# The effect of physician supply on health status as measured in the NPHS

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#### Abstract:

We use data from the Canadian National Population Health Survey and the Canadian Institute for Health Information to estimate the relationship between per capita supply of physicians, both general practitioners and specialists, on health status. Measures of quality of life, self-assessed health status and the Health Utility Index are explored. The sample consists of all individuals who were age 18 or over at the beginning of the survey in 1994, and the sub-sample includes only individuals who were not diagnosed with a chronic condition for the first four years. Most previous studies of the effect of physician supply on health status used data only on individuals who had specific health problems, and many of them used outcomes related to the length of life of the patient. Random effects ordered probits are used to model self assessed health status and quantile regressions are used for the Health Utility Index. A higher supply of specialists is correlated with worse health outcomes, while a higher supply of general practitioners is correlated with better health outcomes as measured by both measures of health status.

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## 1 Introduction

The supply of physicians across Canada and especially in remote areas has been a much publicized issue in the health care debate. The media reports an important brain drain towards the United States, especially for some specialties, and that remote areas have trouble attracting physicians, again especially specialists, and convincing them to stay in the area once they have started practicing there.

Although some areas have urgent needs for some specialties (e.g. anesthetists), not much has been reported about how physician supply affects health care supply and health status. Not much has been reported either about which types of doctors (general practitioners vs. specialists) affect health status of individuals in general (including those who do not have a specific health problem) with the best outcomes.

In previous work, we have found that per capita expenditures in constant dollars on physicians who do not work in a care institution (whether a hospital or another type of institution) often have a negative relation with health status, although not always statistically significant. In this study, we use longitudinal data from the National Population Health Survey (NPHS) and merge them with data from the Canadian Institute for Health Information (CIHI) reporting the supply of physicians across provinces over time according to whether they are general practitioners or specialists. We use these data to evaluate whether fluctuations in the composition of the physician workforce had an impact on the health status of Canadians over the period 1994 to 2000. Using these data enables us to study a broad spectrum of the Canadian population, and not limit ourselves to individuals presenting a specific health condition. We also simultaneously control for risk factors at the individual level, e.g. smoking behaviour, education, drinking behaviour, age, income, etc.

Due to the small numbers of individuals diagnosed with some health conditions in the survey, we are not able to study how physician supply affects differently individuals with specific health problems. We do not differentiate between the different chronic conditions and therefore assume all physicians of different specialties have a similar impact on the health of individuals with different health problems. Moreover, in remote areas, a specialist

might discuss the case of one of his patients with a colleague e.g.: a specialist from another discipline. Although this could also take place in urban areas where physician supply is higher, we think it would be less likely to occur. Moreover, it would be difficult to "limit" the types of doctors (specialties) that could have an effect on the health of an individual given their chronic condition. We test and control for endogeneity of supply, as provinces in which individuals display especially bad health statuses might have policies that would attract more physicians, and control for it in our model.

We estimate a Grossman-type model (Grossman, 1972), in which present health status is both a function of physician supply in the province and past health (in some of the regressions). We are not able to study how the distribution of physicians within a province affects health status. For example, if some provinces have policies which are more effective when trying to entice physicians to practice in remote areas, we cannot control for it. We can control for the fact that an individual lives in a remote area, and, therefore, partly control for the risks and benefits inherent in living in such a setting.

We need to use different econometric techniques to study the impact of physician supply on self-rated health status, which is an ordered categorical variable, and on the Health Utility Index (HUI), which is a continuous, but limited, variable. Random effects ordered probits are used with the former while quantile regressions evaluated at the  $10^{th}$ ,  $20^{th}$  and  $30^{th}$  percentiles of the distribution are used for the HUI. These dependent variables measure quality of life, more than length of life, the dimension of health about which Canadians seem to be most concerned. We limit the time lag of the impact of physician supply to two years, as physicians' services are more likely to have short-term effects on health status, compared to expenditures on capital for example (e.g. an MRI machine). The variables used to control for past health status also help control for the effect of past services rendered by physicians.

We present a brief survey of the relevant literature in section 2. A description of the data sources, the model and the estimation techniques used follows in section 3. We describe the results obtained in the fourth section and discuss their implications as well as problems that could be present in the data and in our estimation methods before concluding remarks.

## 2 Literature Review

#### 2.1 Previous studies

A comprehensive review of studies in the field was done. All studies used American data and therefore, the results are hard to apply to the Canadian case.

Escarce (1992) found that the supply of surgeons in a region is positively correlated with the demand for first-contact appointments but not with the number of surgeries, contradicting earlier studies (e.g. Pasley et al. (1987), cited in Escarce). A study by Roetzheim et al. (2000) found that a higher dermatologist and family physician supply (per capita and per zip code) is associated with earlier diagnosis of melanomas in Florida in 1994. A higher supply of general practitioners, obstetrician/gynecologists and other non-primary care specialists, however, did not have a statistically significant impact. In another study, Roetzheim et al. (1999) found that a higher supply of primary care physicians and of general internists decreased the odds of a late stage diagnosis of colorectal cancer, but the opposite was observed for a higher supply of specialists in the region. They did not find any relationship between overall physician supply and the stage at diagnosis. Similar results were obtained by Ferrante et al. (2000) concerning early detection of breast cancer using the same data. Last, Krishan et al. (1985) study the impact of a higher physician supply on the use of health services in rural Minnesota over a five year period using t-tests and find a positive correlation. The authors evaluate the changes in the use of physician services following the establishment of a Mayo clinic health facility in the area, which staffed two physicians (an additional physician was added to the manpower in the studied area). Although an increase in the number of physician visits was observed, the larger part of this increase came from visits to an established physician rather than visits to the new practitioner.

There are also a number of studies that look at the effect of being treated by a specialist instead of a generalist for some acute health problems. In a study by Nash et al. (1997), treatment by a cardiologist, rather than by an internist or family practitioner, was shown to lower the risk of mortality for patients with an acute myocardial infarction, as well as to shorten the length of the patient's hospital stay. In a similar study of Medicare patients

(individuals over 65 years old) with acute myocardial infarction, Jollis et al. (1996) studied the impact of admission by a cardiologist on the one-year survival rate of the patients. They found that patients who were admitted by a cardiologist were 12% less likely to die within the following twelve months than were patients who had been admitted by a primary care physician. There were differences between the categories of patients admitted by a cardiologist and the ones admitted by a primary care practitioner: the cardiologists' patients were on average two years younger and less likely to be women. Compared to patients admitted by cardiologists, the ones admitted by primary care physicians had lower predicted 30-day mortality. The results showed care by a cardiologist to be associated with the use of more resources in the course of treatment of these patients. Greenfield et al. (1995), using an ANOVA model to study outcomes of patients with hypertension and non-insulindependent diabetes mellitus, found no differences in outcomes of patients at the two-year and four-year follow-ups, except for patients with non-insulin-dependent diabetes mellitus with foot ulcer and infection, who seemed to have better outcomes when followed by an endocrinologist. No statistically significant differences in mortality at the seven-years followup were observed with respect to physician specialties. Drummond et al (1990) studied the difference in treatments by generalists and specialists of problem drinkers using results from a randomized controlled trial of 40 individuals. No statistically significant difference in the outcomes of the two groups was found.

Last, Ayanian et al (1997) studied the difference in treatment and outcomes, measured as mortality at a 30 day and a one year follow-ups, of being treated by a cardiologist versus a generalist physician for Medicare patients admitted to a hospital with acute myocardial infarction in Texas. Cardiologists were more likely to use coronary angiography and angioplasty than generalist but 1-year mortality rates between the two groups of patients were similar. The authors confirm that one of the limitations of this study is that it is not a randomized controlled trial, but an observational study. This limitation also applies to most studies reviewed here, as well as to ours.

#### 2.2 Limitations of the methods used in the literature

Previous studies have used data from the United States where many individuals, other than seniors or the poor, must pay for physician and hospital services out of pocket or through a private insurance plan. Hence, access to a physician might be constrained not just by the supply of physicians in the area, but also by the individual's income. Furthermore, Health Maintenance Organizations (HMOs) may restrain access to care of their members to keep costs down, e.g., by hiring fewer specialists. Roetzheim et al. (2000) estimated their model separately for individuals who were covered by an HMO and for other types of insurance coverage. However, they state their sample sizes were too small to reach strong conclusions regarding the effect of the different insurance plans on the access to services of patients. Hence, it was difficult to isolate the effect of physician supply per se on health outcomes. The universal nature of the public health insurance system in Canada should make it easier to estimate this supply effect.

Most previous studies have not been able to control for socioeconomic status at the level of the individual or family. Instead, they typically used the average of the variables over a geographic unit, e.g., the average level of education in the county. The actual socioeconomic status of the individual is clearly preferred not only to improve estimation precision.

Some studies report that it was difficult to distinguish between the physician that admitted the patient to the hospital and the physician who was responsible for treatment decisions. For example, the patient may have been admitted by a primary care physician, but a specialist may have made most decisions with respect to diagnosis and treatment. Some of the studies that we reviewed report that there might have been errors in some cases. As we look at the effect of physician supply in a province on the health of individuals in general, regardless of where the obtained health care and whether it was from a general practitioner or a specialist, these problems do not apply to our study.

Lastly, most of these studies, unlike this paper, did not use measures of the individual's overall health status, but rather measures of the specific outcomes (mortality rates, complications, stage at diagnosis, etc.) following an acute health problem (myocardial infarction, cancer, etc.). Moreover, none of these studies measured the impact of physician supply on

the health of individuals that were in relatively good health, i.e., were not diagnosed with a chronic or acute condition. Physicians could potentially provide preventive services to these individuals.

## 3 Research Strategy

#### 3.1 The Data

#### 3.1.1 The NPHS Data

We use data from the National Population Health Survey (NPHS) as well as data from the Canadian Institute for Health Information (CIHI). The data available from CIHI provides the number of doctors who worked in each of the ten provinces by specialty from 1980 to 2000.

The NPHS is a survey of approximately 15000 households conducted in Canada by Statistics Canada. The first cycle was in 1994-1995 and three subsequent waves of interviews have been used, every other year up to 2000-2001. Limited information was collected from all household members. One individual aged 12 and over was randomly selected in the household to answer questions about her or his health status, health problems and use of services provided by the health care sector (www.statcan.ca/english/sdds/3225.htm). The households were chosen from a sample drawn for the Labour Force Survey in all provinces but Quebec, for which the sample was drawn from the Enquête sociale de la santé, conducted in 1992-1993. The sample covers all 10 provinces but excludes the population residing on Indian Reserves, Canadian Forces Bases and in some remote areas in Quebec and Ontario. The data enables one to control for inter-provincial migration after the start of the survey but not before. One is able to control for international migration prior to the start of the survey, in that the data indicate when an individual moved to Canada and from which country.

The NPHS data enable one to control at the individual level for lifestyle factors, such

as smoking and drinking, as well as socioeconomic and demographic characteristics, such as education, income, marital status, etc. Moreover, the NPHS covers the post-1994 period during which the cutbacks in federal transfers for health care occurred. The NPHS is a panel, which enables us to observe the individuals' trajectories and changes in health status from the beginning of the federal transfer cutbacks in 1994 up through 2001.

The two principal measures of overall health that we use are the self-assessed health status variable and the Health Utility Index (HUI). Self-assessed health status (excellent, very good, good, fair or poor) is subjective since two individuals may rate the same objective health status differently. The literature shows, however, that self-assessed health status is highly correlated with other measures of health status (Gerdtham et al., 1999, cited in Crossley et al., 2002). The HUI differs from the self-assessed health status measure in several ways. First the HUI is based on reports of attributes such as vision, speech and hearing which may not be taken into account in the self-assessed health variable. Second, the HUI explicitly incorporates inter-personal utility comparisons. Our analysis of the data shows that these two measures of health status tend to measure health status according to different criteria. For example, an individual who needs glasses to recognize somebody on the other side of the street would not have a HUI score of perfect health (1.0) but could rate her own health as excellent. We think both of these measures have merits and use them both. The NPHS is, as far as we know, the best source of Canadian data for these types of health outcome measures.

We also use the available information on chronic conditions. What is of particular use is any observed changes in chronic conditions between waves of the NPHS that could be used to signal an improvement or deterioration in health status.

There are often only a small number of individuals diagnosed with a specific chronic condition in the survey. Hence, we merge together groups of individuals who have different chronic conditions and who use services from different specialists. This empirical strategy assumes that the effect of specialist x on the health status of an individual with chronic condition a is the same as the effect of specialist y on the health status of an individual with chronic condition b. The impact of such aggregation is unclear. We control for the supply of specialists in the model, regardless of their specialty. The reason for this being that while

an individual goes to a specialist relevant to his health problem, this specialist might discuss the case with a specialist from another discipline, either connected to the case at hand, or not (for example if the physician practices in a region where there is a relatively low supply of physicians). This assumption also simplifies the analysis.

Endogeneity between the number and type of physicians and health status of the individuals in a province is theoretically possible. Physicians may go to the provinces where there is the highest need for their services, e.g., psychiatrists could decide to move to the provinces with the highest number of psychiatric patients. However, public policy so far has been geared towards enticing physicians to choose to practice in areas where there are relatively few physicians per capita, not where there are relatively many health problems per capita. Furthermore, these public policies have focused on intra-provincial physician migration and not inter-provincial migration. We test for potential endogeneity using the Smith-Blundell test of exogeneity for probit regressions.

Our sample includes all individuals who were at least 18 years old at the time of the first interview and who did not die, were not institutionalized and were still part of the sample at the end of the period (2000). It includes all individuals who answered to the health questionnaire of the NPHS. Characteristics of the sample are shown in Table A-1-A.

The CIHI data only report the number of generalists and specialists per province. Hence, we are not able to control for differences in access within a province, but only for differences in access between provinces. We are able to control for whether the individuals reside in an urban or rural area, a factor that could have an effect on both health status and on access to health services provided by physicians.

We can look at the progression of per capita physician supply over the same period in Figures 1 and 2. Trends in the supply of general practitioners are shown in figure 1, while the evolution of the supply of specialists is displayed in Figure 2.

### 3.2 Model and estimation strategy

#### 3.2.1 The Grossman model

The Grossman model (1972) is the best-known model in the health production literature. It supposes that an individual maximizes her inter-temporal utility function subject to the fact that if her health stock (or health status) falls below a certain level, she will die. The individual can either invest in her health status or in the composite good. The maximization problem is such that for the  $i^{th}$  period:

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U = U(\phi_0 H_0, \dots, \phi_n H_n, Z_0, \dots, Z_n), the utility function (3.2.1)

H_{i+1} - H_i = I_i - \delta_i H_i, the health accumulation equation (3.2.2)

I_i = I_i(M_i, TH_i; E_i), the investment in health equation (3.2.3)

Z_i = Z_i(X_{i,i}; E_i), the investment in the composite good equation (3.2.4)

Subject to TW_i + TL_i + TH_i + T_i = \Omega, the time constraint (3.2.5)
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Where  $H_0$  is the inherited stock of health,  $H_i$ , is the stock of health in the  $i^{th}$  period,  $\phi_i H_i$  is the consumption of health services,  $Z_i$  is the consumption of the composite good,  $I_i$  is the investment in health,  $M_i$  is medical care,  $E_i$  is education,  $X_i$  is the input needed for the production of the composite good,  $TH_i$ , is the time spent on health production (either on preventive measures, such as exercising, or when getting health care),  $TL_i$  is the time lost due to illness,  $TW_i$  is time worked,  $T_i$ , is the time spent on producing  $Z_i$  (and leisure).

We use a variation of the Grossman model to estimate how health care services, through physician supply, have an effect on health status:  $M_i$  has an effect on  $I_i$  which itself impacts on  $H_i$ . This analysis supposes that physician supply has an effect on access to physician services.

To test that this model applies, we tried to establish, using fixed effects negative binomial regressions and fixed effects logits respectively, if there was a relationship between physician supply per capita and the number of times (number of consultations) the individual saw a general practitioner, a specialist, and on whether he had a regular physician. As we can see in Table A-2, physician supply has a statistically significant effect on whether an individual

has access to physician services. The number of specialists per capita has a significant effect on the number of visits to a specialist during the previous year. The number of general practitioners also has a positive statistically significant effect on health status. We also use the supply of specialists and general practitioners per capita as regressors in a fixed effects logit regression to establish if physician supply has an effect on the likelihood of an individual to have a regular physician. We find that a higher per capita specialist supply has a positive and statistically significant effect in this regression but that the supply of general practitioners has no statistically significant impact.

We estimate a simplified version of the Grossman model in our research to estimate what is the impact of physician supply, through  $M_i$ , on health status,  $H_i$ .

#### 3.2.2 The model

The NPHS is a panel, which will enable us to estimate both fixed effects models and random effects models. Consider the following specification for the determinants of health status of the  $i^{th}$  individual in the  $t^{th}$  time period.

$$Y_{it} = \alpha_i + X_{it}\beta + u_{it}. \tag{1}$$

The random effects specification assumes that unobserved  $\alpha_i$  is not correlated with the observed  $X_{it}$  (explanatory variables).

In our model,

$$Y_{it} = \alpha_i + X_{it}\beta + MD_{it}\gamma + u_{it}. \tag{2}$$

where the  $X_{it}$  variables control for socioeconomic and demographic effects (age, gender, education, income, etc.) which are well known health determinants. The physicians' variables will measure the supply of physicians, both specialists and general practitioners. The

 $MD_{it}$  variable controls for the number of specialists and the number of general practitioners. As the effect physicians' visits might have on health are much more "short term" than the supply of other services might be (e.g. by comparison, expenditures on an MRI might still have an effect on the health of patients in a province numerous years after the expenditure occurred), we limit this length of time to two years. Therefore, in our model, the supply of physicians today will have an effect on the health of individuals two years from now, but not afterwards.

We estimate ordered probit regressions (for ordered polychotomous, or categorical, dependent variables) when using the self-assessed health status variable, and we estimate quantile regressions when using the HUI.

We study how physician supply impacts on the likelihood of an individual to be diagnosed with a chronic condition using fixed effects logit regressions. We also analyze separately those individuals who do not have a chronic condition during any of the four waves and look at whether the per capita number of generalists and specialists in the province has an impact on their health status. Previous studies have looked at the effect of physician supply on early stage diagnosis of different cancers and on mortality rates, but we were not able to find studies reporting on the effect of physician supply on general health or on the likelihood of recovery. In the case of chronic conditions, it also is important to control for the total number of doctors (per capita) in the province. A greater density of physicians per se may lead to improved care for chronic conditions via better sharing of information and professional training.

The effect of an increased supply of physicians on chronic conditions may be twofold. A large supply of physicians could mean not only better access to health care treatment but also more accurate and timely diagnosis of chronic conditions. The NPHS questionnaire specifies that a chronic condition reported by the individual should have been diagnosed by a physician. We might therefore observe that provinces with more physicians have more individuals with chronic conditions due to better access to diagnostic services. Hence, particular care will have to be taken in making inferences from our analysis of the coefficients related to the dummy controlling for the presence of chronic conditions.

We control for gender, the default is male, and whether the individual is an immigrant

(Marmot, 1975 and Marmot and Syme, 1976). We also control for age, through dummy variables, for age 40 to 59, age 60 to 79 and 80 years old and over, in the random effects ordered probits and the quantile regressions, the default is being between the ages of 18 and 39. We expect the individuals to have reported their health status as compared to other individuals who are the same age and expect older individuals to display worse health status as measured by the health utility index and self-assessed health status variables (the distribution of both variables by age categories shows older individuals tend to report worse health status). We control for the marital status of individuals, the default is being single, as well as use interaction terms between gender and marital status. We control for whether the individual lives in a rural area: this could control for better access to health care services of individuals who live in an urban area or for worse environment when living in either an urban area (e.g. exposure to lead, Hertzman, 1994), or a rural one (exposure to pesticides, water quality, etc.). We also control for the logarithm of the size of the household, as a proxy for social interaction (Stoddart, 1995 and McEwen, 1998) which are shown in the literature to be negatively associated with mortality rates and to control for per capita income in the household.

We control for whether the individual owns his dwelling, which might capture a wealth effect. We control for income, using dummies for less than \$20000, \$40000 to \$59999, \$60000 to \$79999 and over \$80000 a year, the default being an income between \$20000 and \$39999 per year. We expect higher categories of income to lead to better health status but this income-health relationship goes both ways. Individuals who are in better health are more likely to work full time and to be able to keep their jobs and are, therefore, more likely to earn higher levels of income. We control for education (Hertzman, 1994) using dummies for less than high school, some post-secondary education and an undergraduate degree or better, the default being high school graduation, in the random effects ordered probits and the quantile regressions. We also control for whether the individual is a smoker and whether he binge drinks (defined as having five drinks or more on one occasion on a monthly basis or more frequently). We also control for the province in which the individual lives, the default being Ontario. Lastly, we control for health status in the preceding period, using dummies controlling for the different levels of self-assessed health in the previous period (the default being very good health) for random effects ordered probits, and the HUI in the preceding period for quantile regressions

## 4 Results

## 4.1 Test of Endogeneity

We used different measures of health status: we dichotomized the self-rated variables into its 5 corresponding dummies (excellent, very good, good, fair and poor health) and created merged categories of health statuses (such as excellent or very good health which was coded as 1 if the individual reported either excellent or very good health in a given cycle). As the Smith-Blundell<sup>1</sup> tests rejected exogeneity at least some of the time, particularly when using excellent health, poor health and excellent or very good health merged together as the dependent variables, we decided to lag the effect of physician supply by one period (two years) and to use the average supply of physician during the two year before the survey. For example, when looking at the health of an individual in cycle 1 (1994-1995) we control for the average supply of specialists and generalists in 1992 and 1993. Although physician supply two years ago can still have an effect on health status today, the reverse is not true. The variables controlling for past supply of physicians, both generalists and specialists, are highly correlated and we therefore think that past supply of physicians is a good indicator of present supply of physicians. Moreover, adding the lagged health variable contributes to lessen the potential for endogeneity: lagged health is an instrument of the effect of past physician supply on health status. As present health might determine present physician demand (and supply), past health can do the same for past physician demand and supply, while present health can be determined by past health but the opposite effect does not exist.

In most regressions, we observe the expected signs for the health determinants for which we control. Smoking and binge drinking are correlated with worse health outcomes when statistically significant. Education has the expected sign; less than a high school degree is correlated with worse reported health and having a bachelor degree is correlated with better health outcomes. When an individual owns his dwelling, he usually reports better

<sup>&</sup>lt;sup>1</sup>The Smith-Blundell test of exogeneity works in a similar manner to the Hausman test and is used for dichotomous dependent variables. One must use instrumental variables for the potentially endogenous variables, in our case lags up to 10 years of general practitioners supply per capita and of specialists per capita.

health status. Income has the expected sign (higher income is correlated with better health outcomes). Being married or widowed is usually correlated with better health outcomes for women, while the effects are not as consistent for men. Being older is correlated with worse health outcomes for both genders. Being an immigrant, when statistically significant, is correlated with worse health outcomes. To save space, we have not reported all of the coefficients in the main tables, but sample of the coefficients obtained can be seen in table A-3.

### 4.2 Random Effects ordered probits

As we can see in table 1, the number of specialists per capita has a negative effect on selfreported health while the number of per capita general practitioners has a positive effect, with coefficients of -0.74 and 0.49 respectively. These coefficients are statistically significant at the 1 and 5% level of confidence respectively<sup>2</sup>. The interaction terms between having a chronic condition and the number of specialists and generalists do not have a statistically significant effect here but the interaction term between the supply of general practitioners and being between the ages of 60 and 79 has a positive effect, with a coefficient of 0.72 significant at the 1% level of confidence, while the interaction term between the supply of specialists and being between the ages of 40 and 59 has a smaller, in terms of absolute value, effect, with a coefficient of -0.22 significant at the 5% level. Living in any province other than Quebec has a significant effect at the 1% level of confidence on health status in this regression, compared to living in Ontario, with coefficients ranging between -0.14 (Nova Scotia) and -0.43 (Saskatchewan). All four dummies controlling for lagged health status have a statistically significant effect on present health and the coefficients are higher and positive for better health statuses (0.60 for excellent health) and negative and progressively bigger for worse health statuses (-0.51 for good health, -1.21 for fair health and -1.98 for poor health).

<sup>&</sup>lt;sup>2</sup>Note that the results for the random effects ordered probits could not be bootstrapped using the method by Yeo, 1999. The command in Stata does not support weights and the models are too computationally intensive to make using the 500 replications of bootstraps suggested impossible in practice. In regressions where bootstrap weights can be used, such as the quantile regressions, we observe that the standard errors obtained in the bootstrapped regressions are consistently higher and that many of the variables that were evaluated to have a statistically significant impact in the non-bootstrapped regressions have no statistically significant impact in their bootstrapped counterparts. Bootstrapped standard errors are larger than standard-errors that allow for Moulton's correction (Moulton, 1990)

All of these health dummies are statistically significant at the 1% level of confidence.

## 4.3 Quantile Regressions

In all three quantile regressions, in Table 2, controlling for lagged health status through lagged HUI, the variables controlling for physician supply are statistically significant: the per capita supply of specialists in the province has a negative coefficient varying between -0.10 and -0.04, significant at the 10% or 5% level of confidence<sup>3</sup>. The per capita number of general practitioners in the province is statistically significant at the 1% level of confidence when using any of the three percentiles and has a positive coefficient varying between 0.06 and 0.32, significant at the 1% level of confidence. The dummies controlling for the presence of a chronic condition have a statistically significant effect in the quantile regressions and the effects are negative, varying between -0.05 and -0.15 and significant at the 5% level of confidence or better, while none of the interaction terms involving this dummy have a statistically significant impact. The only interaction term between age categories and physician supply that is statistically significant is in the 20th percentile regressions: the interaction term between being between the ages of 60 and 79 and the supply of specialists in a province has a positive coefficient of 0.05 statistically significant at the 10% level of confidence. The HUI in the previous period is statistically significant in all three regressions with coefficients ranging from 0.78 to 0.93, all significant at the 1% level of confidence. The few dummies controlling for the province of residence that are statistically significant in the regressions (Nova Scotia, New Brunswick, Manitoba, Saskatchewan, Alberta and British Columbia) all have negative and statistically significant coefficients at the 10% level of confidence or better.

One must note that these regressions are not panel regressions such as the random effects regressions presented earlier in the paper. Individuals who appear in all four waves are treated here as four different observations. The software used did not enable us to count them as one person or as "clusters" of observations which might have things in common.

<sup>&</sup>lt;sup>3</sup>Note that the standard errors are bootstrapped using the method recommended by Yeo, 1999 and the program bswreg written by Pierard, Buckley and Chowhan (2004)

# 4.4 Sub-Sample: Individuals who do not report a chronic condition

We were not able to reject the exogeneity of the physician supply variables in the sample including only individuals who do not have a chronic condition. However, we use the same model as in the larger sample because we wanted to enable comparison between the results. Characteristics of our sub-sample are in table A-1-B.

Although we took care of only eliminating individuals who did not report a chronic condition in the first two cycles, we have a lot less individuals in our sub-sample than just the total size of the sample minus the percentage of individuals who report having a chronic condition in any given cycle. The reason for this is that some individuals go back and forth between having a chronic condition and not reporting one. Although it may be understandable for some conditions, such as cataracts, this does not apply to all conditions for which survey participants are asked about. To ensure that we would not include individuals who may have been heavy users of the health care system, we've decided to not include anybody who reported a chronic condition to later retract themselves and this is why we use such a small sample in our estimations.

#### 4.4.1 Random Effects ordered probits

Going back to table 1, all of the dummies controlling for the health status reported in the previous period display comparable coefficients to the ones obtained when using the larger sample. However none of the physician-supply related variables have a statistically significant impact on self-reported health. The only dummies controlling for the province in which the individuals are living in that are statistically significant are New Brunswick, Manitoba, Saskatchewan and British Columbia, again with negative effect on reported health. These dummies are here only statistically significant at the 5% and 10% level.

#### 4.4.2 Quantile Regressions

In table 3, for the  $20^{th}$  and  $10^{th}$  percentile regressions, the per capita supply of general practitioners is associated with higher HUIs, with coefficients of 0.11 and 0.20 respectively. None of the coefficients corresponding to the supply of specialists are statistically significant and none of the interaction terms are statistically significant. The only dummies controlling for the province of residence of the individuals that are significant in both the  $20^{th}$  and  $10^{th}$  percentile regressions are the ones controlling for the fact that individuals are living in Saskatchewan or in British Columbia: the coefficients are negative but small (-0.03 and -0.08 for Saskatchewan and -0.02 and -0.05 for British Columbia). Lagged health status (the HUI in the preceding period) is the only variable that is statistically significant in the  $30^{th}$  percentile regression: it has a coefficient of 0.39, which is rather low. The value of the coefficient related to this variable is also low in the other regressions, compared to their counterparts using the whole sample.

## 4.5 The likelihood of developing a chronic condition

We also ran regressions to study the effect of physician supply on the likelihood of developing a chronic condition and having it diagnosed by a physician, using fixed effects logit regressions. The results for physician related variables can be found in table 4. Variables pertaining to physician supply and province have no effect on the likelihood of having a diagnosed chronic condition. Controlling for health status in the preceding period has no effect on the likelihood of developing a chronic condition either. Age, especially age squared, has a statistically significant effect on the likelihood of developing a chronic condition. As one would expect, the effect is higher for older individuals. Smoking is also positively related to the likelihood of developing a chronic condition, with coefficients varying between 0.18 and 0.28. A larger household lowers the likelihood of having a chronic condition, at 10% level of statistical significance.

## 5 Discussion

Overall, physician supply-related variables have more of an impact on the health of individuals in the larger sample (including individuals who have a chronic condition at the beginning of the survey). This effect tends to be negative when we look at the per capita supply of specialists and positive in the case of per capita supply of general practitioners. This is the case for both self-assessed health status (in the random effects ordered probits) and the Health Utility Index (in the quantile regressions). There is no constant effect of the interaction terms between age, having a diagnosed chronic condition and physician supply across regressions. The results concerning the variables controlling for the supply of generalists and specialists by themselves (not in interaction with age dummies or the dummy controlling for the presence of a diagnosed chronic condition) confirm what Rotzheim et al. (1999) and Ferrante at al. (2000) had found.

When looking at the results obtained using the quantile regressions, we can see that the effects of physician-related variables seem to be more important for individuals in worse health (the lower quantiles). The size of the coefficient of the variable controlling for per capita supply of specialists becomes larger (in absolute value) and remains negative. This would mean that a higher supply of specialists per capita has a worse effect (negative) on the health status of these individuals, who are already in a bad state of health. However, the size of the coefficient of the variable controlling for the per capita supply of general practitioners also becomes larger across quantiles and increases three-fold between the  $20^{th}$  percentile and the  $10^{th}$ .

The positive effect on health of a higher supply of general practitioners could come from the fact that individuals who are able to see a physician every year for a physical (or have an easy access to physician services when they have small health concerns) benefit from these interactions, and these effects are measured by a higher general state of health. This effect is measured both by our objective measure (the HUI) and in the one which could be deemed as less objective (self-assessed health).

The negative coefficient associated to a higher supply of specialists might come from

the fact that in provinces where more individuals experience health problems requiring the attention and care of a specialist, a higher supply of physicians only means that more individuals get the appropriate care and diagnosis. In the case where these health problems have no cure and for which treatment can only alleviate some of the symptoms, there would likely not be an effect of these treatments on health status. A higher supply of specialists in a province might come from a higher demand for their services. Although these services might be necessary, they might not have an impact on health status per se, as measured in this study.

Another explanation for the negative coefficient associated with the per capita supply of specialists could be related to supplier-induced demand: the negative coefficient associated with a higher supply of specialists could mean that when a specialist faces too much competition from colleagues, he might order more procedures, which could be harmful to health status according to our results, to maintain their desired income.

Lagged health is across regressions the best predictor of present health status, among the variables related to health. The coefficients that correspond to the dummies controlling for the different levels of health status in the preceding period are all statistically significant in the random effects ordered probits and they are among the variables which have the largest effect on health status. In the quantile regressions, the HUI in the preceding period is the variable that displays the largest coefficients. This shows that among the factors we control for, the past stock of health is the best predictor of future health. Health care services (here physician supply) do have an effect on health status, both through physician supply and through the effect past health services had on past health status, according to Grossman's model.

Our methodology does not enable us to control for the number of health services provided to the population by each physician (physician practice style), or how much physicians make per service provided (the provincial fee schedule). We are not able to control for changes to provincial fee schedules, but doubt these would have a large impact: if a province paid its physician much more for the same services, new physicians would likely flood this new market, the same way physicians are currently leaving Canada to practice in the US where work conditions are better and salaries are higher. Some might argue that physician practice style

is influenced by the fee schedule: physicians might order more non-threatening procedures (such as non-invasive tests) if they are paid high fees when they order such procedures. We are not able to control for this factor, whether it would have a positive (from reassurance) or negative (from the procedure) effect on the health of individuals, in this work. We are not able to control for differences in practice-style that might come from differences in the education of physicians across provinces either. For example, some medical schools might advocate for a more aggressive treatment for cancer than medical schools in other provinces, and therefore, cancer patients in one province could fare better than their counterparts in another province. If medical school students have a tendency to stay and practice in the province where they did their medical training, we might observe differences in outcomes of patients across provinces but we are not able to control for these potential differences in physicians' practice style directly.

We are however controlling for provincial fixed effects, using dummies for each province. Although we did not observe a constant pattern across all regressions, we can see that all dummies display negative coefficients when statistically significant. This would suggest that patients in Ontario tend to do overall better than their counterparts in other provinces. These dummies might capture the effect of some variables we do not control for such as other provincial programs (e.g. welfare, education, other measures of health care). They might also help control indirectly for some of the factors we mentioned earlier (e.g. physician practice style). on the health of an individual given a specific health problem.

We are able to study the impact of physician supply on the health status of individuals who do not have a chronic condition. We observe that physician related variables have less of an impact on the health of these individuals. In the random-effects ordered probits, none of the physician-related variables have a statistically significant impact at the 5% level of confidence or better. However, in the quantile regressions, using the HUI as a dependent variable, the supply of general practitioners has a positive effect on health status in the lower  $(10^{th}$  and  $20^{th})$  percentiles. The effect of this variable in the  $10^{th}$  percentile regression was smaller than when using the larger sample including individuals who have a diagnosed chronic condition. This confirms what intuition would suggest: people in worse health benefit more from a better access to health care than healthy people do.

We also tried estimating the effect of physician supply on the likelihood of having a diagnosed chronic condition. We find physician supply has no effect on this variable. This could mean that the effect of physician supply on health status we see in other regressions comes from the effect treatment and services offered have on health status, and not from the effect the diagnosis of health problem could have on health status.

Some of our results are also dependent on the model used. For example, when looking at coefficients of the variables of interest in our quantile regressions without a control for past health, we note that all coefficients have the opposite sign than in the regressions controlling for lagged health status. This is not observed in random effects regressions, where coefficients have the same sign whether we control for lagged health status or not. The size of the coefficients tends to be larger when not using past health status as a regressors in all cases. We think the reason we observe this in the quantile regressions might be that when we are controlling for lagged health status, we are seeing the effect of physician supply, province of origin, etc. on a change in health status rather than on health status itself. However, controlling for lagged health status enables us to lessen the potential for endogeneity. The results for the quantile regressions not controlling for lagged health status can be seen in Appendix A-5-A and A-5-B. Results of random effects ordered probit regressions not controlling for lagged health status can be found in tables A-4.

Last, we cannot control for the fact that there might be some double-counting of physicians in the data. It might be possible for a physician, especially in the Maritimes as the provinces are very close together, to practice in a province, cross a boarder and work more hours in another province. Physicians can earn more income by working in both a hospital setting and in another practice and billing two different provincial governments. We hope only a minority of physicians share their time between provinces and that the effect is not large in our study.

### 6 Conclusion

We examined the effect physician supply could have on measures of health status of Canadians. Using data from the NPHS and CIHI, we performed random effects ordered probits on the self-assessed health variables and quantile regressions when using the HUI. To minimize the effect of the potential endogeneity, we lag the effect of physician supply by one year and hypothesize that the effects lasts for two years. Our model assumes that the lagged health status variable (defined as the HUI in the preceding period in the quantile regressions and as dummies controlling for excellent, good, fair and poor health in the regressions using self-assessed health) controls partly for services rendered by physicians in the preceding periods.

Even after controlling for endogeneity through the lagging of the effect of physician supply, as some endogeneity might remain, we used two samples. We first run regressions on the sample of all individuals who were not lost over the period of the survey (either through death, institutionalization or partial response to the questionnaire) and we repeat the analysis on the sub-sample of individuals who were not diagnosed with a chronic condition before 1994 or over the course of the survey. As some individuals might have developed symptoms needing treatment prior to the diagnosis of a chronic health problem, and that these symptoms might have required visits to a physician, we cannot be sure that all of the endogeneity was removed by the lagging of the effect of physician supply in the larger sample.

The per capita supply of general practitioners is associated with better health outcomes in most regressions using the larger sample. A higher per capita supply of specialists is associated with worse health outcomes in all regressions using the larger sample. When using the reduced sample, only expenditures on general practitioners remain statistically significant in the quantile regressions. Although the HUI and self-assessed health measure different aspects of health status, our results were similar across estimation methods. We do not observe an effect of physician supply on the likelihood of having a diagnosed chronic condition.

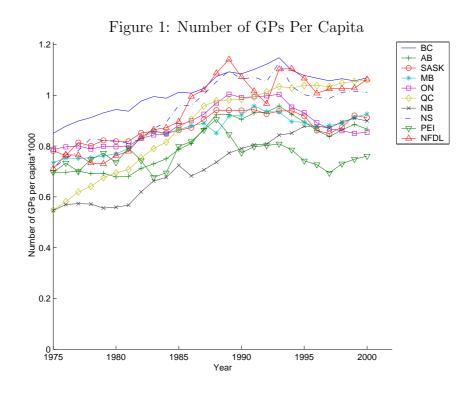
We simultaneously controlled for provincial characteristics in our estimations by using

dummies for the province of residence over the course of the survey. Although none of the dummies had consistent patterns over all estimations of the model, it seems that Ontarians are on average better off than their counterparts living in some of the other provinces.

There are a number of potentially interesting avenues at the end of this work. We could use dynamic modelling to explore how both past and present physician supply affect health status, both past and present. It might also be interesting to use a wider cross-section of the population and to investigate how different physician specialties have an effect on the health status of individuals living with various health problems. Adding data on hospital beds occupancy to our data might also help shed light on some of these results.

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 $<sup>^4</sup>$ For all Tables: Standard errors are in parenthesis; \* means statistically significant at the 10% confidence level \*\*\* means statistically significant at the 1% confidence level In the random effect ordered probits, the second column of stars represents group significance (same rating system)



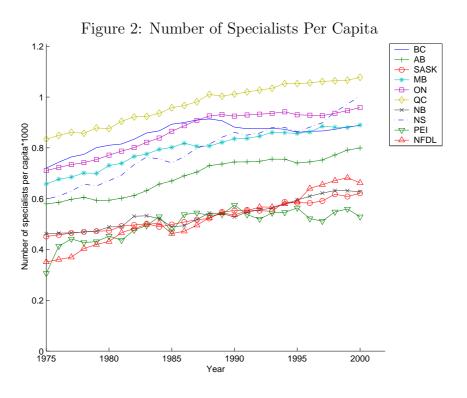


Table 1 Random effects ordered probits

Table 1 R	andom eff					
		e Samp			Samp	le
GPs per capita	0.490	**	***	0.652		
	(0.250)			(0.461)		
Specialists per capita	-0.735	***	***	-0.422		
	(0.200)			(0.385)		
Newfoundland	-0.290	***	***	-0.199		***
	0.075			(0.152)		
Prince Edward	-0.275	***	***	-0.019		***
Island	(0.079)			(0.166)		
Nova Scotia	-0.136	***	***	-0.088		***
1,0,44 500014	(0.039)			(0.091)		
New Brunswick	-0.412	***	***	-0.270	**	***
TVCW Drunswick	(0.067)			(0.137)		
Quebee	0.062		***	-0.012		***
Quebec	1					
7. f	(0.041)	***	***	(0.086)	**	***
Manitoba	-0.164	444	444	-0.147	4.4.	444
	(0.031)	-testeste	-1tt-	(0.069)	-ti-t-	de de de
Saskatchewan	-0.429	***	***	-0.354	**	***
	(0.070)			(0.142)		
Alberta	-0.205	***	***	-0.124		***
	(0.041)			(0.089)		
British Columbia	-0.214	***	***	-0.182	*	***
	(0.048)			(0.102)		
GPs per capita	0.260		***	0.337		
x Age 40-60 years old	(0.189)			(0.381)		
GPs per capita	0.715	***	***	-0.237		
x Age 60-80 years old	(0.220)			(0.624)		
GPs per capita	-0.068		***	0.313		
x Age 80 + years old	(0.396)			(1.790)		
Specialists per capita	-0.222	**	***	-0.018		
x Age 40-60 years old	(0.107)			(0.209)		
Specialists per capita	-0.194		***	0.104		
* * *						
x Age 60-80 years old	(0.124)		***	(0.330) $-0.342$		
Specialists per capita	-0.363					
x Age 80 + years old	(0.232)			(1.194)		
Chronic Condition	-0.129					
	(0.143)		-trate			
GPs per capita	-0.185		**			
x Chronic Condition	(0.174)					
Specialists per capita	-0.160		**			
x Chronic Condition	(0.098)					
Lagged Health	0.595	***	***	0.731	***	***
(Excellent)	(0.025)			(0.042)		
Lagged Health	-0.512	***	***	-0.406	***	***
(Good)	(0.023)			(0.049)		
Lagged Health	-1.211	***	***	-0.940	***	***
(Fair)	(0.036)			(0.126)		
Lagged Health	-1.981	***	***	-2.183	***	***
(Poor)	(0.062)			(0.621)		
Cut Point 1	-3.723	***		-3.249	***	***
Cut Foint 1	1	•			•	•
Ct D.:t 0	(0.264)	***		(0.524)	***	
Cut Point 2	-2.552			<b>28</b> .085		
<u> </u>	(0.262)	داد بله بل		(0.507)		
Cut Point 3	-1.248	***		-0.704		
	(0.260)			(0.504)		
				0.004		
Cut Point 4	0.158			0.684		
Cut Point 4				(0.503)		
Cut Point 4	0.158					

 $\begin{tabular}{ll} Table 2 \\ Quantile \ regressions - Whole \ sample \\ \end{tabular}$ 

	30th percentile		10th percentile
GPs per capita	0.064 ***	_	0.317 ***
GIS per capita	(0.019)	(0.030)	(0.072)
Specialists per capita	-0.036 **		-0.098 *
Specialists per capita	(0.016)	(0.026)	(0.057)
Newfoundland	-0.014 **	/	-0.059 ***
rewioundiand	(0.006)	(0.010)	(0.022)
Prince Edward	-0.002	-0.005	0.032
Island	(0.006)	(0.010)	(0.032)
Nova Scotia	-0.011 **	,	-0.019
Tiova Scotia	(0.005)	(0.009)	(0.019)
New Brunswick	-0.008 **	,	-0.051 ***
New Drunswick	(0.003)	(0.006)	(0.017)
Quebec	-0.005	-0.002	-0.015
Quebec	(0.003)	(0.005)	(0.013)
Manitoba	-0.007 **	,	-0.013
Maiiioba	(0.003)	(0.005)	(0.009)
Saskatchewan	-0.016 ***	,	-0.036 *
Saskatchewan	(0.006)	(0.010)	(0.021)
Alberta	-0.009 **	/	-0.022 *
Ameria	(0.004)	(0.006)	(0.012)
British Columbia	-0.016 ***	/	-0.068 ***
Diffish Columbia	(0.004)	(0.006)	(0.014)
GPs per capita	-0.018	-0.014	-0.027
x Age 40-60 years old	(0.014)	(0.031)	(0.073)
GPs per capita	0.045	0.041	0.100
x Age 60-80 years old	(0.045)	(0.050)	(0.133)
GPs per capita	-0.056	0.148	0.025
x Age 80 + years old	(0.181)	(0.199)	(0.334)
Specialists per capita	0.003	0.001	-0.016
x Age 40-60 years old	(0.007)	(0.015)	(0.034)
Specialists per capita	0.024	0.048 *	-0.015
x Age 60-80 years old	(0.021)	(0.027)	(0.064)
Specialists per capita	-0.191	-0.091	0.060
x Age 80 + years old	(0.128)	(0.108)	(0.177)
Chronic Condition	-0.046 **	/	-0.154 **
Cinomic Condition	(0.018)	(0.028)	(0.072)
Specialists per capita	-0.001	-0.016	0.053
x Chronic Condition	(0.011)	(0.017)	(0.042)
GPs per capita	0.028	0.041	0.032
x Chronic Condition	(0.020)	(0.032)	(0.087)
Lagged HUI	0.778 ***		0.935 ***
2005800 1101	(0.021)	(0.015)	(0.019)
Constant	0.186 ***	,	-0.205 **
Constant	(0.027)	(0.038)	(0.083)
	(0.041)	(0.000)	(0.000)

 ${\bf Table~3} \\ {\bf Quantile~regressions~-~Individuals~without~a~chronic~condition}$ 

Qualitile regressi	30th percentile	20th percentile	10th percentile
GPs per capita	0.030	0.113 **	0.203 **
or 5 per capita	(0.034)	(0.055)	(0.097)
Specialists per capita	-0.028	-0.068	-0.120
Specialists per capita	(0.024)	(0.044)	(0.087)
Newfoundland	-0.004	-0.024	-0.067 **
rowiodifatalia	(0.009)	(0.017)	(0.030)
Prince Edward	-0.006	-0.006	-0.020
Island	(0.011)	(0.020)	(0.039)
Nova Scotia	-0.006	-0.015	-0.027
11070 20010	(0.008)	(0.015)	(0.027)
New Brunswick	-0.003	-0.022 **	-0.023
Trow Brains Wien	(0.008)	(0.011)	(0.015)
Quebec	0.001	-0.006	-0.010
Questo et	(0.006)	(0.010)	(0.019)
Manitoba	-0.003	-0.005	0.002
	(0.006)	(0.008)	(0.013)
Saskatchewan	-0.017	-0.037 **	-0.083 **
	(0.011)	(0.017)	(0.035)
Alberta	-0.004	-0.010	-0.016
	(0.006)	(0.011)	(0.021)
British Columbia	-0.005	-0.024 **	-0.046 **
	(0.006)	(0.011)	(0.019)
GPs per capita	-0.016	0.016	0.070
x Age 40-60 years old	(0.026)	(0.052)	(0.093)
GPs per capita	0.061	0.018	-0.032
x Age 60-80 years old	(0.087)	(0.123)	(0.263)
GPs per capita	-0.054	-0.263	0.635
x Age 80 + years old	(0.394)	(0.499)	(0.602)
Specialists per capita	0.008	0.023	-0.004
x Age 40-60 years old	(0.014)	(0.028)	(0.054)
Specialists per capita	-0.050	0.000	0.054
x Age 60-80 years old	(0.045)	(0.067)	(0.107)
Specialists per capita	0.048	0.164	0.116
x Age 80 + years old	(0.215)	(0.299)	(0.324)
Lagged HUI	0.387 ***	0.475 ***	0.542 ***
	(0.044)	(0.048)	(0.074)
Constant	0.590 ***	0.442 ***	0.305 **
	(0.059)	(0.074)	(0.149)

 ${\bf Table}\ 4$  Likelihood of having a diagnosed chronic condition

Likelihood of having a		
GPs per capita	1.129	0.684
	(2.260)	(3.400)
Specialists per capita	-1.622	-1.448
	(2.180)	(2.953)
Newfoundland	-0.515	-0.806
	(0.511)	(0.756)
Prince Edward	0.062	-0.007
Island	(0.619)	(1.636)
Nova Scotia	0.226	-0.088
	(0.832)	(0.895)
New Brunswick	-0.022	0.198
	(0.567)	(0.721)
Quebec	-0.675	-0.644
	(0.516)	(1.737)
Manitoba	-1.410	-0.664
	(2.254)	(5.539)
Saskatchewan	-1.466	-3.133
	(0.901)	(15.880)
Alberta	-0.025	-0.948
	(0.427)	(0.826)
British Columbia	-0.011	0.080
	(0.491)	(0.931)
GPs per capita	-0.039	-0.030
x Age	(0.050)	(0.073)
Specialists per capita	0.051	0.034
x Age	(0.059)	(0.075)
Lagged Health		-0.016
(Excellent)		(0.094)
Lagged Health		0.100
(Very Good)		(0.089)
Lagged Health		0.012
(Fair)		(0.227)
Lagged Health		0.502
(Poor)		(0.536)

Table A-1-A: Characteristics of the whole sample

Table A-1-A: Characteristics of the whole sample								
Self-assessed Health		cle 1 %		ycle 2 %		cle 3 %		cle 4 %
Poor	151.96602	1.60	158.420	1.67	136.486	1.44	231.271	2.43
Fair	691.40839	7.27	676.632	7.12	710.311	7.47	931.634	9.80
Good	2,485.59	26.14	2576.481	27.10	2567.058	27.00	2717.794	28.59
Very Good	3,635.63	38.24	3789.411	39.86	3804.180	40.02	3607.700	37.95
Excellent	2,542.41	26.74	2306.057	24.26	2287.965	24.07	2016.600	21.21
Total	9507		9507		9506		9505	
		(s-dev)		(s-dev)		(s-dev)		(s-dev)
Mean HUI	0.875	0.2350	0.904	0.2099	0.892	0.2191	0.891	0.2301
Total	9444		9453		9457		9408	
% with a chronic Condition	56.28	0.68	62.72	0.66	63.57	0.64	66.08	0.62
Total	9498		9501		9502		9498	
% with a regular physician	86.48	0.446	86.93	0.501	86.94	0.446	88.36	0.414
Total	9506		9507		9506		9506	
Age	42.93	15.662	44.91	15.667	46.88	15.635	48.97	15.661
Total	9507		9507		9507		9507	
Education	Cy	vcle 1 %	Cy	vcle 2 %	Cy	vcle 3 %	Су	cle 4 %
Less than High School	2185.312	22.99	2062.610	21.70	2021.590	21.27	1984.515	20.88
High School Grad	1572.809	16.54	1470.409	15.47	1412.613	14.86	1375.672	14.47
Some post-secondary	4264.985	44.86	4446.370	46.77	4435.642	46.66	4434.534	46.65
University/Coll Grad	1483.894	15.61	1527.612	16.07	1636.155	17.21	1710.280	17.99
Total	9507		9507		9507		9507	
Income	Cy	cle 1 %	Cy	vcle 2 %	Су	rcle 3 %	Су	cle 4 %
0-19999	1628.311	17.03	1590.353	16.7	1332.909	13.97	1148.338	12.13
20k-39999	2451.120	25.63	2554.880	26.83	2385.286	24.99	1971.769	20.83
40k-59999	2473.005	25.86	2479.290	26.03	2113.051	22.14	1997.904	21.1
60k-79999	1266.373	13.24	1223.333	12.85	1503.210	15.75	1563.456	16.51
80k and over	1323.191	13.84	1137.144	11.94	1738.544	18.21	2138.533	22.58
Total	9507		9507		9507		9507	
Household smokes	Cy	cle 1 %	Cy	vcle 2 %	Су	cle 3 %	Су	cle 4 %
Yes	3504.198	36.87	3265.007	34.36	3019.503	31.78	2617.436	27.54
No	6000.802	63.13	6235.994	65.64	6480.497	68.22	6886.564	72.46
Total	9505		9501		9501		9506	
Individual Smokes	Cy	cle 1 %	Cy	vcle 2 %	Су	rcle 3 %	Су	cle 4 %
Yes	3005.893	31.62	2857.267	30.07	2692.946	28.34	2396.752	25.22
No	6499.107	68.38	6643.733	69.93	6807.054	71.65	7107.248	74.78
Total	9505		9501		9501		9506	
Individual Binge Drinks	Cy	vcle 1 %	Cy	vcle 2 %	Cy	vcle 3 %	Cy	cle 4 %
Yes	1158.734	12.33	1477.950	15.61	1407.750	14.88	1227.613	12.97
No	8237.266	87.67	7989.050	84.39	8055.250	85.12	8240.387	87.03
Total	9396		9467		9464		9469	
<u></u>								

Table A-1-B: Characteristics of the sample excluding individuals with a chronic condition

Self-assessed Health	cycle 1 %   Cycle 2 %   Cycle 3 %			Cycle 4 %				
Poor or Fair	34.475	1.47	38.708	1.65	30.951	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	28.995	4.56
Good	401.542	17.12	394.995	16.84	356.130	19.84	251.373	21.67
Very Good	963.970	41.09	1012.903	43.18	822.839	42.53	655.452	42.15
Excellent	946.012	40.32	899.394	38.34	744.080	35.40	576.180	31.60
Total	2346	40.02	2346	30.34	1954	33.40	1512	31.00
Total		(s-dev)		(s-dev)		(s-dev)		(s-dev)
Mean HUI	0.9273	0.1448	0.9568	0.1046	0.9540	0.1062	0.9578	0.1245
Total	2336		2342		1950		1508	
% with a regular physician	78.63	0.575	79.58	0.595	77.87	0.59	78.52	0.562
Total	2346		2346		1954		1513	
Age	37.586	15.063	39.565	15.060	40.564	15.589	42.066	15.553
Total	2346		2346		1954		1513	
Education	Cy	vcle 1 %	Су	cle 2 %	Су	cle 3 %	Су	vcle 4 %
Less than High School	451.427	19.24	421.649	17.97	323.233	16.54	233.998	15.47
High School Grad	450.066	19.18	421.912	17.98	335.901	17.19	255.832	16.91
Some post-secondary	1075.585	45.85	1118.629	47.68	933.334	47.77	732.527	48.42
University/Coll Grad	368.922	15.73	383.810	16.36	361.532	18.50	290.644	19.21
Total	2346		2346		1954		1513	
Income		cle 1 %	Cycle 2 %		Cycle 3 %		Cycle 4 %	
0-19999	328.123	13.99	293.976	12.53	182.759	9.35	110.295	7.29
20k-39999	557.677	23.77	591.030	25.19	449.696	23.01	276.890	18.3
40k-59999	717.586	30.59	685.450	29.22	489.502	25.05	343.570	22.71
60k-79999	331.791	14.14	330.433	14.09	352.234	18.03	298.676	19.7
80k and over	329.580	14.05	320.297	13.65	385.471	19.73	394.572	26.08
Total	2346		2346		1954		1513	
Household smokes		ycle 1 %		cle 2 %		cle 3 %		vcle 4 %
Yes	927.308	39.53	859.267	36.66	689.648	35.31	461.952	30.53
No	1418.692	60.47	1484.733	63.34	1263.352	64.69	1051.048	69.47
Total	2346		2344		1953		1513	
Individual Smokes		ycle 1 %		cle 2 %		vcle 3 %		cle 4 %
Yes	778.344	33.18	747.380	31.88	591.420	30.28	413.357	27.32
No	1567.656	66.82	1596.620	68.12	1361.580	69.72	1099.644	72.68
Total	2346		2344		1953		1513	
	Cy	vcle 1 %	Cy	cle 2 %		vcle 3 %		cle 4 %
Individual Binge Drinks								
Yes	347.970	15.02	496.935	21.30	397.255	20.43	281.567	18.68
			496.935 1836.065 2333	21.30 78.70	397.255 1546.746 1944	20.43 79.57	281.567 1225.433 1507	18.68 81.32

 ${\bf Table~A-2} \\ {\bf Number~of~Consultations~and~Physician~Supply}$ 

	Special	ists	GP		Regular	
	Consulta	tions	Consultations		Physic	ian
GPs per capita			0.400	***	-0.786	***
			(0.099)		(0.585)	
Specialists per capita	1.319	***			2.570	
	(0.173)				(0.854)	
Constant	-2.530	***	0.097			
	(0.192)		(0.115)			

 $\begin{array}{c} {\rm Table~A\text{--}3} \\ {\rm Sample~of~coefficients~(HUI~30th~percentile)} \end{array}$ 

Sample of coefficients (HUI 3)		ntile)
gender	0.002	
	(0.002)	
Immigrant	-0.003	
	0.002	
Age 40-59	0.008	
	(0.012)	
Age 60-79	-0.085	**
1180 00 10	(0.039)	
Age 80+	0.105	
Age 60+		
T 1	(0.192)	
Lives in rural area	0.001	
	(0.001)	, in
Own the dwelling	0.004	*
	(0.002)	
Log household size	0.000	
	(0.001)	
Income 0-19999	-0.023	***
	(0.006)	
Income 40-59999	0.003	
111001110 10 00000	(0.003)	
Income 60-79999	0.002)	**
Income 00-19999		
I OOL	(0.002)	***
Income 80K+	0.006	***
	(0.002)	
Married Woman	-0.002	
	(0.003)	
Separated Woman	0.000	
	(0.017)	
Divorced Woman	-0.007	
	(0.011)	
Widow	-0.009	
	(0.017)	
Common-law Woman	0.000	
	(0.003)	
Married	0.003	
Married	(0.002)	
Common-law	0.002	
	(0.003)	
Widower	0.002	
	(0.015)	
Separated	-0.012	
	(0.012)	
Divorced	-0.006	
	(0.008)	
Less than High school	-0.010	**
2000 than High belloof	(0.004)	
Some post-secondary	0.004)	
Some post-secondary	l	
	(0.002)	
University/College graduate	0.002	
	(0.002)	.1
Smoker	-0.004	**
	(0.002)	
Binge drinker	0.000	
	(0.002)	
<b>.</b>		

 ${\it Table~A-4} \\ {\it Random~effects~ordered~probits~without~lagged~health~status}$ 

Random effects of					outus	
Q . 1		$\frac{\text{e Sam}}{***}$	pie	Small Sample	**	***
Specialists per capita	-1.014	<u> ተ</u> ተች		-0.997	<b>个</b> 不	ጥጥች
GD.	(0.235)	-1-		(0.400)	داد داد ول	
GPs per capita	0.557	*		1.457	***	
	(0.309)			(0.398)		
Newfoundland	-0.350	***	***	-0.522	***	***
	(0.092)			(0.159)		
Prince Edward	-0.371	***		0.019		
Island	(0.097)			(0.181)		
Nova Scotia	-0.254	***		-0.160		
	(0.060)			(0.119)		
New Brunswick	-0.628	***		-0.537	***	
	(0.084)			(0.160)		
Quebec	0.120	**		0.001		
	(0.055)			(0.090)		
Manitoba	-0.221	***		-0.217	**	
	(0.055)			(0.099)		
Saskatchewan	-0.636	***		-0.634	***	
	(0.087)			(0.163)		
Alberta	-0.282	***		-0.082		
	(0.058)			(0.112)		
British Columbia	-0.308	***		-0.438	***	
Diffish Columbia	(0.063)			(0.108)		
GPs per capita	0.332		*	0.226		
x Age 40-60 years old	(0.290)			(0.470)		
GPs per capita	0.923	***		-0.668		
x Age 60-80 years old	(0.350)					
	$\frac{(0.330)}{0.578}$			(0.783) $2.027$		
GPs per capita						
x Age 80 + years old	(0.618)	*		(2.419)		
Specialists per capita	-0.286	r		0.070		
x Age 40-60 years old	(0.171)			(0.264)		
Specialists per capita	-0.260			0.359		
x Age 60-80 years old	(0.208)	*		(0.437)		
Specialists per capita	-0.699	*		1.042		
x Age 80 + years old	(0.378)	.1.		(1.543)		
Chronic Condition	-0.336	*				
	(0.198)					
Specialists per capita	-0.261	*	*			
x Chronic Condition	(0.136)					
GPs per capita	-0.087					
x Chronic Condition	(0.240)					
Cut Point 1	-4.574	***		-4.055	***	
	(0.318)			(0.511)		
Cut Point 2	-3.236	***		-2.613	***	
	(0.317)			(0.493)		
Cut Point 3	-1.715	***		-0.964	**	
	(0.316)			(0.492)		
Cut Point 4	-0.035			0.680		
	(0.316)			(0.491)		
rho	0.510	***		0.438	***	
1110	(0.007)			(0.014)		
	(0.001)			(0.011)		

 ${\it Table~A-5-A} \\ {\it Quantile~Regressions~without~control~for~Lagged~Health~(Whole~Sample)}$ 

Quantile Regressions v							
	_	30th percentile 20th percent					
Specialists per capita	0.175	***	0.241	***	0.310	***	
	(0.032)	dododo	(0.047)	dododo	(0.079)	dedede	
GPs per capita	-0.172	***	-0.193	***	-0.278	***	
	(0.030)		(0.047)		(0.075)		
Newfoundland	0.098	***	0.141	***	0.190	***	
	(0.012)		(0.017)		(0.028)		
Prince Edward	0.060	***	0.095	***	0.129	***	
Island	(0.013)		(0.018)		(0.029)		
Nova Scotia	0.051	***	0.088	***	0.114	***	
	(0.010)		(0.015)		(0.026)		
New Brunswick	0.015	*	0.003		-0.022		
	(0.008)		(0.016)		(0.033)		
Quebec	0.009		0.018	**	0.028	*	
v	(0.006)		(0.009)		(0.015)		
Manitoba	0.005		0.014		0.014		
	(0.007)		(0.010)		(0.021)		
Saskatchewan	0.059	***	0.090	***	0.122	***	
	(0.012)		(0.017)		(0.028)		
Alberta	0.027	***	0.046	***	0.067	***	
11100100	(0.007)		(0.010)		(0.017)		
British Columbia	0.028	***	0.039	***	0.060	***	
Diffusii Columbia	(0.008)		(0.011)		(0.019)		
GPs per capita	0.002		-0.057		-0.039		
x Age 40-60 years old	(0.032)		(0.054)		(0.107)		
GPs per capita	0.160	**	0.176	*	0.332	*	
x Age 60-80 years old	(0.068)		(0.170)				
	, ,		,		(0.192)		
GPs per capita	-0.217		-0.363		0.004		
x Age 80 + years old	(0.383)		(0.344)		(0.458)		
Specialists per capita	-0.007		0.030		0.035		
x Age 40-60 years old	(0.018)	*	(0.029)	**	(0.050)	**	
Specialists per capita	0.076	*	0.139	**	0.205	<u> </u>	
x Age 60-80 years old	(0.039)		(0.060)		(0.095)		
Specialists per capita	0.010		-0.151		-0.434	*	
x Age 80 + years old	(0.207)		(0.261)		(0.258)		
Chronic Condition	-0.094	***	-0.176	***	-0.266	**	
	(0.031)		0.057		(0.110)		
Specialists per capita	0.023		0.053		0.106		
x Chronic Condition	(0.021)		(0.042)		(0.067)		
GPs per capita	0.021		0.039		-0.004		
x Chronic Condition	(0.036)		(0.064)		(0.126)		
Constant	0.935	***	35 0.856	***	0.784	***	
	(0.037)		(0.053)		(0.094)		

Table A-5-B Quantile Regressions without control for Lagged Health (Small Sample)

Quantile Regressions			10th percentile			
	30th percentile		20th perc	entile ***		centile ***
Specialists per capita	0.193	***	0.197	***	0.391	***
	(0.049)		(0.064)		(0.142)	
GPs per capita	-0.212	***	-0.210	***	-0.339	***
	(0.050)		(0.055)		(0.106)	
Newfoundland	0.087	***	0.093	***	0.167	***
	(0.019)		(0.025)		(0.045)	
Prince Edward	0.049	**	0.061	**	0.124	**
Island	(0.019)		(0.027)		(0.054)	
Nova Scotia	0.057	***	0.057	**	0.114	**
	(0.018)		(0.024)		(0.047)	
New Brunswick	0.026	**	0.032	***	0.065	***
	(0.011)		(0.012)		(0.020)	
Quebec	0.011		0.005		0.016	
	(0.009)		(0.011)		(0.021)	
Manitoba	0.006		0.015	*	0.041	*
	(0.010)		(0.009)		(0.021)	
Saskatchewan	0.057	***	0.057	**	0.087	*
	(0.018)		(0.023)		(0.049)	
Alberta	0.031	***	0.032	**	0.070	**
	(0.010)		(0.015)		(0.028)	
British Columbia	0.047	***	0.046	***	0.077	***
	(0.012)		(0.015)		(0.027)	
GPs per capita	0.043		0.063		0.028	
x Age 40-60 years old	(0.042)		(0.067)		(0.127)	
GPs per capita	0.200	**	0.049		0.158	
x Age 60-80 years old	(0.089)		(0.108)		(0.219)	
GPs per capita	-0.148		0.093		0.784	
x Age 80 + years old	(0.405)		(0.518)		(0.591)	
Specialists per capita	-0.023		0.000		-0.065	
x Age 40-60 years old	(0.026)		(0.040)		(0.081)	
Specialists per capita	-0.039		-0.015		0.008	
x Age 60-80 years old	(0.047)		(0.057)		(0.099)	
Specialists per capita	0.155		0.101		0.064	
x  Age  80 +  years old	(0.218)		(0.322)		(0.340)	
Constant	0.954	***	0.926	***	0.791	***
	(0.053)		(0.073)		(0.157)	
	(0.000)		(0.010)		(0.101)	

### **Bibliography**

- Allen, D. I. and J. M. Kamradt. "Relationship of Infant Mortality to the Availability of Obstetrical Care in Indiana", The Journal of Family Practice, Vol. 33, No. 6, 1991, p.609-613.
- Ayanian, J. Z., E. Guadagnoli et al. "Treatment and outcomes of acute myocardial infarction among patients of cardiologists and generalist physicians" Archive of Internal Medicine, Vol. 157, 1997, p. 2570-2576.
- Crossley, T. et al. "The Reliability of Self-assessed health status", Journal of Health Economics, 21, 2002, p. 643-658.
- Drummond, D.C., B. Thom et al. "Specialist versus general practitioner treatment of problem drinkers", The Lancet, Vol. 336, 1990, p. 915-918.
- Escarce, J. J. "Explaining the Association Between Surgeon Supply and Utilization". Inquiry, 29, 1992, p. 403-415.
- Ferrante, J. M., et al. "Effects of Physician Supply on Early Detection of Breast Cancer".

  Journal of the American Board of Family Practice, 13(6), 2000, p. 408-414.
- Fisher, E.S., D. E. Wennberg et al. The Implications of Regional Variations in Medicare Spending. Part 2: Health Outcomes and Satisfaction with Care, Annals of Internal Medicine, Vol. 138, 2003, p.288-322.
- Gerdtham, U.G., M. Johannesson, L. Lundberg and D. Isacson, A note on validating Wagstaff and van Dooslairs health measure in the analysis of inequality in health. Journal of Health Economics 18 (1999), pp. 117224.
- Greenfield, S. et al. "Outcomes of Patients With Hypertension and Non-insulin-dependent Diabetes Mellitus Treated by Different Systems and Specialties Results from the Medical Outcomes Study", JAMA, Vol. 274, No. 18, 1995, p. 1436-1444.

- Grossman, M. "On the Concept of Health Capital and the Demand for Health", The Journal of Political Economy, Vol. 80, No. 2, 1972, p. 223-255.
- Hertzman, C. "The Lifelong Impact of Childhood Experiences: A Population Health Perspective", Daedalus: Journal of the American Academy of Arts and Science, Vol. 123, No. 4, 1994, p. 167-180.
- Jollis, J. G. et al. "Outcome of Acute Myocardial Infarction According to the Specialty of the Admitting Physician", New England Journal of Medicine, 1996, Vol. 335, p.1880-1887.
- Krishnan, I. et al. "Impact of Increased Physician Supply on Use of Health Services: a Longitudinal Analysis in Rural Minessota", Public Health Reports, Vol. 100, No. 4, 1985, p.379-386.
- Mahajan, R. J. J. S. Barthel and J. B. Marshall. "Appropriateness of Referrals for Open-Access Endoscopy How Do Physicians in Different Medical Specialties Do?", Archives of Internal Medicine, Vol. 156, 1996, p.2065-2069.
- Marmot, M. G. "Social Differentials in Health Within Populations", Prosperity, health and wellbeing: proceedings, 11th Honda foundation discoveries symposium, October 16-18, 1993, Toronto, Canada, Canadian Institute for advance Research, 1993, p.35-49.
- Marmot MG, et al. "Epidemiologic studies of coronary heart disease and stroke in Japanese men living in Japan, Hawaii and California: prevalence of coronary and hypertensive heart disease and associated risk factors", American Journal of Epidemiology, 1975, Vol. 102, p.514-25.
- Marmot M. G., S. L. Syme. "Acculturation and coronary heart disease in Japanese-Americans", American Journal of Epidemiology, 1976, Vol. 104, p. 225-47.
- McEwen, B. S. "Protective and Damaging Effects of Stress Mediators", New England Journal of Medicine, Vol. 338, No. 3, 1998, p.171-179.

- Moulton, B. R. "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units", The Review of Economics and Statistics, Vol. 72, No. 2, 1990, p. 334-338.
- Nash, I. S. et al. "Do Cardiologists do it Better?", Journal of the American College of Cardiology, Vol 29, No 3, 1997, p.475-478.
- Pasley, B. et al. "Geographic variations in elderly hospital and surgical discharge rates, New York State", American Journal of Public Health, Vol 77, No. 6, p. 679-684
- Piérard, E., N. Buckley, J. Chowhan. Bootstrapping Made Easy: A Stata ADO File, in Research Data Centre Information and Technical Bulletin, Vol. 1, No. 1, Spring 2004, p. 20-36.
- Roetzheim, R. G. et al. "The Effects of Physician Supply on the Early Detection of Colorectal Cancer". The Journal of Family Practice, Vol. 48, No. 11, 1999, p. 850-858.
- Roetzheim, R. G. et al. "Increasing supplies of dermatologists and family physicians are associated with earlier stage of melanoma detection". Journal of the American Academy of Dermatology. 43 (2 (Part 1)): p. 211-218, August 2000.
- Stoddart, G. L. The Challenge of Producing Health in Modern Economies, CIAR Program in Population Health, Working Paper No. 46, 1995, 57 p.
- Yeo, D., H. Mantel and T.-P. Liu. "Bootstrap Variance Estimation in the national Population Health Survey", American Statistical Association: Proceedings of the Survey Research Method Section. Baltimore, August 1999.