Is shortening hospital stays counter-productive?

July 27, 2007

Abstract

Shorter stays in hospital may lead to avoidable readmissions reflecting premature discharge. Here we consider the effect of shorter stays on both avoidable readmissions and the total length and cost of hospitalisation. First, patients who require longer stays are more sensitive to policies reducting the length of stay. Second, it would seem that shortening stays is counterproductive, as it leads to a 14 % rise in total costs.

Despite this cost disadvantage, the implementation of the Prospective Payment System will provide financial incentives for hospitals to multiply avoidable readmissions. This will likely render hospitals less efficient.

JEL classification: **C23, H51, I18.**

Keywords: Inefficiency, Hospital costs, Length of stay, Prospective Payment System.

1 Introduction

A tendancy to reduce the length of stay is widely observed. Is there a limit where this change in practice is counter-productive? Shortening the stay is a way to reduce the hospital expenditure. However, a willing to discharge too quickly leads to an avoidable readmission. Drawing on earlier work on the measure "*avoidable readmission*", we assess the determinants of readmissions. The aim is to assess how much extra it costs society to discharge patients prematurely.

In this paper, we focus on readmission judged as avoidable. This type of readmission is viewed as a measurement of healthcare quality. How to measure quality in health care are long-standing and contentious. Various potential proxies for quality have been put forward. Thomas and Hofer (1999) provide a comprehensive review on reliability of quality indicator. However, some authors use the hospital readmission as a quality indicator. The readmission indicators can be from within 5 days of a discharge to within 30 days of the discharge. These authors justify the use of readmission rate for three main reasons. First of all, the risk of readmission are highly negatively correlated with the hospital quality level. Ashton *et alii* (1987) show that the risk of readmission is increased by premature discharge or substandard care during initial hospitalisation. Secondly, readmissions are frequent and involve a wide range of clinical categories, unlike hospital deaths (Anderson *et alii*, 1984). Thirdly, most data required to calculate and adjust readmission rates for case mix are collected routinely (Anderson, 1985). Therefore, to assess the cost of avoidable readmission can be interpreted as an assessment of the healthcare quality issue.

We use data from a Swiss hospital, the University Hospital Center of Vaud canton (CHUV hospital), Lausanne, Switzerland. In Switzerland, there is five university hospitals; In Vaud canton, there is only one university hospital. We focus on one pathology, the myocardial infarction also called heart attack. This pathology is widely used in empirical healthcare studies. From our empirical study, we obtain two main results. First, patients who require longer stays are more sensitive to policies reducting the length of stay. Second, it would seem that shortening stays is counter-productive, as it leads to a 14 % rise in total costs.

This paper is organized as follows. The next section defines avoidable readmissions. The section 3 presents the data and the using variables. The econometric strategy is dealt with in Section 4, whereas the empirical results and the estimation of the model are discussed in Section 5. Section 6 concludes.

2 Avoidable readmissions

A readmission can be planned or unplanned. A readmission is considered as a planned readmission if it was expected to occur as part of a program of phased care at the time of the previous discharge. An unplanned readmission can have different causes. It can be a previously known affection unforeseen at the time of the discharge of the patient but often planned subsequently during the ambulatory follow-up as well as a readmission justified by a relapse or an aggravation of the initial condition. It can be also an unplanned readmission due to an inadequate patient behavior, a readmission for social reasons or a new affection unrelated to any diagnosis made during the previous hospitalisation period. At last, it can be an unplanned readmission due to an iatrogenic complication, premature discharge. How to distinguish an avoidable readmission from the rest of readmissions ? An avoidable readmission is an unplanned readmission for a previously known affection caused by complications of care due to premature discharge[1]. The rate of *avoidable* readmission could be a really good instrument to detect a neglect discharge due to the hospital. Thus far, studies do not have any measure of the avoidable readmission. In the litterature, authors use the unplanned readmission rate that is a roughly proxy of the avoidable readmission (Ashton *et alii*, 1997). This proxy can lead to an inadequate measurement. For instance, readmissions for deliveries or organ transplants are generally unplanned and one cannot regard them as avoidable.

How to detect avoidable readmissions ? "Avoidable" is a subjective notion. None physician can be one hundred percent sure that an admission is effectively avoidable. The healthcare decision does not follow exact rules. This activity depends on the judgement of the physician. In this study, we suggest to use a rigorous measure of the *avoidable readmission* (Halfon *et alii*, 2003). First of all, a computerised algorithm was elaborated and validated, exclusively based on routinely available data, to screen avoidable readmissions. The routinely data contains information on each hospitalisation: demographic patient's characteristics, patient's diagnoses, procedures performed. Secondly, when the algorithm was not sufficient, a group of in-

[1] An avoidable readmission can also due to medical malpractice, discharge with a missing or erroneous diagnosis or therapy

dependant and experienced clinical physicians classified as "avoidable" by consensus from hospital information system and completed using medical records, nursing notes, drug prescriptions, clinical observations, physician letters, investigation results.[2] This process of selection was set up by physicians and validated by them (with publications). Moreover, this process of selection is currently discussed to be adopted by other university hospitals (as the university hospital of Geneva).

The choice of an optimal time interval to spot readmissions that are avoidable is within one month after the discharge. This choice seems to be sufficiently short to minimize cohort attrition (post-hospitalization death, emigration). Frankl et alii (1991) show that most preventable readmissions occur within 10 days after discharge and going to longer periods create errors in the measure. However, these authors do not have any tool to distinguish avoidable readmissions from readmissions. In this study, we use an algorithm to detect avoidable readmissions. Therefore, considered readmissions up to 30 days allows to detect all avoidable readmissions. Moreover, according to Ashton et alii (1997), no specific time interval has been justified clinically or statistically for readmission indicators.

3 Data

The data was collected in the University Hospital Center of Vaud canton (CHUV hospital), Lausanne, Switzerland. The CHUV hospital accounts for about 800 beds. This hospital deals with all areas of medicine except ophthalmology and psychiatry. In the Vaud canton, the readmission within 5 days is not considered as a new hospitalisation because of financial conventions. Nevertheless, chances are that in such cases the medical diagnosis is not modified. Because CHUV provides tertiary level care, it is reasonnable to assume that few patients are readmitted to other hospitals.

The studied population consisted of the ischemic disease [3]admissions on the years 1999 to 2001. Ischemic disease is widely used for empirical work on quality. First of all, the care of this disease is under the control of hospital management and senior physicians within the hospitals, and so outcomes are in part a choice of decisions of the hospital (Thomas *et al.*, 1993; Kessler and McClellan, 1998 ; Propper *et al.*, 2002). Secondly, this pathology affects a

[2]In Appendix A, we present a short resume of the Halfon paper (2003). For more details on the classification, see Halfon *et al.* (2003).

[3]Codes I21 and I22 with the International Statistical Classification of Diseases and Related Problems, 10th revision, 1994 (ICD-10-CM disease codes).

large number of patients which makes it possible to work on extensive data.

In this study, we assume that a patient that was readmitted, could have gone under all the necessary procedures over a single hospital admission that would be shorter than the total of the two hospital admissions. Some patients have more than one avoidable readmission. These observations were considered as meaningless observations and they were deleted. Moreover, for a few patients, it was not possible to define if the readmission was avoidable. We decided to delete these observations. In principle, this selection introduces a problem of biased sampling, but because only very few patients (20 observations) were thereby eliminated we believe that this is neglectful. The population studied is composed of 10,251 observations.

From this data collected routinely (CHUV database), we have information per admission. For each admission, we have information on age, gender, the type of discharge (alive or deceased), diagnosis (up to 15 ICD-10 codes), procedures (up to 12 ICD-9-CM codes)[4], Diagnosis related group (All-Patient -Diagnosis related groups version 12.0), the cost and the length of the admission. The cost per admission is collected routinely. It corresponds to the expenditure of the hospital for this admission and not the admission's charge. The admission's cost is obtained through a complex accountancy method.

From the DRG, we define the indicator variable *Surgical* when a procedure is performed in a operating room. From the diagnosis, we used the Deyo adaptation of the Charlson co-morbidity index, expressed as a six-level variable, to measure the severity of the co-morbidities (Deyo, 1992; Ghali, 1996). This index has been validated as a predictor of mortality in longitudinal studies (Hamilton and Hamilton, 1997). In the following, the term "stay" defines an admission plus a possibly avoidable readmission. The variables "$LOS1$" and "$cost1$" correspond to the length and cost of the first admission. The variables "$LOS2$" and "$cost2$" correspond to the length and the cost of the avoidable readmission. The variables LOS and $Cost$ correspond to the sum of the initial and subsequent admission respectively, for the cost and the length.

The readmission rate is about 7.6 %. The avoidable readmission excludes all readmissions not due to premature discharge. We then obtain a rate of avoidable readmission of 2.6 %. The more the patient is aged, the more the the probability of avoidable readmission is higher (Table 1). We observe that the probability of avoidable readmission is higher for female patients

[4] International Classification of Disease, 9th revision, clinical modification, 1994.

than for male ones (Table 2). One explanation is that male inpatients are much younger than female ones. Moreover on table 2, we observe that the probability of the avoidable readmission increases with the age of inpatients (table 1). If male inpatients have a higher level of severity disease (measured by the Charlson co-morbidity score), the female ones have a longer stay and a higher mortality rate than males. Moreover, procedures in an operating room are performed on half the male inpatients but only on one third of female inpatients. The latter point explains in part that the cost of the stay is higher for male patients than for female ones (Table 2). On Table 3, we compare different outputs in function of the avoidable readmission. We observe a higher mortality rate for patient avoidably readmitted but no variation on the surgical procedure rate. The stay of avoidably readmitted patient is twice more expensive and her length of stay is multiplied by three with an initial admission lengthened (+ 3 days).

How can we explain these results? Are these incredibly important effects on the length and the cost only due to the avoidable readmission or can they be explained by some patient characteristics? To answer these questions, we propose an econometric approach.

4 Econometric strategy

To shorten the length of stay is one response to limit the hospital expenditure. However, the result could be an increase in avoidable readmissions and therefore, an increase in the hospital expenditures. First of all, we analyse the determinants of an avoidable readmission. In a second step, we assess the effect of the avoidable readmission on the global cost stay.

4.1 Determinants of avoidable readmissions

An avoidable readmission is the result of a premature discharge. Is the fact to be readmitted for an avoidable readmission randomized on the whole sample of CHUV patients? From Tables 1 to 3, we suspect that patient characteristics and length of the initial admission have an effect on the probability to be readmitted. The binary decision to undergo an avoidable readmission AR is modeled as the outcome of an unobserved latent variable, AR^*.

$$AR_i^* = X_i'\alpha + u_i \tag{1}$$

i : the stay of inpatient, $i \in \{1, .., N\}$. X corresponds to inpatient characteristics, cost and length for the initial admission.

4.2 Effects of avoidable readmissions

Some authors have found that variations in readmission probability are related to patient's clinical conditions rather than premature discharge (Thomas, 1991,1996; Ludke et al., 1993).

We look for the part of the cost of stay, called extra-cost, due to the avoidable readmission but not due to the patient characteristics. If the extra-cost due to the avoidable readmission is independent of the patient characteristics then this extra-cost is the average cost of the subsequent admission, given in Table 3. Otherwise, we use an econometric method to assess the extra-cost due to the avoidable readmission controlling for patient characteristics.

An avoidable admission is the *result* of a premature discharge during the initial admission and not the *cause*. For the initial admission, the cost per day and the length depend on patient characteristics and procedures performed on patients but not on the avoidable admission. Therefore, we propose an estimation in two steps. In a first step, we explain the cost per day and the length using the information from the initial admission.

$$Y_{1,i} = W'_{1,i}\eta + \varepsilon_i \tag{2}$$

Y_1 corresponds respectively to $\left(\frac{Cost1}{LOS1}\right)$ and $LOS1$. W_1 corresponds to individual characteristics of the initial admission. From this first step, we obtain $\widehat{\eta}$, the estimated coefficient of W_1.

In a second step, we are able to assess the part due to an avoidable readmission using information from the stay (the admission plus the possibly avoidable readmission).

$$Y_i = W'_i\eta + AR'_i\vartheta + v_i \Leftrightarrow Y_i = W'_i\widehat{\eta} + AR'_i\vartheta + v_i + \zeta_i \Leftrightarrow Y_i - W'_i\widehat{\eta} = AR'_i\vartheta + v_i + \zeta_i \tag{3}$$

Y corresponds respectively to $\left(\frac{Cost}{LOS}\right)$ and LOS of the stay ; W corresponds to individual characteristics of the stay. ζ is the measurement error introduced by using the efficient and consistent estimator $\widehat{\eta}$ and not η. Therefore, standard errors are computed using a bootstrap method in order to obtain a consistent estimator of the variance of ϑ. The cost per day and the length are taken in logarithm.

Some variables as the social condition, not observed by the econometrician, may have an effect on the cost of the stay (respectively the length) and be correlated with the probability to be avoidably readmitted. In such a case, AR variable would turn out to be non exogenous variables. So, we test the exogeneity of the avoidable readmission in each model. The avoidable readmission is instrumented by W, crossed variables of W and different proxies of proximity between the patient's residence and the university hospital. The model is identifiable because of these proxies of proximity and because the dependent variable of the equation (**??**) is quantitative and a non-linearity is introduced _AR is discrete_ (Maddala, 1983). For the cost per day (respectively, the length), we reject the hypothesis of exogeneity (Student Test, $p - value = 0.001$) whatever the model). The Sargan test validates the exogeneity of the instruments ($p - value = 0.16$) (respectively, $p - value = 0.17$). However, our instruments could be questionable and be subject to the weak instruments problem (Bound, Jeager and Baker, 1995). The tests define by Staiger and Stock (1997) validate our instrumental variables for each instrumented variables ($p - value = 0.0001$).[5]

After the initial admission, 94% of patients return home. Few of them died during the admission or are transfered to another hospital. To take into account this censore, we modelled a tobit model. A generalized tobit model could be more convenient to fit our model but we do not have suitable instruments. For the length of admission model, a PH model was implemented but it appeared that the tobit regression is the most appropriate model.[6]

5 Empirical results

The patient of reference is a male patient aged between 35 and 55 years without disease gravity (assessed by the Charlson index) and who does not receive any surgical procedure.

5.1 Avoidable readmission

With preliminary statistics, we observe a gender difference on the probability to be avoidably readmitted. Thereby, we can suspect that the avoidable readmission depends on the gender. From the results, male patients aged over 70 years and female patients aged over 60 years have less probability

[5]As Bound, Jeager and Baker (1995) have shown when faced with the choice of using weak instruments and no instruments at all, the latter is often the best empirical strategy because weak instruments may lead to large inconsistencies in the instrumental variable estimates. For this purpose, we present both, LOS model and IV model.

[6]For the length of admission model, a PH model was implemented but it appeared that the tobit regression is the most appropriate model according to Wilcoxon-Beslow test.

to be readmitted. In fact, more than the gender, the age has an effect on the probability to undergo an avoidable readmission because of a premature discharge (Table 4).

A non programmed admission increases the probability of avoidable readmission. The level of the Charlson index does not have any effect on the premature discharge whereas a surgical procedure decreases the probability to be readmitted. It seems that the hospital puts patients under acute monitoring after a surgical procedure. The positive effect on the probability of having an avoidable readmission is evaluated at 22 %. So, these results clearly show the correlation between the avoidable readmission and patient characteristics.

If the cost of the initial admission does not have any effect on the probability to be readmitted, we observe an effect of the length. A longer stay increases the probability to be avoidably readmitted. This result needs some explanations. Indeed, premature discharge means that after controlling for other factors, the patients that are discharged prematurely have on average a lower length of admission. Because here, we control for the length of admission, we focus on patients who need on average a longer admission. For this group of patients, we find that the probability to be discharged prematurely is higher than for the other group of patients. So, patients who require a longer stays are more sensitive to policies reducting the length of stay. For these patients, to shorten the stay is counter-productive and it jeopardizes the quality of hospital healthcare.

5.2 Effect of an avoidable readmission on the cost of hospitalisation

In Table 5a, Column (1) presents the OLS regression, Column (2) presents a Tobit regression that takes the censore due to the death during the stay into account. Results obtained from the Tobit model are similar to the ones obtained from a OLS model.

Whatever the gender, the age of patients has a negative effect on the cost per day. The cost of the hospital care is more expensive for man than for woman and increasingly so with the ageing of patients. We observe that the index of gravity and a surgical procedure has a negative effect on the cost per day. This result is surprising in a first approach. In fact, aged patients or patients with a high index of gravity or with surgical procedure stay longer to the hospital. The expensive part is at the beginning of the stay. So, the cost per day is lower in average for these patients. In the same way, we find that a programmed stay or a death during the stay have a positive effect on the cost per day.

The effect of avoidable readmissions on the cost is shown in Table 5b. A premature discharge at the origin of the avoidable readmission decreases the cost per day by 41 %. This result means that whatever the length of stay and the patient characteristics, a stay split in two admissions decreases the cost per day by 41 %. Thereby, the hospital has an economic incentive to readmit patients.

Whatever the gender, the length of stay of inpatient increases for patients over 65 years and, more strongly for the female patients than male ones. Moreover, the more the disease gravity is important, the more the inpatient has a long stay. In the same way, the surgical procedure increases the total length of stay by 65 %. In addition, as it is observed in various developped countries (TECH, 2001), the trend of length of stay is negative. Results are presented in table 6a.

An avoidable readmission increases by 94 % the length of stay (Table 6b).

For a stay without avoidable readmission, assuming d the length and c the cost per day, the cost is cd. For a stay with an avoidable readmission, the cost of the stay is

$$Cost = 1.94d * (1 - 0.41)c = 1.14cd$$

Actually, we show that to shorten the stay is counter-productive. It leads to an extra-cost of 14%.

5.3 In the view of a DRG system

In Switzerland, hospital reimbursement and price tariffs vary tremendously from one canton to another. The cantons or municipalities own public hospitals. The federal government has state planning authority for inpatient hospital care (of more than one night). For inpatients, three payers finance their hospital healthcare. The federal government provides public subsidies. Cantons and local authorities cover around 50% of the operating costs of "their" public and not-for-profit hospitals. Insurance companies finance also part of the hospital expenditures. For inpatient services provided under compulsory health insurance the fee charged is a per diem rate. The financial negotiations take place between cantonal associations of insurance companies and the individual hospital or a group of hospitals. The insurers part of reimbursement is neglectful compared to the part reimbursed by federal government, cantons and local authorities. During the study period, the Vaud Canton finances hospitals on a global budget basis.

The coming reform of hospital reimbursement has for goal to establish a uniform framework of healthcare regulation for all the Swiss Confederation. This reform proposes a system of payment by DRGs used in the US: a Prospective Payment System (PPS). One drawback of the PPS is its sensitivity to the multiplication of the stays. Indeed, risk is then transferred to the hospitals, and avoidable readmissions are more likely to be caused by financial incentives of the hospitals, which will discharge some patients prematurely. Hospitals have an incentive to readmit the patient even in the cases when the readmission could have been avoided.

Because CHUV hospital is reimbursed by global budget, there is no financial incentive to discharge patients prematurely during the study period. This study gives an input for the coming reform of hospital payment system. The result from our econometric analysis is then used to discuss the effects of the DRG-instrument for reimbursement and its implications for the incentives to readmit patients.

As said, in the context of a regulation based on the DRG system, one issue is its sensitivity to the multiplication of admissions for the same patient with the same pathology. Indeed, a fee whose value is determined by the assigned DRG reimburses each stay. Thereby, the hospital could obtain several fixed payments for the care of the same patient with the same pathology. From our econometric model, we assess this incentive. The length of the stay with an avoidable readmission is lengthened by 94 % compared with stay without avoidable readmission. If this medical care practice in two times is reimbursed as two stays, the hospital earns the savings on the shortening of the length (6 %). In addition, an avoidable readmission generates a decrease of the cost per day by 41 %, ceteris paribus. Consequently, hospitals would have an incentive to practice this avoidable readmission.

6 Conclusion

A rigorous tool had been developped to detect the avoidable readmission due to premature discharge. It provides the highest probability that the readmission is avoidable. In this paper, not only do we look for the determinants of an avoidable readmission but we also assess the effect of the avoidable readmission on the cost and the length of stay. First of all, contrarily to what we could have supposed, to be wrongly readmitted depends neither on the severity of the patient's state, nor on the cost. On the contrary, a non programmed admission and a longer stay increase the probability of being wrongly readmitted, whereas the surgical procedure decreases this probability. Second of all, shortening stays leads to a 14 % rise in total costs. This result highligths the inefficiency to shorten the length in order to reduce the cost of stay.

In this paper, we consider that hospitals have a huge incentive to reduce the length of stay. Therefore, we do not consider a conservative approach that would be to not discharge unless one is absolutely certain that there will not be a readmission. We think that for this pathology and for university hospital, this conservative approach cannot be taken into account[7]. If this argument is arguable, it is clear that such a strategy will result in an increase of the average hospital stays, thus higher costs. Currently, the policy makers aim to reduce the healthcare expenditure. So, with this conservative approach, hospitals would have trouble to be reimbursed for its expenditure.

From this work, we analyse the incentive for such an avoidable readmissions in the view of a regulation based on the DRG system. A fee by admission will create an incentive to wrongly readmit patients. Indeed, we find that a patient wrongly readmitted decreases the cost per day by 41 % and the length of stay is doubled, *ceteris paribus*. This practice could have an impact in the long term on the patients' health. The use of this indicator would allow to detect avoidable readmissions. This way, it allows to reduce the sensitivity of the DRG-system to the mutiplication of avoidable readmissions.

In this study, we do not assess the effect of the avoidable readmission on the probability of mortality. A such work will need the availability of more extensive data. Moreover, the data for the analysis comes from only one hospital. Therefore, the analysis is a case study and it is hazardeous to generalize for policy purposes.

Yet, this study provides highly interesting results, being the first focusing on the hospital efficiency with so accurate information on the avoidable readmissions. To that extent it supplies useful insights on the real cost of

[7]For geriatric disease and small hospital, this conservative approach may be considered

avoidable readmissions in the current context of the process to a regulation based on the DRG system.

7 References

Allison, P. *Survival Analysis Using SAS System: A Practical Guide*, SAS Institute, Gary NC, 1995.

Anderson G. and Steinberg E. (1984), "Hospital readmissions in the Medicare population" , *New England Journal of Medicine*, 311: 1349-53.

Anderson G. and Steinberg E. (1985), "Predicting hospital readmissions in the Medicare population" , *Inquiry*, 22: 251-8.

Ashton C., Wray N., Dunn, J., Scheurich J., Debehnke R. and Friedland, J. (1987), "Predicting readmission in veterans with chronic disease: developpement and validation of discharge criteria", *Medical Care*, 25: 1184-9.

Ashton C., Del Junco D., Souchek J., Wray N. and Mansyur C. (1997), "The association between the quality of inpatient care and early readmission: a meta-analysis of the evidence", *Medical Care*, 35: 1044-59.

Bound J., Jeager, D and Baker, R (1995) "On potential problems with the Instrumental Variables Estimation when the correlation between the instruments and the endogenous explanatory variable is weak", *Journal of the American Statistical Association*, 90: 443-80

Bourguignon, F., Ferreira, F. H. G. and Leite, P. G. (2002), "Beyond Oaxaca-Blinder: Accounting for Differences in Household Income Distribution Across Countries", *Working paper Delta*, 2002-04

Coory M. Scott A. et Brade P. (2002) "Differential effect of socioeconomic status on rates of invasive coronary procedures across the public and private sectors in Queensland" *Journal of Epidem Com Health*, 56: 233-234

DiNardo, J. , Fortin N. M. and Lemieux T. (1996) "Labor market institutions and the distribution of wages, 1973-1992: a semiparametric approach", *Econometrica*, 64 (5): 1001-1044.

Deyo R., Cherkin D. and Ciol M. (1992), "Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases", *Journal of Clinical Epidemiology*, 45: 613-9

Frankl, S. E., J. L. Breeling and L. Goldman. (1991), "Preventability of Emergent Hospital Readmission", *American Journal of Medicine* 90, 667-674.

Ghali W., Hall R., Rosen A., Ash A. and Moskowitz M. (1996), "Searching for an improved clinical comorbidity index for use with ICD-9-CM administrative data", *Journal of Clinical Epidemiology*, 49: 273-8

Halfon P, Eggli Y, van Melle G, Chevalier J, Wasserfallen JB, Burnand B. (2002) "Measuring potentially avoidable hospital readmission's", *Journal of Clinical Epidemiology*, 55(6):573-587.

Hamilton and Hamilton V. (1997) "Estimating surgical volume_outcome relationships applying survival models: accounting for frailty and hospital fixed effects", *Health Economics*, 6: 383-395.

Kessler D. and McClellan M. (2000), "Is hospital competition socially wasteful?", *Quaterly Journal of Economics*, 115(2): 577-615.

Ludke, R. L., B. M. Booth and J. A. Lewis-Beck. (1993). "Relationship between Early Readmission and Hospital Quality of Care Indicators", *Inquiry* 30, 95-103.

Maddala, G. S. (1983), *Limited-Dependent Variables and Qualitative Analysis in Econometrics*, Cambridge: Cambridge University Press.

Propper C., Burgess S. and Green K. (2002), "Does competition between hospitals improve the quality of care? Hospital death rate and NHS internal market", *mimeo.*

The Technological Change in Health Care (TECH) Research Network (2001), " Technological Change Around The World: Evidence From Heart Attack Care. ", *Health Affairs*, 20(3) :25-42.

Thomas WJ, Hofer TP. (1999), "Accuracy of risk-adjusted mortality as a measure of hospital quality of care", *Medical Care* ;37:83–92

Thomas, J. W. (1996). "Does Risk-Adjusted Readmission Rate Provide Valid Information on Hospital Quality?", *Inquiry*, 28: 258-270.

Thomas WJ, Holloway, J.J. and Guire, K.E. (1993) "Validating Risk-Adjusted Mortality as an Indicator for Quality of Care, *Inquiry*, 30: 6-22

Thomas, J. W. and J. J. Holloway. (1991), "Investigating Early Readmission as an Indicator for Quality of Care Studies." *Medical Care*, 29(4): 377-394.

8 Appendix A

To set a unbiased measure of avoidable hospital readmissions, Halfon et alii (2002) addresses the following aspects sequentially: (i) setting the gold standard: identification of unforeseen readmissions for a previously known affection, (ii) definition of the optimal time interval to spot readmissions that are potentially avoidable, (iii) elaboration and validation of a computerized algorithm, exclusively based on routinely available data, to screen potentially avoidable readmissions, and (iv) development of a prediction model that makes it possible to adjust observed readmission rates for the confounding factors constituted by identifiable patient-related risks.

The authors (Halfon et alii (2002) classify types of readmissions in three groups:

- Group A: foreseen readmission: deliveries, transplantation chemo- and radiotherapy, treatment follow-up, rehabilitation care, planned surgical interventions, or other defined procedures. A readmission is considered foreseen readmissions if at the time of the previous discharge it was expected to occur as part of a program of phased care.
- Group B: unforeseen readmissions caused by a new affection;
- Group C: unforeseen readmissions related to a previously known affection. This group detects readmissions attributable to the hospital due to premature discharge.

This classification is established by interpreting the diagnosis and procedures of the initial and subsequent stays [8]

[8] For more details on the classification,see Halfon et alii (2003)

Table 1

Frequency by age groups	Avoidable readmission (%)	On the sample (%)
35 ≤ age ≤ 55	1.81	20.0
55 < age ≤ 65	2.01	21.3
65 < age ≤ 75	2.51	28.0
75 < age ≤ 85	3.06	22.7
age >85	4.06	8.0
Whatever the age	2.6	

CHUV hospital database: 10,251 stays.
An observation with avoidable readmission corresponds to two admissions.

Table 2

	Gender: Male	Gender: Female	Whatever the gender
Charlson index (mean)	1.7	0.95	1.03
Clinical category: surgical (%)	49.3	36.1	44.3
Mortality rate (%)	2.5	3.1	2.7
Length of stay (days)			
Total LOS	8.5	9.4	8.8
LOS of the avoidable readmission	8.2	9.0	8.5
Readmission (%)			
Avoidable readmission	2.4	2.9	2.6
Unavoidable readmission	5.0	3.7	4.5
Cost of the stay* (CHF)			
Mean	17,302	15,727	16,721
(Standard error)	(16,208)	(14,962)	(15,768)
Median	11,606	10,144	10,941

CHUV hospital database: 10,251 stays.

Table 3

	Without AR	With AR		
Male patient (%)	62.28 (0.48)	57.47 (0.50)		
Mean of age (years)	67.5 (13.3)	71.0 (12.9)		
Mortality rate (%)	2.7 (0.16)	3.8 (0.19)		
		Stay	Initial adm.	Avoidable readm.
Length of stay (days)	8.47 (8.26)	21.76 (14.72)	11.74 (10.85)	10.02 (8.40)
Cost of the stay (CHF)*				
Mean	16,216.82	34,151.76	18,252.30	15,899.46
(Standard error)	(15,187.96)	(23453.67)	(17,691.71)	(13,649.17)
Median	10,650.64	27,316.1	11,867.54	11,938.61
Clinical category:				
Surgical procedure (%)	44.24 (0.49)	44.44 (0.49)	29.70 (0.46)	27.20 (0.45)
Charlson index (mean)	1.02 (1.23)	1.46 (1.22)	1.45 (1.33)	1.48 (1.42)

CHUV hospital database: 10,251 stays.
AR: avoidable readmission

Table 4: Influence on the potentially avoidable readmitted of severity cases, length of stay and years (CHF)

Avoidable Readmission	Coef.	Std. Err.
Male: 50-59	-0.15	(0.29)
Male: 60-69	-0.33	(0.27)
Male: 70-79	-0.88***	(0.30)
Male: over 80	-1.14***	(0.42)
Female: 35-49	-0.22	(0.42)
Female: 50-59	-0.58	(0.39)
Female: 60-69	-0.75**	(0.31)
Female: 70-79	-1.10***	(0.29)
Female: over 80	-1.23***	(0.32)
Severity	0.08	(0.18)
Surgical procedure	-0.24**	(0.10)
Log(length)	3.40***	(0.18)
Log(Cost)	0.001***	(0.00)
Year 2000	-0.14	(0.17)
Year 2001	0.32*	(0.17)
Private insurance	-0.21	(0.21)
Live in Vaud canton	-0.34**	(0.14)
Non programmed stay	0.58***	(0.17)
Constant	-8.28***	(0.43)
Pseudo-R^2 = 0.32		

CHUV hospital database: 10,251 stays.
* significant at 10%; ** significant at 5%; *** significant at 1%
Independent variables observed for the initial admission

Table 5a : Cost estimation

	(1)		*(2)*	
	Coeff.	*Std Error*	*Coeff.*	*Std Error*
Male: 55-65 years	-0.034**	(0.015)	-0.037**	(0.015)
Male: 65-75 years	-0.062***	(0.014)	-0.062***	(0.015)
Male: 75-85 years	-0.105***	(0.016)	-0.096***	(0.016)
Male: more than 85 years	-0.158***	(0.028)	-0.135***	(0.028)
Female: 35-55 years	0.009	(0.020)	0.008	(0.020)
Female: 55-65 years	-0.045**	(0.020)	-0.042**	(0.020)
Female: 65-75 years	-0.109***	(0.017)	-0.109***	(0.017)
Female: 75-85 years	-0.172***	(0.016)	-0.163***	(0.017)
Female: more than 85 years	-0.215***	(0.021)	-0.198***	(0.021)
Severity	-0.107***	(0.004)	-0.100***	(0.004)
Surgical procedure	-0.293***	(0.009)	-0.290***	(0.009)
Year 2000	0.066***	(0.010)	0.070***	(0.010)
Year 2001	0.091***	(0.010)	0.091***	(0.010)
Programmed stay	0.298***	(0.009)	0.286***	(0.009)
Death	0.095***	(0.025)	0.412[μ]	(0.003)
Constant	1.888***	(0.013)	1.893***	(0.014)
R^2 ou pseudo-R^2	0.237		0.183	

CHUV hospital database: 10,251 stays.
* significant at 10%; ** significant at 5%; *** significant at 1%
(1) : OLS model; ***(2)*** : Tobit model;
[μ]: Ancillary parameter

Table 5b: Evaluation of the direct cost due to the avoidable readmission

	OLS Model (1)		*OLS Model (2)*		*IV Model*	
	Coeff.	*Std Error*	*Coeff.*	*Std Error*	*Coeff.*	*Std Error*
Avoidable readmission	-0.409***	(0.017)	-0.412***	(0.025)	-0.406***	(0.028)

CHUV Hospital, 10,251 observations.
* significant at 10%; ** significant at 5%; *** significant at 1%
(1) : residuals of the first model from a OLS model; ***(2)*** : residuals of the first model from a Tobit model;
µ: Ancillary parameter
Standard errors are computed using bootstrap method

Table 6a : Length of stay estimation: Tobit model

	Coeff.	*Std Error*
Male: 55-65 years	0.050*	(0.027)
Male: 65-75 years	0.112***	(0.027)
Male: 75-85 years	0.235***	(0.030)
Male: more than 85 years	0.312***	(0.052)
Female: 35-55 years	-0.033	(0.037)
Female: 55-65 years	0.092**	(0.037)
Female: 65-75 years	0.212***	(0.031)
Female: 75-85 years	0.360***	(0.030)
Female: more than 85 years	0.447***	(0.039)
Severity	0.229***	(0.007)
Surgical procedure	0.643***	(0.016)
Death$^{\mu}$	0.753***	(0.005)
Programmed stay	-0.523***	(0.016)
Year 2000	-0.070***	(0.018)
Year 2001	-0.096***	(0.019)
Constant	1.462***	(0.025)
Log likelihood	-11 498.764	

CHUV Hospital, 10,251 observations.
* significant at 10%; ** significant at 5%; *** significant at 1%
µ: Ancillary parameter

Table 6b : Evaluation of the indirect cost due to the avoidable readmission

	OLSModel		*IV Model*	
	Coeff.	*Std Error*	*Coeff.*	*Std Error*
Avoidable readmission	0.945***	(0.046)	0.958***	(0.044)

CHUV Hospital, 10,251 observations.
* significant at 10%; ** significant at 5%; *** significant at 1%
Standard errors are computed using bootstrap method