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Is pro-poor inequity in inpatient care the result of pro-rich inequity in primary care? The case of Ontario, Canada

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1 Introduction

A comparison of income-related inequity in health care utilization across 21 OECD countries conducted by Eddy van Doorslaer, Cristina Masseria, and the OECD Health Equity Research Group in 2004 (van Doorslaer et al. [2004b]) shows the following patterns: the need-standardized[1] concentration index yield estimates for the probability to visit a Family Physician (FP) that are either pro-poor (Germany, Greece and Spain) or clustered around zero (estimated value non statistically significantly different from 0 and lower than 0.01 in absolute value) with the exception of three countries with pro-rich inequity: Canada (+0.016), Portugal (+0.021), and Finland (+0.034)[2]. For the probability to visit a specialist, estimates are consistently positive (pro-rich inequity), between +0.011 in the UK and +0.130 in Portugal. Last, inpatient hospital care is the only sector with large pro-poor estimates: van Doorslaer et al. (2004) observe a negative (pro-poor) value for the index in the probability of inpatient care in Switzerland (-0.065), Canada (-0.051), Australia (-0.049), and the US (-0.038)). The absolute values of these estimates for inpatient care utilization (which are from among the richest countries in the OECD) are comparable to the pro-rich concentrations of specialist care in many countries[3].

A pro-poor concentration of the need-standardized probability to be hospitalized means that a low-income individual is more likely to be hospitalized than a higher-income one for the same level of measured need. It is then described as a pro-poor inequity in inpatient care.

There are several plausible explanations for such a pro-poor inequity in the probability of any inpatient care use.

1. One causal mechanism is that doctors are more likely to hospitalize a poorer individual for a given health problem. This may occur for several reasons, including the perception by doctors that poorer individuals are less likely to comply with a therapeutic treatment or that their environment (e.g., housing) is less favourable to successful recovery.

2. A second explanation is that the variables available in surveys (self-assessed health, self-reported chronic conditions and self-reported functional limitations) are not able to capture "need" properly. If the measurement error

[1] van Doorslaer and Masseria measured need using age, sex, self-assessed health status, presence of a chronic condition, and presence of a functional limitation.

[2] The index could not be calculated separately for FP and specialist visits in five countries: Australia, Germany, Mexico, Sweden, and the US, therefore these are not included in the comparison for FP and specialist visits. For inpatient care, Australia and Norway did not provide data.

[3] Six other countries exhibit negative but non-significant values of the horizontal index for the probability of an inpatient stay: France (-0.000), Denmark (-0.011), Finland (-0.016), Netherlands (-0.021), Germany (-0.033), and Belgium (-0.034). By contrast, countries with pro-rich inequity in the probability of inpatient care are more often among the less wealthy of the OECD: Mexico and Portugal show very high positive (pro-rich) values for the horizontal index of inpatient care utilization (respectively +0.051 and +0.113), and seven countries show positive non significant values: UK (+0.013), Hungary (+0.025), Italy (+0.028), Spain (+0.033), Sweden (+0.035), Greece (+0.040), and Ireland (+0.053)

of need correlates with income (for instance, real need is much higher among the poor for a given level of self-assessed health, as observed, e.g., in Johnston et al. [2009]) the observed pro-poor inequity in the probability of inpatient care would be the spurious result of measurement errors in the need variable. It should be noted, however, that McFadden et al. [2009] do not find any variation across socio-economic status in the predictive power of self-reported health on mortality.

3. A third mechanism is that poorer individuals are more likely to be hospitalized for the same level of need because they have poorer access to quality primary care. It is well documented that good quality primary care, by avoiding acute crises for those suffering from chronic conditions, thereby reduces the likelihood of emergency care and hospitalization. If such a causal mechanism is true, the observation of a pro-poor inequity in the probability of inpatient care utilization is not an indicator of a well-functioning health care system, but rather an indicator of a poorly functioning primary care system, as suggested in Curtis and McMinn [2007][4].

In the present study we investigate the extent to which this third mechanism may explain the finding of a strongly pro-poor distribution of inpatient care coupled with a pro-rich distribution in the probability of visiting a primary care physician. This mechanism needs not be the only one that explains the observed pro-poor inequity in the probability of inpatient care since there could very well be a combination of doctors' decisions, measurement error in the standardization for need, and lower level of primary care use leading to more hospitalizations. We want to check the plausibility of the causal mechanism associating pro-rich inequity in primary care utilization to pro-poor inequity in inpatient care utilization.

To test this we must validate two relationships: first, we must observe that individuals using more primary care services for a given level of need are less likely to be hospitalized. Second, we need to check that neutralizing differences in need-standardized primary care utilization in the equation leading to the Horizontal Inequity Index (HI) for the probability of inpatient care reduces the observed level of pro-poor inequity.

We will test those two steps separately for two types of inpatient stays: those for diagnostic conditions amenable to primary care (referred in the literature as Ambulatory Care Sensitive Conditions, ACSC) and those for all other conditions. ACSC (described in more details below) include, among others, asthma, congestive heart failure, chronic obstructive pulmonary disease, diabetes, epilepsy, or hypertension and are defined by Health Canada (2009) as "conditions where appropriate ambulatory care prevents or reduces the need for admission to hospital". If our hypothesized causal mechanism is true we expect to find a negative relationship between primary care use and the probability of being hospitalized for an ACSC (controlling for all other determinants of the

[4]Of course, a pro-rich index is not good either, for different reasons since it would indicate barriers to access to hospital care, possibly for non-emergency care.

probability of being hospitalized), but no relationship between primary care use and admissions for non-ACSC diagnostics. We therefore use the non-ACSC admissions as a baseline scenario (or control group), the probability of being admitted for an ACSC being the treatment group. If we do not observe any effect of primary care on ACSC or if the effect on ACSC is no different from that on a non-ACSC condition, pro-rich concentration of primary care is unlikely to be a potential cause of the pro-poor concentration of inpatient care.

We use data from Ontario linking administrative data on primary care use and inpatient stays for the period 1999 to 2002 to a health survey conducted in 2000-01. We use information from the survey to construct all the need and non-need variables required to measure the inequity of health care utilization and the administrative data to calculate need-standardized utilization of primary care and the probability of being hospitalized in a given year.

To our knowledge this is the first study to test the effect of the pro-rich concentration of primary care on the pro-poor concentration of the probability to be hospitalized. We add to the literature on equity of health care utilization in that we suggest a plausible causal mechanism, as well as policy recommendations: if we find evidence for the causal mechanism, correcting a strong pro-poor inequity in the probability of hospitalization requires strong action to make sure that primary care is used equitably by individuals of all income levels. It also challenges the interpretation of pro-poor inpatient care as representing a "good" system. We also add to the literature on the link between primary care use and hospitalization: there are some results suggesting a relationship at the aggregate level (jurisdictions with better access to primary care seem to have lower rates of hospitalization) but studies of the link between primary care use and hospitalization at the individual level are still rare. Finally, it extends the burgeoning literature on equity by going beyond simply estimating the extent of inequity, to testing underlying causal pathways to explain the genesis of the observed inequity.

Our findings are as follows: we find a significant and negative effect of the need-standardized utilization of primary care on the hazard of being hospitalized for an ACSC in subsequent months: individuals who use more primary care for a given level of need in a given year are less likely to be hospitalized for an ACSC in the 18 months period following that initial year. Moreover, neutralizing need-standardized primary care use when measuring inequity of inpatient care substantially decreases the level of pro-poor inequity. The most important of our findings is that almost all the effect comes from admissions for ACSC and not from admissions for non-ACSC: being more likely to see a primary care doctor reduces the likelihood of being hospitalized for a condition that is amenable to primary care but not for hospitalizations not sensitive to primary care. Similarly, accounting for need-standardized primary care utilization reduces the pro-poor concentration of admissions for ACSC but not for non-ACSC. Overall, the pro-poor inequity in inpatient care observed in Ontario, Canada, in 2001 would suggest that an effort is needed to make sure access to primary care is more equitably distributed.

2 Previous Literature

Studies of plausible pathways to inequity in health care utilization

To our knowledge, our proposed study will be the first Canadian attempt to assess the impact of equity in the use of one service (physician care) on equity in the use of another (hospital care) based on an explicit causal mechanism (avoidable hospitalization). The empirical literature quantitatively documenting the causal pathways associated with inequity in utilization, especially in Canada, is limited. Some recent examples include Alter et al. [2003] and Pilote et al. [2003], who undertook condition-specific studies (Acute Myocardial Infarction (AMI)) investigating whether variations in the supply of hospital facilities, in the number of specialists and in drug coverage across provinces explain socio-economic gradients in use of cardiac procedures. Other work attempts to document the contribution of financing arrangements to inequity in utilization (e.g., Allin and Hurley [2009], Smart and Stabile [2005], or van Doorslaer et al. [2004a] investigating the role of private insurance in Europe)

Literature on the link between primary care and inpatient care use.

Starfield [1998] has argued perhaps most forcefully that receipt of appropriate primary care can reduce the need for hospital care for a given health status: proper screening and monitoring leads to better control of diseases, decreases the frequency of emergency room episodes, and postpones admissions for non-emergency care. Glazier et al. [2008] provide supporting evidence from Ontario: they show that, among those with a chronic condition in 2000-01, not having a regular doctor, visiting a doctor fewer than three times in a two-year period, and low continuity of care are positively associated with the likelihood of non-elective hospitalization (odd-ratios from 1.19 to 1.35). Area-level analyses of hospitalization rates for ambulatory care sensitive conditions in Manitoba (Roos et al. [2005]) and Canada outside Québec (Sanchez et al. [2008]) document a definite income gradient, with higher rates of ACSC admissions for neighbourhoods in the lowest (neighbourhood) income quintile than for those in the highest income quintile. Ansari et al. [2006] provide empirical evidence of a negative correlation between utilization of primary care and admissions for ACSCs based on individual-level data in Australia. Fortney et al. [2005] provide some support for a causal link between ambulatory care and ACSC admissions: their study used a natural experiment whereby the US Veterans health system increased the density of primary care facilities in some catchment areas but not in others, which allowed the researchers to identify the impact of changes in primary care utilization on inpatient care utilization. The results showed a statistically insignificant but somewhat strong negative relationship: higher levels of primary care utilization was associated with a lower probability of hospitalization. Finally, the potential role of lesser access to community-based physician care in explaining observed distance gradients in hospital care has been emphasized in the literature on the distance-use relationship (Goodman et al. [1997]).

3 Data and Methodology

3.1 Data

We combine information from several datasets.

- Information on standard determinants of inpatient care: the Canadian Community Health Survey (CCHS), Cycle 1.1 (2000/1) provides the need variables (age, sex, self-assessed health, chronic conditions, functional limitations), income (as a continuous variable), and potential determinants of health care utilization that might correlate with income and need (e,g, education, attitude toward risk, ethnicity, marital status, work status, rural/urban residence). CCHS is a large (approximately 130,000 individuals) representative sample of community-dwelling individuals in Canada. The first interview was conducted in September 2000 and the last one in November 2001. We use the sub-sample of Ontarian respondents, which is comprised of 39,278 respondents.

- Information on inpatient stays (the dependent variable): among Ontario respondents, 32,848 respondents (or 83.6% of the Ontario sample) agreed to have their survey responses linked to their provincial administrative health data. The administrative file on inpatient care is the Ontario section of the Discharge Abstract Database (DAD) produced by the Canadian Institute for Health Information (CIHI). We use DAD for fiscal years 1999-2000, 2000-01, and 2001-02 (36 months of data from April 1999 to March 2002). CIHI receives, from all hospitals in Ontario, information on every inpatient admission including date and diagnoses associated with an admission, date of discharge, procedures received, and whether the individual is transferred to or from another hospital. Knowledge of the date of discharge is a key component of our empirical strategy because we want to study the effect of primary care use on subsequent use of inpatient care. It is therefore important we know the admission date of each stay. We also use the admission diagnostic code to identify admissions for ambulatory care sensitive conditions (ACSC): each admission code is an ICD-9 (International Classification of Disease version 9) code or an ICD-9-CM (ICD-9-Clinical Modification), depending on the fiscal year and we can map these codes into a list of ACSC ICD-9 codes using methods described in several published sources (see below, methods section).

- Information on primary care use: we use records from the Ontario Health Insurance Plan (OHIP) administrative records for the same fiscal years, linked to the survey on an individual basis. The OHIP data set includes information on each physician visit and procedure received by an individual that is covered by the public insurance plan (98.5% of all physician expenditures are publicly financed). We use this file to measure utilization of services of family physicians: all claims with one of 35 ambulatory care visits codes to a family physician (excluding visits to an emergency room). We also use these data to identify specialist visits: visits to 28 types of medical doctors identified as specialists, including inpatient visits because the majority of specialist consultations and assessments take place in a hospital.

- Supplementary information: we also have a supplemental data on hospitals, physician supply and other relevant measures. In our estimation of need-standardized utilization of primary and specialist care we control for the supply of primary care doctors and specialists in the geographic area where the individual lives. We obtain that information from the Corporate Provider Database (CPD) of the OMHLTC. The CPD includes the postal codes of practising physicians and we can match it to the postal code of respondents in the survey.

In our estimation of the likelihood of being hospitalized we use information on availability and characteristics of hospital services in the geographic area where the individual lives: it includes location of the nearest hospital (postal codes), number of acute beds and occupancy rate. These data are obtained from two sources: an annual publication, *Guide to Canadian Healthcare Facilities*, published by the Canadian Healthcare Association (CHA [2001]) and *Annual Statistics* produced by the Ontario Ministry of Health and Long-term Care (MoHLTC).

We dropped 3,298 observations from the analysis due to incomplete records (missing variables), mostly for missing income (2,604 observations dropped), the remaining being due to missing information on chronic conditions (283), education (188), other missing variables accounting for a very small number of dropped observations each. Overall, the analysis sample is comprised of 29,540 observations.

3.2 Methods

We want to answer two questions:

1. Are individuals who use more primary care services (controlling for need) in a given period less likely to be hospitalized in subsequent months?

2. Does neutralizing primary care utilization in the calculation of inequity in inpatient care services utilization reduce the level of pro-poor inequity (compared to a situation where need-standardized primary care use is not controlled for)?

In order to answer those questions our first step is to produce a meaningful measure of utilization of primary care services. Such a measure must be standardized for need otherwise those who use more primary care would also be in greater need of any form of care (including inpatient care) and we would find a (spurious) positive relationship between primary care use and the hazard of being hospitalized. Our first step is therefore to standardize primary care use for baseline need.

The second step will be to develop an empirical strategy to explore the link between that variable and the likelihood of inpatient hospitalization in subsequent periods. Because we observe individuals on a limited period of time only and hospitalization is a rare event our data are censored: we don't know if the individual was admitted on the week prior to the start of our period of observation or the week after the end of our period. Failure to take censoring into account can produce seriously biased estimates of the distribution of the risk of being hospitalized. Duration analysis is therefore a natural way to approach our question: do we observe that a higher level of need-standardized primary care in a given period reduces the hazard of being admitted to a hospital in the future?

We present these two steps below: measuring need-standardized primary care utilization (section 3.2.1) and specifying a duration model of the hazard of being hospitalized (section 3.2.2). As will be detailed below, the duration analysis must take into account the fact that a substantial proportion of the population will never be hospitalized, independent of censoring issues.

We also want to test further the logical robustness of such a statistical relationship: if the correlation reflects a causal mechanism it should be observed for admissions for ACSCs but not for other admissions. We detail the way we define and identify ACSC admissions in our data and present the control-treatment strategy that we use in section 3.2.3.

Last, we present briefly in section 3.2.4 the calculation of the HI and how we compare the HI with and without controlling for need-standardized primary care use. Similar to 3.2.3, we use a treatment-control strategy and calculate the effect of neutralizing the role of (need-standardized) primary care use in the calculation of the HI for ACSC admissions and the calculation of the HI for non-ACSC admissions. We expect to find a reduction of pro-poor inequity in ACSC admissions but no change in the level of pro-poor inequity in non-ACSC admissions.

3.2.1 Measuring need-standardized primary care utilization

Our approach first rests on deriving need-standardized primary care utilization. We define primary care as services provided by family physicians outside of hospital or long term care settings. This is the independent variable we want to introduce in our study of the determinants of inpatient care use. We also construct a variable for need-standardized utilization of ambulatory specialist care services and we use it to test whether introducing primary care use in a model can explain inpatient care utilization beyond that already accounted for by the inclusion of a measure of specialist care.

Need-standardized primary care use is measured as the deviation between a person's actual utilization of FP services and their expected level based on their need. It is therefore indirect standardization on the basis of observed average levels of utilization for individuals with similar characteristics (O'Donnell et al. [2008]) rather than standardization based on clinical guidelines. It works as follows: we compare what the individual uses to what is used by an individual with the same need-related characteristics (age, sex, self-assessed health, see list below) and the sample means for all other (non need-related) variables (income, education, see list below).

The process of need-standardization includes three basic steps:

1. estimate an econometric model of each of primary (FP) or specialist care physician utilization;

2. generate needs-adjusted predicted utilization (for each of FP and specialist care) for each observation in the sample;

3. indirectly need-standardize the distribution of utilization for each of FP and specialist services.

We present these basic steps in turn:

- We estimate a two-part utilization model of physician utilization for each of FP and specialist services. Part 1 models the probability of any service using a logistic regression where the dependent variable is 0 for those with no physician services during the observation period and 1 for those with at least one physician visit within the same period. Part 2 models the number of physician visits among those who had at least one physician visit. Part 2 is estimated using a zero-truncated negative binomial model since the number of visits is a count variable.

- Both parts include a set of need-related and non-need related independent variables.

  - Non-need variables are: self-reported household income (adjusted for household size), marital status, work status, urban/rural residence, education, immigration status, language spoken, aboriginal status, access to a family physician.

  - Need variables are age, sex, self-assessed health, activity limitations due to health, number of chronic conditions, number of disability days, a dummy variable indicating any injury during the past 12 months, a dummy variable indicating activity limitations, and smoking behaviour (current smoker, former smoker, never smoker).

- The models can be written as:

  $$MD_i = G(\alpha_0 + \sum_k \beta_k.X_{k,i} + \sum_h \theta_h.Z_{h,i}) + \epsilon_i \qquad (1)$$

  Where MD is the type of physician (FP or specialist, depending on the estimated model) utilization, G is the general functional form (logit or negative binomial model), i indexes individuals, X_k are k different need-related variables, Z_h are h different non-need-related variables and ϵ is a random term.

- We use the parameter estimates from the above econometric models (vectors β and θ) to predict each person's need-standardized utilization of physician care. To do this, we first predict each person's utilization if only their need-related factors influenced utilization by setting the value of non-need variables at their sample means. Therefore, we can remove the effect of variation in non-need factors on utilization patterns. The need-expected physician utilization is as follows:

$$MD_i^N = G(\alpha_0 + \sum_k \hat{\beta}_k . X_{k,i} + \sum_h \hat{\theta}_h . \bar{Z}_h) \quad (2)$$

- We obtain the need-standardized distribution by taking the difference between the actual level of utilization MD_i of the individual and their need-expected level MD_i^N, adding the mean of the need-predicted utilization to make sure the mean of the need-standardized variable is the same as the mean of the original variable (the average deviation is by definition 0):

$$NSMD_i = MD_i - MD_i^N + \bar{MD}^N \quad (3)$$

  In the equation, we use NSMD as a generic term for both need-standardized primary care (NSMD-FP) and need-standardized specialist care (NSMD-SP) utilization.

3.2.2 Duration analysis to explore the relationship between need-standardized ambulatory cares and ACSC hospital admission

We can link the administrative data between April 1st, 1999 and March 31st, 2002 to each individual in the survey who agreed to have their survey responses linked to administrative data. We want to model the link between ambulatory care (primary care or specialist care) in a given period and subsequent inpatient admission.

Primary care and specialist care utilization is therefore defined as the level of utilization of FP or specialist services in the year between October 1999 and October 2000, standardized for individual need as it is measured at the time of the survey (between September 2000 and November 2001).

We then use the information on inpatient admission on the period from October 1st, 2000 to March 31st, 2002 - the follow-up period lasts therefore 18 months. Our duration analysis is summarized in Figure 1.

Estimation: we use a survival analysis to model the hazard of being admitted for an inpatient stay conditional on the level of ambulatory care use in the previous year and controlling for all standard (need and non-need) determinants of hospital admission. This is our test of whether using more ambulatory care (NSMD-FP or NSMD-SP) can reduce subsequent risks of hospitalization. We

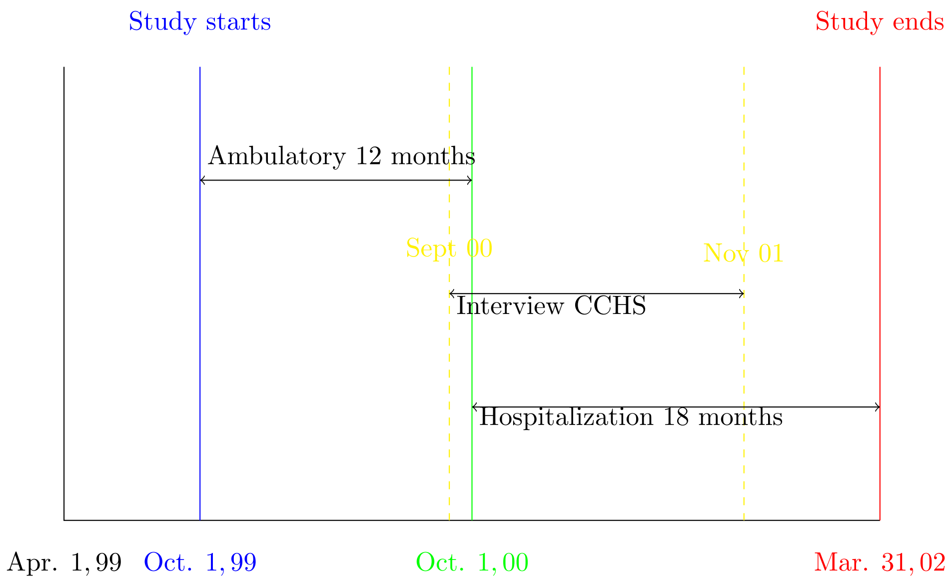


Figure 1: Duration Analysis Diagram

use a duration model to account for the limited period of observation (18 months follow-up), which causes censoring. Standard duration analysis assumes that all individuals are eventually hospitalized and that the only reason why some individuals are not hospitalized is due to censoring. However, this is not true in the specific case at hand and that a subset of the population will never be admitted to a hospital in their remaining years of life (especially for an ACSC). Therefore, we use a Split-population duration model, or SPDM[5], to relax this assumption: in the SPDM the duration process applies only to those individuals who are predicted eventually to being hospitalized in a first stage of the analysis. The likelihood function of the SPDM is the product of a probability function (probability to be hospitalized ever) and a standard hazard function.

The split population model is defined formally as follows:

- Define a proportion "P" - splitting parameter, indicating people who are not at risk of being admitted, with the remaining proportion "1-P" being at risk. For those latter individuals, the survival function will tend toward zero but it will remain at 1 for those in the first group.
- The survival function is a mixture of survival for two populations ("at risk" and "not at risk"):

$$S(t) = P * S_r(t) + (1 - P) * S_{nr}(t) = P + (1 - P) * S_{nr}(t) \quad (4)$$

[5] This is the label in the social sciences (Douglas and Hariharan [1994]). In the bio-statistics literature it is called the Mixture Parametric Cure Model, MPCM (Lambert [2007], Lambert et al. [2007].

Where the index nr refers to "not at risk", and the index r refers to "at risk".

Substituting the mixture density and survival function in the standard likelihood function yields the log-likelihood for the mixture model as:

$$(5) \quad LnL(t,\theta) = \sum_{i=1}^{n} d_i ln[(1-P_i)f_r(t)] + \sum_{i=1}^{n}(1-d_i)ln[P_i + (1-P_i)S_r(t)]$$

where $f_r(t)$ is the density function of the sub-population at risk, $S_r(t)$ is the survival function of that same sub-population, d_i is the censoring indicator. When P=1 for all observations, i.e., when all observations will eventually being hospitalized, the likelihood reduces to a standard duration model with censoring[6].

In the parametric SPDM, the fractions P, are estimated by using a logistic link:

$$(6) \qquad log(\frac{p}{1-p}) = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k$$

Based on tests (fit to data), as shown in the results section, we specify the survival probability as following a Weibull distribution. Its probability density function is:

$$(7) \qquad f(t) = \gamma.\lambda.t^{\gamma-1}exp(-\lambda.t^{\gamma})$$

and its duration function:

$$(8) \qquad S(t) = exp(-\lambda.t^{\gamma})$$

Variables: The dependent variable is the length of time from October 1, 2000 to admission (if any), measured in months. Thus, our outcome variables in the SPDM are: a dummy variable indicating if the individual was hospitalized within the follow-up period; and the length of time until hospitalization for those individuals who are eventually hospitalized. Because we run the duration analysis separately for ACSC and non-ACSC admissions we have four dependent variables: dummy for any ACSC admission and time (in months) before the first ACSC admission and dummy for any non ACSC admission and time (in months) before the first non ACSC admission[7]. We use three censoring indicators corresponding to ACSC (Hosp-ACSC) admission, Non-ACSC (Hosp-NONACSC) admission and all (ACSC or not) hospital admissions (Hosp-ALL), coded 1 if individual was hospitalized and 0 otherwise.

The explanatory variables of interest are those reflecting need-standardized ambulatory care services utilization, based on equation [3].

We also add controls aimed at describing availability of inpatient beds and the likelihood that a condition will be diagnosed and a stay prescribed. This

[6]We also ran a standard duration analysis as robustness check, and findings from both analyses are qualitatively similar albeit less statistically significant, as those estimated with the SPDM. The table of estimated coefficients is available upon request.

[7]A value of 1 would therefore be created on both dummy variables for an individual with two admissions, one for an ACSC diagnostic and one for a non-ACSC.

is based on the idea that availability of acute hospital beds and probability to be diagnosed with a health problem are confounding factors in an analysis of hospital admission (Caminal et al. [2004]):

1. the (logarithm) number of acute beds in the nearest hospital (based on geocoding of the respondent's survey area and hospitals' postal codes),
2. the (logarithm) occupancy rate (for acute beds) of the nearest hospital,
3. the (logarithm) physician supply per 10,000 population for the living area.

Last, we add all need-related and non-need related variables as in the estimation of NSMD-FP and NSMD-SP (see sub-section 3.2.1.).

Table 2 (in section "Results") lists the categories specified for each variable and presents descriptive statistics.

3.2.3 ACSC admissions

Each admission in the DAD is coded with an admission diagnostic: this is the principal diagnostic motivating admission of the patient. These diagnostics are coded using the International Classification of Diseases (ICD) version 9.

The concept of ACSC originated in the early 1990s in the U.S., in efforts to evaluate the quality of primary care providers (Solberg et al. [1990], in Minnesota, and Weissman et al. [1992] in Maryland and Massachusetts). The idea is that "timely and effective outpatient care can help to reduce the risks of hospitalization by either preventing the onset of an illness or condition, controlling an acute episodic illness or condition, or managing a chronic disease or condition" (Billings et al. [1993]). Two empirical studies conducted in the U.S. by (Billings et al. [1993] and Billings et al. [1996]) demonstrated the feasibility of measuring hospitalization rates due to ACSC (preventable ones) and non-ACSC.

A crucial issue in empirical studies of the effect of primary care use on preventable hospitalization is the definition of the list of ACSC (Giuffrida et al. [1999]). There exist several lists of ACSC, usually established based on (clinical) experts consensus guided by a list of objective criteria (the condition is mentioned in prior studies, it is a significant problem with admission rates at least 1 for 10,000 in the population or generating severe health burden, it must be clearly identified in a classification used by hospitals, clinicians must agree hospitalization for such a condition could be prevented but could also be needed in some cases).

We have identified six such lists and comment on five of them here (we exclude the long AHRQ (Agency for Health Research and Quality) list because it measures something broader than ambulatory care sensitive conditions, called marker conditions, which are affected by socio-economic status but not sensitive to the quality of primary care used).

- The initial list suggested by Billings et al. [1993] was comprised of 28 conditions, but only 12 of them are classified in the ICD-9 (Roos et al. [2005]).

- The U.S. based AHRQ produces two lists of ACSC. The shorter one (14 conditions) is called the Prevention Quality Indicators and is used to assess the quality of primary care delivered by health care organizations. The long one is used to monitor access, identify disparities and assess the performance of the safety net (Agency for Healthcare Research and Quality [2004])

- In Canada, Brown et al. [2001] published a list in 2001, based on three independent panels of experts in Ontario (respectively 13, 12, and 11 experts), following Delphi or questionnaire methods. Eight conditions were suggested by all three panels, and 18 overall by at least two panels (nine more were mentioned by one panel only). Here, we include the restricted list of eight as our Brown list of ACSC.

- In 2008 the Canadian Institute for Health Information developed its own list of seven ACSC (Sanchez et al. [2008]), four of which are in the core list in Brown et al. [2001] and all seven being in the list of 18 suggested by at least two panels in that latter publication.

- Last, Caminal et al. [2004] suggest a list of 19 ACSC for the context of publicly reimbursed health care (in the context of Spain).

Overall, 24 conditions appear at least once in these lists (or 27 if one counts diabetes as four different diagnoses: long-term complications, short-term complications, uncontrolled, and amputations due to diabetes), 9 being cited on one list only, 5 on two lists, 4 on three lists, 4 on four lists, and 2 on all five lists. We decided to include all conditions cited in two lists or more (15 conditions), plus five that appear on one list only: congenital syphilis, disorders of the hydro-electrolyte metabolism, disorders of the upper respiratory tract, diseases of the skin, and bleeding or perforated ulcer. That is, we included every ACSC condition listed, to the exception of those that are not relevant to the health care system in Canada (ENT infections, cellulitis, dental conditions). The list and codes in the International Classification of Diseases are provided in table 1.

ACS condition	ICD9 codes
Diabetes, short term complications	2501, 2502, 2503
Appendicitis with complications	5400, 5401
Diabetes, long term complications	2504 to 2509
Chronic Obstructive Pulmonary Disorder	466, 490, 4910-4912, 4918-4920, 4928, 494, 496
Malignant Hypertension	4010, 4019-4020, 4029-84
Congestive Heart Failure	428
Bacterial pneumonia	481, 4822-4824, 4829-4831, 4838, 485, 486
Urinary Tract infection	5901-5903, 5908, 5909, 5950, 5959, 590
Uncontrolled diabetes	2500
Adult asthma	4930-4932, 4938, 4939
Angina	4111, 4118, 4130, 4131, 4139
Dehydration	2765
Low-extremity amputation due to diabetes	841
Gastroenteritis	5589
Immunization and preventable infectious disease	032, 037, 045, 3200, 391
Congenital syphilis	090
Tuberculosis	011-018
Disorders of the hydro-electrolyte metabolism	2765, 2768
Anaemia (iron-deficiency)	280
Epilepsy	345, 7803
Diseases of the upper respiratory tract	382, 463, 465, 475
Bleeding or perforating ulcer	5310, 5312, 5314, 5316, 5320, 5322, 5326, 5330, 5332, 5334, 5336
Disease of the skin	681-683, 686
Pelvic inflammatory disease	614

Table 1: List of ACSC in the study

Including 20 (23) of 24 (27) conditions listed will certainly lead to an underestimate (conservative estimate) of the effect of primary care on the probability to be hospitalized for an ACSC (because some conditions included are not really sensitive to the quality of primary care); being more selective would increase the estimated effects of primary care utilization on the probability to be hospitalized both for ACSC and non-ACSC. Since we use the difference in effects between ACSC and non-ACSC admissions, this should not affect our findings.

3.2.4 Inequity index with and without need-standardized primary care use.

The models presented thus far (sections 3.2.1 and 3.2.2) address the question of the link between primary care use and hazard of hospitalization. If there is such a link we want to explore further the effect of controlling for it when measuring income-related inequity in the probability to be admitted to a hospital.

Our approach is straightforward: we start with a standard calculation of the HI index (entering MD as an explanatory variable) both for ACSC and non-ACSC admissions.

We expect to find pro-poor inequities but, if our hypothesis that primary care use decreases the probability to be admitted to a hospital for an ACSC is true, we should observe a higher pro-poor bias on ACSC admissions than on non- ACSC ones.

We then re-run the HI calculations on a fictitious population where NSMD has been neutralized: we simply give all individuals in the sample the same value for NSMD and recalculate the HI for that population. If our hypothesis is true we should observe a sharp decline in the level of pro-poor inequity for ACSC admissions and no difference for non-ACSC admissions.

The strategy is anologous to a difference-in-difference approach: using the difference between the HI calculations with and without NSMD for non ACSC admissions as our baseline we use the same difference for ACSC admissions as our indicator of the effect of controlling for primary care use in the measurement of pro-poor inequity in inpatient care. If the difference for ACSC admissions is larger than the difference for non-ACSC admissions across the calculation with and without NSMD we will have an indication that some of the observed pro-poor inequity in inpatient care in fact is the product of a positive income gradient of primary care use. We run the simulated HI and the difference-in-difference estimation on a HI based on a logistic regression (predicting the probability of any hospitalization in a given period) and on our duration model (predicting the hazard of the first hospitalization).

4 Results

4.1 Descriptive statistics

Table 2: Descriptive statistics of variables used in the analyses

Variable	Mean	S.D.	Variable	Mean	S.D.
Probability admission	0.07	0.25	Probability FP visit	0.78	0.41
Prob. ACSC admission	0.01	0.09	Probability SP visit	0.55	0.50
Prob. non ACSC admission	0.06	0.24	Conditional # FP visits	3.95	4.89
			Conditional # SP visits	3.77	8.70
Non-need variables					
Income (1)	36,045	29,949	Recent Immigrant (2)	0.09	0.28
Married	0.60	0.49	Long-term Immigrant (3)	0.10	0.30
Separated, widowed	0.11	0.31	Canadian born (4)	0.81	0.39
Never married	0.29	0.45	Language spoken F or E	0.98	0.14
Working	0.63	0.48	Aboriginal	0.02	0.13
Not working, not studying	0.16	0.36	Has regular source of care	0.91	0.28
Student	0.16	0.36			
Location/Urban influence			Education		
Core urban	0.75	0.43	Less than High School	0.22	0.41
Urban fringe w/in CMA/CA	0.03	0.18	Secondary	0.16	0.37
Secondary urban core	0.02	0.14	Some PSE	0.08	0.27
Rural fringe inside CMA/CA urban	0.08	0.26	PSE	0.54	0.50
Urban fringe outside CMA/CA	0.05	0.22			
Rural fringe outside CMA/CA	0.07	0.25			
Need variables					
Self-Assessed Health			Number of chronic conditions		
Excellent	0.223	0.416	Zero	0.30	0.46
Very good	0.392	0.488	One	0.26	0.44
Good	0.277	0.448	Two or three	0.28	0.45
Fair	0.079	0.270	More than 3	0.16	0.36
Poor	0.028	0.165			
Age and Sex			Smoking status		
Female	0.50	0.50			
Younger than 30	0.27	0.45	Current Heavy	0.16	0.37
30-39	0.17	0.38	Current Occasional	0.05	0.22
40-49	0.21	0.41	Former	0.42	0.49
50-59	0.15	0.36	Never	0.37	0.48
60-69	0.10	0.30	Disability days		
70 and older	0.09	0.29	Zero	0.83	0.38
Health Limitations			One or two	0.07	0.26
Rarely	0.77	0.42	3 and more	0.10	0.30
Sometimes	0.13	0.34	Activity Restrictions		
Often	0.09	0.29	Never	0.76	0.43
			Sometimes	0.13	0.34
Injured	0.14	0.35	Often	0.11	0.31

(1) Size-adjusted annual household income, (2) less than 10 years in the country, (3) 10 to 30 years in the country, (4) includes immigrants in the country

for more than 30 years.

Outcome variables (utilization)

Just under 7% of individuals in our sample had at least one in-patient hospital stay during our 18 months follow-up observation period; 1% of our respondents had at least one ASCC admission and 6% at least one non-ACSC admission (the same individual can of course be admitted several times during the observation period, and for ACSC and non-ACSC diagnostics). The average length of stay was 8 nights (this latest result is not shown in Table 2).

78% of our sample visited a FP at least once over our 12 months initial period, and 55% visited a specialist. The mean number of FP and SP visits over the 12 months initial period are 3.95 and 3.77 (conditional on at least one visit) which is very similar to what is observed based on statistics at the provincial level.

Socio-demographic (non-need) variables

The mean adjusted household income is $36,045, 60% are married, over half have a university education, nearly 20% are immigrants, over 60% work, and 98% can speak English or French.

Health status (need variables)

Approximately 90% rate their health as good or better, and a small minority suffer health limitations, activity restrictions, more than 3 chronic diseases, or experienced an injury in the previous year.

Supply-side confounders

The vast majority (91%) of the population has a regular medical doctor. General, acute hospitals in Ontario have an average of 200 beds, but there is substantial variation in hospital size, with nearly a quarter of the hospitals having fewer than 50 beds and just over half having more than 200 beds. The average occupancy rate is 84%, with again, substantial variation. Small hospitals with fewer than 50 beds have an average occupancy rate of 71% while hospitals with 200 or more beds had an average occupancy rate of 87%

4.2 Inequity in inpatient admissions

Table 3 presents the values of the need-standardized income-related index (Horizontal Index) for inpatient admissions, for ACSC and non-ACSC cases. One index is calculated for the probability to ever be admitted over the 18 months period of observation, and one for the time before being admitted (conditional on at least one admission during the period).

Table 3: Income-related inequity index	
Panel A: Probability to be admitted	
ACSC admissions	Non-ACSC admissions
-0.088	-0.039
-0.165; -0.011	-0.065; -0.013
Panel B: Duration before admission	
-0.307	-0.112
-0.384; -0.230	-0.014; -0.084

Note: 95% confidence intervals are provided below the estimates.

Table 3 confirms that ACSC admissions are distributed more pro-poor than non-ACSC admissions, with income-related inequity estimated to be around 50% higher than for the Non-ACSC admission (Panel A). This supports our hypothesis that differences in primary care use may explain some of the pro-poor income gradient in the need-standardized probability to be hospitalized.

Table 4: Decomposition of the HI without controlling for prior ambulatory care use

	ACSC admission	Non-ACSC admission
Log (Income)	-0.0813	-0.0175
Log(Occupancy rate)	-0.0014	-0.0005
Log(Acute beds)	0.0015	-0.0004
Physician supply	-0.0001	0.0000
Education	0.0600	-0.0018
Labour force status	-0.0240	0.0209
Marital status	0.0033	0.0188
Immigration status	0.0392	-0.0045
Aboriginal	0.0018	0.0007
Speaks E or F	0.0018	0.0010
Take flue shot	-0.0013	-0.0003
Urban residence	0.0017	-0.0001
Need	-0.3040	-0.1103

Table 4 reports the decomposition of the Horizontal Index for ACSC and non-ACSC admissions. Among all variables, income, education, immigrant status and physician supply contribute importantly to horizontal inequity for ACSC admission.

4.3 Need-standardized ambulatory care utilization

Tables 5 and 6 below present the estimates of the coefficients for the two-part model of physician services utilization in the initial period (Table 5 for Family Physician and Table 6 for Specialists). In the first two columns we present the coefficients and z statistic for the probability of a physician visit based on a logistic regression; the next two columns report the results of a zero-truncated negative binomial regression on the number of physician visits conditional on having at least one visit and the z statistic associated to the coefficient. The unconditional physician visits obtain as the multiplication of part 1 and part 2.

These results confirm the strong positive income gradient in the utilization of ambulatory care services, even while controlling for need (health) factors. The gradient is steeper for specialist services but significant as well for FP services.

Table 5: Utilization of Family Physician services (1)				
	Probability of any visit		Conditional # of visits	
Co-variate	Coefficient	z statistic	Coefficient	z statistic
Log(Income) (2)	0.0457	2.63	-0.0494	-4.01
Aboriginal	0.1335	1.26	-0.1432	-1.96
Speaks English or French	0.0581	0.57	-0.0287	-0.39
Takes flu shot	0.1800	6.33	0.1472	6.83
FP supply	0.0085	2.40	0.0066	3.51
SP supply	-0.0109	-2.92	-0.0065	-2.27
Education (3)				
Secondary	0.0047	1.00	0.0480	1.64
Some PSE	0.1682	3.14	0.0117	0.31
PSE grad	-0.0166	-0.44	-0.0227	-0.86
Labour force status (4)				
Student	0.0524	0.77	-0.1005	-1.72
Work	0.0405	0.77	-0.0917	-2.87
Marital status (5)				
Married	0.1157	2.72	0.0365	1.13
Separated, widowed	0.1041	1.83	0.1255	3.23
Immigration status (6)				
Less than 10 years in Canada	-0.1780	-2.94	0.2458	4.00
10 to 29 years in Canada	0.2267	4.10	0.1006	2.92
Type of residence (7)				
Urban core	0.1079	2.97	0.1552	5.84
Urban fringe w/in CMA/CA	0.1438	1.98	0.1243	2.01
2ndary urban fringe	0.0651	1.27	0.0397	1.21
Rural fringe w/in CMA/CA	0.0377	0.86	0.0500	1.70
Sex and age (8)				
Male 30 to 39	0.0076	0.12	0.1529	2.52
Male 40 to 49	-0.0303	-0.50	0.1880	3.53
Male 50 to 59	0.1297	1.86	0.2284	4.41
Male 60 to 69	0.1528	1.83	0.3092	5.79
Male 70 and older	0.3708	3.88	0.4211	6.99
Female 30 younger	0.3975	7.89	0.2788	7.19
Female 30-39	0.4846	7.26	0.3537	7.72
Female 40-49	0.2703	4.26	0.3450	6.01
Female 50-59	0.4541	6.24	0.3177	6.43
Female 60-69	0.3110	3.34	0.3178	5.67
Female 70 and older	0.3579	3.63	0.3464	6.08
Self-Assessed Health (9)				
Very Good	0.0362	1.10	0.1146	3.86
Good	0.0734	1.88	0.2179	7.51
Fair	0.0311	0.47	0.3440	7.85
Poor	0.1613	1.67	0.4722	8.51

Table 5: Utilization of Family Physician services, continued (1)

	Probability of any visit		Conditional # of visits	
Co-variate	Coefficient	z statistic	Coefficient	z statistic
Health limitations (10)				
Sometimes	0.0337	0.70	0.0338	0.96
Often	0.1517	2.20	0.0980	2.58
Number of chronic conditions (11)				
One	0.2800	8.45	0.1338	4.75
2 or 3	0.4921	13.67	0.2815	9.55
4 or more	0.7184	11.10	0.4391	12.90
Activity restrictions (12)				
Sometimes	0.0215	0.48	-0.0064	-0.20
Often	-0.0284	-0.46	-0.0335	-0.99
Disability days (13)				
1 or 2	-0.0008	-0.01	0.0492	1.49
3 and more	0.0787	1.59	0.1615	5.26
Injury	0.0941	2.41	0.0034	0.13
Smoking status (14)				
Current, regular	-0.1954	-5.24	-0.0363	-1.27
Current, occasional	0.0096	0.15	-0.0013	-0.02
Former	0.0051	0.15	-0.0223	-0.93
# observations	26,737		20,905	
Pseudo R2 (%)	7.95			
Wald Chi2			2,478.84	
Log Likelihood	-12,899		-52,613	

Table 6: Utilization of Specialist services (1)				
	Probability of any visit		Conditional # of visits	
Co-variate	Coefficient	z statistic	Coefficient	z statistic
Log(Income) (2)	0.0947	5.84	0.0501	2.23
Aboriginal	-0.2230	-2.01	-0.0351	-0.16
Speaks English or French	0.1130	1.15	-0.0249	-0.19
Takes flu shot	0.1202	4.66	0.0845	2.19
FP supply	-0.0012	-0.52	-0.0035	-1.01
SP supply	0.0000	0.01	0.0062	1.32
Education (3)				
Secondary	0.0200	0.53	0.0154	0.27
Some PSE	0.0141	0.28	0.0373	0.57
PSE grad	0.0195	0.57	0.0475	0.89
Labour force status (4)				
Student	0.0761	1.30	0.0078	0.10
Work	-0.0210	-0.48	-0.1153	-2.36
Marital status (5)				
Married	0.1533	3.83	-0.1300	-2.02
Separated, widowed	0.0920	1.79	-0.0591	-0.82
Immigration status (6)				
Less than 10 years in Canada	-0.0645	-1.10	-0.0373	-0.47
10 to 29 years in Canada	0.0294	0.59	-0.0653	-1.11
Type of residence (7)				
Urban core	0.2573	7.54	0.3035	7.19
Urban fringe w/in CMA/CA	0.1103	1.66	0.1742	2.26
2ndary urban fringe	0.1277	2.74	0.1498	2.79
Rural fringe w/in CMA/CA	-0.0125	-0.31	-0.0019	-0.04
Sex and age (8)				
Male 30 to 39	-0.0282	-0.48	0.1312	1.45
Male 40 to 49	0.0795	1.33	0.4332	3.75
Male 50 to 59	0.1851	2.79	0.4970	4.36
Male 60 to 69	0.4525	5.96	0.5478	5.60
Male 70 and older	0.6590	8.01	0.7930	7.01
Female 30 younger	0.2573	5.46	0.1381	1.68
Female 30-39	0.4200	7.00	0.3291	3.69
Female 40-49	0.3586	6.04	0.4483	4.27
Female 50-59	0.4062	6.02	0.5043	4.73
Female 60-69	0.4497	5.87	0.4863	4.41
Female 70 and older	0.4155	5.14	0.5067	4.68
Self-Assessed Health (9)				
Very Good	0.0887	2.84	0.1983	4.56
Good	0.1791	4.96	0.3688	7.43
Fair	0.3796	6.75	0.5505	8.73
Poor	0.5146	5.79	0.7140	8.56

Table 6: Utilization of Specialist services, continued (1)				
	Probability of any visit		Conditional # of visits	
Co-variate	Coefficient	z statistic	Coefficient	z statistic
Health limitations (10)				
Sometimes	0.1449	3.58	0.1826	3.20
Often	0.2945	5.23	0.3719	3.75
Number of chronic conditions (11)				
One	0.1977	6.23	0.1424	2.80
2 or 3	0.3600	10.52	0.2067	3.97
4 or more	0.6007	12.21	0.2973	5.01
Activity restrictions (12)				
Sometimes	0.0204	0.53	-0.1087	-1.96
Often	-0.0394	-0.79	-0.1794	-2.59
Disability days (13)				
1 or 2	0.0965	1.98	0.0644	1.05
3 and more	0.1907	4.50	0.2213	4.22
Injury	0.1101	2.97	-0.0943	-2.35
Smoking status (14)				
Current, regular	-0.1953	-5.54	-0.0304	-0.57
Current, occasional	-0.0126	0.20	-0.2231	-3.23
Former	0.0188	0.63	0.0593	1.36
# observations	26,737		14,848	
Pseudo R2 (%)	9.42			
Wald Chi2			1,319.90	
Log Likelihood	-16,601.48		-42,611	

(1) 2-part model, logistic regression for the probability and negative binomial regression for the conditional # of visits
(2) size-adjusted household income
(3) Reference = Primary
(4) Reference = Not in the labour force
(5) Reference = Never married
(6) Reference = Canadian born or immigrant more than 30 years in Canada
(7) Reference = Rural area outside CMA/CA
(8) Reference = Male 30 and younger
(9) Reference = Excellent
(10) Reference = Never
(11) Reference = 0
(12) Reference = Never
(13) Reference = 0
(14) Reference = Never smoked

4.4 Inpatient admission hazard

Figure 2 shows estimated survival function for the event of being hospitalized for an ACSC admission, non-ACSC admission and any admission. The estimated survival functions asymptotically approach a non-zero probability of not being hospitalized, as time elapses, confirming that a fraction of the population will never experience the event (hospitalization).

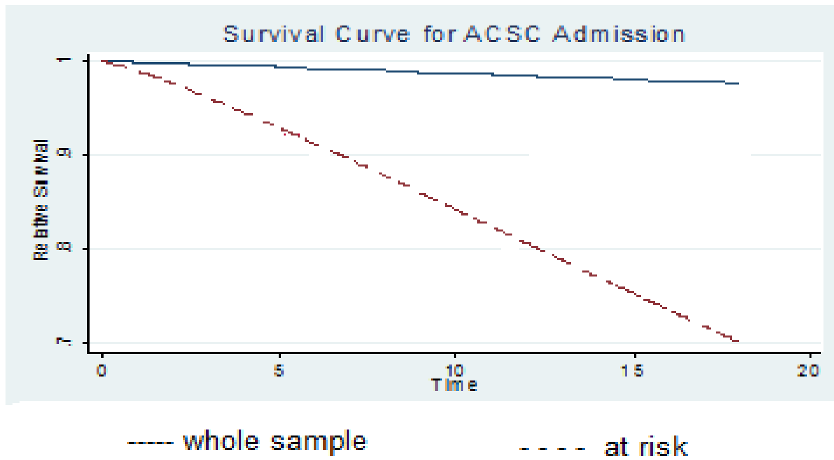
The exponential and Weibull distributions are commonly used in duration analyses. The hazard rate in our data is monotonic and it implies that these two distributions may fit the data. The likelihood values and AIC goodness of fit statistics for four distributional assumptions (exponential, Weibull, log-normal, and Gamma) are as follows:

- exponential: -2,248; 4,612
- Weibull: -2,245; 4,595
- log-normal: -2,251; 4,609
- Gamma: -2,245 ; 4,597

Log-likelihoods and AIC criteria are very similar across distributions and we choose the Weibull based on a slightly better AIC (but it must be stressed that the Gamma distribution is almost as good a fit).

The increase in likelihood values from the standard to the split model is much larger than differences across distributions for the standard duration analysis. We present the results based on the Weibull distribution.

Figure 2: hazard curves for ACSC and non-ACSC admissions:



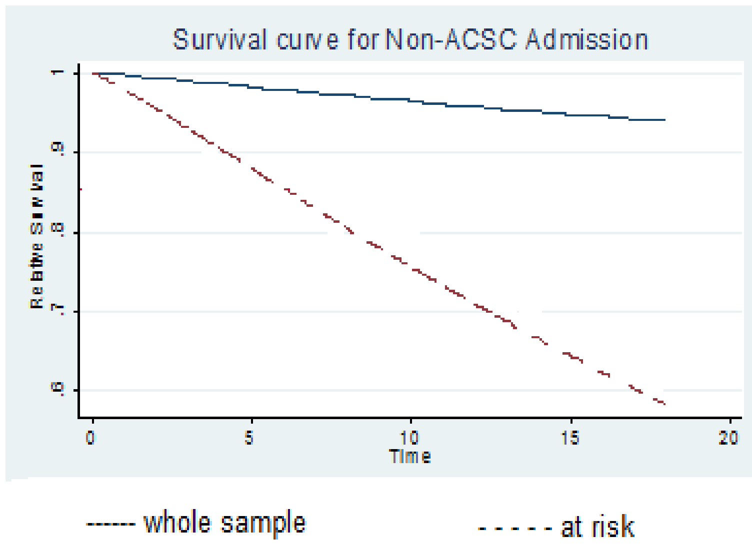

Survival curve for Non-ACSC Admission
Relative Survival
1
.9
.8
.7
.6
0
5
10
15
20
Time
------ whole sample
- - - - - at risk

Table 7: Split Population Duration Model: duration before hospitalization for an ACSC admission

Co-variate	Probability(never hospitalized) Coefficient	z statistic	Duration Coefficient
NSMD - FP	**0.3305**	**1.61**	**0.6658 (***)**
NSMD - SP	-1.9569	-5.3	-2.0491 (***)
Log(income) (1)	0.2013	3.05	0.1180
Aboriginal	1.6848	2.26	0.6584
Speaks English or French	-0.1025	-0.15	-0.2245
Takes flu shot	-0.2820	-1.39	-0.1448
FP supply	0.0133	0.79	0.0051
SP supply	-0.0179	-1.38	-0.0005
Log(Occupancy rate)	0.9478	1.95	0.8257 (*)
Log(# Acute beds)	-0.063	-0.54	0.0009
Education (2)			
Secondary	-0.0888	-0.30	0.1650
Some PSE	-0.3558	-1.03	-0.2453
PSE grad	-0.5853	-2.53	-0.0108
Labour force status (3)			
Student	-0.9563	-1.24	0.4316
Work	-0.2148	-0.80	0.1576
Marital Status (4)			
Married	-0.1995	-0.48	-0.0112
Separated, widowed	-0.3499	-0.83	-0.3742
Immigration status (5)			
Less than 10 years in Canada	1.8345	2.38	1.2737
10 to 29 years in Canada	0.5462	1.17	0.7007
Type of residence (6)			
Urban core	0.3049	1.10	0.2309
Urban fringe w/in CMA/CA	-0.0426	-0.06	0.4644
2ndary urban fringe	-0.0334	-0.10	-0.3822
Rural fringe w/in CMA/CA	0.1191	0.44	-0.1438
Sex and age (7)			
Male 30 to 39	-2.2713	-2.54	-1.2883 (*)
Male 40 to 49	-1.3695	-1.56	-0.9106
Male 50 to 59	-1.6853	-1.96	-1.2707 (*)
Male 60 to 69	-3.2590	-3.67	-2.4100 (***)
Male 70 and older	-3.9941	-4.57	-3.1005 (***)
Female 30 younger	-1.6332	-2.23	-1.4654 (**)
Female 30-39	-1.7698	-2.12	-1.4048 (**)
Female 40-49	-2.1879	-2.52	-1.2484 (*)
Female 50-59	-2.3804	-2.70	-1.6608 (**)
Female 60-69	-2.9502	-3.27	-2.0004 (***)
Female 70 and older	-3.6777	- 3.80	-2.6835 (***)

Table 7: Split Population Model: duration before hospitalization for an ACSC admission, cont'd

	Probability(never hospitalized)		Duration
Co-variate	Coefficient	z statistic	Coefficient
Self-Assessed Health (8)			
Very Good	0.0625	0.19	-0.1810
Good	-0.6503	-1.93	-0.6364 (**)
Fair	-1.114	-3.14	-1.2623 (***)
Poor	-1.2783	-2.77	-1.6866 (***)
Health limitations (9)			
Sometimes	-0.5474	-2.25	-0.4617 (**)
Often	-0.5021	-1.74	0.2877
Number of chronic conditions (10)			
One	0.2240	0.71	-0.2636
2 or 3	-0.1826	-0.59	-0.5055 (**)
4 or more	-0.5355	-1.60	-0.6792 (**)
Activity restrictions (11)			
Sometimes	0.1176	0.54	-0.1103
Often	-0.3152	-1.19	-0.3186
Disability days (12)			
1 or 2	0.6061	1.06	0.8929 (**)
3 and more	-0.4323	-1.53	-0.6285 (***)
Injury	0.1661	0.63	0.0084
Smoking status (13)			
Current, regular	-0.3019	-1.20	-0.0806
Current, occasional	-0.4677	-1.03	-0.2106
Former	-0.2416	-1.06	-0.2666
Log Likelihood	-1,030.59		-2,243.69
log(lamda)			-4.58
log(gamma)			0.21

(1) Size-adjusted household income
(2) Reference = Primary
(3) Reference = Not in the labour force
(4) Reference = Never married
(5) Reference = Canadian born or immigrant more than 30 years in Canada
(6) Reference = Rural area outside CMA/CA
(7) Reference = Male 30 and younger
(8) Reference = Excellent
(9) Reference = Never
(10) Reference = 0
(11) Reference = Never
(12) Reference = 0
(13) Reference = Never smoked
Note: (***): $p \leq 0.01$; (**): $p \leq 0.05$; (*): $p \leq 0.10$.

Table 8: Split Population Model: duration before hospitalization for a non ACSC admission

	Probability(never hospitalized)		Duration
Co-variate	Coefficient	z statistic	Coefficient
NSMD - FP	**0.3020**	**2.61**	**0.1879 (*)**
NSMD - SP	-2.6934	-19.79	-2.6126 (***)
Log(income) (1)	0.1009	1.87	0.0578
Aboriginal	0.4624	1.43	0.2080
Speaks English or French	-0.1079	-0.35	-0.3900
Takes flu shot	-0.0322	-0.37	0.0408
FP supply	0.0035	0.45	-0.0019
SP supply	-0.0064	-0.75	0.0005
Log(Occupancy rate)	0.4964	1.86	0.835 (***)
Log(# Acute beds)	0.0152	0.33	-0.0084
Education (2)			
Secondary	0.1737	1.40	0.0142
Some PSE	0.1348	0.82	0.0046
PSE grad	0.0800	0.71	-0.0273
Labour force status (3)			
Student	1.0969	4.59	1.4186 (***)
Work	-0.0364	-0.30	0.1614
Marital Status (4)			
Married	-1.1563	-7.13	-1.0428 (***)
Separated, widowed	-1.0576	-5.85	-1.0188 (***)
Immigration status (5)			
Less than 10 years in Canada	-0.1177	-0.59	-0.2656
10 to 29 years in Canada	0.3284	1.73	0.4211 (**)
Type of residence (6)			
Urban core	0.0030	0.02	-0.0553
Urban fringe w/in CMA/CA	0.1663	0.76	0.2335
2ndary urban fringe	-0.0128	-0.08	-0.1686
Rural fringe w/in CMA/CA	-0.1907	1.41	-0.2711 (**)
Sex and age (7)			
Male 30 to 39	0.8049	2.80	0.7903 (***)
Male 40 to 49	0.3888	1.49	0.4744 (**)
Male 50 to 59	0.1458	0.59	0.1215
Male 60 to 69	-0.8276	-3.24	-0.7861 (***)
Male 70 and older	-1.0984	-4.07	-1.3881 (***)
Female 30 younger	-1.7889	-8.35	-1.9552 (***)
Female 30-39	-1.3931	-6.03	-1.3451 (***)
Female 40-49	-0.3208	-1.33	-0.159
Female 50-59	-0.2013	-0.75	-0.0801
Female 60-69	-0.6511	-2.33	-0.4951 (**)
Female 70 and older	-0.9375	- 3.50	-0.9348 (***)

Table 8: Split Population Model: duration before hospitalization for a non ACSC admission, cont'd			
	Probability(never hospitalized)		Duration
Co-variate	Coefficient	z statistic	Coefficient
Self-Assessed Health (8)			
Very Good	0.0625	0.19	-0.1810
Good	-0.6503	-1.93	-0.6364 (**)
Fair	-1.114	-3.14	-1.2623 (***)
Poor	-1.2783	-2.77	-1.6866 (***)
Health limitations (9)			
Sometimes	-0.5474	-2.25	-0.4617 (**)
Often	-0.5021	-1.74	0.2877
Number of chronic conditions (10)			
One	0.2240	0.71	-0.2636
2 or 3	-0.1826	-0.59	-0.5055 (**)
4 or more	-0.5355	-1.60	-0.6792 (**)
Activity restrictions (11)			
Sometimes	0.1176	0.54	-0.1103
Often	-0.3152	-1.19	-0.3186
Disability days (12)			
1 or 2	0.6061	1.06	0.8929 (**)
3 and more	-0.4323	-1.53	-0.6285 (***)
Injury	0.1661	0.63	0.0084
Smoking status (13)			
Current, regular	-0.3019	-1.20	-0.0806
Current, occasional	-0.4677	-1.03	-0.2106
Former	-0.2416	-1.06	-0.2666
Log Likelihood	-1,030.59		-2,243.69
log(lamda)			-4.58
log(gamma)			0.21

(1) Size-adjusted household income
(2) Reference = Primary
(3) Reference = Not in the labour force
(4) Reference = Never married
(5) Reference = Canadian born or immigrant more than 30 years in Canada
(6) Reference = Rural area outside CMA/CA
(7) Reference = Male 30 and younger
(8) Reference = Excellent
(9) Reference = Never
(10) Reference = 0
(11) Reference = Never
(12) Reference = 0
(13) Reference = Never smoked
Note: (***): p¡0.01; (**): p¡0.05; (*): p¡0.10.

The first two columns in Tables 7 and 8 provide the estimation of the probability of **never** being hospitalized, for an ACSC, and a non ACSC, respectively, and the z-statistics for each coefficient. A positive coefficient indicates a lower risk of being hospitalized. The third column in these two tables presents the estimated results for the duration of being hospitalized. A positive coefficient indicates delayed hospitalization. These models include the variables for need-standardized FP utilization (NSMD-FP) and Specialist utilization (NSMD-SP). We do not report the coefficients for total number of visits since they are never significant at any usual level.

The results from Tables 7 and 8 (columns 1 and 2) indicate that those who had a higher-than-needed probability of FP visits (co-variate NSMD-FP) are less likely to be hospitalized for an ACSC, as expected; however, the same holds for the likelihood of being admitted for a Non-ACSC (and the estimated coefficients are similar). This suggests that primary care use might correlate with other factors, not controlled for in our equations, which also influence inpatient admissions, ACSC or not. We also note that the income gradient still exists in Table 7 even after controlling for prior use of primary care and supply side characteristics such as the occupancy rate of the nearest hospital (which has a large negative effect on the probability to be hospitalized), the number of acute care beds or the denisty of physicians (FP and specialist) per 10,000 population.

In the (conditional) duration part of the model (column 3), we can see that higher probability to visit an FP has a positive and significant effect on delaying admission and the effect is three time longer for ACSC admissions than for non-ACSC admissions. The excess hazard rate of any ACSC hospital admission is decreased by 49% between a 'no-visit to an FP' and a 'at least one visit to an FP' situation (100*(1-exp(-0.6658))=49%, which is much larger than that of non-ACSC admission (100*(1-exp(-0.1879))=17%)[8]. Interestingly, there is no income gradient on the duration before admission once prior use of primary care (FP visits) is controlled for and this holds true for both ACSC and non-ACSC admissions.

If the occupancy rate in the nearest hospital is higher, the individual will be hospitalized later for ACSC and non ACSC. The number of acute beds and physician density have no association with the duration before hospitalization.

The average "never hospitalized" fraction "p" is estimated to be as 0.923 for an ACSC admission, 0.854 for a Non-ACSC admission and 0.818 for any admission. Considering that 99% of the sample was censored for an ACSC and 94% for a Non-ACSC admission, the model predicts reasonably well the "not at risk" rates. The relative survival function for the whole group approaches the "not at risk" fraction at 0.923.

[8]This is the effect of increasing NSMD-FP by 1, holding the other xs constant. Because the model could be written in a multiplicative form: $H(t) = h_0(t)exp(b_1X_1).exp(b_2X_2)(...)exp(b_kX_k)$.

4.5 HI index, with and without NSMD difference-in-difference

Table 9: Simulated HI, NSMD standardized

	Panel A: logistic regression	
Index	ACSC admissions	Non-ACSC admissions
Horizontal Index	-0.088	-0.039
	[-0.165;-0.011]	[-0.065;-0.013]
Simulated HI, NSMD-FP standardized	-0.024	-0.027
	[-0.038; -0.010]	[-0.035;-0.019]
Decrease in HI due to standardization	73%	31%
	Panel B: Duration	
Horizontal Index	-0.307	-0.112
	[-0.384; -0.230]	[-0.014; -0.084]

Note: 95% confidence intervals are provided below the estimates.

Table 9 reproduces table 3 but adds one row: the HI with all individuals set at the average level of NSMD-FP. We present results for the probability of any admission, not for the duration before admission. The latter results (simulation for duration neutralizing NSMD-FP) are difficult to interpret but overall non significant. It shows that neutralizing income-related differences in the use of primary care would strongly reduce the magnitude of pro-poor inequity in the probability to be hospitalized for an ACSC, by a factor of almost four (from -0.088 to -0.024). It would also have an effect on the index for the probability to be admitted for a non ACSC but a much smaller one (from -0.039 to -0.027). The difference across types of admission in the effect of neutralizing the income gradient in ambulatory care utilization on the inequity of the probability to be admitted to a hospital is much larger than the difference in the effects of ambulatory care utilization on the probability to be admitted across types of admissions. The results of the simulation suggest a baseline level of pro-poor inequity in the probability to be admitted to a hospital around -0.025, which is independent of primary care use. However, income-related differences in primary care use add another -0.060 to the level of pro-poor inequity in the probability to be admitted for an ACSC.

Table 9 reports the simulation for the inequity of all types of hospital admission. If all had the same NSMD-FP, pro-poor inequity would be reduced for, but not eliminated from , both types of admission: simulated inequity would decline by 73% for ACSC admission and 31% only for Non-ACSC admission, again suggesting that primary care utilization plays more of a role for ACSC than for non ACSC admissions, but also that primary care utilization correlates with income and another variable explaining inpatient admission (ACSC or not).

Table 10: Decomposition of the HI, with NSMD

Co-variate	ACSC admissions	Non-ACSC admissions
Log(Income)	-0.1003	-0.0365
Log(Occupancy rate)	-0.0015	-0.0006
Log(Acute beds)	+0.0014	-0.0003
Physician supply	-0.0001	0.0000
NSMD-FP	-0.0032	-0.0022
NSMD-SP	+0.0378	+0.0377
Education	+0.0566	-0.0043
Labour force status	-0.0231	+0.0217
Marital status	+0.0010	+0.0173
Immigration status	+0.0393	-0.0020
Aboriginal	+0.0017	+0.0006
Speaks E or F	+0.0012	+0.0009
Takes flu shot	-0.0011	-0.0001
Urban residence	+0.0010	-0.1168
Residual	+0.1227	+0.0189

Table 10 reproduces Table 4 but now NSMD-FP and NSMD-SP are added to the decomposition of the income-related HI. Among all variables, income, education, immigrant status and work status contribute importantly to horizontal inequity for ACSC admission (Table 7). Because need-standardized FP and Specialist is concentrated among higher-income individuals, and need-standardized FP decrease the likelihood of being hospitalized, it contributes to the pro-poor bias, and need-standardized Specialist increase the likelihood of being hospitalized, it contributes to the poor-rich bias. The inequity of hazard rate based on the Split Population Duration Model is substantially more pro-poor (Table 7), because the split-population model enables us to separate out the effect of individual characteristics on the probability of being hospitalized from their effect on the timing of hospitalization (for those who will ultimately be hospitalized).

5 Discussion and conclusions

This study of the effect of primary care utilization on subsequent inpatient admissions finds the following, based on data collected in Ontario in 2000-01 and linking administrative records on utilization to survey information on socio-economic status (including income):

1. Using more primary care (visits to physicians) than the average individual with the same level of need has a significant effect on preventing (marginally significant) and delaying (strongly significant) inpatient admissions in the follow-up 18 months period.

2. The effect is present for both admissions that are amenable to primary care (ACSC, as we expected it would) and admissions that are not (non-ACSC admissions).

3. More precisely, the effect of need-adjusted primary care use is almost the same on preventing both types of admissions: individuals with higher primary care use in the initial period are more likely to never be hospitalized, either for ACSC or non-ACSC.

4. But the need-standardized use of primary care delays ACSC much more than non-ACSC hospitalizations (by a factor 3).

5. We can therefore conclude that primary care does not decrease the probability to be hospitalized in a lifetime but that it might be able to reduce the frequency with which an individual is hospitalized. This could explain some of the pro-poor inequity in inpatient admission observed in the data.

6. The lack of difference across types of admission (ACSC or not) in the effect of primary care in preventing hospitalization suggests that individual primary care utilization varies with other factors, not measured in our study, that decrease the probability to be hospitalized in general.

7. Such an unobserved factor could be related to "need": we standardize by need, as is common practice in studies of income-related equity in utilization, by using health status as a measure of need. But it could also be the case that need includes more than health status, such as ability to benefit from treatment or social environment (whether one's home is a safe enough environment for instance).

8. It can also be a psychological trait not captured in our survey that would lead the same individual to use more primary care and be careful enough so they do not need to be hospitalized. We try to capture some psychological traits through our variables describing attitude toward treatment and risk through our smoking status and flu shot variables, but it might not be enough to control entirely for attitudinal traits.

9. We also find that, equalizing the level of primary care use across individuals reduces income-related inequity in the probability of inpatient admission by 73% for ACSC admissions and 31% for non-ACSC admissions. Again, it is clear that primary care co-variates with a determinant of hospitalization, explaining this indirect effect on non-ACSC admissions. It is also clear that primary care has more of an effect on ACSC admissions than on non-ACSC ones.

10. Even reducing inequities in primary care use would not suppress income-related inequity in inpatient admissions, and there would still be a pro-poor inequity of -0.024 for ACSC admissions and -0.027 for non-ACSC ones. Of course this is different from the current situation, where pro-poor inequity is at -0.088 for ACSC and -0.039 for non ACSC admissions.

Overall, then, our findings suggest that it is likely that differential use of primary care by income explains some of the pro-poor inequity in inpatient hospital care use, but the effect is not large or clear, as such an effect (albeit a weaker one) also exists for non-ACSC admissions. In future research, we will:

- use two comparators instead of one as done in this study: we will separate non-ACSC admissions into two groups, marker conditions and the rest. Marker conditions are those conditions that are not amenable to primary care - meaning that access to timely and quality primary care cannot prevent or delay hospitalization - but are more likely to generate hospitalizations and are also more frequent among individuals who are less likely to use primary care. Thus we will capture some of the unobservable variation in the probability and frequency of inpatient admission that also correlates with primary care use. As a result the non-ACSC, non-marker admissions should be less influenced by primary care use (and we expect to find no effect at all of primary care use on these admissions).

- add quality to quantity of care in our measure of primary care use: so far we have been using the number of visits to a FP as our measure of primary care use (standardized by need). Because ACSC admission results from the quality of health care as well as its quantity, we could use the dollar value of primary care use (again, standardized by need) instead of the number of visits as our measure of utilization. This would reflect quality in the sense that visits associated with greater intensity may represent better quality of care.

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Appendix

Overlap across lists of Ambulatory Care Sensitive Conditions (1)					
Condition	Billings (2)	Brown (3)	Caminal (4)	AHQR (5)	CIHI (6)
	Five lists				
Angina	YES	YES YES	YES	YES	
CHF (7)	YES	YES	YES	YES	YES
	Four lists				
Asthma	YES	YES	NO	YES (14)	YES
COPD (8)	NO	YES	YES	YES	YES
Diabetes	NO	YES	YES	YES (15)	YES
Hypertension	NO	YES	YES	YES	YES
	Three lists				
Epilepsy	YES	NO	YES (16)	NO	YES
Pneumonia	YES	NO	YES	YES	NO
Pelvic inflammation	YES	YES	YES	NO	NO
Gastroenteritis	YES	YES	YES (17)	NO	NO
	Two lists				
Tuberculosis	YES	NO	YES	NO	NO
Urinary infection	NO	NO	YES	YES	NO
Anemia (iron)	YES	NO	YES	NO	NO
Immunization (9)	NO	YES	YES	NO	NO
Appendicitis (10)	NO	NO	YES	YES	NO
	One list				
ENT infections	YES	NO	NO	NO	NO
Cellulitis	YES	NO	NO	NO	NO
Dental	YES	NO	NO	NO	NO
Syphilis	NO	NO	YES	NO	NO
HEM (11)	NO	NO	YES	NO	NO
URT (12)	NO	NO	YES	NO	NO
Skin	NO	NO	YES	NO	NO
LBW (13)	NO	NO	NO	YES	NO
Dehydration	NO	NO	NO	YES	NO

(1) Conditions are listed by descending order of number of lists in which they are mentioned, from 5 to 1.

(2) Billings et al. 1993

(3) Brown et al. 2001

(4) Caminal et al. 2004

(5) AHRQ, short list, 2004

(6) Canadian Institute for Health Information, 2009

(7) Congestive Heart Failure

(8) Chronic Obstructive Pulmonary Disease

(9) Infectious diseases that can be prevented by immunization

(10) Complications of appendicitis

(11) Disorders of the hydro-electrolyte metabolism

(12) Disorders of the upper respiratory tract
(13) Low birth weight
(14) Adult
(15) Four types of complications of diabetes (four ACSC)
(16) Convulsions
(17) Ulcer