policy response depends on the bed capacity, I group admissions by a measure of the pre-reform bed occupancy rate at the hospital's orthopedic surgery unit. The bed occupancy rate is calculated by, for each day, dividing the volume of hospitalized patients by the number of beds. As I do not have data on the number of beds at the specialty level, the bed stock is approximated by the yearly maximum number of patients hospitalized from one day to the next.[22] The very few admissions to hospitals with no beds are given a maximum bed occupancy rate. The variation across hospitals is shown in Figure 2b. The mean bed occupancy rate is about 0.53, while the median is 0.55 and the standard deviation 0.26.

[21] Included DRGs are listed below, where DRGs within parenthesis are grouped together: (209A, 209B, 209O), (210, 211, 212, 212O), (213, 213O), (214A, 214B, 214C, 215B, 215C, 215O), (216, 216O), (217, 217O), (218, 219, 220, 220O), (221, 222, 222O, 222P), (223, 223O), (224, 224O), (225, 225O), (226, 227, 227O), (228, 228O), (229, 229O), (230, 230O), (231, 231O), (232, 232O), (233, 234, 234O), (471, 471N), (491, 491O)

[22] This assumes that hospital units operate at maximum capacity at least once during a year. Results do not change appreciably if I instead set the number of beds at 95% of the maximum. In an alternative specification, I construct the capacity measure at the hospital - rather than specialty - level. This approach may be preferred if specialties can borrow beds from other departments whenever needed. However, results from this model are similar to those presented.



(a) Yearly trends

(b) Yearly trends by high/low price groups

Figure 3: Total admissions and share staying longer than one day.
Panel (a): Histogram shows the number of admissions per year. Connected dots illustrate the yearly share of patients staying longer than one day. Panel (b): Share of patients staying longer than one day by high/low price change groups.

Figure 3a shows that the overall volume of patients has increased throughout the period, while the average share of patients staying longer than one day has decreased. Though we would expect an increase in the latter if hospitals responded to the policy change, it is also worth noting that technological progress works in the opposite direction, towards shorter hospital stays. When splitting the sample by admissions to high vs. low price groups as in Figure 3b, it seems that the trends have evolved fairly synchronized over time. These trends will be examined more thoroughly in the empirical section.

The rest of the sample is described in Appendix A2.

5 Results

5.1 Average response

I begin the presentation of results by discussing the overall effect on the probability of patients staying longer than one day. Figure 3 indicated descriptively that any policy induced change in the probability of staying longer than one day is at maximum modest. This picture is reiterated in Figure A4.1, where I plot the probability of staying longer than one day purged of hospital by diagnosis fixed effects. More precisely, the figure plots the residuals after a regression of a binary indicator for staying longer than one day on hospital-diagnosis fixed effects. Although there might be indications that the trend is flattening out, there is no sign of any abrupt increase in 2010, despite the large financial incentives. In Table 1 I show that the estimate of the post indicator from Equation (3.1) is almost zero, in fact marginally negative with a point estimate of -0.007. The estimate is quite precise, and effect sizes larger than 0.008 can be rejected at a 95% significance

Table 1: Effects of policy change on patient stays longer than one day

	Length of stay>1 day		
	(1)	(2)	(3)
Post	-0.007	-0.002	-0.002
	(0.004)	(0.004)	(0.004)
Linear time trend	✓	✓	✓
Quadratic time trend		✓	✓
Patient controls			✓
Dep. mean	0.545	0.545	0.545
N	546,383	546,383	546,383

Notes: Results from estimation of Equation (3.1). All models include fixed effects for hospital-diagnosis. Linear time trend is included in column (1), quadratic time trend is included in column (2), and patient age, gender and the number of secondary diagnoses are included in column (3). Robust standard errors clustered at hospital level in parentheses; * p<0.05, ** p<0.01, *** p<0.001.

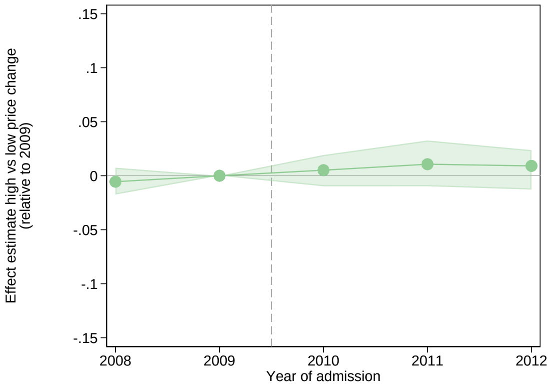
level. The estimate decreases somewhat when allowing for a quadratic time trend. Now, estimates higher than 0.006 percentage points can be rejected at a 95% significance level. Adding patient controls does not seem to affect the point estimate, which suggests that hospitals do not start attracting a different type of patients, which would have biased the estimate. The effect on the log volume is likewise minimal and non-significant, with point estimates ranging from -0.042 to -0.052 (see Table A4.1). Taken together, there is strong evidence of no average response to the new payment schedule.

5.2 Response by magnitude of marginal payments

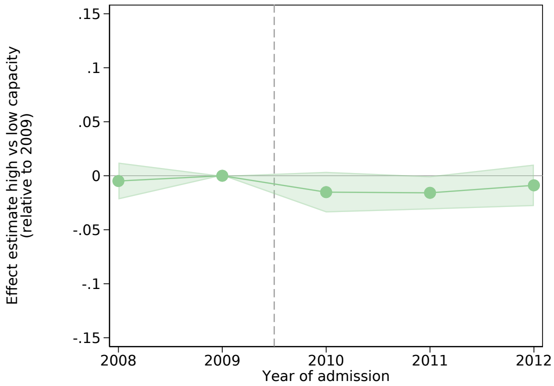
The absence of any increase at the time of the reform may hide heterogeneous responses across groups, for example due to capacity constraints. For instance, hospitals may retain fewer patients in low price groups in order to free up beds for patients admitted to groups subject to high price changes, rendering a zero average effect.

I continue by presenting results from the event-study equivalent to Equation (3.2). Figure 4a serves two purposes: one is to test the identifying assumption of there being no trends in the outcome variable prior to the reform; the second is to give a visual presentation of any potential effect. The effect of high relative to low price changes is estimated for each year relative to 2009. The figure displays no systematic pattern before the policy change, lending support to the specification described by Equation (3.2).

A second takeaway from Figure 4a is that the effect of a high price change on staying longer than one day is not significantly different from a low price change. This result is further quantified in Table 2 where I present results from Equation (3.2). Column (1) shows that patients subject to higher price changes are slightly more likely to stay longer than one day, but the estimate is small and non-significant (0.01). The effect size decreases when controlling for diagnosis-specific time trends in column (2). This is easiest explained by Figure A4.2 which plots the residualized outcome over years separately for low and



(a) Response by price change



(b) Response by bed capacity

Figure 4: Probability of staying longer than one day – by size of price change and bed capacity.
Panel (a) plots the event study estimate of high price changes, while panel (b) shows the event study estimates for excess capacity. Both models include year and hospital-diagnosis fixed effects.

Table 2: Effects of price changes on patient stays longer than one day

	Length of stay>1 day		
	(1)	(2)	(3)
$HighPrice \times post$	0.011	0.005	0.014
95% CI	[-0.009, 0.031]	[-0.011, 0.023]	[-0.005, 0.033]
p-value	*0.27*	*0.55*	*0.15*
Linear DRG time trend		✓	
Patient controls			✓
Observations	546,383	546,383	546,383
Dependent mean	0.545	0.545	0.545

Notes: Results from estimation of Equation (3.2). Table shows the effect of high price changes (above vs below median price change) on staying longer than one day at the hospital. All models include fixed effects for year and hospital-diagnosis. Diagnosis-specific time trends are included in column (2), and controls for age, gender and comorbidities are added in column (3). P-values and 95% confidence intervals are calculated by clustering at the diagnosis group level using the wild bootstrap method (Cameron and Miller, 2015; Roodman, 2015); * p<0.05, ** p<0.01, *** p<0.001.

high price change groups. The figure reveals a slight upward pre-trend in the high price group, which will bias the effect estimate from column (1) upwards. When taking account of this small pre-trend, the point estimate falls to 0.005, still non-significant.

In Table A4.2 I show that results are robust to alternative treatment indicators. This includes comparing only admissions to the top and bottom price group quartiles, and including the price change variable linearly. None of the models find any significant effects of price changes on the probability of staying longer than one day.

Table A4.3 presents evidence that price changes do not appear to have affected the volume of patients either. The estimated effect of high price changes on the log volume of patients is small (0.5%) and non-significant.

Table 3: Effects of policy change on patient stays longer than one day by bed capacity

	Length of stay>1 day		
	(1)	(2)	(3)
$ExcessCapacity \times post$	-0.011	-0.021	-0.012
	(0.008)	(0.011)	(0.009)
Linear hospital time trend		✓	
Patient controls			✓
Observations	546,383	546,383	546,383
Dependent mean	0.545	0.545	0.545

Notes: Results from estimation of Equation (3.3). Table shows the effect of the policy change for admissions to hospitals with excess capacity relative to admissions to hospitals with lower capacity (below vs above median bed occupancy rate) on staying longer than one day at the hospital. All models include fixed effects for year and hospital-diagnosis. Hospital-specific time trends are included in column (2). Robust standard errors clustered at the hospital level; * p<0.05, ** p<0.01, *** p<0.001.

5.3 Capacity constraints

Binding capacity constraints may prevent hospitals from retaining any type of patients, regardless of the size of the price incentives. Figure 4b shows the event study equivalent of Equation (3.3), where I group hospitals by their pre reform capacity rate. There does not appear to be any differential trends in the probability to stay longer than one day in the years before the policy change, lending support to the difference-in-differences model. Moreover, there does not seem to be any indications that hospitals with relatively high spare capacity are more likely to shift patients into longer stays following the policy change. This finding is consistent with the difference-in-differences estimates presented in Table 3, which are modestly negative and non-significant. There is also no indications of any volume effects, but precision is low (see Table A4.5).

5.4 Patient health

Since the policy change did not seem to shift patients into longer stays, health outcomes cannot be impacted through an increase in the length of stay. Health outcomes may, however, be directly affected through other channels, e.g. if hospitals compromise on quality to avoid incurring financial losses from the policy change. To test this, I use the model in Equation (3.2) to estimate the effect of price changes on patient health indicators. The overall finding is that price changes do not carry over to patient health, but precision is fairly low across all models. Results are presented in Table A4.4.[23]

[23]The indicators for in-hospital complications, infections and sentinel events all have low sample means, for which linear probability models are known to perform poorly. Nonetheless, when alternatively using a logit model, effects are minor and still non-significant.

6 Discussion

A thorough understanding of how providers respond to incentives is crucial for policy makers to affect costs and ultimately patient welfare. In this paper I show that, within the Norwegian healthcare system, hospitals are notably insensitive to price incentives.

Capacity constraints seem unlikely to be the reason for the absence of any response. This was formally examined in the model described in Equation (3.3), where I grouped hospitals by their pre-reform capacity constraints. In this model, capacity was depending on a time invariant measure of bed capacity. In an alternative model, I have also examined time-variant measures of capacity, where the capacity measure is allowed to vary within hospitals at a daily basis. This model brought the same conclusion as the one presented: capacity constraints do not seem to explain the absent price response.[24]

High marginal costs form one potential explanation for why hospitals do not appear to respond to price changes. Even if the marginal costs resembled by the bed occupancy rate do not seem to be a driving force, there could be other marginal costs, such as for personnel and equipment. This story seems however unlikely: since 2012, municipalities are by law required to pay hospitals \$500 per night for medical patients who are ready to be discharged from the hospital but are not yet offered a bed at a nursing home. To the extent that these marginal costs are generalizable to surgical patients at the one-day margin, there is a sufficient profit margin to be gained - recall that the average marginal revenue was around \$2000.[25]

A theoretical model predicting hospital behavior would likely include a parameter that captures physician morale or ethics. Physician ethics is a possible explanation for the absence of price response if, pre reform, patients were already staying the optimal length. In this case, staying longer at a hospital may worsen the patient outcomes, e.g. through the risk of contracting hospital infections, or simply because individuals prefer shorter hospital stays. Under the assumption that the welfare gain of a second day at the hospital is negligible or negative, the findings are consistent with hospital objectives that value patient welfare sufficiently more than revenues.

A final explanation for no price response could be that the actual decision maker - the clinician - is unconnected to the incentives of the hospital. As explained in Section 2, physicians at hospitals are paid by a fixed salary, whereas the price changes studied are at the hospital level. Meanwhile, there are several examples of physicians who express worry about the perverse financial incentives (see, e.g. Lieng et al., 2013), and Januleviciute et al. (2016) find that Norwegian hospitals indeed respond to (relatively small) price incentives. It thus seems likely that hospital incentives, at least to some extent, trickle down to the decision making level. Nevertheless, if physician incentives are only partly related to the

[24]If hospitals with no excess capacity have by construction no way to respond to the new payment scheme, the model in Equation (3.3) is not ideal. However, when estimating a model similar to the one described in Equation (3.1), which include a time trend rather than time fixed effect, on a sample of hospitals with excess capacity only, I find again no indications of any response.

[25]The potential implications of marginal heterogeneous costs were discussed in Appendix Section A3.

hospital payment scheme, it may be difficult to estimate effects of their true incentives.

The findings of this paper have important policy implications. Prospective, activity-based prices are used in many countries to give hospitals incentives to contain costs. Critics argue that hospitals may be inclined to attract profitable patients, and to lower the quality for a given patient. This paper's findings suggest less concern for perverse incentives within systems similar to that of Norway, and are consistent with a model in which physicians act as agents for the patients. Nonetheless, the results imply that the current payment policy yields little scope for policymakers to affect the provision of healthcare.

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Appendix

A1 Details on the price recalibration made by the Norwegian Directorate of Health

The Norwegian Directorate of Health receives account data from a sample of hospitals. These data are grouped by the following cost categories (Helsedirektoratet, 2011b):

1. Fixed, by hospital department
2. Direct costs related to care, by hospital department
3. Surgery
4. Intensive care
5. X-ray
6. Laboratory work
7. Pharmaceuticals

When splitting DRGs into separate groups for inpatients and outpatients, The Directorate of Health employed data from year 2007, and used discretion in the choice of relative weights for the cost categories. Categories (1), (2) and (7) were weighted by 0.5 for outpatient groups. Moreover, the costs related to surgery (category (3)) were set based on the lowest costs within the original diagnosis group. Costs related to care (category (2)) were given 0.1 points per days at the hospital, hence 0.5*0.1=0.05 per outpatient admission. Outpatient DRGs were not given costs related to category (4), (5) and (6). The recalibration was budget neutral at the aggregate level, but caused distortions at the hospital level. (In particular, hospitals mainly focusing on outpatients would yield relatively less reimbursement).

A2 Descriptive statistics

Table A2.1 describes the estimation sample. Analogous to the decrease in the share staying longer than one day, the average length of stay has decreased throughout the study period. The patient background indicators age, female and number of secondary diagnoses are fairly stable over the period; so are the patient health indicators: 30-days and 90-days emergency readmission rate and 1-year re-surgery. Re-surgery is defined as the readmission of a patient within the same surgical diagnosis group for which she was initially admitted.

The patient safety indicators have very low sample averages; i.e. operative and post-operative complications, hospital-acquired infections, and sentinel events, are extremely rare. These indicators are computed using secondary diagnosis codes following Drösler (2008) (see also, e.g. Kittelsen et al., 2015). The full set of diagnosis codes used to construct these measures are described in Table A2.2.

The number of hospitals decrease throughout the time period studied due to a fall in the number of private hospitals. However, private institutions are small, such that this decrease amounts to less than 2% of the patient volume.[26]

There are in total 20 diagnosis groups, 11 in high price change groups and 9 in low price change groups.

Table A2.1: Descriptive statistics

	(1) 2008	(2) 2009	(3) 2010	(4) 2011	(5) 2012
Length of stay	3.27	3.06	3.01	2.88	2.65
Female	0.53	0.53	0.53	0.53	0.53
Comorbidities	0.78	0.75	0.74	0.72	0.73
Age	54.0	53.9	54.1	54.3	54.3
30d emg readm	0.080	0.091	0.088	0.099	0.096
90d emg readm	0.10	0.12	0.11	0.12	0.12
1-year resurgery	0.41	0.44	0.46	0.45	0.43
Complications	0.0070	0.0062	0.0069	0.0062	0.0064
Infections	0.0010	0.00098	0.00082	0.0011	0.00088
Sentinel events	0.000047	0.000074	0.000027	0.000045	0.000027
Hospitals	50	51	51	47	49

Notes: Descriptive statistics of the estimation sample.

[26] Entry and exit into the market is regulated, and private hospitals are not allowed to offer any treatment they like. To make sure entry and exits for reasons unrelated to the price change affects the estimates, I also estimate an alternative model where I group all private hospitals together (as hospitals enter through the hospital-diagnosis fixed effects). This does not appreciably affect any results (available upon request).

Table A2.2: Quality indicators

Patient Safety Indicator		ICD10-codes
Hospital-acquired infections		
Infection due to medical care	PSI7	T802, T827, T880
Decubitus ulcer	PSI3	L89
Operative and post-operative complications		
Complications of anaesthesia	PSI1	Y48, Y653
Postoperative hip fracture	PSI8	S720, S722, S721
Postoperative pulmonary embolism (PE) or deep vein thrombosis (DVT)	PSI2	I260, I269, I828, I829, I80
Postoperative sepsis	PSI13	A40, A41, R578, T811
Technical difficulty with procedure	PSI15	Y60, T812
Postoperative respiratory failure	PSI11	J960
Iatrogenic pneumothorax	PSI6	J95
Sentinel events		
Transfusion reaction	PSI16	T803, T804, Y650
Foreign body left in during procedure	PSI5	T815, T816, Y61

Notes: Definitions for patient safety indicators (PSIs) are taken from Drösler (2008).

A3 Price incentives

This section discusses the price incentives implied by the policy change in presence of marginal costs for staying an additional day, and focus on behavior along the intensive margin. Let profits $\pi_j^t(los)$ in period $t \in (0,1)$ for diagnosis j be a function of length of stay los, where $los \in (1,2)$. $MC_j(\perp\!\!\!\perp t)$ is the marginal cost of staying an additional day at the hospital; costs related to initial surgery are abstracted from. Table A3.1 shows profits for stays lasting two days $\pi_j^t(2)$ and one day $\pi_j^t(1)$, before ($t=0$) and after ($t=1$) the policy change.

Table A3.1: Profits before and after policy change

	Before ($t=0$)	After ($t=1$)	Δ
$\pi_j^t(2)$	$p_j - MC_j$	$\overline{p}_j - MC_j$	$\overline{p}_j - p_j$
$\pi_j^t(1)$	p_j	$\underline{p}_j$	$\underline{p}_j - p_j$
$\pi_j^t(2) - \pi_j^t(1)$	$-MC_j$	$\overline{p}_j - \underline{p}_j - MC_j$	$\overline{p}_j - \underline{p}_j$

Notes: Price incentives induced by the policy change.

Consider a profit maximizing hospital, and assume first a situation in which there is only one diagnosis j. Before the policy change, the hospital should never let the patient stay an additional day, because $\pi_j^0(1) > \pi_j^0(2)$ as long as $MC_j > 0$. After the policy change, the patient is shifted to a two-days stay if $\pi_j^1(2) > \pi_j^1(1) \Rightarrow \overline{p}_j - \underline{p}_j > MC_j$.

Now consider two types of diagnosis groups, $j \in (A, B)$. The hospital should choose $los = 2$ for type A rather than B if (i) a two-days stay for patient A is profitable:

$$\pi_A^t(2) > \pi_A^t(1), \tag{A3.1}$$

and (ii) a two-days stay for patient A is more profitable than a two-days stay for patient B:

$$\pi_A^t(2) - \pi_A^t(1) > \pi_B^t(2) - \pi_B^t(1). \tag{A3.2}$$

Prior to the policy change, Equation (A3.1) reduces to $-MC_A > 0$, while Equation (A3.2) yields

$$\begin{aligned} -MC_A &> -MC_B \\ \Rightarrow MC_B &> MC_A \end{aligned} \tag{A3.3}$$

Now, presumably $MC_A > 0$, hence Equation (A3.1) is not satisfied. More generally, since $MC_j > 0$, the hospital should not retain any patient.

After the policy change, hospitals should retain type A if (from (A3.1)):

$$\overline{p}_A - \underline{p}_A > MC_A, \tag{A3.4}$$

and (from Equation (A3.2)):

$$\begin{aligned} \overline{p}_A - \underline{p}_A - MC_A &> \overline{p}_B - \underline{p}_B - MC_B \\ \Rightarrow \left(\overline{p}_A - \underline{p}_A\right) - \left(\overline{p}_B - \underline{p}_B\right) &> MC_A - MC_B \end{aligned} \tag{A3.5}$$

The empirical section implicitly assumes that Equation (A3.4) holds, and moreover, that $MC_A = MC_B$. In that case, Equation (A3.5) implies hospitals should choose $los = 2$ for patient A rather than B if $\overline{p}_A - \underline{p}_A > \overline{p}_B - \underline{p}_B$.

In reality, however, it may be the case that $MC_A > MC_B$. If so, the profit maximizing choice *could* be to let patient B rather than patient A stay for two days.

A4 Additional results

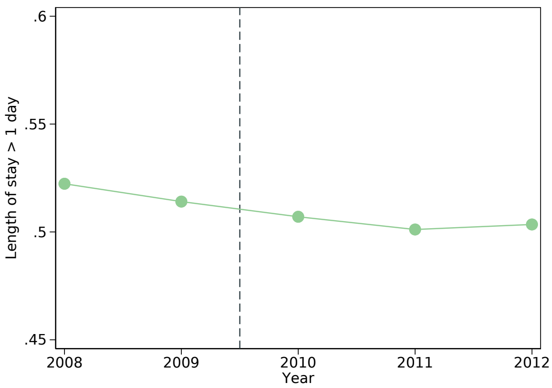
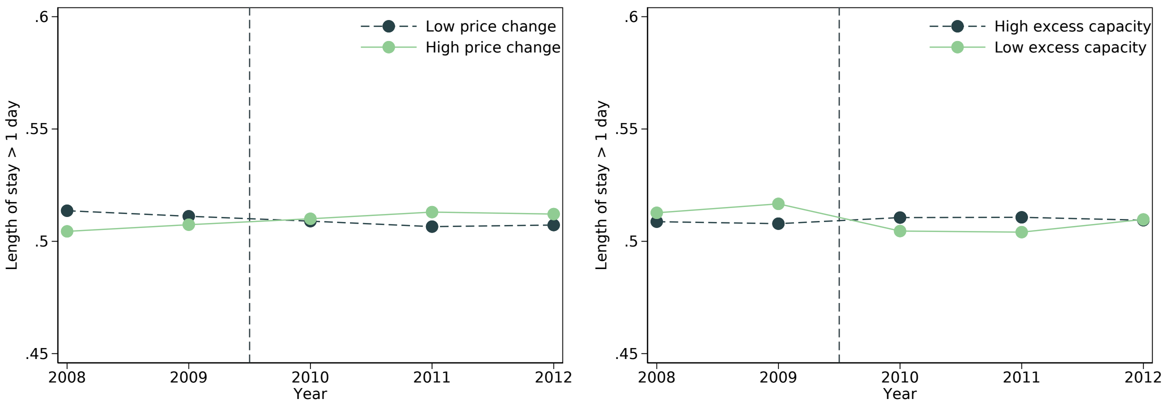


Figure A4.1: Overall probability of staying longer than one day.
Figure plots the probability of staying longer than one day, purged of hospital-diagnosis fixed effects. Sample means are added back in to facilitate interpretation of the axes.

Table A4.1: Effects of policy change on admission volume

	Log Volume		
	(1)	(2)	(3)
Post	-0.042	-0.052	-0.043
	(0.048)	(0.047)	(0.048)
Linear time trend	✓	✓	✓
Quadratic time trend		✓	✓
Patient controls			✓

Notes: Results from estimation of Equation (3.1). Models include fixed effects for hospital-diagnosis. Linear time trend is included in column (1), column (2) additionally adds a quadratic time trends, while and patient age, gender and number of secondary diagnoses are included in column (3). Standard errors clustered at the hospital level; * p<0.05, ** p<0.01, *** p<0.001.



(a) High/low price change   **(b)** High/low excess capacity

Figure A4.2: Probability of patients staying longer than one day.
Panel (a) plots the probability of staying longer than one day by size of the price change (above vs below median price change), purged of year and hospital-diagnosis fixed effects. Panel (b) plots the probability of staying longer than one day by hospitals' bed occupancy rate (above vs below median occupancy rate, i.e. low vs high excess capacity), purged of year and hospital-diagnosis fixed effects. Sample means are added back in to facilitate interpretation of the axes.

Table A4.2: Effects of price changes on patient stays longer than one day - alternative definitions of treatment

	Length of stay>1 day (1)	N/Dep.mean (2)
Above/below median (baseline)	0.011 [-.009, .031]	546,383
p-value	*0.27*	0.545
Top/bottom quartile	0.033 [-.035, .069]	256,511
p-value	*0.12*	0.748
Linear price change	0.011 [-.013, .034]	546,383
p-value	*0.41*	0.545

Notes: Results from estimation of Equation (3.2) with alternative treatment indicators: top vs bottom quartile price change, and linear price. Models include fixed effects for year and hospital-diagnosis. p-values and 95% confidence intervals are calculated by clustering at the diagnosis group level using the wild bootstrap method (Cameron and Miller, 2015; Roodman, 2015); * p<0.05, ** p<0.01, *** p<0.001.

Table A4.4: Effects of price changes on patient health

	(1) 30-day emg readm	(2) 90-day emg readm	(3) 1-year re-surgery
HighPrice	0.00413	0.000447	0.00828
95% CI	[-.01255, .01553]	[-.0118, .008835]	[-.01997, .03575]
p-value	*0.51*	*0.92*	*0.58*
Dep. mean	0.0908	0.114	0.439
	PSI (operative compl.)	PSI (infections)	PSI (sentinel events)
HighPrice	-0.000154	0.0000448	0.0000367
95% CI	[-.00144, .001336]	[-.000418, .0005856]	[-.00007503, .0001599]
p-value	*0.85*	*0.87*	*0.48*
Dep. mean	0.00656	0.000954	0.0000439
N	546,383	546,383	546,383

Notes: Results from estimation of Equation (3.2). Table shows the effect of high price changes (above vs below median price change) on measures of patient health. All models include fixed effects for year and hospital-diagnosis. Diagnosis-specific time trends are included in column (2), and controls for age, gender and comorbidities are added in column (3). p-values and 95% confidence intervals are calculated by clustering at the diagnosis group level using the wild bootstrap method (Cameron and Miller, 2015; Roodman, 2015); * p<0.05, ** p<0.01, *** p<0.001.

Table A4.3: Effects of price changes on the log number of patients

	Log Volume		
	(1)	(2)	(3)
$HighPrice \times post$	0.005	0.031	0.005
95% CI	[-0.109, 0.122]	[-0.088, 0.142]	[-0.088, 0.151]
p-value	*0.93*	*0.62*	*0.62*
Linear diagnosis group time trend		✓	
Patient controls			✓

Notes: Results from estimation of Equation (3.2). Table shows the effect of high price changes (above vs below median price change) on the number of admitted patients. All models include fixed effects for year and hospital-diagnosis. Diagnosis-specific time trends are included in column (2), and controls for age, gender and comorbidities are added in column (3). p-values and 95% confidence intervals are calculated by clustering at the diagnosis group level using the wild bootstrap method (Cameron and Miller, 2015; Roodman, 2015); * p<0.05, ** p<0.01, *** p<0.001.

Table A4.5: Effects of policy change on admission volume by bed capacity

	Log volume		
	(1)	(2)	(3)
$ExcessCapacity \times post$	-0.035	-0.036	-0.035
	(0.083)	(0.084)	(0.072)
Linear hospital time trend		✓	
Patient controls			✓
Observations	546,383	546,383	546,383
Dependent mean	0.545	0.545	0.545

Notes: Results from estimation of Equation (3.3). Table shows the effect of excess capacity (below vs above median bed occupancy rate) on the number of admitted patients. All models include fixed effects for year and hospital-diagnosis. Hospital-specific time trends are included in column (2), and controls for age, gender and comorbidities are added in column (3). Robust standard errors clustered at the hospital level; * p<0.05, ** p<0.01, *** p<0.001.

Table A4.6: Elective admissions: Effects of price changes on patient stays longer than one day

	Length of stay>1 day		
	(1)	(2)	(3)
$HighPrice \times Post$	-0.001	-0.005	0.006
95% CI	[-0.026, 0.014]	[-0.030, 0.012]	[-0.012, 0.020]
p-value	*0.92*	*0.56*	*0.59*
Linear diagnosis time trend		✓	
Patient controls			✓
Observations	546,383	546,383	546,383
Dependent mean	0.394	0.394	0.394

Notes: Results from estimation of Equation (3.2) on a sample of elective patients. Table shows the effect of high price changes (above vs below median price change) on staying longer than one day at the hospital. All models include fixed effects for year and hospital-diagnosis. Diagnosis-specific time trends are included in column (2), and controls for age, gender and comorbidities are added in column (3). p-values and 95% confidence intervals are calculated by clustering at the diagnosis group level using the wild bootstrap method (Cameron and Miller, 2015; Roodman, 2015); * p<0.05, ** p<0.01, *** p<0.001.

Table A4.7: Elective admissions: Effects of price changes on the log number of patients

	Log Volume		
	(1)	(2)	(3)
HighPrice	-0.022	0.029	-0.021
95% CI	[-0.146, 0.104]	[-0.128, 0.193]	[-0.143, 0.106]
p-value	*0.73*	*0.71*	*0.76*
Linear diagnosis group time trend		✓	
Patient controls			✓

Notes: Results from estimation of Equation (3.2) on a sample of elective patients. Table shows the effect of high price changes (above vs below median price change) on staying longer than one day at the hospital. All models include fixed effects for year and hospital-diagnosis. Diagnosis-specific time trends are included in column (2), and controls for age, gender and comorbidities are added in column (3). p-values and 95% confidence intervals are calculated by clustering at the diagnosis group level using the wild bootstrap method (Cameron and Miller, 2015; Roodman, 2015); * p<0.05, ** p<0.01, *** p<0.001.

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