INNOVATION DIFFUSION UNDER BUDGET CONSTRAINTS

Microeconometric evidence on heart attack in France

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Abstract

This paper studies the relationship between the diffusion of innovative procedures for the treatment of heart attack and distributions of the cost and length of hospital stays. Using a sample of 5,681 stays observed in French public hospitals, we use microsimulation techniques to highlight various effects on the shifts in the overall distribution of the costs and length of stays: (i) the effect of the adoption of new techniques by hospitals (between hospital diffusion); (ii) the effect of the diffusion of technological progress within hospitals; (iii) the effect of changes in patients’ characteristics (age, comorbidities). This decomposition approach is used in the studies on the relationship between education and income distribution where observed distributions are compared to counterfactual distributions built by replacing some estimated parameters with their counterparts estimated from another country or time period. Our work shows that between 1994 and 1997 hospitals faced two main causes of rises in costs: firstly, diffusion of technological progress, with increasing use of costly innovative procedures such as angioplasty; secondly, patients’ epidemiological state worsened, since they became older and had more secondary diagnoses. These two factors induced sizeable shocks in cost distribution. Over this period, French public hospitals were financed by a global budget, and their budgets increased very slowly. However, international comparison shows that diffusion of technological progress for AMI treatment was similar in France and in comparable countries. How did French hospitals deal with their financial constraints? Our study shows that they greatly reduced the length of stays for patients at the bottom of the distribution. This reduction in the length of stays appears to have enabled hospitals to finance the diffusion of angioplasty. Obviously, such a strategy cannot be sustained in the long run without jeopardizing the quality of care.
1 Introduction

This paper studies the relationship between the diffusion of innovative procedures and changes in costs and lengths of hospital stays. In contrast with macroeconomic analyses, where the influence of technological progress is often reduced to a trend, microeconomic empirical evidence is used here. Data relative to individual hospital stays provide direct information about the diffusion of technological progress which makes it possible to evaluate the effects of technological progress on costs at different points in the cost distribution.

In the case of health care, direct information on technological progress diffusion can be gathered by observing changes in the use of innovative treatments and substitution between treatments. We focus on patients hospitalized with acute myocardial infarction. For these patients, the use of innovative procedures such as angioplasty is growing rapidly in all developed countries (TECH, 2001). These procedures are less costly than traditional ones such as bypass surgery. They are less invasive and more respectful of patients' quality of life. Innovative procedures can replace more traditional procedures. However, their use is spreading above and beyond this type of substitution.

Cutler and McClellan (1996) have studied the impact of technological progress on the treatment of heart attack in the U.S. After showing that the prices paid for a given level of technology are fairly constant over time, they conclude that growth in treatment costs results entirely from diffusion of innovative procedures.

This diffusion affects treatment costs in several ways. The implementation of innovative procedures induces a direct increase in cost for each stay. In addition, there may be an indirect increase if the procedure lengthens stay duration. Furthermore, diffusion of innovative procedures leads to more frequent use and thus amplifies the increase in the average cost of heart attack treatment.

Performing innovative procedures requires investment in specific training and high-tech equipment. The process of diffusion of technological progress in heart attack treatment is thus composed of two steps: firstly, adoption of new techniques by hospitals; secondly, an increase in the use of innovative procedures by hospitals which are able to perform them.

Our data covers public and private not-for-profit hospitals in France. We have at our disposal a database with three dimensions (stays-hospitals-years) relative to 11,573 stays for acute myocardial infarction observed over the period 1994 to 1997. Concentrating our analysis on cross-sections
relative to years 1994 and 1997, we finally retained a sample of 5,681 stays.

The study is carried out in four stages.

We firstly use a descriptive approach to characterize the pace and patterns of diffusion of innovative procedures for treating heart attacks, as well as the main features of AMI patients.

In the second stage, we estimate a four equation model that explains, for a given AMI-patient in a given year, the cost and the length of stay, the probability of being assigned to an innovative hospital (which has adopted the new techniques), and - conditional on the assignment to an innovative hospital- the probability of use of an innovative procedure. This model is estimated for 1994 and 1997, the first and last years of our observation period. The results show a rise in the use of innovative procedures between 1994 and 1997. The estimates allow us to evaluate the extra cost attributable to the use of an innovative procedure.

In the third stage, we use the estimates of our four-equation model to compute decompositions on means of the overall changes observed between 1994 and 1997, in the spirit of the Oaxaca (1973) decomposition.

In the fourth stage we focus on changes in the distributions of treatment costs and length of stays. The principle of our analysis is the following: we use the probability of implementation of an innovative procedure, estimated on the basis of the 1997 data, to simulate the cost and length of stays for patients observed in 1994. Comparison of the result with actually observed costs for 1994 allows us to assess the impact of technological progress diffusion on the distributions of costs and lengths of stays. In other words, we perform microsimulation techniques where observed distributions are compared to counterfactual distributions built by replacing some estimated parameters with their counterparts estimated from another year. This approach highlights various causes of shifts in the overall distributions: (i) the effect of adoption of new techniques by hospitals (between hospital diffusion); (ii) the effect of diffusion of technological progress within hospitals; (iii) the effect of changes in patient characteristics (age, gender, comorbidities).

One important feature in our analysis is that we go beyond the traditional Oaxaca decomposition on means and consider distributions. Indeed, not all patients are treated by an angioplasty. Therefore the process of technological progress diffusion and its impact on costs are likely to depend on the location of the patient stay in the distributions of length of stays or costs. Our approach allows
us to examine whether the estimated shocks occurred at different places of the distributions under study. This allows us to draw conclusions about how an increasing use of innovative procedures was possible within the context of a rather severe budget constraint.

This article is organized as follows. In section 2, we describe the pace and patterns of technological progress diffusion in France in the treatment of heart attacks. Section 3 is devoted to the specification and estimation of a four-equation model explaining length and cost of AMI stays. In section 4, we use the estimates of the model to analyse the average changes that occurred between 1994 and 1997. Methods and results of our microsimulations are presented in section 5, where we analyse the changes in distributions. Section 6 concludes.

2 Pace and patterns of innovative procedure diffusion

We have at our disposal a sample of 11,538 stays for acute myocardial infarction (AMI) observed in 44 French public hospitals over the period 1994-1997. In France and in the present study, the term "public hospitals" refers to government hospitals and to private-not-for-profit hospitals which are regulated by the global budget system (i.e. most of private-not-for-profit hospitals). Our sample does not record admissions in private-for-profit hospitals.

In France, public hospitals account for the majority of admissions (2/3 of admissions for AMI). While in the U.S. public hospitals serve a large proportion of indigent people, this is not particularly the case in France, where the clientele of public hospitals is varied. In France, all teaching hospitals are public and large public hospitals generally provide a high quality of care.

Our sample has been extracted from the PMSI\(^1\) cost database. Classification of stays by Diagnosis Related Group (DRG) is performed on the basis of diagnoses and procedures implemented during the stay. In order to obtain a high degree of homogeneity in patient pathologies, we selected patients aged at least 40 years with acute myocardial infarction (AMI) as the main diagnosis, grouped in DRGs 178 (complicated AMI) and 179 (uncomplicated AMI). For our empirical work, we restricted the sample to two cross-sections: 2,269 and 3,412 stays observed in 1994 and 1997.

\(^1\)PMSI stands for the \textit{Programme de médicalisation des systèmes d’informations}, which collects information about hospital activity. Information about the cost of stays is available from a hospital sub-sample called "Base nationale de coûts".
2.1 Treatment for AMI

Together with drug therapy (aspirin, beta blockers, etc.), AMI patients can receive various treatments such as thrombolytic drugs, cardiac catheterization (hereafter denoted as CATH) and percutaneous transluminal coronary angioplasty (PTCA). Catheterization is a procedure used to view the blood flow to the heart in order to improve the diagnosis. Angioplasty appeared more recently than bypass surgery. It is an alternative, less invasive procedure for improving blood flow in a blocked artery by inflating a balloon to create a channel through the blockage\(^2\). This procedure is costly: its implementation induces for one stay an increase in cost which ranges between 30% and 60%.

Statistics computed from the total sample of all AMI patients show that most angioplasties are grouped in DRGs 179 and 178. Bypass surgery is implemented for a very small proportion of AMI patients, less than 3%. Angioplasty may reduce AMI treatment cost when it replaces a more costly procedure such as bypass surgery. However, the savings arising from this substitution are rather marginal, given the low frequency of bypass surgery. This paper does not study this substitution effect. Therefore, we have restricted our sample to non surgical DRGs, (DRG 178 and 179), excluding AMI patients treated by bypass surgery.

2.2 Incentives to use innovative procedures within the French regulatory system

In France, public hospital budgets have been based on a global budget system for more than ten years, including the years 1994-1997 that we study. A complete information system which classifies inpatient stays by DRG has been set up, but a prospective payment system (PPS) with fixed payment per stay in a given DRG has not been implemented yet. A gradual introduction of a PPS is planned for 2004-2005. Budgets have no direct link to actual hospitals’ activity. In practice, the actual budget depends on annual negotiations between the hospital manager and the regulator, who is a regional representative of the Ministry of Health. The outcome of these negotiations is influenced by the number of stays recorded in all DRGs and by the hospital’s reputation. There

\(^2\)More recently, angioplasty has increasingly been performed with implantation of one or more stents (a kind of spring which keeps the vessel dilated) in order to improve outcomes. For the period under study, the use of stents was not very widespread. In this paper, the term angioplasty refers to angioplasty with or without stents.
is no real incentive to improve efficiency. Hospitals are managed by salaried administrators and do
not keep the gains resulting from cost reduction efforts. The budget constraint is soft in the sense
that hospitals are almost never forced to close solely on the basis of a financial deficit. However,
a hospital which overspends its budget may incur severe shortages. These shortages may prevent
the hospital from buying supplies for angioplasties, for instance, and force it to stop this kind of
activity for several months at the end of the year.

In France, financial incentives to use innovative procedures are quite different in the private and
public sectors (Jacobzone and alii (2002) and Milcent (2003)). While doctors in public hospitals
are salaried, physicians working in the private sector are paid on the basis of fee-for-service and
receive additional fees for performing angioplasties. As concerns investment in angioplasty, in public
hospitals, there is, for the period under study, no regulation requiring prior approval of technology
acquisition. A deterrent to public sector use of innovative procedures is the financing of supplies
from a global budget, which may limit the purchase of expensive devices. In addition, the use of
angioplasty does not lead to classification of a stay into a specific DRG in France during the years
1994 to 1997. Therefore, even when the global budget takes hospital’s activity into account, it does
not take angioplasty into account and the public hospitals which use it are penalized. On the other
hand, private hospitals are financed on the basis of a fee-for-service system: supplies such as stents
are reimbursed ex-post in addition to the fee-for-service payment.

These features seem to have limited the pace of angioplasty diffusion in the French public sector.
A comparative analysis between our data and data on AMI stays in Medicare hospitals has shown
that the growth in the use of angioplasty is slower in French public hospitals, in comparison to what
is observed in the US for Medicare hospitals (Delattre et al., 2002).

However, we will see below that angioplasty diffusion in French public hospitals is far from
negligible. Its pace is comparable to what is observed in other developed countries. Obviously, for
physicians working in the public sector, there are many indirect financial incentives, as well as non
financial incentives for the acquisition and development of innovative procedures. A career in public

\[\text{\textsuperscript{3}}\text{In the US classification, stays with angioplasty are grouped in a specific DRG (DRG 112).}\]

\[\text{\textsuperscript{4}}\text{As regards the French private sector, it was possible for us to carry out only a static comparison for year}
\text{1997 because of data limitations. This comparison shows that French private hospitals use angioplasty much more}
\text{frequently than French public hospitals. (The rate of angioplasty in Medicare hospitals lies between the two.) This}
\text{might be due to spillover from the public sector, where there might be waiting lists. Alternatively, it might be the case}
\text{that angioplasty is used too intensively in the French private sector because of the fee-for-service payment system.}\]
hospitals is rather prestigious in France. In teaching hospitals, physicians are involved in international research competition and their careers depend on their success in scientific publications. In addition, as we have seen, the level of the global budget depends partly on the hospital’s reputation, which can be enhanced if it is innovative.

2.3 Basic features of the data

As stated above, our sample concerns stays in French public hospitals which are regulated by a global budget system. The period 1994-1997 that we study is characterised by very slow budget growth. In fact, the increase in budgets was close to zero in real terms.

Table 1 reports statistics computed for the first (1994) and last (1997) year of our observation period. Our empirical study focuses on changes between these two years.

Most of the patients are men. The average age of the patients, both in 1994 and in 1997 is 67 years. A characteristic of heart disease appears in table 1: male AMI patients are rather young (in the age group 40-64) and female AMI patients are much older. The proportions of males and females in age category are rather similar in the years 1994 and 1997. Patients are slightly older in 1997, especially women.

The epidemiological state of AMI patients is worse in 1997: the number of secondary diagnosis is much greater (table 1). The proportion of patients with at least one non coronary secondary diagnosis is greater, as well as the proportion of patients with at least one coronary secondary diagnosis. Other statistics\(^5\) we have computed show an increase in the frequency of secondary diagnoses such as arrhythmia, hypertension, heart failure, cerebrovascular disease and peripheral arterial disease\(^6\).

Our indicator of the use of innovative procedures is the proportion of patients treated by angioplasty. The table shows that the overall rate of use of this procedure is growing rapidly in France: it went from 4.8% of stays in 1994 to 15.6% in 1997.

\(^5\)Unpublished here but available on request.
\(^6\)This increase in secondary diagnoses might be due to a worsening of patients' states. It could also be the result of more systematic registration of diagnoses by physicians. Changes in registration behavior could be encouraged by the prospect of a reform in the hospital payment system. It is possible for a hospital manager to create incentives for physicians to register diagnoses more systematically by allocating the budget between units in relation to their contribution to the hospital’s activity.
Performing innovative procedures requires investment in specific training and high-tech equipment. The process of diffusion of technological progress is thus composed of two steps: first, the adoption of new techniques by hospitals; second, the increase in the use of innovative procedures by hospitals which are able to perform them. We call the first step *between hospital diffusion*. The second step is linked to a process of learning by doing (Ho (2002)): we call it *within hospital diffusion*. Cutler and McClellan (1996) stress the importance of distinguishing between acquisition and use of technology, when analysing incentives for technology development. Between and within diffusion are illustrated by figure 1. The proportion of hospitals able to perform innovative procedures is increasing rapidly. The proportion of angioplasty implemented within innovative hospitals is growing even more rapidly. These patterns in France are comparable to the pace of technological progress diffusion observed in comparable developed countries (TECH, 2001, Cutler and McClellan, 1996, Cutler et al.,1998).

Table 1 also gives some information about the average length (*LOS*) and cost (*C*) of stays. The average length of stay decreases sharply between 1994 and 1997. It does not seem to be influenced by the performance of angioplasty. On the other hand, a stay is much more costly when angioplasty has been implemented. The average cost per stay increased slightly, from 4,361.7 Euros in 1994 to 4,611.2 Euros in 1997, i.e. an increase in nominal terms of 5.7%.

This rather limited cost increase illustrates the strength of the global budget. Between 1994 and 1997, growth in the average hospital budget was close to zero in real terms. During the same period, the pace of technological progress diffusion was rapid (figure 1). How did hospitals manage to increase the use of innovative procedure in the context of such a financial constraint? What is the link between the decrease in the length of stays and technological progress diffusion?

### 3 Designing a four-equation model to explain length and cost of AMI stays

To answer these questions, we use microsimulation techniques to examine the influence of various effects on the shifts in the distributions of the cost and length of stays. The first step of this approach

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*The hospitals able to perform innovative procedures are called "innovative hospitals" and denoted IH.*
is specification and estimation of a four-equation model explaining assignment to an innovative hospital, treatment by an angioplasty, length and costs of stays.

### 3.1 Econometric specification

For patient $i$ and year $\tau$, we consider the following model:

$$IH_{i\tau} = 1_{IH_{i\tau} > 0} \text{ with } IH_{i\tau}^* = x'_{i\tau} B_{\tau} + \nu_{i\tau} \quad (1)$$

$$proc_{i\tau} = 1_{Pr_{oc_{i\tau}} > 0} \text{ with } proc_{i\tau}^* = x'_{i\tau} D_{\tau} + \mu_{i\tau} \text{ if } IH_{i\tau}^* > 0 \quad (2)$$

$$\log(LOS_{i\tau}) = x'_{i\tau} d_{\tau} + IH_{i\tau} a_{\tau} + proc_{i\tau} p_{\tau} + c_{\tau} + \xi_{i\tau} \quad (3)$$

$$\log(C_{i\tau}) = x'_{i\tau} \delta_{\tau} + LOS_{i\tau} \theta_{\tau} + IH_{i\tau} \alpha_{\tau} + proc_{i\tau} \pi_{\tau} + \gamma_{\tau} + u_{i\tau} \quad (4)$$

This model has a recursive structure$^8$ and entails two assignment equations and two equations explaining respectively the length and the cost of the stay.

The first assignment equation (1) explains assignment to an innovative hospital, given a patient’s demographical and epidemiological characteristics $x'$. $IH$ is a dichotomic variable equal to 1 if the patient is assigned to a hospital that is able to perform angioplasty. The second assignment equation (2) explains, conditional on assignment to an innovative hospital, the probability of being treated by angioplasty. $proc$ is a dichotomic variable equal to 1 if the patient is treated by angioplasty. Equation (3) explains the logarithm of the length of the stay by patient characteristics $x'$, potential assignment to an innovative hospital and potential treatment by angioplasty. Equation (4) explains the logarithm of the cost of the stay using the same explanatory variables and the length of stay.

We aim to analyse changes in the distributions of the lengths of stays and costs that occurred between 1994 and 1997. For that purpose, we estimate this four-equation model on the cross-sections relative to years 1994 and 1997. Owing to the rather limited number of observations provided by our sample (5,681), we adopt a parametric approach.

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$^8$One has : $(1) \Rightarrow (2) \Rightarrow (3) \Rightarrow (4)$.
3.2 Econometric estimates

The recursive model defined by (1) to (4) has been estimated equation by equation for years 1994 and 1997. A simple probit estimator has been used for equation (1), which explains assignment to an innovative hospital. Conditional on this assignment, equation (2) explains the probability of being treated by angioplasty. It has been estimated by a probit estimator with selection\(^9\). For identification purposes, the selection equation entails other regressors\(^{10}\) in addition to the explanatory variables of (2). Denoting \(\rho\) the correlation coefficient between the disturbances of the probit equation and the selection equation of (2), the LR test leads us not to reject \(\rho = 0\) for the year 1994, but to reject \(\rho = 0\) in 1997 (5\%).

The estimates\(^{11}\) of (1) and (2) reveal that age has a significant negative influence on the probability of being assigned to an innovative hospital and on the probability of being treated with an innovative procedure. The constants of the two equations rise sharply between 1994 and 1997. In addition, the influence of a non coronary secondary diagnosis on the assignment to an innovative hospital increases significantly between these two years. These results illustrate the rapid between and within hospital diffusion of technological progress.

Table 2 displays the estimates of (3) and (4). We performed Hausman’s tests to check for exogeneity of the length of stay and of the dichotomous variables \(IH\) and \(proc\) describing assignment to an innovative hospital and treatment by angioplasty. We have used an instrumental variable estimator\(^{12}\) when exogeneity was rejected. This was the case for the length of stay in the cost equation for both years 1994 and 1997 and for \(proc\) in 1997.

A decrease in the length of the stay is indicated by the change in the constant of equation (3) : -22.5% for the reference patient, i.e. a male aged 40-65 with no secondary diagnosis, who is not in an innovative hospital and has not been treated by angioplasty. The explanatory variables of (3) and (4) relative to patient characteristics \(x’\) include cross effects of patient gender and age (four levels) and two dichotomous variables indicating whether the patient has at least one non coronary secondary diagnosis and/or at least one coronary secondary diagnosis. We do not report the estimates of the

\(^{10}\)Additional indicators of secondary diagnoses, hospital size, cross effects of patient’s age and gender.
\(^{11}\)Not reported here, available on request.
\(^{12}\)For identification purposes, we had to consider instruments in addition to the explanatory variables of (3) in the structural model : we thus included age squared, age raised to the third power and detailed indicators of secondary diagnosis, such as arrhythmia, hypertension, heart failure, cerebrovascular disease and peripheral arterial disease. These instruments are used for the estimation of (4) and to perform the exogeneity test.
coefficients relative to the cross effects of gender and age: they are all significant in equation (3) and show that the length of stay increases with age and is higher for women at all ages. These effects all increase between 1994 and 1997, indicating that the decrease in the length of stays revealed by the change in the constant is not homogenous for all patients.

Being assigned to an innovative hospital has a significant effect on the length of stay (Table 2). This influence is positive in 1994, but becomes negative in 1997. This result is understandable in the French context of the global budget system. From 1994 to 1997, budgets stagnated and had no direct link to hospitals’ actual production. In that context, one way to expand the use of innovative and costly procedures was for an establishment to reduce the length of stays. We observe that this behavior concerns all patients treated in an innovative hospital: for a given stay, the performance of an angioplasty does not significantly influence the length of the stay.

Secondary diagnoses have a positive and significant influence on the length of the stay. On the other hand, their direct influence on the cost of the stay is not significant (see the two last columns of table 2). Yet they have an indirect influence on cost through their impact on the length of stays. Indeed, LOS has a significant influence on cost with a coefficient close to 0.9 in 1994 and 1997.

Costs are significantly higher in innovative hospitals. In 1994, they are 27.8% higher. The estimated difference drops to 17.4% in 1997. In addition, performing angioplasty significantly increases the cost of a stay: +30.1% in 1994. The corresponding coefficient is 38.9% in 1997. This increase may be linked to changes in the technology of angioplasty (introduction of stents) and changes in supply prices.

To sum up, age and secondary diagnoses have a positive effect on the length of stay, which, in turn, influences positively the cost of a stay. Costs are significantly higher in innovative hospitals and when an angioplasty has been performed. Our descriptive analysis has shown that the patients’ state is worsening and that the use of innovative procedures, as well as the proportion of innovative hospitals, are increasing rapidly. Therefore, the cost of stays is likely to be subject to strong positive shocks. Our purpose is to study, within this context, the effect of the cost-containment induced by the global budget constraint on the distributions of the cost and the length of stays.

\[^{13}\text{This last coefficient appears to be not significant. However, we lost much of the variability of proc since we had to use its predicted values to deal with the outcome of the Hausman test.}\]
4 Average changes between 1994 and 1997

In this section we use the estimates of our four-equation model to compute decompositions on means of the overall changes observed between 1994 and 1997. Average changes are split into changes due to shifts in coefficients and changes due to shifts in patients’ observable characteristics. This allows us to check the robustness of our results and to raise questions which are addressed in the analysis of distributions in the last section.

4.1 Decomposition of average changes

We consider decompositions on means of the overall changes between 1994 and 1997, in the spirit of the Oaxaca (1973) decomposition. For the sake of simplicity, we refer to the notation of a linear model (such as equations (3) and (4)). One has:

\[ Y_{i0} = X_{i0}\beta_0 + u_{i0} \quad \text{and} \quad Y_{j1} = X_{j1}\beta_1 + u_{j1}, \]

where \( i \) and \( j \) are relative to patients observed, respectively, in years 0 and 1. In general, there is no reason for the same patient to be observed in the two years. \( X_{i0} \) and \( X_{j1} \) are horizontal vectors of explanatory variables for patients \( i \) and \( j \). Denoting by \( Y_0, Y_1, X_0, X_1 \) the sample means of the corresponding variables, and by \( \hat{\beta}_0 \) and \( \hat{\beta}_1 \) the estimated coefficients, we can compute the following decomposition:

\[ Y_1 - Y_0 = X_0(\hat{\beta}_1 - \hat{\beta}_0) + (X_1 - X_0)\hat{\beta}_1 \]  

(5)

The first part of the right-hand side is the average change in \( Y \) due to shifts in the coefficients \( \beta \). The second part is the change in \( Y \) due to the average shift in patients’ observable characteristics \( X \).

This decomposition takes year 0 as the reference for variables \( X \). Choosing year 1 as the reference for \( X \) leads to another decomposition:

\[ Y_1 - Y_0 = X_1(\hat{\beta}_1 - \hat{\beta}_0) + (X_1 - X_0)\hat{\beta}_0. \]  

(6)

The result of this last computation can be different but should be close to the result of (5).
We use the estimates of equations (1) to (4) to compute the decompositions defined on means by (5) and (6). Notice that our approach is not limited to decompositions which would be implemented equation by equation. In a rigorous approach, we take the full information arising from our recursive four-equation model into account. For example, changes in the coefficients of (1) and (2) induce changes in the length of stay which is an explanatory variable of cost in (4). Altogether, the use of this full-information approach imply that changes due to shifts in explanatory variables are entirely attributable to changes in patients’ observable characteristics, i.e. age, gender and secondary diagnoses. The other variables are endogeneously set by the equations of the model.

Our results are reported in table 3. They show that the rise in the average probability of being assigned to an innovative hospital (+ 6.8 %) is due to shifts in coefficients (+ 2.8 %) and to changes in patient characteristics (+ 4.0 %). By contrast, the dramatic increase (+ 32 %) in the use of angioplasty within innovative hospitals is entirely due to changes in practices.

Changes in coefficients induce a very sharp decrease in the length of stays (- 31.2 %), which is only slightly compensated by shifts in the explanatory variables (+ 6.55 %). The changes in the explanatory variables which induce a lengthening of stays are linked to patient ageing, especially for women, and to secondary diagnoses: they have a positive influence on the length of stays and their frequency rises between 1994 and 1997. Nevertheless, the overall change in the length of the stays is strongly negative (-24.7 %) since the impact of changes in behavior, which tend to shorten stays, is predominant.

Finally, the average increase in cost per stay is rather small: + 5 % only, for nominal cost. This illustrates the strength of the global budget constraint during this period. How did hospitals deal with this financial constraint? The decomposition of table 3 shows that changes due to shifts in explanatory variables are positive (+ 7.9 %) whereas changes due to shifts in coefficients are negative (- 2.9 %). This negative effect of changes in behavior stems from the tendency to shorten stays which is only partly offset by the extra costs arising from the increasing use of angioplasty.

To sum up, changes in cost determinants follow very different patterns: the length of stays decreases sharply; the probability of being assigned to an innovative hospital rises; the probability of being treated by an angioplasty rises. Taken together, these behavior changes result in a negative average effect on cost, equal to - 2.9 %. In the next section, we will focus on changes in the
distributions and identify the respective impacts of technological progress diffusion, changes in patient characteristics and shifts in LOS behavior.

4.2 Robustness of the results

Before turning to the analysis of changes in distributions, it is important to check the robustness of our results.

One weakness of our estimates is that few good instruments are available. To allow for the non-exogeneity of the length of stay, we have considered instruments such as higher order power of age and detailed indicators of secondary diagnosis. These instruments are used for the estimation of (4) and to perform the exogeneity tests. Given that they are different from the regressors of equations (3) and (4), the model is identifiable. However, there is no reason to think that there is a valid exclusion restriction here. We cannot draw strong causal statements from our instrumental variable estimates. To examine whether our estimates of (4) depend strongly on the method used, we have estimated this equation by OLS and then computed again the decomposition of average changes between 1994 and 1997. Results are displayed in table 4 (appendix A), line (4). They show that changes due to shifts in explanatory variables are equal to +9.6 % whereas changes due to shifts in coefficients are equal to -4.6 %. These evaluations are very close to what was obtained with the instrumental variable estimates (respectively, +7.9 % and -2.9 %).

Another difficulty stems from the fact that the increase in secondary diagnoses might be due to more intensive coding in 1997 in reaction to the prospect of a reform of the hospital payment system. If this is the case, our severity adjustment uses overstated changes in patient characteristics. Accordingly, severity-adjusted length of stay would appear to fall more than in reality. One important result of our study is that changes in the length of stay behavior make it possible for hospitals to finance a more intensive use of angioplasty. Therefore, it is crucial for us to examine whether the changes estimated for LOS behavior are robust to a potential coding bias. For this purpose, we have re-estimated the four-equation model while excluding secondary diagnoses from the list of regressors. With this approach, secondary diagnoses are treated equally in 1994 and 1997: they are part of unobserved patient heterogeneity in the disturbance. Then we have computed again the decomposition of average changes between 1994 and 1997 as regards LOS (equation (3)). Results
are displayed in table 4 (appendix A), line (3). As anticipated, changes due to shifts in explanatory variables are now much smaller (+1.5 % instead of +7.9 %). However, we observe that changes due to shifts in coefficients are only slightly reduced and still quite sizable: -26.1 % (instead of -31.2 %). Thus, the result relative to strong changes in the LOS behavior seems to be robust to the treatment of secondary diagnoses.

5 Analysing changes in the distributions of treatment costs and length of stays

We now consider LOS and cost distributions instead of means. Denote by $\Lambda_\tau$ the overall distribution of $\log(\text{LOS})$ at time $\tau$ and by $\Gamma_\tau$ the overall distribution of $\log(C)$ at time $\tau$. Given that patient characteristics are the only exogenous explanatory variables in our recursive four-equation model, these distributions can be expressed as vector functions of observable and unobservable patient characteristics and of the parameters at date $\tau$. In our study, $\tau$ is equal to 1994 or 1997, denoted by 0 or 1 for the sake of simplicity. One has: 

$$\Lambda_\tau = \Lambda \{x'_i, \epsilon_i, (B_\tau, D_\tau, d_\tau, a_\tau, p_\tau, c_\tau)\},$$

where $\epsilon_i = (\nu_i, \mu_i, \xi_i)$ and $\Gamma_\tau = \Gamma \{x'_i, \epsilon_i, (B_\tau, D_\tau, d_\tau, a_\tau, p_\tau, c_\tau, \delta_\tau, \theta_\tau, \alpha_\tau, \pi_\tau, \gamma_\tau)\}$, where $\epsilon_i = (\nu_i, \mu_i, \xi_i, u_i)$. These expressions correspond to the reduced form of our model. They include the exogeneous explanatory variables $x'_i$, as well as the disturbances and parameters of equations (1) to (4).

These distributions are represented in graphs 1 and 2. Changes in the distributions between 1994 and 1997, $\Lambda_1 - \Lambda_0$ and $\Gamma_1 - \Gamma_0$, are displayed in graphs 1a and 2a. They are explained by several factors:

- increasing adoption of new techniques by hospitals. This between hospital diffusion is linked to a change from $B_0$ to $B_1$ in the coefficients of (1). With given demographical and epidemiological characteristics, a patient has a higher probability of being assigned to an innovative hospital in year 1 than in year 0.

- within hospital diffusion linked to a change from $D_0$ to $D_1$ in the coefficients of (2). With

---

The distributions reported in this paper are kernel density estimates displayed by Stata software. We used the Epanechnikov as the kernel function and the default value chosen by the software for the bandwidth. The differences in densities displayed in this paper have been smoothed using a program provided by Stata.
given characteristics, a patient assigned to an innovative hospital has a higher probability of being
treated by an angioplasty in year 1 than in year 0.

- changes in patients’ demographical (age, gender) and epidemiological (secondary diagnoses)
characteristics. This population effect is related to changes in observable ($x_{i,0}'$) and unobservable
($\varepsilon_{i,0}, \varepsilon_{i,1}$) patient characteristics.

The effects of between and within hospital diffusion on the cost and length of stays can be
amplified by indirect effects. These are captured through the coefficients $a_r, p_r, \alpha_r, \pi_r$ and $\theta_r$ in
equations (3) and (4). For instance, changes from $\pi_0$ to $\pi_1$ can be linked to changes in supply prices.
Shifts in the overall distributions depend on the three effects mentioned above and on changes in
all other coefficients.

5.1 Simulating counterfactual distributions: the methodology

Consider the overall distributions $\Lambda_0$ and $\Gamma_0$ of the logarithms of the length of stays and of costs
at time 0:

$$\Lambda_0 = \Lambda \left\{ x_{i0}', \varepsilon_{i0} ; (B_0, D_0, a_0, p_0, c_0) \right\}$$

(7)

$$\Gamma_0 = \Gamma \left\{ x_{i0}', \varepsilon_{i0} ; (B_0, D_0, a_0, p_0, c_0, \delta_0, \theta_0, \alpha_0, \pi_0, \gamma_0) \right\}$$

(8)

The effects defined above can be evaluated as follows:

1) Between hospital diffusion

The between hospital diffusion is linked to the change from $B_0$ to $B_1$ in the coefficients of (1).
The results of our estimates reveal that this change if far from negligible. With given characteristics,
a patient has a higher probability of being assigned to an innovative hospital in 1997 than in 1994.
Using the estimates, we can simulate the counterfactual distribution:

$$\Lambda_{0,1(B)} = \Lambda \left\{ x_{i0}', \varepsilon_{i0} ; (B_1, D_0, a_0, p_0, c_0) \right\}$$

(9)

This counterfactual distribution is the distribution of the length of stay that would be observed
if the patients observed in 1994 were assigned to innovative hospitals with probabilities of 1997,
all other behaviors being equal to those estimated for 1994 as regards equations (2) to (4). The
effect of between hospital diffusion on the distribution of the length of stay is then evaluated by the
difference between the counterfactual distribution of the length of stay $\Lambda_{0,1(B)}$ and the distribution observed in 1994, i.e. $\Lambda_0$:

$$d\Lambda_{0,1(B)} = \Lambda_{0,1(B)} - \Lambda_0$$ (10)

2) Within and between hospital diffusion

Within hospital diffusion is linked to the change from $D_0$ to $D_1$ in the coefficients of (2). We have seen that the spread in the use of angioplasty is very rapid and entirely due to a change in the coefficients of (2): with given characteristics, the probability of being treated by angioplasty is much higher in 1997 than in 1994. To evaluate the effects of between and within hospital diffusion on the distribution of the length of stays, we use the estimates to simulate the counterfactual distribution $\Lambda_{0,1(B,D)} = \Lambda \{x'_{i0}, \varepsilon_{i0}; (B_1, D_1, d_0, a_0, p_0, c_0)\}$, that gives the distribution of the length of stays that would be observed if the patients observed in 1994 were assigned to innovative hospitals and treated by angioplasties with the probabilities of 1997, all other behaviors being equal to those estimated for 1994.

The cumulated effects of between and within hospital diffusion on the distribution of the length of stays is then evaluated by the difference between the counterfactual distribution of the length of stay $\Lambda_{0,1(B,D)}$ and the distribution observed in 1994, i.e. $\Lambda_0$:

$$d\Lambda_{0,1(B,D)} = \Lambda_{0,1(B,D)} - \Lambda_0$$ (11)

The same reasoning applies to the analysis of the impact of between and within diffusion on the distribution of the logarithms of the costs of the stays. The distribution in year 1994, denoted $\Gamma_0$, is defined by (8). The effects mentioned above can be defined in the same way for costs by computing differences between counterfactual distributions and the distribution observed in 1994. As concerns the cumulated effects of between and within hospital diffusion, one has:

$$d\Gamma_{0,1(B,D)} = \Gamma_{0,1(B,D)} - \Gamma_0$$ (12)

3) Changes in patients’ demographical and epidemiological characteristics.

We can decompose the population effect into what is due to observable characteristics and
what is due to unobservable heterogeneity. As stated by Bourguignon et al. (2001), it is possible to simulate a change in the distribution of unobservable characteristics through a rank-preserving transformation. When this distribution is assumed to be normal with a zero mean, this transformation is equivalent to:

\[
\varepsilon_{i,0,1} = \varepsilon_{i0} \frac{\sigma_1}{\sigma_0},
\]

(13)

where \(\varepsilon_{i,0,1}\) is the rank-preserving transformation\(^{15}\) of the distribution of \(\varepsilon_{i0}\) in the distribution observed at time 1. More exactly, it is the simulation of the unobserved heterogeneity of patient \(i\), observed in year 0, if he or she were ill in year 1.

To evaluate the effects of changes in patients’ unobserved heterogeneity, one can compute:

\[
d\Lambda_{0.1(\varepsilon)} = \Lambda_{0.1(\varepsilon)} - \Lambda_0,
\]

(14)

where \(\Lambda_{0.1(\varepsilon)}\) is the counterfactual distribution defined by: \(\Lambda_{0.1(\varepsilon)} = \Lambda \{x'_{i0,\varepsilon_{i,0,1}} ; (B_0, D_0, d_0, a_0, p_0, c_0)\}\).

To evaluate the cumulated effects of changes in unobservable and observable characteristics, we have to consider the individuals observed in year 1:

\[
d\Lambda_{0.1(x,\varepsilon)} = \Lambda_{0.1(x,\varepsilon)} - \Lambda_0
\]

(15)

where \(\Lambda_{0.1(x,\varepsilon)}\) is defined by: \(\Lambda_{0.1(x,\varepsilon)} = \Lambda \{x'_{j1,\varepsilon_{j,1}} ; (B_0, D_0, d_0, a_0, p_0, c_0)\}\). This latter expression is the counterfactual distribution that would prevail if the patients observed in 1997 were assigned and treated with the behaviors of 1994.

The same reasoning is applied to evaluate the effects on the cost distribution of changes in observable patient characteristics and unobservable heterogeneity.

Let us briefly comment on the principle underlying our computations. As concerns for instance between and within diffusion effects, we compare the observed distribution at date 0 with a hypothetical (counterfactual) distribution obtained by simulating on the patients observed at date 0, the behaviors at date 1. This change in behaviors due to technological progress diffusion is reflected by changes in coefficients from \(B_0\) to \(B_1\) and from \(D_0\) to \(D_1\). We evaluate the impact of these changes

\[^{15}\text{More generally, a rank-preserving transformation of the distribution of } \varepsilon_{i0} \text{ observed in } 0 \text{ in the distribution } \varepsilon_{i1} \text{ observed in } 1 \text{ is given by: } \varepsilon_{i,0,1} = F_1^{-1}[F_0(\varepsilon_{i0})]. \text{ Indeed, this leads to: } F_1(\varepsilon_{i,0,1}) = F_0(\varepsilon_{i0}).\]
on the costs and length of stays distributions. Given the number of parameters of our four-equation model, it would be possible to simulate a very high number of combinations for the various possible effects. Considering them exhaustively seemed to us of low interest. We preferred to focus on the effects detailed above and to try to answer questions of specific interest.

As stated by DiNardo et alii (1996) and Bourguignon et alii (2002), this approach can be seen as an extension of the Oaxaca methodology for decomposing the effects of discrimination between two groups of individuals into differences in mean income due to different mean characteristics of individuals in the two groups (here, our patients’ characteristics) and differences in how these characteristics are remunerated within each group (here, the changes in parameters: how the same epidemiological characteristics can lead to more frequent use of innovative procedures in year 1 than in year 0). The main change in our approach is that the decomposition is performed on the full distribution rather than on means. Indeed, since innovative procedures are not used to treat every AMI patient, this diffusion of technological progress is likely not to affect the cost in the same way at each point of the distribution 16.

5.2 Results

Graphs 3a-d and 4a-d display the main results of our microsimulation. All these graphs represent differences between distributions. Graph 3a (respectively, 4a) gives the overall change $\Lambda_1 - \Lambda_0$ that is observed for the distribution of the log of the length of stays (respectively, the log of the costs, $\Gamma_1 - \Gamma_0$) between 1994 and 1997. The other graphs (3b-d and 4b-d) give differences between our simulated counterfactual distributions and the distributions observed in 1994. They show the main shocks that affected the distributions of LOS and costs between 1994 and 1997 17. We have used the same scale for all graphs in order to compare the magnitudes of the various effects. Additional graphs provide detailed results in appendix B.

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16 This kind of decomposition may depend on the year taken as reference. Therefore, we have computed, for the different effects, the evolutions $d\Lambda_1(0,\cdot)$ and $d\Gamma_1(0,\cdot)$, in order to check for the robustness of the results. The results are available on request.

17 In this paper, we present the main shocks that have affected the distributions. There is of course a "residual" which results from all the other effects. These are available on request.
5.2.1 The impact of technological progress diffusion

The cumulated effect of between and within diffusion on the distribution of $\log(LOS)$ is shown in graph 3b. It appears to be rather small. As concerns the within effect, this is not surprising: the performance of angioplasty has no significant influence on the length of the stay (table 2). As for the between diffusion effect, the estimates revealed that being assigned to an innovative hospital has a significant, but rather small positive influence on the length of the stay in 1994. Graph 3b’ in appendix B isolates the effect of between hospital diffusion on the distribution of $\ln(LOS)$. Comparing graph 3b and 3b’ leads to the conclusion that the cumulated effect is mainly due to the between hospital diffusion effect, and that this effect is very small.

Turning now to cost distribution, graph 4b gives the cumulated effects of between and within diffusion. Both effects appear to be quite sizeable. They induce a rise in costs: the frequency of low-cost stays decreases whereas the frequency of expensive stays increases. The cumulated effect of between and within diffusion (graph 4b) is much larger than the between effect alone (graph 4b’ in appendix B). However the latter is far from negligible: it amounts to about half of the cumulated within-between impact. It is interesting to note that the positive shocks on costs are limited to a specific place in the distribution. This result gives empirical support to a lump-sum payment for AMI treated by angioplasty, under a prospective payment system.

5.2.2 The impact of the worsening of patients’ epidemiological state

The descriptive analysis of our data revealed that AMI patients age slightly and that their epidemiological state worsens: the number of secondary diagnoses increases rapidly. In addition, the estimates show that age and indicators of coronary and non coronary secondary diagnoses significantly influence the length of stays (table 2).

The effect on the distribution of $\log(LOS)$ of changes in observable and unobservable patients’ characteristics is quite sizeable (graph 3c). It is huge in comparison with the impact of technological progress diffusion (graph 3b). The worsening of the epidemiological state of patients in 1997, together with their aging, tend to lengthen hospital stays. Graph 3c’ in appendix B shows that the impact on length of stay of changes in patients’ unobservable heterogeneity is rather limited and

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18 This coefficient is the one which is used to simulate the counterfactual distribution.
result in more variability of the length of the stay.

For costs, the change arising from shifts in patients’ observable and unobservable characteristics is quite sizeable and results in an increase in the average cost per stay (graph 4c). Given that age and secondary diagnoses are not significant in the cost equation, this effect results from the influence of these variables on \( LOS \), which is a significant explanatory variable of the cost. Indeed, we have just seen that a sharp increase in the length of stays occurred because of changes in patients’ characteristics.

### 5.2.3 The role of shifts in LOS behavior

Our results show that between 1994 and 1997 hospital costs were subject to two positive shocks: diffusion of technological progress and worsening of patients’ epidemiological state. The combined effect of these two factors leads to a sizeable shock on cost distribution, which is much larger than the total change in cost distribution observed between 1994 and 1997 (compare graphs 4b and 4c to graph 4a). In fact, costs in the French public hospitals were limited by their budgets. Nonetheless, they were able to carry out rapid diffusion of costly innovative procedures, despite two unfavorable conditions: cost containment and the worsening state of patients.

How did hospitals manage to do this? They sharply reduced their length of stay. Indeed, the most marked change that occurred during the period was a change in the coefficients of the \( LOS \) equation between 1994 and 1997, which induced a tendency to shorten stays. More precisely, the results of the estimates (see subsection 3.2) show that there is a substantial reduction in the constant of equation (3) between 1994 and 1997: \(-22.5\%\). In addition, being assigned to an innovative hospital has a significant positive influence on the length of the stay in 1994, which becomes negative in 1997. The impact of these behavior changes on the \( Log(LOS) \) distribution is represented by graph 3d.

Graphs 3a-d show changes in the \( Log(LOS) \) distribution and the main shocks which affected this distribution between 1994 and 1997. Overall, length of stays has shortened (graph 3a). Decomposition of this change into its main components shows that the impact of technological progress diffusion is positive but very small, inducing a slight lengthening of stays (graph 3b). In contrast, the impact of changes in patient characteristics, which tends also to lengthen stays, is quite sizeable.
(graph 3c). However, these two effects taken together are smaller than the very large impact of behavior change, represented in graph 3d. This negative effect more than offsets the impact of the worsening of patients’ state.

This change in hospital behavior as regards length of stays induced cost savings. To evaluate these savings, we simulated the cost distribution in the year 1994, with the patients observed in 1994, but with the behavior estimated in 1997 as regards exclusively the length of stays. In other words, we simulated the counterfactual distribution, denoted $\Gamma_{0.1(LOS)}$, which gives the distribution of the log costs of stay that would be observed if the patients observed in 1994 had their lengths of stays determined by the behaviors estimated in 1997, all other behaviors being equal to those estimated for 1994, as regards assignment to innovative hospitals, treatment by angioplasty and levels of costs.\(^{19}\) The difference: $d\Gamma_{0.1(LOS)} = \Gamma_{0.1(LOS)} - \Gamma_0$ is displayed in graph 4d. It gives the savings in costs due to changes in the coefficients of the length of stay function. This graph reveals the magnitude of the cost savings induced by change in LOS behavior.

Graphs 4a-d show changes in the cost distribution and of main shocks that occurred between 1994 and 1997. The overall change is a rather limited rise in costs, linked to the small increase in global budgets (graph 4a). Decomposition of this change into its main components shows that (i) the impact of technological progress diffusion is positive and sizeable (graph 4b); (ii) the impact of changes in patient characteristics is positive and even larger (graph 4c); (iii) the saving effect of shifts in the coefficients of the length of stay equation (graph 4d) is larger and more than offsets the effects on costs of the diffusion of innovative procedures (graph 4b). On the whole, this last and negative effect partially offsets the cumulated impact of the technological progress diffusion and of the worsening of the patients’ state: the overall rise in costs is limited.

How did hospitals succeed in shortening the length of stays? Graph 5 allows us to examine more thoroughly the changes that occurred in the LOS distribution. We have seen (graphs 3c-d) that this distribution was subject to two main shocks: the worsening state of patients and changes in behavior. The lines corresponding to these two effects are superimposed on graph 5, together with a vertical line which represents the first quartile of the length of stays in the year 1994. The effect of

\(^{19}\) $\Gamma_{0.1(LOS)}$ is defined by $\Gamma_{0.1(LOS)} = \Gamma\{x_{0,1}; \epsilon_0; (B_0, D_0, d_1, a_1, p_1, c_1, \theta_0, \alpha_0, \pi_0, \gamma_0)\}$. Notice that $d$, $a$, $p$ and $c$ are the coefficients of the LOS equation.
the shortening of the stays due to the changes in LOS behavior takes place around the first quartile, i.e. more on the left of the distribution in comparison to the lengthening of stays due to changes in patient characteristics. This result shows that hospitals concentrate their stay shortening effort on patients situated at the bottom of the length of stay distribution, who are likely to be patients without complications. This strong shortening of stays might entail risks for such patients.

6 Conclusion

Between 1994 and 1997, hospitals faced two main causes of rises in costs: on the one hand, diffusion of technological progress, with increasing use of costly innovative procedures such as angioplasty; on the other hand, patients’ epidemiological state worsened, since they became older and had more secondary diagnoses. These two factors induced shocks in cost distributions.

During the same period, French public hospitals were financed by a global budget, and their budgets increased very slowly. Hence, growth in overall average costs was limited. However, international comparisons show that diffusion of technological progress for AMI treatment is similar in France and in comparable countries (TECH (2001)). How did French hospitals deal with their financial constraints?

The specification and estimation of a model describing angioplasty diffusion and explaining the cost and length of stays allowed us to perform decompositions of the average changes that occurred between 1994 and 1997. Our results show that hospitals shortened stay duration to create savings in order to compensate for the extra cost arising from the increasing use of angioplasty. However, these changes did not affect all patients uniformly. Our analysis shows that stays were shortened especially for patients at the bottom of the distribution. This large reduction in the length of stays for patients with few complications appears to have enabled hospitals to finance the diffusion of angioplasty, despite a budget shortage. Such a strategy cannot be sustained in the long run without jeopardizing the quality of care.

Turning to the issue of technological progress, it is remarkable to observe how hospitals got round the financial difficulty to maintain a rather high pace in the adoption and use of angioplasty. This shows the strength of indirect financial incentives, linked to the hospital’s reputation and the involvement of physicians in international competition in research.
7 References


Table 1: Basic features of the data

<table>
<thead>
<tr>
<th></th>
<th>1994</th>
<th>1997</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of stays</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2,269</td>
<td>3,412</td>
<td></td>
</tr>
<tr>
<td><strong>Patient’s characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender (proportion of female)</td>
<td>29.7</td>
<td>31.2</td>
</tr>
<tr>
<td>Average age (year)</td>
<td>67</td>
<td>67</td>
</tr>
<tr>
<td><strong>Male age distribution</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40-64</td>
<td>50.9</td>
<td>51.7</td>
</tr>
<tr>
<td>65-74</td>
<td>29.5</td>
<td>27.4</td>
</tr>
<tr>
<td>75-84</td>
<td>15.1</td>
<td>16.2</td>
</tr>
<tr>
<td>85 and over</td>
<td>4.5</td>
<td>4.7</td>
</tr>
<tr>
<td><strong>Female age distribution</strong></td>
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</tr>
<tr>
<td>40-64</td>
<td>17.5</td>
<td>16.0</td>
</tr>
<tr>
<td>65-74</td>
<td>31.2</td>
<td>26.9</td>
</tr>
<tr>
<td>75-84</td>
<td>33.9</td>
<td>34.8</td>
</tr>
<tr>
<td>85 and over</td>
<td>17.4</td>
<td>22.3</td>
</tr>
<tr>
<td><strong>Number of secondary diagnoses (percentage):</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>26.6</td>
<td>10.6</td>
</tr>
<tr>
<td>1-3</td>
<td>57.7</td>
<td>51.8</td>
</tr>
<tr>
<td>Over 3</td>
<td>15.7</td>
<td>37.6</td>
</tr>
<tr>
<td><strong>At least one non coronary secondary diagnosis (percentage):</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>45.0</td>
<td>71.1</td>
</tr>
<tr>
<td><strong>At least one coronary secondary diagnosis (percentage):</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>59.1</td>
<td>70.7</td>
</tr>
<tr>
<td><strong>Angioplasty (percentage):</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.8</td>
<td>15.6</td>
</tr>
<tr>
<td><strong>Length of stay</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average LOS (days)</td>
<td>11.6</td>
<td>9.7</td>
</tr>
<tr>
<td>(Standard deviation)</td>
<td>(7.1)</td>
<td>(7.0)</td>
</tr>
<tr>
<td>Stay without angioplasty</td>
<td>11.6</td>
<td>9.3</td>
</tr>
<tr>
<td>(Standard deviation)</td>
<td>(7.1)</td>
<td>(7.0)</td>
</tr>
<tr>
<td>Stay with angioplasty</td>
<td>11.8</td>
<td>8.5</td>
</tr>
<tr>
<td>(Standard deviation)</td>
<td>(6.1)</td>
<td>(6.8)</td>
</tr>
<tr>
<td><strong>Cost</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average cost (euros)</td>
<td>4,361.7</td>
<td>4,611.2</td>
</tr>
<tr>
<td>(Standard deviation)</td>
<td>(2,980.0)</td>
<td>(3,088.9)</td>
</tr>
<tr>
<td>Stay without angioplasty</td>
<td>4,252.7</td>
<td>4,334.5</td>
</tr>
<tr>
<td>(Standard deviation)</td>
<td>(2,947.9)</td>
<td>(2,914.5)</td>
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<tr>
<td>Stay with angioplasty</td>
<td>6,542.7</td>
<td>6,109.3</td>
</tr>
<tr>
<td>(Standard deviation)</td>
<td>(2,784.8)</td>
<td>(3,546.9)</td>
</tr>
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</table>

PMSI database: 2,269 and 3,412 AMI stays in 1994 and 1997
Figure 1: PTCA diffusion (Between and Within)

Graph 1: Distribution of the logarithm of the length of stay in 1994 ($\Lambda_0$) and 1997 ($\Lambda_1$)

Graph 1a: Change in the distribution between 1994 and 1997 ($\Lambda_1 - \Lambda_0$)

PMSI database: 2,269 and 3,412 AMI stays in 1994 and 1997
Graph 2: Distribution of the logarithm of the cost of stay in 1994 ($\Gamma_0$) and 1997 ($\Gamma_1$)

Graph 2a: Change in the distribution between 1994 and 1997 ($\Gamma_1 - \Gamma_0$)

PSDI database: 2,269 and 3,412 AMI stays in 1994 and 1997
Table 2: Estimated coefficients for Equations (3) Length of stay and (4) Cost

<table>
<thead>
<tr>
<th></th>
<th>Log(LOS)</th>
<th>Log(C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>in coronary</td>
<td>0.314** (0.029)</td>
<td>0.074** (0.029)</td>
</tr>
<tr>
<td>secondary diagnosis</td>
<td>0.163** (0.031)</td>
<td>0.332** (0.031)</td>
</tr>
<tr>
<td>coronary secondary</td>
<td></td>
<td></td>
</tr>
<tr>
<td>diagnosis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>age (LOS)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Hausman Test for</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H_0$ : exogeneity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Innovative Hospital</td>
<td>0.129** (0.031)</td>
<td>-0.139** (0.032)</td>
</tr>
<tr>
<td>Hausman Test for</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H_0$ : non rejected</td>
<td>(0.050)</td>
<td>(0.845)</td>
</tr>
<tr>
<td>Angioplasty</td>
<td>-0.028 (0.061)</td>
<td>-0.008 (0.047)</td>
</tr>
<tr>
<td>Hausman Test for</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H_0$ : non rejected</td>
<td>(0.269)</td>
<td>(0.163)</td>
</tr>
</tbody>
</table>

**: The estimated coefficient is significant at 1% level. *: The estimated coefficient is significant at 5% level.
Models also included patient characteristics.

Table 3: Average changes between 1994 and 1997: first decomposition

<table>
<thead>
<tr>
<th>Equation</th>
<th>Total changes 1994 – 1997 (%)</th>
<th>Changes due to shifts in coefficients (2)</th>
<th>Changes due to shifts in explanatory variables (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>Assignment to an innovative hospital</td>
<td>+ 6.8</td>
<td>+ 2.8 (+ 6.5)</td>
</tr>
<tr>
<td>(2)</td>
<td>Treatment by an angioplasty</td>
<td>+ 32.0</td>
<td>+ 32.0 (+ 27.0)</td>
</tr>
<tr>
<td>(3)</td>
<td>Length of stay</td>
<td>- 24.7</td>
<td>- 31.2 (- 35.36)</td>
</tr>
<tr>
<td>(4)</td>
<td>Cost of stay</td>
<td>+ 5.0</td>
<td>- 2.9 (- 10.1)</td>
</tr>
</tbody>
</table>

The decompositions given here take the year 1994 as a reference for the explanatory variables. In parentheses are given the decompositions resulting from the other possible computation, which takes the year 1997 as a reference for the explanatory variables.
Graphs 3:

Graph 3a: Overall change in the distribution between 1994 and 1997 ($\Lambda_1 - \Lambda_0$)

Graph 3b: Cumulated effect of between and within diffusion on the distribution of ln(LOS)

Graph 3c: Effect of changes in unobservable heterogeneity and observable patients' characteristics on the distribution of ln(LOS)

Graph 3d: Change in the distribution due to shifts in the coefficients
Graphs 4:
Distribution of log(\text{Costs}): overall change and main shocks between 1994 and 1997.

Graph 4a: Overall change in the distribution between 1994 and 1997 (E_1 - E_0)

Graph 4b: Cumulated effect of between and within diffusion on the distribution of log(cost)

Graph 4c: Effect of changes in unobservable heterogeneity and observable patients' characteristics on the distribution of log(cost)

Graph 4d: Savings in cost due to changes in LOS behavior between 1994 and 1997
Graph 5: LOS distribution: comparison of effect of changes in behavior and effect of changes in patients' characteristics.

Vertical line: first quartile of ln(LOS), 94.

Appendix A

Table 4: Overall changes between 1994 and 1997: checking for the robustness of the results

<table>
<thead>
<tr>
<th>Equation</th>
<th>Total changes 1994 – 1997 (%)</th>
<th>Changes due to shifts in coefficients</th>
<th>Changes due to shifts in explanatory variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td></td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>(4)</td>
<td>Cost of stay</td>
<td>+ 5.0</td>
<td>(- 8.6)</td>
</tr>
<tr>
<td>(3)'</td>
<td>Length of stay</td>
<td>- 24.7</td>
<td>(- 27.2)</td>
</tr>
</tbody>
</table>

The decompositions given here take the year 1994 as a reference for the explanatory variables. In parentheses are given the decompositions resulting from the other possible computation, which takes the year 1997 as a reference for the explanatory variables.
Appendix B: Detailed results of the simulations

1) Effect of between hospital diffusion between 1994 and 1997 on the distributions of $\ln(\text{LOS})$ and $\ln(\text{cost})$. The cumulated effects of between and within diffusions are given in graphs 3b and 4b.

<table>
<thead>
<tr>
<th>Graph 3b'</th>
<th>Effect of between hospital diffusion on the distribution of $\ln(\text{LOS})$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Graph 3b" /></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Graph 4b'</th>
<th>Effect of between hospital diffusion on the distribution of $\ln(\text{cost})$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image2" alt="Graph 4b" /></td>
<td></td>
</tr>
</tbody>
</table>

2) Effect of changes in patients’ unobservable heterogeneity between 1994 and 1997 on the distributions of $\ln(\text{los})$ and $\ln(\text{cost})$. The cumulated effects of changes in unobservable heterogeneity and observable patients’ characteristics are given in graphs 3c and 4c.

<table>
<thead>
<tr>
<th>Graph 3c'</th>
<th>Effect of changes in patients’ unobservable heterogeneity on the distribution of $\ln(\text{LOS})$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image3" alt="Graph 3c" /></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Graph 4c'</th>
<th>Effect of changes in patients’ unobservable heterogeneity on the distribution of $\ln(\text{cost})$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image4" alt="Graph 4c" /></td>
<td></td>
</tr>
</tbody>
</table>