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Reimbursement Schemes for Hospitals: The Impact of Case and Firm Characteristics*

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Abstract

We use data from a German health insurer to study how the impact of switching from a fee for service system (FFS) to a high powered incentive scheme (prospective payment system; PPS) depends on the characteristics of patients and hospitals. As hospitals had a transition period of several years to complete the switch, we can adopt a difference-in-differences approach by adding hospital fixed effects and a time trend. Our results support hypotheses drawn from an incentive and selection perspective: PPS reduces the length of stay of older relative to younger patients, of more severe relative to less severe cases, and in smaller relative to larger hospitals. Hospitals which adopted PPS earlier provide higher quality under PPS as proxied by the case-specific readmission rate.

JEL Classification: I11, D22, I18

Keywords: Hospital reimbursement; high-powered incentives; readmission; length of stay; difference-in-differences estimation.

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1 Introduction

The impact of policy interventions often varies considerably across different subpopulations. For instance, treatment effects of education programs differ among individuals with different abilities (List and Rasul (2011)), and introducing high-powered incentive schemes in the electricity industry leads to a large variety of reactions by market players (Armstrong and Sappington (2006); Ter-Martirosyan and Kwoka (2010)). These findings are in line with the fundamental insight from the theory of regulation that firms' responses will be geared towards incentivized outcomes, whereas efficiency losses may be experienced in other areas (Crew and Kleindorfer (2002); Folland, Goodman, and Stano (2007)). If firms are exposed to those incentivized areas to different extents, then their reactions are likely to differ as well.

In this paper, we investigate how the impact of moving from a cost reimbursement scheme (fee-for-service; FFS) to a prospective payment system (PPS) for hospitals depends on case characteristics (such as the patient-specific complication risk and age) and firm characteristics (such as the size and the ownership of the hospital). Our original data include all about 194,000 in-hospital cases between 2001 and year-end 2008 reimbursed by a German health insurance company. Germany moved to PPS between 2003 and 2006, so that we have cases before and after the system change for each hospital. The dependent variables in our analysis are cost reductions proxied by the length of stay in hospital (LOS) and the quality of service measured by the one-year readmission rate to any hospital with the same main diagnosis.

While we find no impact of the system change on the *average* LOS and readmission rate, it turns out that results differ significantly between patients and hospitals in ways suggested by the economic theory of selection and incentives: patients older than 65, who are likely to have lower opportunity costs, are discharged relatively earlier after the system change than younger patients. The same holds for patients with more severe secondary diagnoses. Interestingly, these changes in LOS had no impact on long-term readmission rates. However, we find that the readmission rate decreased in hospitals that switched early to the new system; relative to those hospitals which delayed the adoption of the new system as long as possible. This supports the intuition that hospitals expecting to do well under the new system were eager to adopt it as soon as possible, whereas hospitals that were likely to struggle with PPS sought to delay the system change. Furthermore, there is some tentative evidence that private hospitals responded stronger to the change in the incentive structure than public hospitals.

Substituting FFS by PPS is one of the most controversially discussed cases of switching from cost reimbursement to high powered incentive schemes (see the overview in Ellis and

Miller (2009)). Under FFS, hospitals are reimbursed for all justifiable costs, so that there are hardly any incentives for cost-cutting. At the same time, however, financial incentives for quality provision are also weak as readmissions lead to additional reimbursements.¹

Starting in the 1980s with Australia and the USA, most countries have now switched to PPS where payments are based on diagnosis related groups (DRGs). The system change influences the hospitals' incentives in two directions: On the one hand, PPS sets incentives for cost savings by reducing the LOS and potentially also the quality of treatment, because payments are to a large degree fixed (see section 2 for details). In Germany, this has triggered serious concerns about "bloody discharges", which have delayed the system switch by many years.²

On the other hand, however, financial incentives for quality provision are also higher as readmissions are more likely if the quality of care is low. Under PPS, hospitals have strong financial incentives to avoid patients to be readmitted with the same main diagnosis within a period of 30 days, as the two stays in hospital would be consolidated in such a case, with no additional reimbursements. Thus, both cost-cutting and quality incentives are larger under PPS, so that average effects are theoretically ambiguous. After having described the incentive structures in greater detail in section 2, however, we can draw hypotheses on the case- and hospital-specific impact of the system change.

The main advantage of using data from a health insurance company instead of data from single hospitals only is that we can follow the patient's history also when she is readmitted to a different hospital. This is important as, under PPS, hospitals have incentives to trigger readmissions to other hospitals in order to avoid case consolidations. As no such incentive exists under FFS, using data from single hospitals would systematically overestimate the treatment quality under PPS compared to FFS. We have patient specific information about primary and secondary diagnoses, in-hospital complications, dates of admissions and discharge, surgeries and treatments, discharge categories, sex and age. In addition, we collected hospital-specific information such as the number of beds and the ownership structure from various official statistics. For all hospitals in our data set, we have observations under both systems, but partially at different times as hospitals had some discretionary power on when to adopt the new system. These features of our data allow us to apply a difference-in-differences approach, where we consider cases under FFS as control group and cases under PPS as treatment group. Furthermore, we can control

¹In addition, the evidence required to trigger liability for medical malpractice is high in Germany, and average amounts awarded to plaintiffs are about ten times higher in the US; see e.g. Kennedy and Grubb (2000) and Faure and Koziol (2001). Thus, financial incentives to provide high quality are low.

²See e.g. Deutscher Bundestag, Drucksache 16/6083 which reports the discussion from July 13th 2003 in the German Bundestag (Parliament) about the risk of 'bloody discharges' under the new system as well as Deutscher Bundestag (2007).

for unobserved heterogeneity by estimating coefficients with hospital fixed effects, and we can control for technical progress and other changes over time with a time trend.

The majority of papers analyzing the impact of switching from FFS to PPS restricts attention to LOS, potentially amended by other cost measures. Most papers find that the average LOS is lower after the introduction of PPS (e.g. DesHarnais, Kobrinski, Chesney, Long, Ament, and Fleming (1987); Ellis and McGuire (1996); see Cutler and Zeckhauser (2000) for an overview). Most closely related to our paper are studies which also have the opportunity to apply a difference-in-differences approach as not all hospitals are affected by the system change, or because hospitals switch to PPS at different times. For the time period in China considered by Yip and Eggleston (2001), six out of the fourteen hospitals included in their data switched from FFS to PPS. They find that PPS reduced expenditures and LOS, but they do not extend to quality measures such as readmission rates. Similar results are obtained by Zhang (2010), who also restricts attention to cost measures and LOS. By contrast to those papers, we find no significant overall impact on the system change on LOS, but we do find differences among patients and hospitals.

Several different measures such as time per patient spend, the degree of satisfaction of patients as stated in questionnaires and mortality rates have been used in the literature to proxy the quality of treatment, but the most commonly used proxy is readmission rates. Many studies are confined to descriptive statistics (Louis, Yuen, Braga, Cicchetti, Rabinowitz, Laine, and Gonnella (1999)), only one hospital (Rich and Freedland (1988)) descriptive cross-country analyses (see Busse, Schreyögg, and Smith (2008) and Stargardt (2008)) or to a few diagnoses, or they lack a control group as all health care providers were forced to switch to PPS at the same time. Kahn, Draper, Keeler, et al. (1992) were among the first to use the readmission rate as a quality measure, but they restrict attention to six medical conditions and neither account for time-trends nor for readmissions to other hospitals. Cutler (1995) shows that distinguishing between different time horizons can be an important issue. Specifically, he finds that the mortality rate in the hospital itself or shortly after discharge is higher with PPS, but that there is no difference in the one-year-mortality rate. Furthermore, the effect may be triggered by coding changes rather than by true changes in morbidity. In the context of policy changes which have led to adjustments in the remuneration for many diagnoses, Dafny (2005) finds that hospitals respond strongly to incentives, albeit mainly for re-coding, while actual treatments are only slightly modified.

More recently, a few papers apply a difference-in-differences approach for readmissions. Busato and von Below (2010) utilize the fact that PPS was introduced in Swiss cantons at different times. They find higher readmission rates for a 90-day period in DRG areas, which they tentatively attribute to suboptimal quality and potentially to

poor organization of care in these areas. However, they emphasize that their results need to be treated with care as they compare readmission rates for the whole population without controlling for case- or patient-specific characteristics. We can take care of this problem as our data contain all anonymous patient files, and thus all primary and secondary diagnoses. Hamada, Sekimoto, and Imanaka (2012) use data from Japan and report higher 30-day readmission rates under DRG. However, their study suffers from selection problems as hospitals had complete discretion on whether and when they switch to PPS. Furthermore, only those hospitals that voluntarily submitted the data could be considered. In their study on Taiwan, Cheng, Chen, and Tsai (2012) can avoid the selection problem as the assignment to treatment and control groups is exogenous. Just like we do, they find no significant increase in the 30-day readmission rate. While Cheng, Chen, and Tsai (2012) confine attention to patients listed in the cardiovascular surgical DRG category, we consider many different main diagnoses to identify average effects of the system change. Furthermore, we control for secondary diagnoses, hospital fixed effects and the timing when the new system was adopted.³

The remainder of this paper is structured as follows: In the following section, we describe the details of the reform in Germany and derive some testable hypotheses on its impact on the length of stay and the readmission rate. We describe the data in Section 3. Section 4 explains our estimation strategy. 5 presents our main results. Robustness checks with respect to the treatment of secondary diagnoses and the period for the readmission rate are discussed in section 6. Section 7 concludes.

2 The Reform and Incentives for Hospitals

Reimbursement Schemes Before and After the Reform. Before 2003, German hospitals were reimbursed according to a mixed system in which most payments were made on a fee-for-service (FFS) base. About 80% of hospitals' budgets originated from reimbursements for every day a patient stayed in hospital (Lüngen and Lauterbach (2003)). The exact amount of this per-day reimbursement depended on the costs for the patient's treatment and on whether the total occupancy of a hospital during a year was above or below a certain negotiated level. The prospective payment system (PPS) was enacted by the Health Reform Act ('*GRV-Gesundheitsreformgesetz*') in 2000, which required hospitals to switch to the new system by 1st January 2004; the earliest possible switching date being the 1st January 2003. Hospitals could ask to postpone the introduction of PPS

³Gaynor, Moreno-Serra, and Propper (2013) exploit a policy change in the UK that led to higher competition in the health care industry to apply a difference-in-differences approach and find evidence that higher competition has no cost effect, but increases quality.

under certain circumstances. The requirements for getting permission turned out to be quite mild until the 31st August 2004, but got increasingly demanding thereafter. By 1st January 2006, almost all hospitals in our dataset had introduced PPS.⁴

The German PPS is a version of the Australian 'AR-DRG' system. For each case, hospitals are reimbursed a fixed amount depending on the diagnosis related group (DRG) of the case and the severity of secondary diagnoses. Secondary diagnoses are transformed into the "Patient Clinical Complexity Level" (PCCL), which is an index that can take values from zero (no complications requiring additional expenditures) to four (highest level of complications)⁵. If the actual LOS is far above or below the average LOS of that DRG, a surcharge or deduction applies, respectively. If a patient is readmitted to the same hospital within 30 days with the same main diagnosis, or with a complication that occurred due to the treatment of the original diagnosis, both cases are consolidated. Consolidation means that hospital stays are reimbursed as a single case, i.e. the DRG fee is paid only once.

General Incentive Effects of PPS. The introduction of PPS created countervailing incentives for cost effectiveness and quality of treatment: Under FFS, all medically justifiable treatments were reimbursed, so that hospitals did not need to be too concerned about costs. In particular, the reimbursement for each additional day a patient spent in hospital exceeded marginal costs, so that hospitals with free capacities had incentives to keep patients in hospital. However, hospitals without free capacities may have had incentives for early discharges in order to take on patients with higher contribution margins. This latter point may be important as there was no financial incentive to reduce the risk of complications and readmissions under FFS, because additional treatment costs after readmission were covered by the health insurer.

Under PPS, there are lower bounds and upper bounds for the LOS for each DRG (and partially depending on secondary diagnoses). Within these two bounds, the reimbursement is independent of the LOS. Thus, when a patient is discharged one day earlier within these bounds, a hospital just saves the cost for this day. Similarly, hospitals reap the full financial benefits of saving other kinds of treatment cost. On the other hand, however, hospitals also have incentives to avoid complications and readmissions as they do not normally get any additional payment for patients readmitted within 30 days. Hence, from a purely financial perspective, the benefit of cost saving needs to be compared to

⁴These hospitals represent 99.98% of all cases in our full dataset, and all of the cases in the sample used for our regression analysis.

⁵In 2014, PCCL-levels of 5 and 6 were added in order to allow for a more fine-tuned differentiation for particularly severe cases.

the expected costs from a higher probability that the patient is readmitted within thirty days.⁶

Summing up, hospitals under FFS have neither strong incentives for cost-cutting nor for avoiding readmissions, whereas they do have such incentives under PPS. Furthermore, the enhanced cost-cutting incentives under PPS create a countervailing effect to the enhanced quality incentives and vice versa, as cutting cost of medical treatment is likely to increase the readmission rate. It follows that the comparisons between the LOS and the readmission rate under PPS and FFS are theoretically ambiguous.

Incentive Effects Depending on Case and Hospital Characteristics. Although we cannot make clear-cut theoretical predictions regarding the average effect of adopting PPS, our discussion of the incentive structure allows us to draw the following three hypotheses on how this effect differs across case and hospital characteristics: First, if hospitals with free capacities under FFS want to extend a patient's stay in hospital, a patient with high opportunity costs is more likely to object. Thus, we hypothesize that the LOS of patients with low opportunity costs decreases after the system switch relative to patients with high opportunity costs, and we use an age above 65 as a proxy for low opportunity costs.

Second, we assume that the variance in capacity utilization decreases in the number of beds in hospital, so that the incentive to keep patients longer under FFS should be higher for small hospitals. Third, private hospitals are likely to respond stronger to financial incentives. However, as we do not have a clear-cut hypothesis about whether hospitals' incentives to keep patients in hospital are lower under PPS in order to save costs or higher in order to avoid readmissions, we cannot hypothesize about whether the treatment effect on LOS for private hospitals will be higher or lower than that for public hospitals either. However, as readmissions yield financial losses only under PPS, we might conjecture that the interaction term between private ownership and the system dummy is negative for the readmission rate.

Documentation of Secondary Diagnoses. Another feature of FFS was that secondary diagnoses only were relevant for reimbursement in very specific cases where they made additional treatments necessary. As a consequence, there was no need to document them unless they were important information for subsequent treatments or they were

⁶If a patient is discharged before the lower bound or after the upper bound, then deductions and surcharges apply, respectively. Thus, financial incentives are somewhat less pronounced beyond the lower and the upper threshold. Still, these additional payments or deductions are below the actual daily costs, so that there are no incentives to keep a patient unnecessarily long in hospital.

needed to justify the costs of in-hospital treatments. Under PPS, however, the detailed case characteristics are taken into account to calculate the correct reimbursement for that case. Hence, all secondary diagnoses are relevant in every case, so that incentives for exact documentation are high. There is even reason to believe that hospitals (illegally) upcode the secondary diagnoses under PPS.⁷

This difference in the incentives to document secondary diagnoses under both systems has an important implication for our data: When using the secondary diagnoses actually documented by the hospital to calculate which PCCL a case reimbursed under FFS would have been assigned under PPS, this variable will systematically underestimate the severity of secondary diagnoses under FFS. We will, therefore, take this systematic measurement error into account when constructing such a variable. In Section 3, we will explain in more detail how we construct a measure for the severity of secondary diagnoses that is comparable between cases reimbursed under both systems.

3 Data

Our data set consists of all 193,943 in-hospital cases between 2001 and the end of 2008 covered by a German health insurer. 45,732 cases were reimbursed under the old system (FFS) and 148,211 cases under the new system (PPS). The patient files contain information on primary and secondary diagnoses, DRGs, PCCL (as part of the raw data under PPS, and calculated by us for cases under FFS by using the documented secondary diagnoses and the *Groupier* software applied by hospitals), dates of admissions and discharge, surgeries and treatments, discharge categories such as "regular" and "after hospital treatment", gender and age. Not all hospitals switched to the prospective payment system at the same time due to the aforementioned fact that there was a transition year (2003) where hospitals could choose between the two systems. The exact dates when the hospitals adopted PPS were taken from the official statistics of the national association of health insurance companies (AOK Bundesverband).

The advantage of using data from a health insurer instead of data from hospitals is that it contains readmissions to *any* hospital, so that we can safely use readmissions with the same main diagnosis as a proxy for treatment quality. As pointed out in the introduction,

⁷For instance, Abler, Verde, Stannigel, Mayatepek, and Hoehn (2011) and Jürges and Köberlein (2015) show that upcoding plays a large role in neonatology, where downscaling the birth weight by only a few gram yields a sharp increase in reimbursements, and where upgrading is hardly detectable since infants lose about 10% of their birth weight within the first few days. At an aggregated level, Schönfelder, Balázs, and Klewer (2009) estimate that more than three billion Euros paid as reimbursements to hospitals between 2004 and 2009 can be attributed to upcoding.

this is important as PPS sets incentives to trigger readmissions to other hospitals in order to avoid case consolidations. A disadvantage of the fact that just one health insurer is included is that we have only a few cases for many of the primary diagnoses in many of the 603 hospitals in our dataset. As we want to run regressions with hospital fixed effects in order to control for unobserved heterogeneity, we need to restrict attention to hospitals with sufficiently many observations for each DRG considered. We hence restrict attention to the 50 most frequent primary diagnoses, defined at the three-digit ICD level, and to hospitals which have, on average, at least ten cases per year for these primary diagnoses. This leaves us with 54 hospitals and 58,472 cases, of which 15,396 (26.3 %) were reimbursed according to the old FFS system. Table 11 in the Appendix provides an overview of the numbers of cases in these hospitals and the dates at which they switched to PPS.⁸

Table 1 structures information on the dependent variables (LOS and readmission rates) and on the explanatory variables used in our main regressions for the sample used in the empirical analysis. The average LOS has decreased from 7.2 to 6.3 days after PPS was introduced. This, however, needs to be interpreted with caution as there may be a time trend we need to control for. Recall that cases are consolidated when patients are readmitted to the same hospital with the same primary diagnosis. For those cases, hospitals report only the aggregated LOS of both stays, so that we need to exclude them when calculating the average LOS, and when analyzing the impact of the system change on LOS.

Next, table 1 shows that the average readmission rate within a year to any hospital is about 12.8% lower under the new system (0.360 compared to 0.413), and an even larger reduction of about 17% (0.082 compared to 0.099) is observed for the 30-day threshold within the same hospital, which is decisive for case consolidation. This lends some support for the hypothesis that hospitals strategically delay readmissions or trigger readmissions to other hospitals during the 30-day-period, while the fact that both readmission rates are lower under PPS is likely due to a time trend reflecting technical progress and the tendency to transfer after-hospital treatments to doctors' offices.

Recall from Section 2 that the severity of secondary diagnoses under PPS is summarized by the categorical variable PCCL reaching from PCCL0 (no additional complications expected) to PCCL4 (most severe secondary diagnoses). While PCCLs were not directly reported under FFS, we were able to calculate them from the secondary diagnoses reported in the patient files by using the software program 'Grouper' applied by all hospitals in Germany under PPS. However, for the reasons discussed in Section 2, there was no

⁸The average size is calculated as the average number of beds in the respective hospital during the observation period minus the average.

Table 1: Summary Statistics.

	Fee for service (FFS)		Prospective payment system (PPS)		<i>t</i> -value
	Mean	Std. Dev.	Mean	Std. Dev.	
Average Length of stay (LOS) (excl. consolidated cases)	7.241	8.908	6.348	7.255	11.177***
Readmission within 1 year to any hosp.	0.413	0.492	0.360	0.480	11.607***
Readmission within 30 days to same hosp.	0.099	0.298	0.082	0.275	6.066***
PCCL0	0.872	0.334	0.747	0.435	36.566***
PCCL1	0.005	0.067	0.008	0.091	-5.343***
PCCL2	0.064	0.244	0.114	0.318	-20.101***
PCCL3	0.045	0.206	0.087	0.282	-19.763***
PCCL4	0.015	0.123	0.044	0.205	-20.381***
Severity of Secondary Diagnosis	0.253	0.311	0.253	0.435	0.000
Patients discharged after upper limit	0.163	0.369	0.057	0.233	33.138***
Average number of beds	588.5	352.8	585.9	331.3	0.804
Private Ownership	0.394	0.489	0.368	0.482	-4.802***
Age (70 years = 0)	-25.7	19.5	-28.8	23.3	15.807***
Male	0.697	0.460	0.633	0.482	14.689***
Surgery	0.610	1.051	0.734	1.252	-11.899***
Discharge categories:					
Regular	0.869	0.338	0.895	0.307	-8.407***
Death	0.007	0.085	0.009	0.093	-1.694*
Rehabilitation	0.018	0.134	0.021	0.142	-1.921*
After Hospital Treatment	0.053	0.225	0.029	0.185	12.194***
Change of Hospital	0.034	0.180	0.023	0.149	6.735***
Other	0.019	0.136	0.024	0.154	-3.941***

incentive for complete documentation under FFS, which implies that PCCLs calculated from the patient files are systematically higher under PPS compared to FFS (see Table 1).

In order to account for this problem, we proceed as follows: First, in order to keep the analysis straightforward, we treat PCCL as a binary variable by distinguishing only between cases where PCCL is zero ($P = 0$) or positive ($P = 1$). This seems to be justified as PCCL is zero in about 80% of all cases. We then implement a transformation of PCCLs observed under FFS that ensures that the average PCCL is the same under both systems. Specifically, we proceed as follows: First, we estimate a Probit model of the probability that PCCL is positive (i.e., $P = 1$) using all cases under PPS. Table 2 shows the estimated parameters from this regression.

Table 2: Probit Regression of $PCCL > 0$ under DRG.

Age	0.0147*** (0.0009)
Male	0.1016*** (0.0239)
Constant	0.3147*** (0.0954)
N	43,071

Coefficients of Probit Regression, which includes fixed effects for hospitals, the calendar month and the primary diagnosis. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

We then use the parameters from Table 2 to predict the probability that a case where PCCL is zero under FFS would have had a positive PCCL *if it had been treated under PPS*.⁹ We denote this probability by \hat{P} . Next, we assign $\hat{P} = 1$ to all cases which have a positive PCCL (i.e., $P = 1$) even under FFS. The underlying assumption is that there are no cases where the PCCL calculated from the secondary diagnoses in the patient files

⁹In other words, our procedure is based on the assumption that the correlation of PCCL with other case and hospital characteristics for a case reimbursed under PPS is an informative predictor of the probability that a case under FFS would have had a positive PCCL had it been reimbursed under PPS. In a robustness check, we will present results based on an alternative way of adjusting the PCCL for cases with $P = 0$ under FFS that does not rely on this assumption, assuming instead a fixed probability of a positive 'true' PCCL for all cases with $P = 0$ under FFS, independent of the observable case characteristics. We will explain this alternative transformation in greater detail before presenting the robustness check in Section 6.

is positive under FFS, but would have been zero under PPS. Given that there were no incentives for upcoding under FFS, this assumption seems reasonable. Furthermore, this procedure ensures that no case with $P = 1$ under FFS can have a lower \hat{P} than a case with $P = 0$ under FFS.

However, this procedure inevitably causes the average \hat{P} under FFS to be above the average P under PPS: Those cases for which PCCL=0 under FFS are assigned the probability of a positive PCCL predicted from the Probit estimation, so that the average \hat{P} for this group of cases is equal to the average P under PPS. At the same time, we leave cases with positive PCCL under FFS at $\hat{P} = 1$, thus pushing the average \hat{P} for all cases under FFS above the average P of all cases under PPS. In order to balance the overall averages under both systems, we add the following final transformation \tilde{P} : We leave $\tilde{P} = \hat{P} = P = 1$ for all cases with positive PCCL under FFS and multiply the \hat{P} for all cases with PCCL=0 under FFS with a fixed factor such that the average of the resulting \tilde{P} over all cases under FFS is the same as the average P over all cases under PPS.¹⁰ The line 'Severity of Secondary Diagnosis' in Table 1 displays descriptive statistics on this new variable \tilde{P} .

Next, recall that under PPS, the hospital's reimbursement is fixed below the upper bound, so that hospitals have strong incentives to discharge patients before this threshold is reached. In line with this, table 1 show that only 5.7% are discharged after the threshold, while this holds for 16.3% of all cases under FFS.¹¹

As readmissions may well depend on the specificities of the hospitals, we add hospital fixed effects and, in some regressions, the interaction of the system dummy with certain hospital characteristics such as the number of beds or the ownership structure. In addition, we consider hospital-specific time trends in our robustness checks. The information on hospitals is taken from the official statistics at a federal level.

Table 1 furthermore shows that the patients' average age slightly decreased over time, and the percentage of females has increased due to the fact that, until 1996 all so-called industry health insurance companies insured only employees, but have been open for all people since then. Finally, the last row captures the different discharge categories expressed as percentages of all discharges. Apparently, the share of regular discharges has increased, while the share of discharges with a planned post-hospital treatment has

¹⁰Using N_P^{FFS} and N_P^{PPS} to denote the number of cases with observed P under FFS and PPS, respectively, and μ to denote the average \hat{P} conditional on $P = 0$ under FFS, this requirement is equivalent to $\frac{N_1^{FFS} + \frac{\tilde{P}}{\hat{P}} \mu N_0^{FFS}}{N_1^{FFS} + N_0^{FFS}} = \frac{N_1^{PPS}}{N_1^{PPS} + N_0^{PPS}}$, so that $\tilde{P} = \frac{N_1^{PPS} N_0^{FFS} - N_1^{FFS} N_0^{PPS}}{(N_1^{PPS} + N_0^{PPS}) \mu N_0^{FFS}} \hat{P}$ whenever $P = 0$ in cases under FFS.

¹¹Under FFS, there was no upper bound as hospitals just needed to justify the LOS in order to get the additional costs reimbursed. Thus, we calculated how many patients under FFS were discharged after the upper threshold that applies under PPS.

decreased by almost 50%. This can be explained by the fact that, under the DRG system, post-hospital cases within the upper threshold have to be consolidated and jointly reimbursed with the inpatient case, which reduces the economic incentive for post-hospital treatments.

4 Empirical Strategy

For identifying the impact of the system change on the average LOS and the readmission probability, comparing hospitals under FFS with hospitals under PPS is not sufficient as one could not tell which part of the difference is due to the system and which part due to differences in hospitals. Similarly, when comparing a cross section of hospitals before with the same cross section after the system change, the difference may be attributable to technical progress. To address these issues, we follow the general idea of the difference-in-differences approach which compares the performance difference of a treatment group and a control group in two different periods; after and before the treatment group is treated. In the simplest setting, this difference can be obtained in a regression with a period dummy (to distinguish between the period before and after treatment) and a treatment group dummy (to distinguish between the treatment group and the control group). The coefficient for the interaction of these two dummies is then the difference-in-differences estimator.

Our data differs from the simplest case by the important fact that all hospitals were eventually treated (i.e. switched from FFS to PPS), so that the distinction between a treatment and a control group cannot be applied at the hospital level. However, as we have sufficiently many pre-treatment and post-treatment observations for each hospital, we can consider all cases under PPS as treatment group and all cases under FFS as control group. The problem of unobserved heterogeneity at the hospital level can be solved by adding hospital fixed effects. Furthermore, our dataset includes information on the admission and release dates of each case, and each of these dates may have different sets of hospitals under each reimbursement system. Hence, we can replace the period dummy in the simplest difference-in-differences approach by a time trend to control for the fact that cases under PPS generally received medical care later.

A potential problem in our data is that hospitals had some discretion on when to adopt PPS. This casts some doubts on the interpretation of the system dummy as the average treatment effect as hospitals anticipating larger benefits from adopting PPS are likely to do so earlier. Figures 1 and 2 display mean LOS and readmission rates by year and reimbursement system, where the red bars indicate cases under PPS. The first group of bars represents cases in hospitals that adopted PPS in 2003, whereas cases in the last

group of bars are hospitals that did so in 2005. While the patterns for LOS look similar across these groups, there seems to be some selection with regards to the readmission rate: Hospitals that seem to struggle with quality under FFS and anticipate to continue to do so after adopting PPS seem to delay the system change as long as possible. This is plausible as readmissions are costly under PPS but were fully reimbursed under FFS.



Figure 1: Mean LOS by system, year and timing of PPS adoption.

While the figures support the intuition that the timing of the adoption of PPS is subject to selection, our estimation of the average treatment effect is independent of when each hospital chose to adopt PPS. The reason is that we have pre-treatment and post-treatment data for all hospitals, so that each hospital's treatment effect is considered in the same way when estimating the coefficient of the PPS dummy. Furthermore, in order to capture the impact of unobserved hospital characteristics on the time trend even more exactly, we present an additional regression as a robustness check in which we interact the hospital fixed effects with the time trend.

Another point that needs to be discussed is that the difference-in-differences method assumes that the dependent variables in the treatment and control groups follow a common pre-treatment trend. In our case, this means that hospitals which adopt PPS early follow the same trend as those that do so later. Comparing time trends of hospitals that adopted PPS in different years in Figures 1 and 2 does not indicate a violation of this assumption. However, this may be due to unobserved heterogeneity in case or hospital

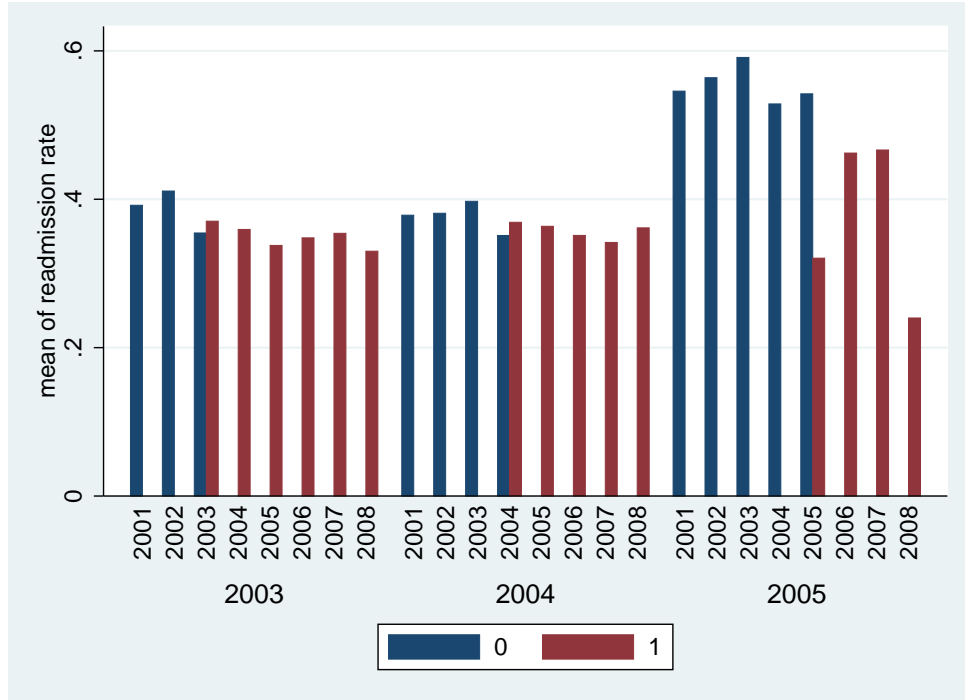


Figure 2: Mean readmission rates by system, year and timing of PPS adoption.

characteristics. We, therefore, test more rigorously whether the common trend assumption is met by looking at regressions of our dependent variables LOS and readmission on the time trend and all variables included in our main regressions. In particular, we restrict attention to the time before the first hospital adopted PPS, i.e. to the years 2001-2002. In order to test the common trend assumption, we include the interaction of the time trend with a variable that indicates whether a hospital has adopted PPS earlier or later. An insignificant coefficient of this interaction then indicates that the common trend assumption is justified.

Table 3: Time of Adoption of PPS by Number of Hospitals and Cases

PPS adopted in	Number Hospitals	Number Cases	Percentage of Cases
2003	27	29,491	50.44
2004	21	23,122	39.54
2005	6	5,859	10.02

Table 3 shows that half of the hospitals adopted PPS in 2003. We hence test the common trend assumption by comparing hospitals which adopted PPS in 2003 with those that did so after 2003. Table 4 presents the results of these regressions. The interaction of the time trend with a dummy variable that indicates whether a hospital has switched

to PPS after 2003 has an insignificant coefficient for both regressions for LOS (model (1)) and (model (2)). This supports the common trend assumption.

Table 4: Test of the Common Trend Assumption.

Dependent variable	2001–2002		2006–2007	
	(1) Length of stay	(2) Readmission	(3) Length of stay	(4) Readmission
Time trend	-0.0020*** (0.0004)	0.0000 (0.0000)	-0.0007* (0.0004)	0.0000 (0.0000)
Time trend * Switch after 2003	0.0004 (0.0009)	-0.0001 (0.0001)	-0.0001 (0.0004)	-0.0000 (0.0000)
Adjusted PCCL>0	4.4680*** (1.2952)	0.0805** (0.0321)	2.4373*** (0.1746)	0.1038*** (0.0093)
Older than 65	1.1706*** (0.2931)	0.0807*** (0.0192)	1.1485*** (0.1593)	0.0924*** (0.0084)
Male	0.0777 (0.2958)	-0.0178 (0.0124)	0.0697 (0.0890)	0.0290*** (0.0061)
Constant	3.9296*** (0.9691)	0.4346*** (0.0770)	5.6746*** (0.5957)	0.1997*** (0.0470)
No. of observations	8,236	8,236	24,757	25,097
No. of hospitals	54	54	54	54
No. of pr. diagnoses	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Furthermore, the fact that all hospitals had to adopt PPS eventually allows us to test whether early and late adopters had common trends *after* all hospitals had switched. As the last hospital in our dataset adopted PPS on 1st December 2005, we test for common trend after treatment by performing the same regressions from models (1)-(2) for the years 2006-2007. Models (3) and (4) of Table 4 show that there is no significant difference in the time trends between early and late adopters for these years either.

5 Results

Tables 5 and 6 show our main regression results. All regressions include dummies for primary diagnoses, a time trend, hospital fixed effects, and the calendar month in which the patient was admitted to account for seasonal effects. Coefficients are estimated using

OLS since we estimate readmission (models (2), (4) and (6)) within a linear probability model throughout.

Table 5: Benchmark Regressions and Impact of Case Characteristics.

Dependent variable	(1) Length of stay	(2) Readmission	(3) Length of stay	(4) Readmission	(5) Length of stay	(6) Readmission
System	-0.1356 (0.1351)	-0.0065 (0.0090)	-0.0311 (0.1402)	-0.0107 (0.0096)	0.2913 (0.2247)	-0.0099 (0.0105)
Adjusted PCCL>0	2.7613*** (0.1837)	0.1026*** (0.0070)	2.7688*** (0.1842)	0.1023*** (0.0070)	4.0904*** (0.5327)	0.0917*** (0.0146)
System * Adjusted PCCL>0					-1.5074*** (0.4808)	0.0123 (0.0159)
Older than 65	1.1928*** (0.1264)	0.0903*** (0.0085)	1.7549*** (0.2256)	0.0676*** (0.0173)	1.1941*** (0.1252)	0.0903*** (0.0085)
System * Older than 65			-0.7304*** (0.2148)	0.0294 (0.0176)		
Male	0.0785 (0.0743)	0.0162*** (0.0042)	0.0826 (0.0743)	0.0161*** (0.0042)	0.0754 (0.0741)	0.0163*** (0.0042)
Time trend	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0009*** (0.0001)	-0.0000 (0.0000)
Constant	6.1230*** (0.2655)	0.2667*** (0.0264)	6.0373*** (0.2605)	0.2701*** (0.0259)	5.8035*** (0.2710)	0.2693*** (0.0256)
No. of observations	57,945	58,472	57,945	58,472	57,945	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Models (1) and (2) present the main estimations of LOS¹² and the readmission probability. The system dummy is insignificant both for LOS and the readmission rate. Thus, the observation from the descriptive statistics that patients are discharged earlier under PPS can be attributed to the significantly negative time trend rather than to the system change, and there is also no evidence for a reduction in treatment quality. This suggests that the countervailing effects discussed in section 2 offset each other, which contradicts the widespread view that the new system would lead to early discharges and potentially also to lower treatment quality. The controls for the observable case characteristics are in the expected direction: More severe cases as measured by our adjusted values for secondary diagnoses (PCCL>0; recall the procedure discussed in section 3) are kept in hospital longer and have higher readmission probabilities in both systems. Similarly, both

¹²Recall that the LOS regressions (1), (3) and (5) do not include consolidated cases, which is why they have slightly less observations.

LOS and readmission probability of patients older than 65 years are significantly larger than for younger patients.

While models (1) and (2) of Table 5 indicate that the average effect of PPS on all cases is not significantly different from zero, our main interest is how these treatment effects vary with certain case and hospital characteristics. A quick glance at Table 4 seems to support our hypothesis that the effect of adopting PPS on patients older than 65 is very different than for younger patients: When comparing model (1) of Table 4, which is the estimation of LOS based on a period in which all hospitals still used FFS, with model (3) of the same Table, which shows the result for the very same regression but based on a period in which all hospitals had already adopted PPS, the coefficient for the age dummy seems smaller in the latter case. Similarly, a positive PCCL seems to have a much smaller effect on LOS under PPS (model (3) of Table 4) than under FFS (model (1)), which would, in turn, mean that the effect of adopting PPS on LOS is smaller for cases with secondary diagnoses indicating more severe cases.

In order to test these effects more formally, we add the interaction terms between the system dummy and the age dummy, and between the system dummy and the adjusted value for PCCL, respectively, in models (3) and (5) of Table 5. Both interactions are significant at the 1-percent level.¹³ The first interaction term supports our hypothesis that the LOS of patients who are less likely to have high opportunity costs reacts more to the adoption of PPS than that of younger patients. The same interaction term is insignificant for the readmission rate (see model (4)), which indicates that patients with low opportunity costs might in fact have been kept unnecessarily long in hospital under FFS. A comparable result is obtained for the interaction between the system dummy and our adjusted measure for PCCL: While the adoption of PPS reduced the LOS of more severe cases to a greater extent than that of less severe cases (model (5)), this had no impact on the readmission rate (model (6)).

Summing up, the results reported in Table 5 suggest that the new system has led to earlier discharges of elderly patients and patients with more severe secondary diagnoses without affecting the treatment quality measured by the risk of readmission within a year.

While Table 5 focused on the interaction of case characteristics (age and adjusted PCCL) with the system dummy, Table 6 reports interaction of hospital characteristics (time of switching to PPS, ownership and size) with the system dummy. Estimating system dummies separately depending on the year in which a hospital adopted PPS adds some analytical rigor to the selection issue discussed in Section 4. Model (1) in Table 6

¹³Recall that table 4 contains only the cases for years in which all cases were treated under either FFS or PPS, whereas table 6 contains all cases.

supports the impression from Figure 1 that the pattern for LOS does not seem to depend on when hospitals switched to PPS. However, recall that Figure 2 indicated that hospitals may have self selected into different timings of adopting PPS according to the anticipated effect on readmission rates. Indeed, model (2) in Table 6 confirms that PPS reduced the readmission rate for early adopters but increased it for late adopters. This supports the intuition that hospitals expecting to do well under the new system were eager to adopt it as soon as possible, whereas hospitals that were likely to struggle with PPS sought to delay the system change.

Table 6: Impact of Hospital Characteristics.

Dependent variable	(1) Length of stay	(2) Readmission	(3) Length of stay	(4) Readmission	(5) Length of stay	(6) Readmission
System	-0.0201 (0.2077)	-0.0281** (0.0113)	-0.1583 (0.1570)	0.0014 (0.0096)	-0.1475 (0.1352)	-0.0064 (0.0089)
System*Switch2004	-0.2188 (0.2305)	0.0375*** (0.0112)				
System*Switch2005	-0.1154 (0.3053)	0.0383** (0.0158)				
System*Private			0.0653 (0.2489)	-0.0224* (0.0124)		
System*Size					0.0059*** (0.0022)	-0.0000 (0.0001)
Adjusted PCCL>0	2.7583*** (0.1837)	0.1030*** (0.0070)	2.7604*** (0.1839)	0.1029*** (0.0070)	2.7630*** (0.1831)	0.1026*** (0.0070)
Older than 65	1.1926*** (0.1262)	0.0903*** (0.0085)	1.1923*** (0.1261)	0.0905*** (0.0085)	1.1957*** (0.1259)	0.0903*** (0.0085)
Male	0.0787 (0.0743)	0.0162*** (0.0042)	0.0785 (0.0743)	0.0162*** (0.0042)	0.0780 (0.0744)	0.0162*** (0.0042)
Time trend	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0008*** (0.0001)	-0.0000 (0.0000)
Constant	6.2096*** (0.2494)	0.2532*** (0.0266)	6.1437*** (0.2531)	0.2596*** (0.0267)	6.0280*** (0.2387)	0.2668*** (0.0263)
No. of observations	57,945	58,472	57,945	58,472	57,945	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Next, we argued in section 2 that, due to higher fluctuations in capacity utilization, smaller hospitals have more often incentives under FFS to keep patients unnecessarily long in the hospital. This hypothesis is supported by the negative interaction term of size and the system dummy in model (5) of Table 6.

Finally, models (3) and (4) can be used to analyze how ownership of a hospital affects the impact of adopting PPS. Recall that we argued in Section 2 that privately owned hospitals are likely to react stronger to financial incentives, but that there is no clear-cut theoretical prediction as to whether PPS increases or reduces the financial incentive to keep patients in hospital, due to the countervailing effects of the high-powered cost saving incentives and the negative consequences of readmission under PPS. Model (3) shows that the interaction between private ownership and the system dummy is insignificant, which gives some indication that these countervailing effects cancel out. Furthermore, as there were no financial incentives for higher quality under FFS, one would expect less quality effort in private hospitals under FFS compared to the new system. We indeed observe that the interaction of private ownership with the system dummy in model (4) is negative, but the result is to be treated with caution as the coefficient is only significant at the 10% level.

6 Robustness Checks

Re-adjusting PCCL. Recall that we accounted for the fact that PCCLs are relatively underestimated in FFS compared to PPS in a three-step-procedure: First, as there is no incentive for upcoding under FFS, we assume that all cases with $PCCL > 0$ under FFS would also have been assigned $PCCL > 0$ under PPS. Second, we used the estimated probabilities of $PCCL > 0$ under PPS to predict the probability that cases with $PCCL = 0$ under FFS would have been assigned $PCCL > 0$ had they been reimbursed under PPS. As these two steps together imply that the average values estimated for FFS are above the values actually observed under PPS, we multiplied the estimated values for all cases under FFS that had originally $PCCL = 0$ with a factor that ensures that the average values are the same under both systems.

The underlying assumption of the second step of this procedure was that the probabilities for $PCCL > 0$ estimated under PPS provide useful information also for predicting the PCCLs under FFS. A more radical and rather simple assumption is that the secondary diagnoses of FFS that would have been recorded had these cases been reimbursed under to PPS are uncorrelated with observable case characteristics.¹⁴ If this is the case, then the best one can do is to assign all cases with $PCCL = 0$ under FFS the same probability \tilde{P}' , and we get this value by ensuring that the average \tilde{P}' for all cases under FFS is equal to the ratio of cases with $PCCL > 0$ under PPS.¹⁵ Tables 7 and 8 show the coefficients

¹⁴We still assume that secondary diagnoses reported under FFS are never upcoded, so that all cases with $PCCL > 0$ under FFS are assigned the probability $\tilde{P}' = 1$.

¹⁵Recalling that N_P^{FFS} and N_P^{PPS} denote the number of cases with observed $PCCL > 0$ ($P = 1$) and

that the regressions presented in Tables 5 and 6 would yield when using this alternative way of adjusting PCCLs.

Table 7: Robustness Check: Alternative Measure for Secondary Diagnoses (1)

Dependent variable	(1) Length of stay	(2) Readmission	(3) Length of stay	(4) Readmission	(5) Length of stay	(6) Readmission
System	-0.1237 (0.1409)	-0.0061 (0.0087)	0.0221 (0.1460)	-0.0089 (0.0094)	0.3220 (0.2493)	-0.0153 (0.0103)
Adjusted PCCL>0 (alternative)	2.6307*** (0.1770)	0.0954*** (0.0073)	2.6610*** (0.1784)	0.0948*** (0.0073)	3.9684*** (0.5705)	0.0678*** (0.0143)
System * Adjusted PCCL>0					-1.5488*** (0.5510)	0.0318** (0.0156)
Older than 65	1.2167*** (0.1291)	0.0915*** (0.0084)	1.9948*** (0.2220)	0.0765*** (0.0176)	1.2257*** (0.1288)	0.0913*** (0.0084)
System * Older than 65			-1.0139*** (0.2100)	0.0194 (0.0179)		
Male	0.0863 (0.0746)	0.0166*** (0.0042)	0.0914 (0.0745)	0.0165*** (0.0042)	0.0859 (0.0746)	0.0166*** (0.0042)
Time trend	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0009*** (0.0001)	-0.0000 (0.0000)
Constant	6.1456*** (0.2682)	0.2682*** (0.0268)	6.0218*** (0.2628)	0.2705*** (0.0264)	5.8195*** (0.2729)	0.2749*** (0.0263)
No. of observations	57,945	58,472	57,945	58,472	57,945	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

First, the system dummy remains to be insignificant for both LOS and the readmission rate. Second, the adjusted value for PCCL>0 and the age dummy are again highly significant in the expected directions. Third, our hypothesis on the impact of the system change on the impact of age on LOS is further supported as the interaction between the system dummy and the age dummy is still significant at the 1% level. Also in line with Table 5, the interaction of system and adjusted PCCL>0 is again significantly negative.

The only important difference to our main regressions is that the interaction between the system dummy and our measure for secondary diagnoses is now positive at the 5% level for readmissions. A reasonable explanation for this is that our procedure to upscale all cases with PCCL=0 under FFS at the same degree systematically underestimates

PCCL=0 ($P = 0$) under FFS and PPS, respectively, this requirement is equivalent to $\frac{N_1^{FFS} + \tilde{P}'N_0^{FFS}}{N_1^{FFS} + N_0^{FFS}} = \frac{N_1^{PPS}}{N_1^{PPS} + N_0^{PPS}}$, so that $\tilde{P}' = \frac{N_1^{PPS}N_0^{FFS} - N_1^{FFS}N_0^{PPS}}{(N_1^{PPS} + N_0^{PPS})N_0^{FFS}}$ for all cases with recorded PCCL0 under FFS.

Table 8: Robustness Check: Alternative Measure for Secondary Diagnoses (2)

Dependent variable	(1) Length of stay	(2) Readmission	(3) Length of stay	(4) Readmission	(5) Length of stay	(6) Readmission
System	0.0365 (0.2172)	-0.0261** (0.0111)	-0.1308 (0.1705)	0.0023 (0.0096)	-0.1354 (0.1416)	-0.0061 (0.0087)
System*Switch2004	-0.2654 (0.2431)	0.0357*** (0.0113)				
System*Switch2005	-0.3428 (0.3364)	0.0301* (0.0165)				
System*Private			0.0203 (0.2665)	-0.0240* (0.0120)		
System*Size					0.0058** (0.0024)	-0.0000 (0.0001)
Adjusted PCCL>0 (alternative)	2.6310*** (0.1794)	0.0955*** (0.0071)	2.6303*** (0.1777)	0.0959*** (0.0071)	2.6315*** (0.1760)	0.0954*** (0.0073)
Older than 65	1.2167*** (0.1288)	0.0915*** (0.0085)	1.2165*** (0.1288)	0.0916*** (0.0084)	1.2196*** (0.1286)	0.0915*** (0.0084)
Male	0.0861 (0.0745)	0.0166*** (0.0042)	0.0863 (0.0746)	0.0166*** (0.0042)	0.0859 (0.0748)	0.0166*** (0.0042)
Time trend	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0009*** (0.0001)	-0.0000 (0.0000)	-0.0008*** (0.0001)	-0.0000 (0.0000)
Constant	6.2354*** (0.2556)	0.2549*** (0.0271)	6.1521*** (0.2561)	0.2605*** (0.0271)	6.0533*** (0.2435)	0.2683*** (0.0268)
No. of observations	57,945	58,472	57,945	58,472	57,945	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

(overestimates) PCCL for more (less) severe cases, whereas cases with higher probabilities of $PCCL > 0$ under PPS are in fact more severe. Thus, while the interaction term with system is not robust with respect to the adjustment of PCCL under FFS, it suggests that the procedure applied in our main regressions is more reliable. Finally, note from inspection of table 8 that all results are qualitatively the same as in table 6.

30-day-readmission rate. Recall that the 30-day threshold is important under PPS as cases are consolidated if patients are readmitted to the same hospital within thirty days. We hence perform the same regressions for readmissions as in tables 5 and 6 for the 30-day threshold. Thereby, we distinguish between all readmissions within this period and readmissions to the same hospital only.¹⁶ For PCCL, we use the same adjustments as in our main regressions.

Table 9: Robustness Check: Measures for Readmission (1)

Dependent variable	(1) Readm. 30d	(2) Readm. 30d to same hosp.	(3) Readm. 30d	(4) Readm. 30d to same hosp.	(5) Readm. 30d	(6) Readm. 30d to same hosp.
System	-0.0026 (0.0054)	0.0006 (0.0055)	0.0057 (0.0064)	0.0020 (0.0055)	0.0018 (0.0066)	0.0034 (0.0052)
Adjusted PCCL>0	0.0424*** (0.0070)	0.0354*** (0.0056)	0.0533*** (0.0074)	0.0355*** (0.0056)	0.0410*** (0.0113)	0.0442*** (0.0120)
System * Adjusted PCCL>0					0.0139 (0.0150)	-0.0099 (0.0150)
Older than 65	0.0018 (0.0068)	0.0067 (0.0059)	0.0002 (0.0082)	0.0144* (0.0076)	0.0001 (0.0072)	0.0067 (0.0059)
System * Older than 65			-0.0001 (0.0126)	-0.0100 (0.0117)		
Male	0.0147*** (0.0034)	0.0135*** (0.0022)	0.0144*** (0.0035)	0.0135*** (0.0022)	0.0144*** (0.0035)	0.0135*** (0.0022)
Time trend	-0.0000** (0.0000)	-0.0000* (0.0000)	-0.0000 (0.0000)	-0.0000* (0.0000)	-0.0000 (0.0000)	-0.0000* (0.0000)
Constant	0.0774*** (0.0108)	0.0173* (0.0096)	0.0733*** (0.0109)	0.0161* (0.0090)	0.0763*** (0.0100)	0.0151 (0.0094)
No. of observations	58,472	58,472	58,472	58,472	58,472	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

¹⁶Note that, by contrast to tables 5 and 6, tables 9 and 10 restrict attention to readmissions as the readmission rate, and how it is measured, is irrelevant for regressions on LOS.

Table 10: Robustness Check: Measures for Readmission (2)

Dependent variable	(1) Readm. 30d	(2) Readm. 30d to same hosp.	(3) Readm. 30d	(4) Readm. 30d to same hosp.	(5) Readm. 30d	(6) Readm. 30d to same hosp.
System	-0.0007 (0.0073)	0.0021 (0.0067)	0.0079 (0.0071)	0.0007 (0.0057)	0.0057 (0.0058)	0.0007 (0.0054)
System*Switch2004	0.0134* (0.0077)	0.0006 (0.0075)				
System*Switch2005	-0.0001 (0.0159)	-0.0176 (0.0208)				
System*Private			-0.0062 (0.0079)	-0.0002 (0.0102)		
System*Size					0.0000 (0.0001)	-0.0001 (0.0000)
Adjusted PCCL>0	0.0535*** (0.0074)	0.0354*** (0.0056)	0.0534*** (0.0074)	0.0354*** (0.0056)	0.0534*** (0.0074)	0.0353*** (0.0056)
Older than 65	0.0002 (0.0072)	0.0067 (0.0059)	0.0002 (0.0072)	0.0067 (0.0059)	0.0001 (0.0073)	0.0066 (0.0059)
Male	0.0144*** (0.0035)	0.0135*** (0.0022)	0.0144*** (0.0035)	0.0135*** (0.0022)	0.0144*** (0.0035)	0.0135*** (0.0022)
Time trend	-0.0000 (0.0000)	-0.0000* (0.0000)	-0.0000 (0.0000)	-0.0000* (0.0000)	-0.0000 (0.0000)	-0.0000* (0.0000)
Constant	0.0675*** (0.0109)	0.0157 (0.0099)	0.0714*** (0.0108)	0.0172* (0.0100)	0.0731*** (0.0112)	0.0183* (0.0097)
No. of observations	58,472	58,472	58,472	58,472	58,472	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Comparing tables 9 and 5 shows that all results are robust: the adjusted value for PCCL, gender and the age dummy are all highly significant in the same directions, while system itself and both interactions with system are insignificant for the readmission probability. However, the impact of the years in which hospitals adopt the new system on the system’s impact on readmissions is now different (cf. the interactions in model (6) in 6 to models (5) and (6) in table 10: In the regressions reported in table 6, we found that hospitals which switched later had significantly higher one-year-readmission rates, while the respective interaction terms are insignificant for the 30-day-threshold. This finding reinforces the importance of using a quality measure that is not directly linked to hospitals’ financial incentives: As hospitals suffer financial losses only from patients readmitted within thirty days, they have strong incentives to avoid these readmissions, so that hospitals with quality issues will want to focus their efforts on avoiding readmissions particularly within this time frame. Using readmissions within 30 days as a proxy for quality would, in this case, conceal how late adopters of PPS struggle with quality and how hospital self select into different timings of the system change.

A potential objection to the results of our main regressions is that they do not account for the possibility that hospitals may follow different time paths. Hence, Tables 12 and 13 in the Appendix present regressions with hospital-specific time trends. All results remain qualitatively the same.

7 Conclusion

We have used a difference-in-differences approach to estimate the impact of introducing a high-powered incentive scheme on cost and quality provision in the healthcare sector. While we found no significant impacts of the system change on the average length of stay in hospital and the readmission rate, there are interesting impacts of patient and hospital characteristics, which are in line with the economic perspective on incentives and selection. Compared to younger patients, patients at an age above 65 are kept longer in the hospital under PPS, which we attribute to their lower opportunity costs. Patients with more severe secondary diagnoses are discharged relatively earlier under PPS compared to FFS, and the LOS increases under PPS for smaller hospitals. By contrast, all of the mentioned variables do not influence the system’s change impact on readmission rates.

Turning to selection effects, our most interesting result is that hospitals that adopted PPS earlier have reduced their one year-readmission rates to a larger extent under PPS than those that switched later. This is in line with the fact that hospitals may suffer financially from readmissions under PPS, but not so under FFS. Furthermore, we do not find this effect when we substitute the one year-readmission rate by the 30-day-threshold

which is decisive for case consolidations, i.e. for whether hospitals under PPS get additional money for treating patients after readmissions. This is likely to be attributable to the incentives to focus quality provisions on cases that might be readmitted within this period, so that selection becomes less important compared to incentives.

Our data allow for identifying these effects with a difference-in-differences approach, because we observe hospitals under both systems at the same time during the whole transition period, and cases under both systems for every hospital. We can then control for unobserved heterogeneity by hospital fixed effects and for technological progress by a time trend. In contrast to most other papers analyzing quality effects, our data contain primary and secondary diagnoses, which enables us to calculate PCCLs as a measure for the severity of secondary diagnoses also for FFS. Another important advantage of our data is that we can observe readmission to any hospital, so that incentives to trigger readmissions to other hospitals under PPS in order to avoid case consolidations is no issue for our data. Still, there are two caveats: First, while we did our best to account for the problem that incentives to report secondary diagnoses are lower under FFS, there seems to be no way to fully eliminate the problem. Second, we have only data for readmissions to hospitals, but not for after discharge treatments in doctors' offices. If those treatments have systematically increased under PPS, then our empirical strategy overestimates the quality under PPS.

From an overall regulatory perspective, our results are twofold: First, the fact that we do not find a lower quality under PPS can most likely be attributed to the incentives to avoid case consolidations. Thus, whenever one implements a high-powered incentive scheme, one needs to think about smart devices for internalizing the externalities from lower quality provision. For instance, electricity providers in Germany pay high fines for blackouts and for less severe signals on quality reduction, while liabilities for delays in rail transportation are still so low that they hardly implement sufficient quality incentives. Second and more specifically, our results show that one needs to take case and firm characteristics carefully into account when predicting the impacts of regulatory transitions.

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Appendix

Table 11: System Change Dates by Hospital.

nr	system change	private	Average size (mean=0)	no of cases
1.	01jan2003	1	.7814782	2609
2.	01jan2003	0	-221.3474	263
3.	01jan2003	1	-215.344	2386
4.	01jan2003	0	-221.844	951
5.	01jan2003	1	-452.098	697
6.	01jan2003	0	230.2076	2695
7.	01jan2003	0	-246.4475	95
8.	01jan2003	1	83.6284	2705
9.	01apr2003	1	-357.9182	1185
10.	01may2003	1	-420.5224	758
11.	01may2003	0	-226.6285	1083
12.	01jul2003	0	-375.5528	381
13.	01aug2003	0	-244.2047	747
14.	01aug2003	0	-233.1813	105
15.	01aug2003	0	-473.5528	120
16.	01aug2003	0	-56.90832	1499
17.	01aug2003	0	-299.732	173
18.	01aug2003	0	14.42551	184
19.	01aug2003	1	599.2391	4271
20.	01aug2003	1	-120.4715	160
21.	01aug2003	0	-230.3518	821
22.	01sep2003	0	-496.5528	301
23.	01sep2003	1	435.604	2934
24.	01sep2003	0	-355.3307	1522
25.	01oct2003	0	-162.239	102
26.	01oct2003	1	-199.345	207
27.	01oct2003	0	-472.3517	537
28.	01jan2004	0	-190.182	163
29.	01jan2004	0	-337.4944	137
30.	01jan2004	0	139.6812	718
31.	01jan2004	0	-336.5528	327
32.	01mar2004	0	-348.5528	904
33.	01apr2004	1	-433.9028	140
34.	01apr2004	0	786.3763	3084
35.	01apr2004	0	-378.4302	938
36.	01jun2004	0	-272.6604	1152
37.	01jun2004	0	-221.5822	1734
38.	01jun2004	0	-28.93138	2068
39.	01jun2004	0	-76.20374	3997
40.	01jul2004	0	-182.1454	1451
41.	01jul2004	0	-175.926	1369
42.	01jul2004	0	-122.784	1466
43.	01aug2004	0	-424.1227	386
44.	01sep2004	0	-205.3175	1836
45.	01sep2004	0	-192.1915	656
46.	01nov2004	0	-464.5628	199
47.	01nov2004	0	734.6019	291
48.	01dec2004	0	-490.4207	106
49.	01jan2005	1	-191.4406	107
50.	01jan2005	1	-291.588	369
51.	01jan2005	0	-100.5448	1750
52.	01jul2005	0	-75.19981	204
53.	01jul2005	1	-225.9949	190
54.	01dec2005	1	85.04559	3239

Table 12: Robustness Check: Hospital Specific Time Trends (1)

Dependent variable	(1) Length of stay	(2) Readmission	(3) Length of stay	(4) Readmission	(5) Length of stay	(6) Readmission
System	-0.1387 (0.1580)	-0.0086 (0.0099)	-0.0381 (0.1606)	-0.0130 (0.0102)	0.2890 (0.2492)	-0.0111 (0.0112)
Adjusted PCCL>0	2.7613*** (0.1875)	0.1032*** (0.0069)	2.7680*** (0.1876)	0.1029*** (0.0069)	4.0810*** (0.5255)	0.0956*** (0.0151)
System * Adjusted PCCL>0					-1.4976*** (0.4728)	0.0086 (0.0162)
Older than 65	1.1990*** (0.1259)	0.0906*** (0.0085)	1.7285*** (0.2249)	0.0676*** (0.0177)	1.1994*** (0.1248)	0.0906*** (0.0085)
System * Older than 65			-0.6881*** (0.2119)	0.0298 (0.0182)		
Male	0.0814 (0.0748)	0.0167*** (0.0042)	0.0852 (0.0749)	0.0165*** (0.0042)	0.0781 (0.0747)	0.0167*** (0.0042)
Constant	5.6051*** (0.2615)	0.3493*** (0.0247)	5.5579*** (0.2620)	0.3513*** (0.0242)	5.2879*** (0.2793)	0.3511*** (0.0238)
No. of observations	57,945	58,472	57,945	58,472	57,945	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital Specific time trends	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.

Table 13: Robustness Check: Hospital Specific Time Trends (2)

Dependent variable	(1) Length of stay	(2) Readmission	(3) Length of stay	(4) Readmission	(5) Length of stay	(6) Readmission
System	-0.0379 (0.2132)	-0.0346** (0.0134)	-0.2428 (0.1871)	-0.0013 (0.0108)	-0.1460 (0.1513)	-0.0085 (0.0096)
System*Switch2004	-0.3437 (0.2862)	0.0452** (0.0181)				
System*Switch2005	0.4548 (0.3544)	0.0860*** (0.0168)				
System*Private			0.2494 (0.2996)	-0.0176 (0.0210)		
System*Size					0.0064* (0.0033)	-0.0001 (0.0003)
Adjusted PCCL>0	2.7623*** (0.1897)	0.1039*** (0.0070)	2.7606*** (0.1874)	0.1033*** (0.0070)	2.7627*** (0.1879)	0.1032*** (0.0069)
Older than 65	1.1985*** (0.1255)	0.0907*** (0.0085)	1.1981*** (0.1256)	0.0907*** (0.0085)	1.1997*** (0.1257)	0.0906*** (0.0085)
Male	0.0811 (0.0747)	0.0168*** (0.0042)	0.0812 (0.0748)	0.0167*** (0.0042)	0.0810 (0.0749)	0.0167*** (0.0042)
Constant	5.5489*** (0.2727)	0.3534*** (0.0245)	5.5811*** (0.2682)	0.3509*** (0.0243)	5.6059*** (0.2622)	0.3493*** (0.0247)
No. of observations	57,945	58,472	57,945	58,472	57,945	58,472
No. of hospitals	54	54	54	54	54	54
No. of pr. diagnoses	50	50	50	50	50	50
Primary Diagnosis FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital Specific time trends	Yes	Yes	Yes	Yes	Yes	Yes

All regressions are OLS. Robust standard errors clustered at hospital level in parentheses. *, ** and *** denote significance at 10-percent, 5-percent and 1-percent levels, respectively.