The Quicker and Sicker Issue Revisited. The case of British Columbia

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Abstract

The quest to reduce the cost of health care in the industrialized countries has led to the introduction of cost reduction policies. In 1994, the Canadian province of British Columbia adopted a set of policies that involved the reduction in hospital utilization rates and the transfer of care from hospitals to communities and to patients’ homes. This paper uses maternity data to estimate the effect of these policy changes on hospital length of stay and readmission rates. The results show that the policy reduced hospital length of stay and increased readmission rates for maternity patients.
1. Introduction

From the mid 1980s to 1993, the hospitals in British Columbia (BC) faced limited growth in their budgets because of economic recession, government deficits and the high cost of borrowing, (McGrail et. al., 2001). This was reflected in the gradual reduction in hospital inpatient use and capacity (McGrail et. al., 2001). However, inpatient use dropped sharply in 1994, when the Closer to Home Fund was established to support community or public care and so reduce hospital care (McGrail et. al., 2001; Hansard, 1995).

In the case of maternity care, the fund allowed hospitals to send low risk mothers and newborns home soon after childbirth so that they could receive care at home through community care providers. (Hansard, 1995; BC Reproductive Care Program, 2002). Since all medical care and hospitals are publicly funded, the cost of care to the government is likely to be lower when the care is delivered at home than when it is delivered in the hospital. The objective of the policy-induced reduction in length of hospital stay then was to reduce the cost of care to government, (Hansard, 1995). However, this transfers the cost to patients, their families and friends.

Concerns have been raised about the consequences of earlier discharge for the health of maternity patients (BC Reproductive Care Program, 2002). However, no study has yet been done on the effect of the policy on health outcomes of maternity patients. This paper estimates the effect of the hospital downsizing policy on the readmission rate of maternity patients. A change in readmissions could represent a change in rates of morbidity, and therefore can be interpreted as an indicator of changes in health outcomes. Investigating the effect of the policy on the readmission rate also contributes to our
understanding of the actual magnitude of cost savings. Because readmissions are expensive, a small increase in readmissions could substantially offset the cost savings from the early discharge policy (Weissman et al., 1994). The effect of the downsizing on readmission rates therefore provides necessary information for assessing the cost effectiveness of the policy.

A lot of the studies that use maternity data to examine the effect of the reduction in length of stay use the United States (US) data. Maternity care in the US hospitals is funded through both private insurance and public insurance (under the Medicaid Program) administered by private companies such as the Health Maintenance Organization (HMO). While the other private insurance are likely to reimburse care by the fee for service scheme, the HMOs use prospective payment or capitation systems. Prospective payment refers to a payment scheme under which the reimburser makes a fixed payment to the health care provider regardless of the total quantity and the quality of care. Prospective payment is similar to downsizing in that both force health care providers to adopt cost control policies such as reduction in length of stay.

Gazmararian and Koplan (1996) compare the length of stay after delivery and readmission rates of mothers under different types of insurance plans. They find that length of stay varies with insurance plan, and is lower for HMOs. This result confirms the perception that the incentive to minimize cost under prospective payment comes at the expense of reduction of quantity of care (length of stay). However, the authors of this study do not find an association between the readmission rate of maternity patients and length of stay or plan type.
Tai-Seale et al., (2001), use longitudinal data on Medicaid patients in three counties in California to examine the effect of capitation on the use of obstetric services. Like prospective payment, under capitation the health care provider receives a fixed payment per patient regardless of how much care is provided. They compare length of stay and readmission rates of patients under fee for service to those under capitation. Like Gazmararian and Koplan (1996), they find that the cost saving that accompanies capitation comes at the expense of reduction in the provision of prenatal care and delivery length of stay but does not cause any significant change in readmission rates.

Several other papers use non-maternity data to examine the effect of prospective payment and its accompanying reduction in length of stay on readmission or mortality rates. The results of these papers are mixed. Some authors find that after the introduction of the prospective payment patients are more likely to be discharged in an unstable condition (Kosecoff, et. al, 1990; Rubenstein, et. al., 1990) and to be ill at the time of admission (Keeler, et. al., 1990), and that readmission and mortality rates increased (Keeler et al 1990). Other authors find no significant effect on readmission or mortality rates (Manton et al. 1993, DesHarnais et al. 1987) while Kahn et al. (1990) find that mortality rates fell.

This paper provides empirical estimates of the effects of the downsizing policy in BC on the length of stay and readmission rates of maternity patients. The results show that the length of stay following delivery decreased, likely reducing the public cost of maternity care. Maternal readmission rates increased, especially for mothers who did not experience medical complications (the low risk mothers) and for aboriginal mothers.
The paper is organized as follows. Section 2 describes the data. Section 3 focuses on the estimation and results of the length of stay equation. Section 4 estimates and reports the results of the readmission equation and Section 5 concludes.

2.a. Data Analysis

The paper uses maternity data on all deliveries in seventeen acute care hospitals in BC from fiscal year 1993 through fiscal year 1996. The data, which are administered and provided by the BC Ministry of Health and Ministry Responsible for Seniors, consist of hospital records that include information on a host of variables including age, procedure, diagnosis, hospital, local health areas, dates of admission and discharge, patient’s aboriginal status, doctor’s specialty as well as transfers between hospitals. The seventeen hospitals included in the sample, which form about 21% of the eighty hospitals that provide obstetrics in the province, were chosen to provide a broad geographical representation of the province.

Of the seventeen hospitals, four are located in the interior region of the province, three on the northern part of the province, three in the Vancouver Island and the remaining seven in the Lower Mainland, with four in the Vancouver and Richmond area, and three in the Fraser valley. Selecting about half of the hospitals from the Lower Mainland is consistent with the population distribution in the province because about half the population of the province is concentrated in the Lower Mainland. During the four-year period of study, 92,594 deliveries and 3939 maternity readmissions occurred in the selected hospitals. This comprises about 50% of the total maternity cases in the province during the period (Vital Statistics, 2001).
This study isolates aboriginal mothers from non-aboriginal mothers because of concerns about aboriginals’ health. Aboriginal people in BC are more likely than non-aboriginals to live in rural areas (Shrier & Ip, 1994). In addition, aboriginal women are more likely to be teen parents, single mothers, low-income earners, and victims of physical and substance abuse (Health Canada, 2002). Aboriginals are also likely to face barriers accessing health care because of their language and culture (Health Canada, 2002). Consequently aboriginal women on average have poorer health outcomes than non-aboriginals (Health Canada, 2002). It is therefore of considerable policy interest to explore any differences in the effect of the policy change on health outcomes of aboriginals and non-aboriginals. Obviously non-aboriginals is a cluster of many races and so it would have been more interesting to include other races, but such information was not available.

Table 1a shows that the patients have an average age of 29.4 and about 4.3 of them were readmitted. While 20.6% of them underwent Caesareans, more than 65% of them had complications.\footnote{Complications refer to hemorrhage of pregnancy, complications in labour and delivery as well as complications of the puerperium. Complications of pregnancy include hypertension, diabetes and anemia developed during pregnancy. Complications of labour and delivery include postpartum hemorrhage and damage to pelvic joints and ligaments. Examples of complications of the puerperium include infection of the nipple and failure of lactation.} About 3.2% of the patients are aboriginals who are on average five years younger than the non-aboriginals and are less likely to undergo Caesareans or have complications but are more likely to be readmitted. Though aboriginals form 3.2% of the deliveries they form 5% of the readmissions.

The high percentage of patients with complications shows how common such complications are among women in maternity. For example, because pregnancy increases
pressure on the kidneys and the bladder, it is common for a woman’s blood pressure to change or for her to have circulation problems during pregnancy. In addition, lactation problems can be common. However, a lot of these complications are mild and cease after childbirth. Some complications however develop or persist after discharge and so cause readmissions. Information on the severity of these complications would show the degree of severity that can cause readmission. This information is however not available.

Because patients without complications are likely to be low risk and the policy is likely to send low risk patients home early, it is interesting to control for complications and study how the effect of the policy varies according to complications.

Table 1b shows the trend of the proportion of patients who had complications and those who underwent Caesareans over the four years of study. The percentage of patients who underwent Caesareans or had complications remained fairly stable throughout the four years of study for the whole sample and for non-aboriginals as well. Thus, in general there was no significant change in the proportions of the patients who had complications or who underwent Caesareans.

Figure 1 shows the frequency distribution for length of stay for each year. The graph shows that the proportion of patients who were discharged after one to three days increased over the four years. Thus, the proportion of those who stayed for four or more days decreased over the four years. While the distribution for 1993 peaked at three days, the rest of the years had their peaks at two days. The graph also shows that frequencies for the last two years are almost identical implying a similar pattern of length of stay in each of the two years after the policy change.
The first panel of Table 2 shows that, with the exception of patients with complications whose length of stay increased in 1994, length of stay decreased steadily during the four years of study. In general, as shown in the last column of Table 2, patients who underwent Caesareans stayed longer than those who had vaginal delivery and patients with complications stayed longer than those without complications. There is a greater difference between the length of stay of patients who had Caesarean and those who had vaginal delivery than between those who did or did not have complications. Length of stay decreased more for patients who underwent Caesareans than for those who had vaginal deliveries. As shown in the last two panels of Table 2, with the exception of aboriginals with complications and Caesareans, the steady reduction in length of stay occurred for both aboriginals and non-aboriginals but was greater for non-aboriginals. The policy must have increased length of stay for at least some of the most vulnerable mothers, aboriginals with complications and/or underwent Caesareans. In general however the policy was successful in reducing the length of stay for maternity patients and so is likely to have reduced the hospital cost of delivery.

Figure 2a and 2b show the cumulative readmission rates for the first 7 and 90 days after discharge. The readmission rates for 1994 exceed those of 1993 throughout the first 90 days. As shown in Figure 2a, 1994 had the highest readmission rate at the end of the 90 days. Since 1994 is the transitional year this increase in the readmission rate may at least be partly due to transitory detrimental effect of the policy on patients.

An increase in the readmission rate in the period immediately after discharge indicates a deterioration in health outcomes that could be prevented through a longer hospital stay (Weinberger et al., 1988). When patients are sent home too early and in
unstable condition, it is more likely that they will be readmitted shortly after discharge rather than later because health stability increases with time. In general, most readmissions during the first seven days after discharge reflect the existence of premature or sub-optimal discharge (Welch, et al., 1992). This may explain why daily readmission rates are highest soon after discharge, reflected in the steep slope of the readmission rates plot close to the origin. Figure 2b shows that 1996, when the average length of stay was shortest, had the highest readmission rate in the early days following discharge.

While the 7-day readmission rates reflect the effect of length of stay on patient stability immediately following discharge, the 90-day readmission rate also includes any longer-term effects of the policy on patient health. Examples of diagnoses that cause readmission in the later days after discharge include hemorrhoids, psychoses, as well as types of complications mentioned above. Ninety days is the approximate length of time it takes for a woman to make a full physical recovery, which takes up to sixty days, and adjust emotionally following childbirth, which takes at least ninety days (BC Reproductive Care Program, 2002). Any effect of the policy on women’s health outcomes therefore will be realized within these ninety days.

Table 3a and 3b show the 7-day and 90-day readmission rates respectively when patients are classified according to race, the type of delivery and the occurrence of complications. In general the readmission rates of aboriginals exceed those of non-aboriginals. Both Tables show that regardless of race and year, the readmission rates for patients who underwent Caesareans exceed those who had vaginal delivery. For non-aboriginals the readmission rates of patients with complications slightly exceed those without complications. With the exception of the 7-day readmission rates for vaginal
deliveries which show a downward trend for non-aboriginals and fairly constant for aboriginals, the readmission rates for the other categories of patients including the 90-day readmission rates for vaginal deliveries fluctuated over the years. Because non-aboriginals dominate the sample the fluctuations of non-aboriginals are similar to those of aboriginals and non-aboriginals combined. The fluctuation of the readmission rates for aboriginals however differs from that of non-aboriginals. Thus, in general the health outcome for aboriginals is different from those of non-aboriginals and so isolating aboriginals helps reveal the difference.

In summary, the tables so far show that length of stay decreased and readmission rates increased in the later years of the sample. The increase in readmission rates could be an indication that the home care made possible by the Closer to Home Fund probably was either not well organized and so some patients did not receive care on time or that the quality of care that the patients received at home was lower than what they received in the hospital. However, these changes cannot readily be attributed to the policy change because they could be due to changes in patients’ characteristics. Thus to find out the extent to which the policy caused length of stay and readmission rates to change, holding patients’ characteristics constant, I use regression analysis to estimate the effect the downsizing on length of stay and readmission rates.

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2 Note that the home care program for maternity patients is only one of the variety of home care programs supported by the Closer to Home Fund. The fund provided home care for cancer patients as well.
3. The Length of Stay Equation

3.a: Empirical Framework

The number of days a maternity patient spends in hospital following delivery will depend on the type of delivery (vaginal or Caesarean section), the patient’s characteristics that affect the rate of healing, and on the policy in effect at the time of delivery. Of the relevant patient characteristics, data are available on the patient’s age, race and whether she experienced health complications. Policy changes are captured through dummy variables representing years in the sample period. The specification of the regression model is as follows:

\[ LOS_i = \beta_0 + \beta_1 Y_{DEAR} + \beta_j Z_i + B_j Y_{DEAR} * Z_i + u_i \] (1)

where \( LOS_i \) is the length of stay in days of patient \( i \) in the hospital, \( DYEAR \) is a vector of dummies for the year of delivery, and \( Z_i \) includes an indicator of the method of delivery as well as the patient’s, aboriginal status, an indicator of whether she has experienced health complications, and her age, and \( B_j \) is a vector of corresponding coefficients. The variables in \( Z_i \) are also interacted with the year of delivery dummies to allow for differential effects of the policy on the length of stay of patients with different characteristics. A dummy variable for aboriginal status is included because of the well-known differences between the average health conditions and outcomes of aboriginal and non-aboriginal people. Complications are coded according to the “most responsible diagnosis.” If this does not fall under ICD-9 Codes 650 – 659.99, which refer to normal delivery, and care during pregnancy, labour, delivery, a patient is coded as having experienced complications. As already mentioned, diagnoses that are considered as complications include hemorrhage of pregnancy as well as complications in labour and
delivery. Age is included because it is an important factor in maternal health and so affects how a patient responds to care. To ensure flexibility of the relationship between age and length of stay I include the square and inverse of age. The model is estimated using ordinary least squares.

3b. Results

The estimated coefficients of the length of stay equation are reported in Table 4. The first column of Table 4 shows the results of the length of stay equation without interactions with the year dummies. The results show that after controlling for age, complications and type of delivery, aboriginals on average stay longer than non-aboriginals. The slope of the length of stay equation with respect to age is \(-0.134 + 0.004\times\text{age}\) which is zero when age is 33.5 implying that the effect of age on length of stay divides the patients into two depending on whether they are younger or older than 33.5. Within the young group, younger mothers stay longer than older mothers. This is perhaps because younger mothers, who are likely to be teenagers and in early twenties, require more assistance in taking care of themselves than do older mothers who may have experience of childbirth. However, in the older group older mothers are likely to stay longer than younger mothers. This is probably because, given that complications are controlled for, mothers above thirty-three are likely to respond slowly to care and so require more care or monitoring.

There is no statistically significant difference in the length of stay for patients with complications and those without complications. This is not surprising because, as already explained, many of the cases classified as complications may be mild. However,
the length of stay of patients with Caesarean deliveries is greater than those with vaginal deliveries. The year dummies show that length of stay decreased steadily through the four years. The reduction in length of stay is highest in 1995 and lowest in 1996. Thus, even though the policy continued to reduce length of stay over the years the reduction decreased after the second year of the policy.

The second column of Table 4 shows the results of the length of stay equation when the year dummies are interacted with the other variables. The results show no statistically significant difference in the reduction in length of stay for the different categories of patients. Thus, the variations in the reduction in lengths of stay among the different categories of patients observed in Table 2 are not statistically significant.

The policy was effective in reducing the length of stay of patients and so must have succeeded in reducing the hospital cost of care. It however transferred cost partly onto public care through the home care program and partly to the patient and their families as they take of the care of the mothers. Since the reduction in hospital care is replaced by home care, the patient is made worse off if the quality of the home care is below that of the hospital. To find out how this policy affected the quality of care I now examine the extent to which it increased the rate of readmissions.

4. The Readmission Equation

4.a. Empirical Framework

Since quality of care refers to the effectiveness of treatment, there is a negative relationship between quality of care and the readmission rate. The production function for quality of care can be written as \( Q = F(\text{hospital effort input}, \text{home effort input}) \). Quality
of care is positively related to the effort input by the health care provider. Effort input refers to all service inputs by the hospital that contribute to the outcome of a given stay in the hospital. Following Ma and McGuire (1998), I define effort broadly to include all effort inputs that improve patients’ comfort as well as those that improve treatment, such as monitoring the patient’s condition to match a given problem with a specific therapy. The home effort input refers to the care that the patient receives at home from family and friends. The production function for the readmission rate then can be written as: \( R = F(Q, \text{patient characteristics}) \) which in turn implies that \( R = F(\text{hospital effort input, home effort input , patient characteristics}) \). I use type of delivery (Caesarean or vaginal) to represent effort input. I use the same vector of characteristics that were included in the length of stay equation: age, complications, and race. Again, these characteristics are interacted with the year dummies.

Social factors such as education, marital status (or support from friends and family), and income may also be important in determining the readmission rate. For example a married mother or a woman who does not live alone may be more likely to receive help at home (home effort input) and so be less likely for her condition to worsen after discharge than a single mother who lives alone. Even if she lives alone, a high-income mother may be more likely to afford hiring a nanny and so may receive a better care at home after discharge than a low-income mother and so be less likely to be readmitted. Finally a mother with high education may be more likely to take care of herself at home than one with low education and so the higher the education of the mother the less likely she may be readmitted.
These variables are not included in the specification above simply because they were not available. The omission of such variables in the estimation can bias the results if the omitted variables are correlated with the variables in the equation. The most likely variable in the estimation to be correlated with these social factors is aboriginal status. Having home support, income and education may not affect the type of delivery, age or complications. Reasons for Caesareans include mother’s bone structure, fetus’ health, as well as mother’s age and obstetrics health. The complications in the readmission equation refer to complications before discharge and they may not be correlated with income marital status or education. As already explained, aboriginals are likely to be low-income earners and single mothers. Thus the omission of the social factors in the readmission equation is likely to affect results on aboriginals and so the results are interpreted with caution.

4.b. Method of Estimation

I use the discrete duration model as described in Kennedy (1998) to find the effect of the change the independent variables on the readmission rate. A duration model, rather than logit or probit models that do not take time into account, is more appropriate in assessing the effect of the downsizing on the readmission rate. As already explained, changes in readmission rates shortly after discharge reflect changes in length of stay. A duration model described below is able to factor in the effect of time on the probability of readmission. I now describe the duration model for the specification.³

³ See Kennedy (1998) and Greene, (1994)
Let \( f(t) \) be the probability of being readmitted at time \( t \) after discharge and \( F(t) \) be the cumulative probability of readmission by time \( t \). The survival function, the probability of not being readmitted to hospital during the first \( t \) days following discharge, is defined as \( S(t) = 1 - F(t) \). The hazard function, \( \lambda(t) \), is the probability of being readmitted \( t \) days after discharge, conditional on not being readmitted previously. I use the estimates of the hazard function to compute the probability of interest, the unconditional probability of being readmitted \( t \) days after discharge. The relationships between the hazard function, the unconditional probability and the survival function are as follows:

\[
f(t) = \lambda(t)S(t), \quad \lambda(t) = -\frac{d \ln S(t)}{dt}
\]

It follows from the above that: \( S(t) = \exp[-\int_{0}^{t} \lambda(u)du] \). This relationship allows the likelihood function to be written in terms of the hazard function. When the patient is readmitted during the sample window, her observation enters the likelihood function as \( f(t) \) but when the patient is not readmitted the observation enters as \( S(t) \). The likelihood function for the continuous time model is:

\[
L = \prod_{i=1}^{N} \lambda(t)^{\delta_i} \exp[-\int_{0}^{t} \lambda(u)du]
\]

(3)

where \( N \) represents the number of observations and \( \delta_i \) equals one when the patient is readmitted at time \( t \) and equals zero otherwise\(^4\). The patients that are not readmitted after 90 days are the censored observations and those who are readmitted are uncensored. I estimate the model over the first 90 days following the initial discharge.

\(^4\) Note that \( f(t)S(t) = [\lambda(t)S(t)]^{\delta_i} S(t)^{1-\delta_i} = \lambda(t)^{\delta_i}S(t) \)
The data provide the dates but not the time of day of discharge and readmission, and so are discrete. With discrete-time estimation, a likelihood function is built for each of the 90 days after discharge. For the first day after discharge a patient is either readmitted or not readmitted. The likelihood function for the day captures this. For each patient, whether the she is readmitted or not determines her contribution to the day 1 likelihood function. For the second day those who have not yet been readmitted are either readmitted or not readmitted and so the likelihood function for this day also captures such difference. Thus patients contribute several observations to the likelihood function. For example, a patient that is readmitted on the fourth day after discharge contributes four observations, one each for day one to three where she is not readmitted and one on the fourth day when she is readmitted. She does not appear in the likelihood functions for the remaining eighty-six days. Thus the censored individuals appear in all the likelihood functions for all the ninety days and so each would contribute ninety observations. The product of the ninety likelihood functions for the individual days produces the likelihood function for the full sample. I specify a logit functional form for the hazard model. The likelihood function therefore can be estimated using a standard logit procedure.

To choose a baseline hazard for the estimation, I compute the Kaplan Meier estimates and graph them in Figure 3.\footnote{The Kaplan Meier estimates for the readmission rates show the fraction of the patients that are readmitted for the first time for each day. For example to get fraction for day five I divide the number of patients readmitted on the fifth day by all those that have survived in not being readmitted. Figure 3 shows that this fraction falls as the days after discharge increases. The Kaplan Meier estimates for the survival function (the opposite of the readmission) then shows the fraction of those that survive in not being readmitted. For each day I subtract those readmitted from those not yet readmitted and divide the result by those not yet readmitted. Figure 3 shows that this fraction increases as the days after readmission increases.} The pattern of the estimates shows a downward trend over time with a spike on the second day. In addition the estimates decrease at a
decreasing rate and so reveal a convex pattern. Adding a baseline to the characteristics already included in the model yields the following specification for the logit:

\[
\Pr(y_d = 1) = \frac{e^{X_i \beta + \gamma t}}{1 + e^{X_i \beta + \gamma t}}
\]

Where \(X\beta = \beta_0 + \beta_1 \text{DYEARS} + \beta_1 Z + B \text{DYEARS} \times Z\)

and

\[\gamma(t) = \gamma_1 t + \gamma_3 t^2 + \gamma_2 T2\]

The variable \(T2\) takes on the value one when \(t = 2\) and takes on the value zero otherwise. This dummy is included to incorporate the spike in day 2 in the Kaplan Meier estimates.

The likelihood function for the discrete estimation is:

\[
L = \prod_{i=1}^{N_1} \frac{e^{X_i \beta + \gamma t}}{1 + e^{X_i \beta + \gamma t}} \prod_{j=1}^{N-N_1} 1 \prod_{i=N_0}^{N-N_0} e^{X_i \beta + \gamma t} \prod_{j=1}^{N-N_1} 1 + e^{X_i \beta + \gamma t}
\]

where \(X\) is a vector the explanatory variables, \(\beta\) is a vector of the coefficients to be estimated, \(N_1\) is the number of those readmitted on the first day after discharge and \(N-N_1\) is the number of those not readmitted on the first day. Thus a total of \(N-N_1\) observations make it to the likelihood function for the second day. Out of these some are readmitted on the second day and so a total of \(N-N_2-N_1\) observations make to the third day and so on.

Thus for an individual, the probability of being readmitted on the \(tth\) day after discharge, having not been readmitted before \(t\), is \(\lambda(t) = \frac{e^{X_i \beta + \gamma t}}{1 + e^{X_i \beta + \gamma t}}\). The survival function at time \(t\) for an individual in (3) can be written as

\[
\prod_{i=1}^{T} \frac{1}{1 + e^{X_i \beta + \gamma t}}.
\]

For a censored individual, \(T = 90\).
4.c. Results

The logit results are reported in Table 5. The first column of Table 5 shows the results of the readmission equation when no interactions between explanatory variables are included in the specification. The results show that after controlling for age, year and complications, aboriginals have a higher readmission hazard than non-aboriginals. As already explained the omission of social factors could bias the results on aboriginals. Thus the readmission hazard for aboriginals explains the extent to which the outcome of care is due to the genetic characteristics of aboriginals as well as the environmental, economic and social effects that are specific to the race. The high readmission hazard for aboriginals is consistent with other evidence that aboriginals have poor health outcomes compared to non-aboriginals.

The coefficient on age is negative on the coefficient on its square is positive. Again the slope with respect to age is zero at 25.5 and so among the patients that are younger than 25.5 years, a younger mother has a higher readmission hazard than an old mother. As already discussed, a young mother may be less likely to take care of herself after discharge than an older mother. The readmission hazard however increases with age when the patient is older than 25.5 years. The readmission hazard for patients with complications is greater than that for those with no complications. This result is consistent with Table 3b that shows higher readmission rates for patients with complications when all the years are combined. The readmission hazards for the year dummies show a jump in 1994 a slight fall in 1995 and another increase in 1996.
The results also show that *CAESAREAN* is not statistically significant. This implies that after controlling for all the other variables, there is no statistically significant difference in the readmission hazards of patients who had caesarean deliveries and those who had vaginal deliveries. This differs from Table 3a and 3b where the readmission rates of patients who had Caesarean exceed those of patients who had vaginal delivery. The results in Tables 3a and 3b could be driven by age because older mothers are likely to undergo Caesarean. Thus given that age is controlled for the results from the regression then mean that the type of delivery per se does not affect the readmission hazard.

The results also show that time has a negative sign and is statistically significant. The T2 dummy is not statistically significant implying the spike at \( t = 2 \) in the Kaplan Meier estimate does not represent a statistically significant difference between \( t = 2 \) and the general trend of the readmission hazard with respect to time. The square of time has a positive but small coefficient and so the slope remains negative throughout the ninety days but becomes flatter with time revealing a convex relationship between the probability of readmission and time. Consistent with the Kaplan Meier estimates, these results imply that the readmission hazard falls as the days after readmission increase but at a decreasing rate.

The second column of Table 5 reports the results of the readmission equation with the interactions. The inverse of *AGE*, the interactions of *AGE* with the year dummies, of *T2* and the year dummies as well as the interactions of *CAESAREAN* with the year dummies were not significant and so were not included in the final specification reported in Table 5. The results show that the policy had a smaller effect on the readmission
hazard of patients with complications and aboriginals than those without complications and non-aboriginals respectively. The interactions with time show that the readmission hazard declines more rapidly with duration in the later years of the sample. This is consistent with the steeper slopes of the Kaplan Meier estimates for the last three years as shown in Figure 3.

I use the results from the second column of Table 5 to compute the estimated unconditional readmission rates at different durations for each of the four years. I report the unconditional readmission rate because it is more natural to think of readmission rates as unconditional than as hazard and it is possible to compare the estimated unconditional readmission rates with the actual readmission rates in Table 3a and 3b. The estimated readmission rates are obtained by computing the estimated survival rate for each patient at each duration, subtracting it from one and averaging over all patients. These estimated unconditional readmission rates are reported in Table 6a, 6b and 6c. Even though the readmission rates in Table 6 focuses only on seven, sixty and ninety days, the duration model allows the calculation of readmission rates for any number of days up to 90 days. The duration model allows all readmission rates to be computed from a single estimation. I compute the 60-day readmission rates because as already explained it takes that long for the body to return it to the pre-pregnancy state.

Since there is no statistically significant difference between the readmission rates of Caesarean and vaginal deliveries, I classify the patients according to race and complications and compare with the actual readmission rates in Table 3a and 3b. The estimated readmission rates are similar to the actual readmission rates in Table 3a and 3b in size as well as in trend. The increased readmission rates over the years cannot readily
be attributed to the policy because it could be due to some changes in the patient’s characteristics. I use the estimates of the readmission coefficients to compute the effect of the policy. The similarities in the estimated and actual readmission rates imply a good estimation of the readmission regression and so these estimates can confidently be used to estimate the effect of the policy on readmission rates.

4.d. Effect of the Policy on Readmission Rates

To find the effect of the policy on readmission rates I first compute the unconditional readmission rates for each of the years after 1993 using the data from each year. For example for 1994, I use the 1994 data and the coefficients from the second column of Table 5, but without the year dummies or interaction variable coefficients, to compute the unconditional readmission rates. These readmission rates represent what the readmission rates would have been without the policy. I then subtract these from the readmission rates reported in Table 6. The difference between the two readmission rates represents the effect of the policy on the 1994 readmission rates, holding everything else constant. These are reported in Table 7a, 7b and 7b. Because I use data on the same patients to compute the two readmission rates, taking the difference eliminates the effect of the patients’ characteristics on the readmission rates.

The numbers in Table 7a, b, and c shows the effect of the policy on the readmission rate in the relevant year. For example, the 1996 column shows the predicted readmission rate in 1996 had the 1993 policy remained in place. The first panel shows the weighted averages of the readmission rates when aboriginals and non-aboriginals are combined. In general the effect was smaller 1995 than in 1994, and was bigger in 1996.
This pattern may imply that the high increase in readmission rates in 1994 probably prompted some short-term adjustment to improve the quality of care but the quality worsened again with time. The table shows that the effect of the policy increases with the days after discharge. The policy then had both short term and long-term detrimental effects on quality of care.

As already explained, if there is any effect of the reduction in length of stay on readmission rates it will be greatest on the readmission rates shortly after discharge. The effect of the policy on the 7-day readmission rate represents the short-term effect of the policy. These are shown in Table 7a. Even though there was no statistically significant difference in the reduction of length of stay for the categories of patients, the effect on readmission rates varies. The readmission rates for aboriginals increased more than those of non-aboriginals. In addition the effect is greater on the readmission rates of patients without complications than those with complications. The greater effect of the policy on readmission rates of patients without complication is not surprising because given that both patients with and without complications go home early and both require home care, it is possible that the patients with complications got better home care supported by the Closer to Home Fund.

Table 6b and 6c show the cumulative effect of the policy on the 60-day and 90-day readmission rates is greater than those of the 7-day readmission rates. The greater cumulative effect on the 60-day and the 90-day readmission rates imply that the transfer of care from the hospitals had long term as well as short term effect on readmission rates. As already explained, the puerperium takes about sixty days and so the high cumulative effect on the 60-day readmission rates implies that the policy impeded the body’s
adjustment to the pre-pregnancy state. The higher cumulated effect of the policy on the 90-day readmission rates relative to the 60-day readmission rates could also imply that the policy affected the psychological adjustment of the mothers to childbirth. The long-term effect is also higher for aboriginals and patients without complications than non-aboriginals and patients with complications respectively.

5. Conclusion

This paper has shown that the transfer of care from hospitals to home succeeded in reducing hospital length of stay. Since the policy of early discharge reduces the hospital utilization rates, hospitals are able to reduce the cost of care. The Closer to Home Funds allows care to continue in the patient’s home. In this way the patient receives the care she needs but the hospital does not have to pay for the housekeeping cost. This cost is borne by the patient. If it is cheaper for the patient’s family to provide the housekeeping service than the hospital then the policy reduced the social cost of care, otherwise the policy simply transferred cost to the patient and did not improve social welfare.

The paper also shows that any cost saving that must have been achieved by the hospitals as a result of the policy must have come at the cost of the possible deterioration of the quality of care that patients received shown through the increase in readmission rates. The deterioration of the quality of care may be due to inadequate home care provided through public care. An improvement in the organization of the home care by the public care then could reduce such deterioration of health.
Statistically, the length of stay for delivery decreased by the same degree for both aboriginals and non-aboriginals. However, the policy must have deteriorated the quality of care of aboriginals more than non-aboriginals because the readmission rates of aboriginals increased more than those of non-aboriginals. The home care provision then may not have taken the tendency of aboriginals to have a poor health outcome into account. Further steps should be taken to improve the health outcome for aboriginals.
References


