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ABSTRACT

Physician Payment Mechanisms, Hospital Length of Stay and Risk of Readmission: Evidence from a Natural Experiment*

We provide an analysis of the effect of physician payment methods on their hospital patients' length of stay and risk of readmission. To do so, we exploit a major reform implemented in Quebec (Canada) in 1999. The Quebec Government introduced an optional mixed compensation (MC) scheme for specialist physicians working in hospital. This scheme combines a fixed *per diem* with a reduced fee for services provided, as an alternative to the traditional fee-for- service system. We develop a model of a physician's decision to choose the MC scheme. We show that a physician who adopts this system will have incentives to increase his time per clinical service provided. We demonstrate that as long as this effect does not improve his patients' health by more than a critical level, they will stay more days in hospital over the period. At the empirical level, we estimate a model of transition between spells in and out of hospital analog to a difference-in-differences approach. We find that the hospital length of stay of patients treated in departments that opted for the MC system increased on average by 5.3% (0.35 days). However, the risk of readmission to the same department with the same diagnosis does not appear to be overall affected by the reform.

JEL Classification: J33, I10, I12, I18, C41

Keywords: physician payment mechanisms, mixed compensation, hospital length of stay, risk of re-hospitalisation, duration model, natural experiment

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1 Introduction

Most empirical studies on physicians responses to various payment mechanisms focus on their activities as measured by their volume of services, their hours of work, or their productivity. In general, this research does provide evidence that these choices are influenced by physician remuneration schemes. See, among others, Gaynor and Pauly (1990), Hemenway, Killen, Cashman, Parks, and Bicknell (1990), Hurley, Labelle, and Rice (1990), Ferrall, Gregory, and Tholl (1998), Barro and Beaulieu (2003), Hadley and Reschovsky (2006), Devlin and Sarma (2008), and Dumont, Fortin, Jacquemet, and Shearer (2008). However, very few studies have analyzed the impact of alternative methods of physician remuneration on their hospital patients' *length of stay* (LOS) and the risk of their re-hospitalisation post-discharge.[1]

This is unfortunate for at least three reasons. Firstly, for a given diagnosis, outcomes such as LOS in hospital are potentially verifiable, albeit imperfect, measures of inputs that may affect specialists' quality of service (Chalkley and Malcomson 2000). For instance, an increase in LOS in hospital may reflect more time spent by a specialist to better identify the nature of his patient's health problem and to improve the quality of treatment. Of course, an increase in LOS in hospital may just reflect the fact that specialists spend more time on nonclinical activities (*e.g.*, teaching, administrative tasks and research) and less time on clinical activities. In this case, one should not expect an increase in the quality of treatment at least in the short run, *ceteris paribus*. Secondly, the risk of *re-hospitalisation* post-discharge to the same department is a natural measure of adverse outcome and is often used as a proxy for morbidity (*e.g.*, Cutler 1995). Therefore, one may expect that a longer LOS in hospital, as long as it leads to better service quality in hospital, will reduce the risk of re-hospitalisation post-discharge. Finally, LOS in hospital is generally considered as a major determinant of hospital costs per patient, while hospitalisations account for a large portion of total health care costs, even if they are a relatively rare occurrence.[2] Note however that an increase in LOS in hospital is likely to reduce alternative care costs, given the potential substitution

[1] One exception is Hutchinson, Birch, Hurley, Lomas, and Stratford-Devai (1996) who analyzed the impact of primary care physician payment mechanisms on hospital utilization rates among patients in Ontario. They found that capitation payment, with an additional incentive payment to encourage low hospital utilization rates, did not reduce hospital use. One limitation of the research is the small number of physicians (39) whose method of payment was converted from fee-for-service to capitation over the period.

[2] This is one reason why the *prospective payment system* (PPS) was introduced for Medicare in 1983 in the U.S. Under the PPS, the federal government reimbursed hospitals a fixed price for each patient treated (based on his diagnosis) that is independent of the actual costs of treatment (in contrast with the previous cost reimbursement method). It was expected that the PPS system would introduce strong incentives on hospitals to keep costs down by reducing, among others, LOS in hospital. However, there was also fear that such a system could reduce the quality of services in hospital and may result in worse outcomes (*e.g.*, Cutler 1995).

between hospital and post-hospital care (*e.g.*, convalescent home, home care).

This paper attempts to partly open the black box of the impact of physician payment mechanisms on LOS in hospital and the readmission to the same department with the same diagnosis. To do so, we exploit a major reform of physician-payment mechanisms implemented in the Province of Quebec (Canada) by the Quebec Government. This reform introduced an optional mixed compensation system (MC) for specialists working in hospital, as an alternative to the traditional fee-for-service (FFS) system.[3] The MC system combines a fixed *per diem* with a discounted (relative to the FFS system) fee for services provided. Upon the introduction of the MC system, each department voted on its adoption, switching to the MC system only if the vote passed unanimously.[4] In 2008, close to 50% of all specialists had opted for this system in Quebec.

In economic terms, the two main objectives of the government in introducing this reform can be stated as follows. Firstly, it was aimed at reaching a more efficient quantity-quality trade-off in health care provided by specialists. Since the MC system introduces a *per diem* independent of the number of clinical services provided and strongly reduces the fees per service (at about 41% of the average fee), specialists who opt for MC may have incentives to reduce their supply of clinical services. This effect may improve the efficiency in health-care allocation of resources as long as the volume of clinical services provided under FFS is excessive. For instance, a FFS specialist may have incentives to abuse his role as a medical adviser and multiply the number of non-necessary services in hospital to advance his own economic self-interests. This phenomenon of *physician-induced-demand* (PID) may occur when an asymmetry of information exists between provider and consumer in the physicians service market. Note however that competition among physicians, constraints imposed by hospitals, and non-financial motives such as physicians' altruism are forces that may limit PID. Note also that waiting lists to see specialists are very long in Quebec. Under these circumstances, FFS specialists' incentives to induce demand are likely to be reduced.[5] On the other hand, physicians who choose the MC system are expected to spend more

[3]In Quebec, as in each of the Canadian provinces and territories, all physicians work within a universal public Health Care System.

[4]The MC system is available only for activities completed in health establishments (mainly hospitals). Services provided within private clinics continue to be generally paid under the FFS system. Also, there are restrictions on the number of *per diems* a physician can claim and the time-period during which he can claim them. Half *per diems* are claimed on a 3.5-hour basis. The maximum number of half *per diems* that a physician can claim during a two-week period is 28 and these can only be claimed Monday to Friday between 7AM and 5PM. Once the maximum number of *per diems* is reached, or when a physician works outside the *per-diem* claimable hours, he is paid on the FFS basis. See Dumont *et al.* (2008) for more detailed description of the reform.

[5]Literature on PID is plentiful but empirical evidence is mixed. See McGuire (2000) and Léger (2008) for a recent

time per clinical service provided, as they are paid more in time and less in clinical services. This effect may improve the quality of clinical services.[6] All in all, these predictions are consistent with Dumont *et al.* (2008) according to which the 1999 Quebec reform induced specialists who switched to MC to reduce their volume of clinical services by 6.15% while increasing their average time spent per clinical service by 3.81%. These results suggest a potential quality-quantity substitution.

A second objective of the reform was to improve efficiency in the allocation of time between clinical and nonclinical activities. Since the latter are not remunerated under the FFS system, they are likely to be neglected. As long as they are included in the *per diem* under MC, [7] this system is likely to stimulate these activities. Results from Dumont *et al.* (2008) also confirm this prediction. Specialists who adopted MC increased their time spent on administrative and teaching tasks (activities not remunerated under FFS) by 7.92% while they reduced time spent on clinical activities by 2.57%. Thus, the reform may favour a more efficient allocation of tasks within departments that adopted a MC system.[8]

We assess the effects of the introduction of the 1999 Quebec reform on both LOS in hospital and the risk of re-hospitalisation of patients treated in departments that opted for the MC system (average treatment effects on the treated). Our contribution is both theoretical and empirical. At the theoretical level, we provide a static model that shows that, under realistic assumptions, the reform induces a physician who opts for the MC system to perform less clinical services per unit of time. Therefore, he will spend more time per clinical service. Assuming for simplicity fixed on-the-job leisure and nonclinical activities, this is likely to increase the quality of services. However, as long as this effect does not reduce the required volume of services to treat a patient by less than a critical level, his time spent in hospital will increase over the period. Our static model thus allows us to predict the impact of the reform on the product (or on the sum of log) of the two basic outcomes of interest: a MC patient's LOS in hospital and his risk of re-hospitalisation per

survey.

[6]Ma and McGuire (1997) suggest the use of average time spent per service as a proxy for the intensity or quality of treatment provided by the physician. Of course, time spent per service is an imperfect measure of quality − physicians may simply be taking longer breaks between services, or spending more time with patients without affecting health outcomes.

[7]The *per diem* only applies to certain activities, principally time spent on administration, teaching and seeing patients.

[8]A third objective of the reform was to improve horizontal equity between specialists with different behaviours in terms of clinical and nonclinical activities. For instance, the pay gap between specialists who mainly do clinical tasks and those who do a higher proportion of administrative tasks is likely to be reduced in departments that opted for MC.

unit of time. Note that while the static nature of our model does not allow us to make predictions on each of these outcomes, it is still useful in order to predict the effect of the reform on the total MC patient's hospitalization cost over the period. Also, our model allows us to make conditional predictions. For instance, conditional on a zero or negative impact of the reform on the risk of re-hospitalization, our model will predict that the reform will positively affect an MC patient's LOS in hospital. Besides, if the reform has an effect on the reallocation of tasks toward less clinical and more nonclinical activities in MC departments, our model predicts that the effect of the reform of a MC patient's time spent in hospital will increase over the period, as long as it is positive. This result is intuitive as the MC physician spends less time to treat his patients.

As we cannot exploit a randomized experiment, our empirical methodology uses a quasi-experimental design based on a two-state mixed proportional hazard model analog to a difference-in-differences approach. The control groups are defined by departments that remained within the FFS system. We make clear the assumptions we adopt to allow our empirical approach to identify the impact of the reform, given that the decision of a department to move to the MC system is endogenous. To estimate the model, we take advantage of a unique administrative patient-level dataset from a major teaching hospital in Quebec (Sherbrooke University Hospital Center).[9]The number of observations include as many as 144,510 spells in hospital and 125,291 spells outside hospital.

One originality of our approach lies in the fact that our estimates take into account the heterogeneity of patients through the diversity of diagnoses. Indeed, a variation in the average length of stay in a given department can reflect changes in the sickness distribution of patients due to supply or demand factors. For instance, the fact that a department is flexible enough to choose the distribution of patients before and after a change in the physician compensation scheme can bias our estimates of the impact of the reform. Hence, using diagnostic-related group dummies can correct part of the selection bias since fixed effects can adjust for baseline differences in levels.

Overall, our empirical results suggest that the length of stay increased on average by 5.3% (0.35 days) in departments that moved to a MC system (average treatment effect on the treated). However, the risk of re-hospitalisation does not appear to be affected by the reform, at least not at the global level. The positive impact of the reform on time spent in hospital by patients treated

[9]Sherbrooke is the 6th largest city in Quebec with a population of 155, 583 people in 2010. Sherbrooke University Hospital Center, a 682-bed multi-facility hospital, is the only university and regional hospital in that region of Quebec.

in MC departments is consistent with our static model. The absence of effect on the probability of re-hospitalisation at the global level may be partly explained by the fact that the reform does not influence patients' health in hospital. The reform may also induce MC physicians to reallocate their time toward more nonclinical activities (teaching and administration) but less clinical activities, thus increasing the length of stay of patients in hospital but with little effect on the risk of re-hospitalisation.

The paper is structured as follows. Section 2 presents a theoretical model of the impact of a mixed payment system on the length of stay. Data are presented in Section 3. Section 4 introduces the econometric framework. Section 5 presents the results. The last section concludes.

2 Theoretical Model

The determination of the average duration and frequency of hospitalisation is a result of a complex process of interaction between patient characteristics, social environment, hospital characteristics, firms offering covered post-hospital care, (public and private) insurers, and medical practice (see Picone, Wilson, and Chou 2003). However, given the aims of this study and the nature of our data, we focus on medical practice, assuming the characteristics and behaviour of all the other agents to be constant .[10] In particular, the patients are assumed to be passive and to have no influence on their number of days spent in hospital over the period. In the context of excess health care demand observed in Quebec, it is indeed plausible to suppose that the patients have no power to negotiate for health services in the hospital. Moreover, following our discussion in the introduction, physician-induced demand (PID) is ignored, since long waiting lists in Quebec are likely to be used as a substitute for generating non-necessary services. To motivate our empirical approach, we present a simple static model of the impact of the introduction of an optional MC system on a physician's medical practice and, as a consequence, on the average number of days spent by his patients in hospital over the period.

Consider a representative physician who works in a hospital department and spends his working time performing clinical services.[11] His preferences are represented by a standard utility func-

[10]Most studies on length of stay have focused primarily on the effects of patient and hospital characteristics. See Ellis and Ruhm (1988) for a theoretical model of hospital length of stay along these lines.

[11]To simplify the presentation, we ignore nonclinical services.

tion given by

$$U = U(X, e, D), \tag{1}$$

where X represents his total consumption, e his effort at work, and D his number of working days. The utility is twice-differentiable, strictly quasi-concave, increasing with X and decreasing with e and D. The physician faces the following simple budget constraint:

$$X = pS + wD + y, \tag{2}$$

where S is a Hicksian aggregate of clinical services (i.e. a group of clinical services which relative prices do not vary and can thus be treated as one single clinical service), p is the corresponding fee per service, w is the *per diem* and y is his nonlabour income. In this model, there are two prices, one for the services performed, and one for the days worked. Under a FFS system, $p > 0$ and $w = 0$; under a wage compensation system, $p = 0$ and $w > 0$; and under a mixed compensation (MC) system, $p > 0$ and $w > 0$. Under a public health system such as the one prevailing in each Canadian province, prices are exogenous to the physician as they are determined by the government. The physician's effort, e, is approximated by the volume of his (clinical) services per working day. Inversely, time spent per service, $1/e$, can be taken as a proxy for the quality of services $-$ changes in which are a valid measure of changes in time spent providing services as long as on-the-job leisure is fixed. The (Cobb-Douglas) production function for clinical services is thus given by $S = eD$. Substituting in (2), the budget constraint becomes:

$$X = peD + wD + y \tag{3}$$

The physician is assumed to choose his effort e (or, equivalently, the quality of his services, $1/e$), his number of working days D; as a consequence, his consumption X maximizes his utility function (1) subject to his budget constraint (3).

The optimization program to be solved is not standard since the budget constraint is nonlinear in effort e, but linear in the number of days D (given e). The standard approach to solve this problem (*e.g.*, Becker and Lewis 1973, Blomquist 1989) is to linearize the budget constraint at the optimum. From this linearization, one can define the *virtual* (or *local*) price of effort as $p_e^v = pD$, the virtual price of working days as $p_D^v = pe + w$, and the virtual nonlabour income as $y^v = y - peD$. A key feature of this analysis is that the virtual price of effort increases with the number of working days, the virtual price of working days increases with effort, and the virtual non-labour income decreases with effort and working days. Therefore a change in p or in w will in general affect both virtual prices and the virtual nonlabour income, since e and D are choice variables. Assuming a unique interior solution to the program, the structural (Marshallian) equations for effort and working days supplied are given by:

$$\begin{aligned} e &= e(pD, pe+w, y-peD) \text{ and} \quad (4)\\ D &= D(pD, pe+w, y-peD). \quad (5)\end{aligned}$$

Now let us first assume that the compensation system in place at the start is a FFS. The impact of the introduction of an optional MC that reduces the FFS by Δp and introduces a *per diem*, w, on physician's effort, can be approximated by differentiating the structural equations (4) and (5), and by using Slutsky equations that decompose virtual price effects into substitution and income effects.[12] Note that symmetry and positive semidefinitiveness of the Slutsky matrix impose standard restrictions on substitution effects.[13]An important point here is that since the MC is optional, the physician will opt for the MC system only if it increases his earnings at constant behaviour, *i.e.,* only if $e_0\Delta p + w > 0$, where the subscript 0 denotes the FFS initial situation.[14] This means that a physician will adopt MC if his effort e_0 is smaller than $w/(-\Delta p)$.
One obtains:

$$\begin{aligned} \Delta e &\approx \Omega^{-1}[A\Delta p + Bw + CD(e_0\Delta p + w)] \quad \text{if } e_0\Delta p + w > 0 \quad (6)\\ &= 0 \quad \text{otherwise}\end{aligned}$$

where

$$\begin{aligned} \Omega &= 1 - (\widetilde{e}_1\widetilde{D}_2 - \widetilde{e}_2{}^2) - 2\widetilde{e}_2 p,\\ A &= (\widetilde{e}_1\widetilde{D}_2 - \widetilde{e}_2{}^2)ep + \widetilde{e}_1 D + \widetilde{e}_2 e,\\ B &= (\widetilde{e}_1\widetilde{D}_2 - \widetilde{e}_2{}^2)p + \widetilde{e}_2, \text{ and}\\ C &= (\widetilde{e}_1 D_3 - \widetilde{e}_2 e_3)p + e_3.\end{aligned}$$

In (6), Ω^{-1} is the *fundamental non-linearity scalar.* It transforms linear income and substitution effects into nonlinear ones (see Blomquist 1989, p.282). It is easily shown that Ω is positive if the product of the own compensated elasticities of effort and working days supplied is smaller

[12]The Slutsky decompositions are: $e_1 = \widetilde{e}_1 + ee_3$, $e_2 = \widetilde{e}_2 + De_3$, $D_1 = \widetilde{D}_1 + eD_3$, and $D_2 = \widetilde{D}_2 + DD_3$, where $\sim$ stands for a compensated effect.

[13]The Slutsky restrictions are : $\widetilde{e}_1 \geq 0$, $\widetilde{D_2} \geq 0$, $\widetilde{e}_2 = \widetilde{D}_1$, and $\widetilde{e}_1\widetilde{D}_2 - \widetilde{e}_2{}^2 \geq 0$.

[14]This is strictly correct when changes in p and w are infinitesimal. With finite changes, one must compare the physician's (indirect) utility levels under MC and FFS systems.

than $1 + w/e_0p$, which is greater than 1. In the following, we will assume that this is the case since almost all estimated (compensated) labour supply elasticities are smaller than 1 (*e.g.*, Blundell and MaCurdy 1999).

The first two expressions within the brackets on the right-hand side of (6) represent the substitution effects respectively associated with the change Δp in the fee and the introduction of the *per diem* w, and the third expression represents the income effect. Without additional assumptions, the impact of the MC on the physician's effort is ambiguous. However under plausible *sufficient* assumptions, it is possible to sign it.

Firstly, assume that effort and working days are net substitutes in the physician's preferences ($\widetilde{e}_2 \leq 0$) and that leisure at work and leisure outside work are normal goods (*i.e.*, $e_3 \leq 0$ and $D_3 \leq 0$). In this case, the income effect of the reform is negative (since $C \leq 0$). This result is intuitive: the physician who opts for MC benefits from an increase in his income (at constant behaviour) which induces him to reduce his effort at work. Second, under the assumption that the own compensated elasticity of effort exceeds its corresponding cross elasticity (in absolute value), one has $A \geq 0$. Therefore, the substitution effect of the reduction in the fee ($\Delta p \leq 0$) induces the physician to reduce his effort. Again, this result is intuitive: with a decrease in the piece rate per service, the physician will perform less services per day.

The substitution effect of the introduction of the *per diem* is more difficult to sign. However, one can easily show that if the cross compensated elasticity of effort (in absolute value) exceeds the product of the own compensated elasticities of effort and working days, which is not an implausible assumption, one has $B \leq 0$. In this case, the substitution effect of the *per* diem on effort will be negative. The intuition of this result is also clear: the *per diem* induces the physician to substitute working days for effort. In short, under plausible assumptions, both income and substitution effects induce the physician to reduce his effort at work under MC.

We should now examine the following question: what is the relationship between the physician's effort and the average number of days spent by his patients in hospital? To provide an answer to this question, let us first define the following variables:

$$a \equiv \frac{S}{N}, \text{ the average volume of services per patient, and} \tag{7}$$

$$d \equiv \frac{D}{N}, \text{ the average number of days in hospital per patient,} \tag{8}$$

where N is the number of patients treated by the physician over the period. Therefore, one has $d = \frac{S/N}{S/D} = a/e$. Now, we assume that the patient's health improves when a physician spends more time to perform clinical services. In that case, the average volume of services per patient necessary to treat health problems will increase with e, the volume of services performed by the physician per working day.[15] Since we assume no PID, it is realistic to assume that the physician provides the number of services just necessary to treat his patients. We thus have:

$$a = f(e), \quad \text{with} \quad f'(e) \geq 0. \tag{9}$$

Substituting (9) in $d = a/e$, one obtains:

$$d = \frac{f(e)}{e}. \tag{10}$$

Differentiating (10), the average change in time spent in hospital by patients treated by a physician who opts for MC can be approximated by:

$$\frac{\Delta d}{d_0} \approx -\frac{\Delta e}{e_0} + \eta_{a,e}\frac{\Delta e}{e_0} = (\eta_{a,e} - 1)\frac{\Delta e}{e_0}, \tag{11}$$

where $\eta_{a,e}$ is the elasticity of a with respect to e evaluated at the initial FFS situation, 0.[16]

The right-hand side of (11) makes clear that the introduction of a MC system yields two opposite effects on d, the average time spent in hospital by patients. On the one hand, a physician who adopts the MC system reduces his volume of services per working day ($\frac{\Delta e}{e_0} < 0$). This effect tends to increase d, *ceteris paribus*. On the other hand, since e decreases and $\eta_{a,e} > 0$, the patient's health tends to increase for a given level of services and therefore less services are needed to treat patients. This effect tends to reduce d. The second right-hand side of (11) shows that the net effect depends on whether the elasticity of a with respect to e, $\eta_{a,e}$, is smaller or greater than one. As long as the negative effect of the reform on the volume of services required by patient is not too strong (*i.e.*, the volume of services required to treat a patient is inelastic to the time spent per treatment, $\eta_{a,e} < 1$), the average time spent by treated patient by MC physicians will increase over the period.

Now we can decompose the average number of days spent in hospital by patients over the

[15] We assume that the volume of beds attributed to a physician per working day is exogenous as it is determined by the hospital. Therefore e is proportional to the volume of services per bed per working day.

[16] Using (8) and (10), the number of patients N is given by $N = \frac{D}{d} = \frac{De}{f(e)}$.

period into the product of their average length of stay in hospital, l, and their average frequency of hospitalisation, g, the two variables of interest in our analysis. One has: $d = lg$. Given that the size of $\eta_{a,e}$ is smaller than one, our static model can sign the impact of the reform on the product of these two variables (or the sum of their log) but not on each variable individually. However, our model is still useful since it can be used for instance to evaluate the impact of the reform on the total cost of a MC patient's hospitalization over the period, or to make conditional predictions. Thus, one can use our theoretical framework to predict that the impact of the reform will be positive on a MC patient's LOS in hospital, given that the reform involves no effect or a negative one on the frequency of readmission (which is tested in the empirical section of the paper).

The impact of the reform on the reallocation of tasks between clinical and nonclinical activities in MC departments (ignored up to now for simplicity) must also be taken into account. One should expect that MC physicians will spend less time in clinical activities and more time in nonclinical activities per working day, as the fee for clinical services is smaller than under the FFS scheme while non-clinical services are now remunerated by the *per diem* (substitution effect). This suggests that this effect will amplify the negative impact of the reform on the volume of a MC physician's clinical services per working day, and therefore its positive impact on the number of days in hospital a MC patient will spend over the period (see eq. (11)).

All in all, our model predicts that the reform will increase the time spent by a MC patient in hospital (as long as $\eta_{a,e} < 1$) over the period. Moreover, the reform will increase LOS in hospital, at least as long as it has a zero or negative effect on the risk of readmission. Our empirical analysis attempts to test these predictions by estimating a reduced form transition model of hospitalisation and re-hospitalisation analog to a difference-in-differences (DD) approach. This model allows us to evaluate the impact of the reform on the average LOS in hospital and the risk of re-hospitalisation of patients treated in MC departments.

3 Data Description

The data concerns patients' hospitalisations in a teaching hospital (Sherbrooke University Hospital Center). Only patients who stayed in hospital one day or more are observed in the database. Each patient discharged from hospital was registered in the database over a period of 9 years (1999-2007) with their precise time of admission to hospital, age, gender and department of admission, as well as the time when the patient left the hospital, department, Diagnosis-Related-Group (DRG)[17] and Major Diagnosis Category (MDC)[18] when leaving.

Due to problems of access to data, we could not use a sample period starting before 1999. One could argue that this reduces the period of observation to a small number of months before the reform, since the latter was implemented on September 1st 1999, while our sample period starts on January 1st 1999. Note however that the average LOS in hospital is 6.3 days. Therefore, there is still a large number of spells in hospital (13,445 visits) within this time interval. Also, not all treated departments moved to the MC system in September 1999. The first move to MC occurred on September 27th 1999 and the last on April 18th 2005 (see column 3, Table 1). In fact, most treated departments (12 over 19) chose to opt for MC in 2000 or later. This corresponds to two thirds of all spells in treated departments. One reason why they did not make the move at the start of the reform is that the applicable date at which a speciality could adopt MC (see column 3, Table 1) was negotiated at the provincial level by the government and each medical specialist association. A second reason is that departments were waiting for information or recommendations from their own association. The potential endogeneity of the date at which a department moved to MC and how we deal with this problem in our econometric model is discussed in Section 4.

Each patient leaving the hospital was registered over a 9-year period, from January 1st 1999 to December 31st 2007. Hence, this data set allows us to calculate the complete LOS in hospital and the length of stay out of hospital for each patient over this period. As regards spells in hospital, there is no left-censoring since the time of admission is available for all patients. However, right-censoring exists since we do not have information on the duration of hospital spells in the case of individuals who were still hospitalised on December 31th 2007. Moreover, 2.5% of patients (see last column of Table 1) died in hospital and their spells are therefore censored.[19] Also, there is no left-censoring for spells outside of hospital after a first period of hospitalisation within the sample period. Nevertheless, right-censoring is present for two reasons. Firstly, some individuals were out of the hospital at the end of the sample period. Secondly, since we focus on returns to hospital

[17]The DRG system classifies hospital cases expected to have similar hospital resources use into approximately 500 groups DRGs are assigned by an algorithm based on the International Statistical Classification of Diseases and Related Health Problems (ICD) diagnosis codes, Current Procedural Terminology (CPT) codes, age, gender, and the presence of complications or co-morbidities. An example might be the group of females aged 55 and older with a Breast Cancer diagnosis, a Mastectomy procedure code and an osteoporosis diagnosis (comorbidity).

[18]The MDC are formed by dividing all principal diagnoses into 25 mutually exclusive diagnosis areas. DRG codes also are mapped, or grouped, into MDC codes. Table (4) displays the list of them.

[19]Later on we discuss the possibility of considering this destination within a competing risks model.

in the same department with the same DRG, spells ending in hospital but in another department or DRG are considered censored.[20] Our econometric model takes these right-censored spells into account.

Table 2 summarizes descriptive statistics over the sample period. As mentioned above, the LOS in hospital is 6.3 days on average (ignoring right-censoring). Its median value is 3 days; the 25th percentile is 2 days while the 75th percentile is 7 days. The length of stay outside of hospital is 455.9 days on average (ignoring right-censoring), with 80% of the population going back to hospital after staying 10 (10th percentile) to 1262 days (90th percentile) out of hospital. The number of spells in hospital per patient is on average 1.6, with a 25th percentile of 1 and a 75th percentile of 2. 90% of the population return to the hospital 3 times or less over the period considered. If we consider patients returning to hospital, the average number of spells in hospital is 2.9, whereas this average is 1.7 when considering individuals coming back to the same department. The average number of spells in hospital falls to 1.3 for individuals returning to the same DRG. The age of patients is on average 40.9, with 75% being less than 66 years old, and the percentage of males being 45.1%.

Since the last move to the MC system occurred in April 2005, we chose to restrict our observation window to the period from January 1999 to April 2006. Given this choice, spells in hospital are no longer right-censored, except for episodes lasting more than 8 months (they are very few) or censored by the death of the patient (they represent 2.5% of the sample; see table 1).

4 Empirical Framework

In this section, we present a two-state transition model which allows to identify the impact of the reform on two outcomes for hospital departments that opted for the MC system (the treatment groups): patients' exit rates from hospital and their risk of re-hospitalisation to the same department and the same DRG. These outcomes can also be expressed in terms of the corresponding average duration in and out of the hospital. Our approach extends the model developed by Fortin, Lacroix, and Drolet (2004) to account for the presence of many treatment and control groups.

We assume that two states are possible for a patient: (i) in hospital ($s = 1$) and (ii) out of hospital ($s = 2$). Here, two remarks are in order. Firstly, as suggested by Picone, Wilson, and

[20] Note that estimates considering patients returning to hospital in the other departments with other DRG would be difficult to interpret.

Chou (2003), we also implemented a competing risks model with several post-hospital destinations for a patient in hospital. Given the administrative nature of our data, we could consider only two mutually exclusive destinations: (a) death in the hospital and (b) other out of the hospital destinations. However, in no specification did the reform have any overall effect on death in the hospital destination. Therefore, we have decided to restrict our analysis to a two-state model with spells with death in the hospital assumed to be censored. Secondly, with regards to spells out of hospital, we considered a competing risk approach to deal with destination in hospital but not in the same department or DRG. However, this did not change our results in any significant way. Therefore, these destinations are also considered censored.

Our model contains many treatment groups and the time at which they are treated varies across groups. A department is a treatment group if it moves to the MC system within the sample period.[21] Otherwise, it is a control group. There are K_s (with $K_1 = 23$ and $K_2 = 22$)[22] departments considered in the hospital ($k = 1, ..., K_s$), of whom the first R_s's (with $R_1 = 15$ and $R_2 = 14$) opted for the MC scheme within the sample period.

Consider a patient i, who has occupied a state s for a duration t, in his spell j, in the department k_{ij} (it refers to the last department where he was hospitalised if he is out of the hospital), at calendar time $\tau_{ij}\ \ (= \tau_{ij}(t))$, with a health problem belonging to the Major Diagnosis Category MDC_{ij} (it refers to his MDC at the end of his last stay in hospital if he is out of hospital), and with $\mathbf{x}_{ij}\ \ (= \mathbf{x}_{ij}(t))$ time-varying observed characteristics. The calendar time at which a treated department k switched to MC is given by c_k. We assume a flexible mixed proportional hazard (MPH) model based on the Prentice-Gloeckler approach generalized by Meyer (1990) to allow for unobservable heterogeneity. The model is time-continuous but interval-censored, that is, not directly observed, but observed to fall within a known interval (*e.g.*, one day). The individual's conditional hazard (or exit rate) function for each state s is given by:

$$\lambda^s(t|z^s_{ij}(t), \nu^s_{ij}) = exp(z^s_{ij}(t))\lambda^s_0(t)\nu^s_{ij}, \quad s = 1, 2, \tag{12}$$

[21] No MC department moved back to the FFS scheme over the period.

[22] The total number of departments is 26 (see Table 1). However, given the very low number of patients in neuropediatrics, radio-oncology, and pneumopediatrics in our sample period, these departments have been removed from all our estimations. Moreover, given the small number of returns in neonatology, this department has also been removed from our re-hospitalisation estimations.

with

$$
\begin{aligned}
z_{ij}^{s}(t) = \sum_{k=1}^{K_s} \alpha_{1k}^{s} I(k = k_{ij}) \quad &+ \quad \sum_{k=1}^{R_s} \alpha_{2k}^{s} I(\tau_{ij} \geq c_k) + \mathbf{P}^{'}(\tau_{ij}) \boldsymbol{\gamma}^{s} \\
+ \sum_{MDC=1}^{25} \boldsymbol{\alpha}_{MDC}^{s} I(MDC = MDC_{ij}) \tau_{ij} \quad &+ \quad \sum_{k=1}^{R_s} \beta_{k}^{s} I(k = k_{ij}) I(\tau_{ij} \geq c_k) + \mathbf{x}_{ij}^{'} \boldsymbol{\delta}^{s}, \quad (13)
\end{aligned}
$$

where $I(A)$ is an indicator function equal to 1 when A is true and 0 otherwise, and $\mathbf{P}(\tau_{ij})$ is a polynomial function of time. Eq. (12) specifies the hazard rate as the product of three components: a regression function, $exp(z_{ij}^{s})$, that captures the effect of observed explanatory variables, a baseline hazard, $\lambda_0^s(t)$, that captures variation in the hazard over the spell, and a random term, ν_{ij}^{s}, that accounts for the patient's and his treating doctor(s)' unobserved characteristics.[23]

The regression function (in log) is given by eq. (13). It corresponds to a standard DD approach translated into a regression equation, when there are many treatment and control groups. The first expression in the right-hand side of (13) introduces department-specific fixed effects. They take into account departments' time-invariant unobservable characteristics. The second expression takes into account a hazard break *common* to all departments, after each time c_k a treated department k switches to MC. The third expression is a polynomial function of time which allows for a nonlinear trend in hazard that is common to all departments. The fourth expression allows for a trend in the hazard rate from each state s for each of the 25 MDCs. These trends may differ from one diagnosis category to another given that the technological progress (or other trend factors) is not the same for each type of health problem. These trends allow to take into account the possibility that some of the adopting departments are those who have been experiencing a growing LOS relative to non-adopting department due to the nature of their medical treatments. The fifth expression accounts for the change in the hazard (over the common break and trend) that occurs for each *treated* department k (with $k = 1, ..., R_s$), after the time c_k it switches to MC. The β_k^s's coefficients are interpreted as the impact of the reform on treated departments (the average effect of treatment on the treated). Finally, the covariates $\mathbf{x}_{ij}$ account for patient's characteristics such as his gender, his age and his diagnosis (365 DRG dummies).

As mentioned earlier, using DRG dummies can control for the selection bias due to the choice of a department to change the distribution of patients after a move to MC. Indeed, different DRG

[23]For reasons of confidentiality, no information has been provided on the patient's doctor.

have different relative lengths of stay. So, given the flexibility of certain departments, they may choose to allocate resources differently after a change to MC by changing the distribution of the treated patients across their DRGs. This will alter the average duration of hospitalisation due to a change in patients characteristics. An increase in the proportion of patients with longer length of stay might consequently increase the gain of a switch to MC. On the other hand, some other departments might not be able, because of various constraints, to change the distribution of patients by DRG and so the potential gain of the reform is less obvious for them. Using DRG dummies will thus correct for the differences in average length of stay between departments that are due to the realization of potential gains of the reform.

The MPH model is nonparametrically identified under standard assumptions including minimal variations in covariates and independence between the covariates and the individual random term [see Van den Berg (2001) for a recent survey]. The latter assumption raises a number of important issues in our setting. Firstly, our econometric approach must address the selectivity bias associated with departments' decision to opt for MC. Recall that it is not the physician but the department, by a vote at unanimity, that decides to make such a choice. This endogeneity problem may render difficult the identification of the impact of the reform. For instance, the incentive to move to MC is likely to be stronger in departments where physicians' treatment approach is to favour longer hospital lengths of stay. This may create a positive bias on the effect of the reform on the duration of spells in hospital. In this setting, it is plausible to assume that the department-specific fixed effects take this problem into account. More precisely, a condition for identification is that these effects capture the unobserved common characteristics of physicians' preferences regarding the change of payment system within a department.[24] Secondly, related to the latter point, we suppose that, conditional on department-specific fixed effects and other covariates, c_k is strictly exogenous. This means that the department's decision to choose MC at time c_k within the sample period is independent from the treating physician's unobservable characteristics other than those taken into account by his department's fixed effect. With this regard, the introduction of trend variables that may differ across the 25 MDCs helps the identification of the model. This allows to account for the fact that technical progress (and other trend factors) in treating specific health problems may influence the decision of some departments to adopt MC and the date at which this choice is made (*i.e.,* the choice of c_k).

[24]Note that other factors could influence the decision to move to MC –such as the recommendations by specialist associations at the provincial level.

A related identification issue is whether the β_k^s's coefficients can be interpreted as the impact of the reform on treated departments. As in the standard DD approach, a basic condition is that, once controlling for common shocks and common time effects across departments, there is no shock other than the reform that affects the treated departments' outcomes after their adhesion to MC. Again, the presence of trend variables that may vary across the MDCs helps the identification of the model. This allows to take into account the fact that trend factors in medical treatments may differently affect patients' average LOS and their risk of rehospitalisation in adopting and non-adopting departments. Also, patients in departments that remained under FFS (control groups) must not be affected by the reform (no general equilibrium effects). Dumont *et al.* (2008) provides a test which rejects the presence of a general equilibrium effect in the case of this reform. Finally, one must assume that patients did not move from one department to another within a same spell because their department opted for the MC system.

In line with the Meyer model, the baseline hazard for each state is approximated by a finite number of parameters, each representing the average exit rate per time interval considered. This allows for flexibility in the relationship between the spell duration and the hazard rate from a state.

The heterogeneity terms ν_{ij}^s are assumed to be distributed as a parametric Gamma function with mean normalized to one and variance equal to $(\sigma^2)^s$. We use this parametric function rather than a non-parametric approach for a number of reasons. Firstly, it has been recently proved by Abbring and Van den Berg (2007) that the distribution of unobserved heterogeneity in MPH models converges to a Gamma distribution under realistic assumptions.[25] Therefore, using a Gamma function is likely to provide asymptotically more efficient estimators. Second, contrary to the Heckman and Singer (1984) (HS) alternative approach which assumes a nonparametric specification of the heterogeneity by introducing an exogenous discrete number of support points, the Meyer model yields an asymptotically normal estimator so that standard large sample inference can be used. Indeed, one basic problem with the HS estimator is that its asymptotic distribution is not known. Monte Carlo simulations by Baker and Melino (2000) have shown that the HS approach provides inconsistent estimates of the MPH model, when the baseline hazard is left fairly free. Thirdly, Han and Hausman (1990) reports empirical results indicating that a flexible specification of the hazard function sharply reduces the sensitivity of the estimates to a parametric heterogeneity assumption.

[25]Given the very large number of observations in our data set, the asymptotic properties of our estimators are likely to hold.

Here a number of remarks are in order. Firstly, since ν_{ij}^s includes both a patient's and his treating physician(s)' unobservable characteristics, we cannot assume that it is invariant across various spells within a same state as in a standard multi-spell model. Indeed, a patient may change physicians from one spell at the hospital to another. Note however that within a given spell j, patient i's heterogeneity term is time-invariant. This accounts for the problem of inconsistent estimated standard errors in the presence of serially correlation of outcomes (see Bertrand, Duflo, and Mullainathan 2004). However, we ignore the presence of dependency between unobserved heterogeneity across spells of a same individual.[26] Nevertheless, we do introduce some dependency across spells by allowing the re-hospitalisation hazard of a patient outside of hospital to be related to his diagnosis in his preceding spell of hospitalisation. Also, we ignore occurrence and lagged duration dependence (*i.e.*, dependence of the termination probability of the spell in progress on either the number or the duration of previous spells) as well as serially correlated unobserved heterogeneity. Incomplete information regarding previous hospital spells leaded us to adopt this strategy. Also, introducing diagnosis dummies is likely to partly control for these problems. Finally, as discussed earlier, left-censoring of the first spell is not a problem in our panel data, while right-censoring are taken into account in the estimations.

5 Results

In what follows, we provide maximum likelihood estimation results from our two-state MPH model.[27] We also present a robustness analysis of our results with respect to various specifications. In all of them, we included six time intervals (in days) to account for our flexible baseline hazard in each state. The intervals considered are 0, 1, 5, 10, 15, 20 + in the case of spells in hospital and 0, 10, 50, 100, 500, 1000 + in the case of spells out of hospital.[28] These intervals were chosen based on histograms of spells in each stage. A number of experiments suggest that the impact of other covariates are little affected by changes in the number and the size of these intervals.

As regards the covariates, after a number of experiments, we have introduced a quadratic time

[26]We provide some evidence later on that this is unlikely to affect the parameters of interest estimators very much.

[27]See Meyer (1990) for a derivation of the maximum likelihood function.

[28]The percentiles of the days used as cutoffs for intervals are respectively the 16th, 70th, 85th, 91th and 94th percentiles for hospital length of stay and the 5th, 14th, 20th 43th and 62th for the length of stay out of hospital.

polynomial (Trend and Trend^2). Introducing higher power levels in time did not change the parameters of interest (*i.e.*, the β's) in any significant way. Also, a quadratic polynomial in age, a gender dummy and six dummies for the day at which the patient was admitted in the hospital have been included as covariates. In the latter case, one expects that a patient admitted on Saturday or Sunday will stay longer in hospital since medical exams and treatments are usually less numerous during the weekend.

Table 3 provides the parameter estimates of the hazard rate from hospital. We test several specifications of the same model. In the first specification (model 1), we use Gamma heterogeneity of the error term but we add neither DRG dummies nor specific trends for the 25 MDCs. The β coefficients (which measure the average treatment effect on each treated department) are negative for 12 departments/specialities and, among these, significant at the 5% level for 8 departments out of 15 which have moved to MC in our sample. Patients in these 8 departments represent 68.26% of all MC patients in our sample. The coefficients are positive and significant for only two departments (vascular surgery and hematology). Patients in these departments represent 12.4% of all MC patients in our sample. This indicates that the rate of exit from hospital is reduced in most departments that moved to MC. The negative effect varies from 7.6% in general pediatrics to 36.2% in rheumatology.

Interestingly, we find that the variance of the Gamma distribution (θ) is not statistically significant according to the LR test.[29] The rejection of unobserved heterogeneity is a standard result in the literature especially in the presence of a flexible parametric representation of the baseline hazard (see Baker and Melino 2000). To analyse the robustness of this result, we re-estimated the model using the Inverse Gaussian distribution. In that case also, we could not reject the null hypothesis that the variance of the distribution is zero. The absence of unobserved heterogeneity problems partly justify our assumption that spells in and out of the hospital are independent.

In model 2, we add the 365 DRG dummies while excluding Gamma heterogeneity.[30] The

[29] Note that the test is a *boundary* one that takes into account the fact that the null distribution is not the usual chi-squared (with one degree of freedom) but is rather a 50:50 mixture of a chi-squared (degree of freedom = 0) variate (which is a point mass at zero) and chi-squared (degree of freedom = 1). The standard chi-squared test is incorrect since the model with no unobservable heterogeneity is not nested in the model with Gamma heterogeneity. Furthermore, in a previous version of the paper, we estimate a Cox specification analog to model 2 and found very similar parameters' estimates.

[30] When adding both DRG and Gamma heterogeneity, the variance of the Gamma distribution still appears to be not statistically significant and parameters estimates are almost the same as in model 2.

DRG dummies are jointly significant at the 1% level according to a LR test. Model 2 slightly alters our results. The reform still has a significantly negative impact on the exit rate from hospital of 8 departments out of 15. However, in this specification, it is not positive and significant for any department, which is consistent with what we expected. The negative effect varies from 7.7% in general pediatrics to 48.4% in rheumatology. This specification suggests that the reform has increased LOS in hospital for 68.26% of all MC patients in our sample while it has had no influence on LOS for the other patients.

Model 3 provides results when adding a trend for each of the 25 MDC. Based on a LR test, these trends are significantly different from zero at the 1% level. Estimates in models 2 and 3 are slightly different. The reform now has a significantly negative impact on the exit rate from hospital of the vascular surgery department, while it is no longer significant for the general pediatrics department. As in model 2, the impact of the reform on the exit rate from hospital is negative whenever it is significant (8 departments). Finally, model 4 yields estimates when imposing the equality of the β coefficients. However, A LR test rejects this restriction which conducts us to prefer Model 3 specification. According to results from model 4, the exit rate from hospital decreased by about 6.6% on average in departments that moved to MC, with this effect being significant at the 1% level.

Looking at other covariates in model 3, we find, as expected, that age has a negative impact on the exit rate from hospital and that starting hospitalisation during the week-end has a negative impact as well. Being a male has a positive impact on the exit rate (presumably due to a higher average opportunity cost in terms of wage earnings and easier substitutability between home and hospital care). The effect of the MCD trends variables appears to be positive whereas most post-change department dummies (the α_2's) have a negative impact or are not significant.

Based from model 3 results, we simulate the impact of the reform on the duration of hospitalisation in Table 5 using Katz and Meyer's (1990) approach. Relative effects of the change in the payment system on expected duration are also provided. They are estimated for each treated department over the sample period 1999-2006. The simulations use parameter estimates to predict the expected duration of hospitalisation over the sample period, with or without the effect of the change. The simulation procedure states as follows. Firstly, the predicted survivor function is simulated for each patient and each day of hospitalisation and then aggregated for the sample over individuals. Second, the predicted mean duration is calculated by accumulating the aggregate survivor function by day.[31] Finally, we estimate the difference between expected durations estimated with and without the change. Relative effect is obtained by dividing the difference by the expected duration estimated without the change.

We find that LOS in hospital has increased by 0.35 days overall in treated departments. This corresponds to a percentage increase of 5.3%. The department of rheumatology experienced the largest impact with an increase in LOS by 3.40 days (or 58.4%) while the department of neonatology experienced the lowest positive impact with a LOS increase of 0.27 days (or 6.4%). Inner medicine has also experienced a low positive and significant impact on days in hospital. These small increases may partly be explained by the fact that fewer services are provided by these specialists. Moreover, regarding neonatology, the discharge of newborns does not generally depend on the volume of services provided and thus may not be strongly influenced by the reform. For instance, in the case of acute medical problems, in order to be discharged, premature infants must know how to feed by themselves and grow; cardiorespiratory stability is also a prerequisite that may only depend on time. On the other hand, the discharges in rheumatology may be more dependent on the volume of services provided.

Table 6 presents the parameter estimates for the risk of re-hospitalisation to the same department with the same DRG. Model 1 includes neither DRG dummies nor MDC trend variables and assumes Gamma heterogeneity with the covariates given by age, age^2, gender and a quadratic time trend as in the model of hazard rates from the hospital. Results indicate that the impact of the reform is non significant for 9 departments, positive and significant for four departments (vascular surgery, neurosurgery, inner medicine, and rheumatology), and negative for only one department (endocrinology), out of 14 MC departments.[32] This specification suggests that the reform has increased the re-hospitalisation rates for 25.7% of MC patients and has reduced these rates for 0.76% of them. In this specification, the variance of the Gamma distribution is high and significantly different from zero, which suggests the presence of unobserved heterogeneity.

Model 2 adds DRG dummies while still allowing for Gamma unobserved heterogeneity. In this specification, the impact of the reform is no longer significant for neurosurgery so that the impact of the reform is now not significant for 10 departments. As a consequence, the reform is predicted to increase the re-hospitalisation rate for 17.5% of MC patients.

[31] Note that the number of days used for this computation should be large enough in order for the procedure to converge.

[32] Recall that neonatology has been removed from our re-hospitalisation rates specifications.

Model 3 provides results when adding a trend for each of the 25 MDC. Again, based on a LR test, these trends are significantly different from zero at the 1% level. The reform is now not significant for 12 departments out of 14 MC departments. It is no longer significant at the 5% level for vascular surgery but still negative and significant for endocrinology and positive and significant for inner medicine and rheumatology. However, in Model 4 (our preferred specification), which imposes all the β coefficients to be equal (not rejected at the 5% level), the average impact of the reform is not significant. This result thus suggests that the reform had no impact on the re-hospitalisation rate at the global level. As regards the other covariates in model 4, we find, as expected, that age has a positive impact on re-hospitalisation rates over a critical level. However, being a male has no significant effect on the risk of re-hospitalisation.

All in all, our results are consistent with our theoretical framework according to which patients treated by physicians who move to MC spend more days in hospital over the period. It is also consistent with the prediction that, given that the reform has no effect on a patient's risk of re-hospitalization, it will increase his LOS in hospital. Empirically, this effect is reflected by an increase in the duration of hospitalisation but no change in the risk of re-hospitalisation at the global level.

6 Conclusion

This paper aims at analysing the impact of a reform in Quebec that introduced an optional mixed compensation system for specialists in hospital, combining a fixed per diem with a reduced fee for services provided, as an alternative to the standard fee-for-service scheme. Using patient-level data from a major teaching hospital, this paper assesses the effect of the reform upon patients' length of stay in hospital and their risk of re-hospitalisation to departments that opted for this new system. Based on the estimates of a two-state transition model analog to a difference-in-differences approach, our results are twofold. Firstly, we find that the length of stay in hospital has increased on average by about 5.3% in these departments. This corresponds to an average increase of 0.35 days in hospital. Secondly, at the global level, the risk of re-hospitalisation does not seem to be affected by the reform. These results are consistent with our theoretical model which suggests that such a reform will induce physicians who opt for the mixed compensation scheme to adopt a practice pattern which increases their patients' number of days of hospitalisation per period, as well as their patients' length of stay in hospital, for a given risk level of re-hospitalisation.

These effects are relatively strong and were probably not anticipated by policy makers. Moreover an increase in patients' hospital length of stay is likely to be seen as a perverse impact of the reform. However, the full policy implications of our analysis are mixed. On the one hand, an increase in patients' number of days in hospital is costly both in time and money, *ceteris paribus*. Indeed, this is why a large number of health care policies such as the prospective payment system introduced in the U.S. mainly aim at reducing hospital length of stay. On the other hand, such an increase may be partly justified for two reasons. Firstly, it may be associated with more time spent by physicians on nonclinical activities such as teaching and administrative tasks, which are likely to be neglected under a fee for service scheme. As mentioned earlier, Dumont *et al.* (2008) provide evidence consistent with this effect as related to the Quebec reform. Second, as long as physicians spend more time treating their patients in hospital, this may improve patients' health. However, our results do not suggest this is the case since the risk of re-hospitalisation has not decreased at the global level in any treated departments. On the contrary, two departments (namely inner medicine, and rheumatology) have increased their re-hospitalisation rate of patients with the same diagnosis.

A natural extension of our research would be to compare the evolution of health status of two random groups of patients with a same diagnosis but one treated by physicians under a fee-for-service scheme and the other one by physicians under a mixed compensation scheme. We leave that for future research.

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Table 1: Department Characteristics.

Speciality	Remuneration scheme	Applicable date	Date of change	Percent of patients	Percent death at hospital
All	-	-	-	100.00	2.50
Cardiac surgery	MC	11.13.2000	01.05.2004	1.15	5.21
Cardiology	FFS	09.01.1999	n/a	11.23	3.40
Diagnostic radiology	FFS	09.01.1999	n/a	0.12	0.00
E.N.T.	MC	09.01.1999	11.27.2000	1.35	1.28
Endocrinology	MC	09.01.1999	11.08.1999	0.42	0.13
Gastroenterology	MC	09.01.1999	04.15.2002	0.51	0.55
General pediatrics	MC	09.01.1999	09.27.1999	8.82	0.25
General surgery	MC	09.01.1999	10.23.2000	6.23	2.34
Hematology	MC	01.01.2002	11.18.2002	2.04	5.32
Inner medicine	MC	09.01.1999	01.08.2001	4.35	8.29
Microbiology-infectiology	FFS	n/a	n/a	0.10	0.00
Neonatology	MC	09.01.1999	06.26.2000	13.26	0.38
Nephrology	MC	09.01.1999	10.09.2001	2.49	6.14
Neurology	FFS	09.01.1999	n/a	3.57	6.03
Neuropediatrics	MC	09.01.1999	10.10.2001	0.09	0.00
Neurosurgery	MC	09.01.1999	11.08.1999	4.52	4.32
Obstetrics-gynecology	FFS	09.01.1999	n/a	20.51	0.21
Orthopedic surgery	MC	09.01.1999	11.08.1999	4.37	1.33
Pedopsychiatry	MC	09.01.1999	06.12.2000	0.19	0.00
Pneumology	FFS	09.01.1999	n/a	4.03	8.38
Pneumopediatrics	MC	09.01.1999	11.08.1999	0.01	0.00
Radio-oncology	MC	09.01.1999	03.12.2001	1.03	8.55
Rheumatology	MC	09.01.1999	11.29.1999	0.52	1.27
Thoracic surgery	MC	11.13.2000	(*)	0.55	2.31
Urology	FFS	09.01.1999	n/a	3.79	0.73
Vascular surgery	MC	11.13.2000	04.18.2005	4.76	3.45

Source: Authors' computations using hospital health record database. Note: (*) payment scheme has not changed since this department was created.

Table 2: Patient Characteristics.

	Mean	Std	Min	P10	P25	P50	P75	P90	Max
Length of stay in hospital (days)	6.3	11.3	1	1	2	3	7	14	1192
Length of stay out of hospital (days)									
Returning patients	455.9	570.8	0	10	40	204	693	1262	3232
Returning in same Dept.	397.0	517.5	0	8	32	147	628.5	1104	3205
Returning in same DRG	602.0	545.5	1	40	110	519.5	896	1324	3190
Number of spells in hospital									
All patients	1.6	1.4	1	1	1	1	2	3	53
Returning patients	2.9	1.8	2	2	2	2	3	5	53
Returning in same Dept.	1.7	1.5	1	1	1	1	2	3	25
Returning in same DRG	1.3	0.9	1	1	1	1	1	2	17
Age	40.9	28.3	0	0	18	43	66	77	102
Percent Male	45.1	-	-	-	-	-	-	-	-

Source: Authors' computations using hospital health record database.

Table 3: Estimates of Hazard Rates from Hospital.

		model 1		model 2		model 3		model 4	
		Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
α_1	Cardiology	1.214	0.000	1.096	0.000	1.095	0.000	1.008	0.000
	Cardiac surgery	0.467	0.001	1.412	0.000	1.295	0.000	1.182	0.000
	General surgery	1.083	0.000	1.440	0.000	1.401	0.000	1.298	0.000
	Orthopedic surgery	0.850	0.000	1.229	0.000	1.162	0.000	1.167	0.000
	Thoracic surgery	0.724	0.000	1.451	0.000	1.452	0.000	1.366	0.000
	Vascular surgery	0.834	0.000	1.478	0.000	1.526	0.000	1.429	0.000
	Endocrinology	1.360	0.000	1.545	0.000	1.548	0.000	1.400	0.000
	Gastroenterology	2.263	0.000	2.414	0.000	2.376	0.000	2.236	0.000
	Hematology	0.682	0.000	0.843	0.000	0.860	0.000	0.822	0.000
	Inner medicine	0.855	0.000	0.890	0.000	0.886	0.000	0.799	0.000
	Microbiology-infectiology	1.622	0.000	1.617	0.000	1.635	0.000	1.531	0.000
	Neonatology	0.807	0.000	0.822	0.000	0.768	0.000	0.685	0.000
	Nephrology	0.766	0.000	0.844	0.000	0.837	0.000	0.720	0.000
	Neurosurgery	0.787	0.000	1.311	0.000	1.255	0.000	1.227	0.000
	Neurology	0.860	0.000	0.969	0.000	0.974	0.000	0.887	0.000
	Gynecology	1.310	0.000	1.480	0.000	1.484	0.000	1.396	0.000
	E.N.T.	1.410	0.000	1.826	0.000	1.746	0.000	1.578	0.000
	General pediatrics	0.917	0.000	1.065	0.000	1.021	0.000	0.975	0.000
	Pedopsychiatry	-	-	-	-	-	-	-	-
	Pneumology	0.810	0.000	0.894	0.000	0.896	0.000	0.810	0.000
	Diagnostic radiology	2.645	0.000	3.084	0.000	3.056	0.000	2.972	0.000
	Rheumatology	1.251	0.000	1.465	0.000	1.420	0.000	1.016	0.000
	Urology	1.407	0.000	1.581	0.000	1.584	0.000	1.498	0.000
α_2	Cardiac surgery	0.220	0.000	0.165	0.000	-0.087	0.000	-0.089	0.000
	Orthopedic surgery	0.019	0.607	-0.009	0.817	-0.035	0.349	-0.030	0.424
	Vascular surgery	0.213	0.000	0.184	0.000	-0.067	0.000	0.071	0.000
	General surgery	0.060	0.030	0.004	0.900	-0.059	0.031	-0.061	0.025

Table 3 (continued from previous page)

	E.N.T.	0.024	0.459	0.036	0.267	0.026	0.418	0.026	0.430
	Gastroenterology	0.105	0.000	0.094	0.000	-0.015	0.321	-0.016	0.292
	Inner medicine	0.000	0.987	0.013	0.597	-0.059	0.014	-0.058	0.015
	Nephrology	0.106	0.000	0.065	0.000	-0.063	0.000	-0.065	0.000
	Rheumatology	-0.003	0.925	-0.003	0.921	-0.048	0.134	-0.050	0.120
	General pediatrics	0.132	0.000	0.126	0.000	0.043	0.067	0.048	0.040
	Neonatology	0.118	0.003	0.111	0.005	0.076	0.056	0.076	0.056
	Pedopsychiatry	0.003	0.944	-0.013	0.747	-0.064	0.103	-0.062	0.111
	Hematology	0.114	0.000	0.085	0.000	-0.081	0.000	-0.077	0.000
β	Cardiac surgery	-0.049	0.448	-0.053	0.414	-0.099	0.127	-0.066	0.000
	General surgery	-0.169	0.000	-0.144	0.000	-0.087	0.002	-0.066	0.000
	Orthopedic surgery	-0.012	0.789	-0.042	0.345	0.038	0.425	-0.066	0.000
	Vascular surgery	0.285	0.000	0.020	0.612	-0.152	0.000	-0.066	0.000
	Neurosurgery	-0.010	0.832	-0.057	0.229	0.001	0.987	-0.066	0.000
	E.N.T.	-0.153	0.003	-0.280	0.000	-0.174	0.003	-0.066	0.000
	Endocrinology	-0.145	0.248	-0.138	0.275	-0.136	0.291	-0.066	0.000
	Gastroenterology	-0.201	0.005	-0.227	0.002	-0.161	0.030	-0.066	0.000
	Inner medicine	-0.095	0.001	-0.082	0.006	-0.067	0.027	-0.066	0.000
	Nephrology	-0.101	0.005	-0.127	0.000	-0.113	0.002	-0.066	0.000
	Rheumatology	-0.362	0.001	-0.484	0.000	-0.418	0.000	-0.066	0.000
	General pediatrics	-0.076	0.012	-0.077	0.012	-0.020	0.521	-0.066	0.000
	Neonatology	-0.156	0.000	-0.137	0.000	-0.061	0.021	-0.066	0.000
	Pedopsychiatry	0.066	0.652	0.037	0.817	0.044	0.795	-0.066	0.000
	Hematology	0.090	0.012	0.067	0.064	0.062	0.109	-0.066	0.000
λ_0	const1	-2.357	0.000	-4.063	0.000	-4.155	0.000	-4.077	0.000
	const2	-1.840	0.000	-3.417	0.000	-3.506	0.000	-3.428	0.000
	const3	-2.221	0.000	-3.550	0.000	-3.633	0.000	-3.556	0.000
	const4	-2.435	0.000	-3.647	0.000	-3.726	0.000	-3.649	0.000
	const5	-2.639	0.000	-3.762	0.000	-3.840	0.000	-3.763	0.000

Table 3 (continued from previous page)

	const6	-3.092	0.000	-3.977	0.000	-4.053	0.000	-3.975	0.000
Age		-0.014	0.000	-0.006	0.000	-0.006	0.000	-0.006	0.000
Age^2		0.000	0.826	0.000	0.000	0.000	0.000	0.000	0.000
Male		0.019	0.002	0.031	0.000	0.031	0.000	0.030	0.000
Tuesday		0.048	0.000	0.043	0.000	0.042	0.000	0.042	0.000
Wednesday		0.037	0.000	0.038	0.000	0.037	0.000	0.037	0.000
Thursday		0.052	0.000	0.032	0.002	0.031	0.003	0.031	0.002
Friday		0.013	0.207	0.013	0.224	0.012	0.236	0.012	0.230
Saturday		-0.029	0.006	-0.053	0.000	-0.054	0.000	-0.054	0.000
Sunday		-0.038	0.002	-0.056	0.000	-0.058	0.000	-0.058	0.000
Trend		-0.058	0.000	-0.034	0.007	-	-	-	-
$Trend^2$		-0.001	0.064	-0.001	0.044	-	-	-	-
Trend $\times$ MDC	MDC 1	-	-	-	-	0.022	0.000	0.022	0.000
	MDC 2	-	-	-	-	0.006	0.458	0.006	0.492
	MDC 3	-	-	-	-	0.016	0.000	0.015	0.000
	MDC 4	-	-	-	-	0.021	0.000	0.021	0.000
	MDC 5	-	-	-	-	0.041	0.000	0.041	0.000
	MDC 6	-	-	-	-	0.022	0.000	0.022	0.000
	MDC 7	-	-	-	-	0.015	0.000	0.014	0.001
	MDC 8	-	-	-	-	0.020	0.000	0.021	0.000
	MDC 9	-	-	-	-	0.012	0.003	0.013	0.002
	MDC 10	-	-	-	-	0.025	0.000	0.025	0.000
	MDC 11	-	-	-	-	0.022	0.000	0.021	0.000
	MDC 12	-	-	-	-	0.031	0.000	0.031	0.000
	MDC 13	-	-	-	-	0.029	0.000	0.029	0.000
	MDC 14	-	-	-	-	0.018	0.000	0.018	0.000
	MDC 15	-	-	-	-	0.021	0.000	0.021	0.000
	MDC 16	-	-	-	-	0.026	0.000	0.027	0.000
	MDC 17	-	-	-	-	0.032	0.000	0.035	0.000
	MDC 18	-	-	-	-	0.018	0.000	0.018	0.000

Table 3 (continued from previous page)

MDC 19	-	-	-	-	0.027	0.000	0.028	0.000
MDC 20	-	-	-	-	0.023	0.069	0.023	0.069
MDC 21	-	-	-	-	0.025	0.000	0.025	0.000
MDC 22	-	-	-	-	0.067	0.000	0.068	0.000
MDC 23	-	-	-	-	0.017	0.000	0.017	0.000
MDC 24	-	-	-	-	-0.022	0.145	-0.022	0.147
MDC 25	-	-	-	-	0.021	0.011	0.022	0.008
ln(theta)	-13.127	0.342	-	-	-	-	-	-
LR-test theta	0.000	1.000	-	-	-	-	-	-
Log L	-193710		-178513		-178300		-178321	
Number of observations	144510		144510		144510		144510	
Gamma heterogeneity	YES		NO		NO		NO	
DRG dummies	NO		YES		YES		YES	

Source: Authors' computations using hospital health record database. Note: Piecewise constant hazard specification is used for all models.

Table 4: List of major diagnostic categories (MDC).

#	MDC
1	Nervous system
2	Eye
3	Ear, nose, mouth, throat
4	Respiratory system
5	Circulatory system
6	Digestive system
7	Liver, bile duct and pancreas
8	Bones, aritculations, muscles
9	Skin, breasts
10	Endocrinal, metabolic or nutritional troubles
11	Urinal system
12	Male reproductory system
13	Female reproductory system
14	Pregnancy, childbirth and puerperium
15	Newborns
16	Blood, immunatory system
17	Immunoproliferative troubles and undefined tumors
18	Infections diseases and parasites
19	Mental and behavioural problems
20	Drug-related mental and behavioural problems
21	Wounds, poisoning and other external troubles
22	Burns
23	Other elements affecting health and use of substances
24	IHV-related problem
25	Multiple traumatic lesions

Table 5: Impact of the reform on the simulated expected duration in hospital.

Department	Difference (days)	Relative effect
Cardiac surgery	1.80	0.118
	(1.18)	
General surgery	0.67	0.100
	(0.24)	
Orthopedic surgery	-0.39	-0.042
	(0.53)	
Vascular surgery	1.05	0.176
	(0.31)	
Neurosurgery	-0.01	-0.001
	(0.53)	
E.N.T.	0.96	0.206
	(0.47)	
Endocrinology	0.47	0.148
	(0.44)	
Gastroenterology	0.30	0.176
	(0.18)	
Inner medicine	0.88	0.076
	(0.42)	
Nephrology	1.49	0.134
	(0.49)	
Rheumatology	3.40	0.584
	(0.80)	
General pediatrics	0.07	0.021
	(0.14)	
Neonatology	0.27	0.064
	(0.17)	
Pedopsychiatry	-0.59	-0.049
	(2.37)	
Hematology	-0.68	-0.067
	(0.46)	
All departments	0.35	0.053
	(0.14)	

Source: Authors' computations using hospital health record database. Notes: Standard errors in parentheses. Katz and Meyer's (1990) approach has been used to convert estimated exit rates into expected durations. Model 3 specification is used for the simulation of expected durations of each department over the period 1999-2006.

Table 6: Estimates of Re-hospitalisation Hazard Rates

		model 1		model 2		model 3		model 4	
		Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|	Coef.	P>|z|
α_1	Cardiology	1.275	0.000	-0.077	0.886	-0.174	0.754	-0.229	0.642
	Cardiac surgery	-1.057	0.044	0.606	0.389	0.524	0.465	0.367	0.570
	General surgery	0.186	0.583	-0.260	0.631	-0.294	0.600	-0.313	0.521
	Orthopedic surgery	-0.041	0.914	-0.635	0.291	-0.700	0.261	-0.446	0.383
	Thoracic surgery	0.338	0.392	0.344	0.578	0.260	0.681	0.200	0.730
	Vascular surgery	1.186	0.000	0.209	0.699	0.136	0.806	0.100	0.839
	Endocrinology	2.232	0.000	0.142	0.817	0.002	0.997	-0.598	0.237
	Gastroenterology	0.684	0.069	-0.665	0.244	-0.783	0.182	-0.871	0.094
	Hematology	2.089	0.000	-0.247	0.646	-0.303	0.584	-0.423	0.387
	Inner medecine	0.764	0.025	-0.687	0.203	-0.723	0.194	-0.590	0.223
	Microbiology-infectiology	0.488	0.350	-0.560	0.419	-0.646	0.359	-0.709	0.280
	Nephrology	1.579	0.000	0.508	0.346	0.496	0.372	0.310	0.525
	Neurosurgery	0.919	0.010	0.722	0.203	0.714	0.222	0.733	0.132
	Neurology	0.839	0.011	-0.303	0.571	-0.387	0.482	-0.440	0.369
	Gynecology	1.712	0.000	-0.438	0.422	-0.533	0.342	-0.588	0.239
	E.N.T.	-0.364	0.345	-0.925	0.121	-0.947	0.124	-1.141	0.032
	General pediatrics	0.397	0.237	-0.541	0.315	-0.493	0.374	-0.727	0.130
	Pedopsychiatry	-	-	-	-	-	-	-	-
	Pneumology	2.189	0.000	0.220	0.680	0.131	0.811	0.075	0.877
	Diagnostic radiology	0.963	0.054	-0.497	0.455	-0.646	0.342	-0.717	0.256
	Rheumatology	0.808	0.041	-0.027	0.964	-0.210	0.733	0.251	0.626
	Urology	0.869	0.009	-0.044	0.935	-0.142	0.800	-0.200	0.690
α_2	Cardiac surgery	-0.203	0.000	-0.216	0.000	-0.120	0.053	-0.117	0.057
	Orthopedic surgery	-0.160	0.239	-0.126	0.454	-0.198	0.259	-0.211	0.205
	Vascular surgery	-0.073	0.252	-0.037	0.604	0.189	0.003	0.208	0.001
	General surgery	0.024	0.797	0.003	0.980	-0.049	0.672	-0.045	0.694
	E.N.T.	0.142	0.181	0.157	0.228	0.144	0.288	0.118	0.374

Table 6 (continued from previous page)

	Gastroenterology	-0.234	0.000	-0.230	0.000	-0.282	0.000	-0.278	0.000
	Inner medecine	-0.242	0.002	-0.310	0.001	-0.422	0.000	-0.389	0.000
	Nephrology	-0.286	0.000	-0.318	0.000	-0.428	0.000	-0.439	0.000
	Rheumatology	-0.001	0.994	0.007	0.964	-0.075	0.621	-0.025	0.861
	General pediatrics	0.049	0.561	0.102	0.345	-0.037	0.727	-0.074	0.476
	Pedopsychiatry	-0.203	0.000	-0.252	0.001	-0.401	0.000	-0.411	0.000
	Hematology	-0.008	0.874	0.021	0.701	0.012	0.827	0.010	0.853
β	Cardiac surgery	-0.026	0.917	-0.029	0.914	-0.146	0.588	0.003	0.938
	General surgery	-0.044	0.690	0.136	0.270	0.058	0.676	0.003	0.938
	Orthopedic surgery	-0.096	0.631	0.381	0.132	0.346	0.203	0.003	0.938
	Vascular surgery	0.638	0.000	0.349	0.009	0.215	0.119	0.003	0.938
	Neurosurgery	0.943	0.000	0.169	0.384	0.076	0.711	0.003	0.938
	E.N.T.	-0.185	0.332	-0.128	0.574	-0.190	0.430	0.003	0.938
	Endocrinology	-0.694	0.001	-0.666	0.029	-0.596	0.070	0.003	0.938
	Gastroenterology	-0.034	0.854	-0.101	0.609	-0.067	0.742	0.003	0.938
	Inner medecine	0.218	0.050	0.350	0.006	0.263	0.048	0.003	0.938
	Nephrology	-0.030	0.803	-0.087	0.509	-0.201	0.150	0.003	0.938
	Rheumatology	0.457	0.010	0.495	0.026	0.577	0.013	0.003	0.938
	General pediatrics	-0.077	0.395	-0.052	0.649	-0.195	0.111	0.003	0.938
	Pedopsychiatry	0.198	0.367	0.066	0.807	0.062	0.828	0.003	0.938
	Hematology	0.127	0.191	-0.072	0.547	-0.132	0.311	0.003	0.938
λ_0	const1	-9.435	0.000	-11.666	0.000	-12.208	0.000	-12.142	0.000
	const2	-6.500	0.000	-9.077	0.000	-9.605	0.000	-9.541	0.000
	const3	-6.892	0.000	-9.129	0.000	-9.644	0.000	-9.581	0.000
	const4	-7.848	0.000	-9.981	0.000	-10.495	0.000	-10.433	0.000
	const5	-7.750	0.000	-9.719	0.000	-10.220	0.000	-10.160	0.000
	const6	-9.000	0.000	-10.891	0.000	-11.379	0.000	-11.319	0.000
Age		-0.026	0.000	-0.013	0.000	-0.012	0.000	-0.012	0.000
Age^2		0.000	0.000	0.000	0.502	0.000	0.000	0.000	0.000
Male		-0.063	0.015	-0.009	0.773	-0.007	0.818	-0.008	0.795

Table 6 (continued from previous page)

Trend		-0.143	0.001	-0.161	0.003	-	-	-	-
Trend^2		0.012	0.000	0.013	0.000	-	-	-	-
Trend $\times$ MDC	MDC 1	-	-	-	-	0.001	0.000	0.001	0.000
	MDC 2	-	-	-	-	-0.002	0.313	-0.002	0.312
	MDC 3	-	-	-	-	0.001	0.000	0.001	0.000
	MDC 4	-	-	-	-	0.001	0.000	0.001	0.000
	MDC 5	-	-	-	-	0.001	0.000	0.001	0.000
	MDC 6	-	-	-	-	0.001	0.000	0.001	0.000
	MDC 7	-	-	-	-	0.000	0.330	0.000	0.321
	MDC 8	-	-	-	-	0.001	0.000	0.001	0.001
	MDC 9	-	-	-	-	0.001	0.000	0.001	0.000
	MDC 10	-	-	-	-	0.000	0.001	0.000	0.002
	MDC 11	-	-	-	-	0.001	0.000	0.001	0.000
	MDC 12	-	-	-	-	0.001	0.066	0.001	0.066
	MDC 13	-	-	-	-	0.000	0.005	0.000	0.005
	MDC 14	-	-	-	-	0.000	0.012	0.000	0.012
	MDC 15	-	-	-	-	-0.002	0.521	-0.002	0.493
	MDC 16	-	-	-	-	0.001	0.001	0.001	0.001
	MDC 17	-	-	-	-	0.000	0.004	0.000	0.010
	MDC 18	-	-	-	-	0.001	0.026	0.001	0.028
	MDC 19	-	-	-	-	0.001	0.018	0.001	0.016
	MDC 20	-	-	-	-	0.000	0.698	0.000	0.710
	MDC 21	-	-	-	-	0.001	0.018	0.001	0.022
	MDC 22	-	-	-	-	-0.008	1.000	-0.008	1.000
	MDC 23	-	-	-	-	0.001	0.014	0.001	0.012
	MDC 24	-	-	-	-	0.002	0.036	0.002	0.035
	MDC 25	-	-	-	-	-0.003	1.000	-0.003	1.000
ln(theta)		-10.426	0.635	-0.228	0.005	-0.101	0.187	-0.103	0.180
LR-test theta		0.000	1.000	225.3	0.000	241.4	0.000	-	-
Log L		-43008		-38044		-38019		-38030	

Table 6 (continued from previous page)

Number of observations	125291	125291	125291	125291
Gamma heterogeneity	YES	YES	YES	YES
DRG dummies	NO	YES	YES	YES

Source: Authors' computations using hospital health record database. Note: Piecewise constant hazard specification is used for all models.