ECONOMIC ASPECTS OF PHYSICIAN SERVICES UTILIZATION

AN EMPIRICAL INVESTIGATION OF ECONOMIC ASPECTS OF PHYSICIAN SERVICES UTILIZATION

by

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Abstract

This thesis is an empirical exploration into a range of issues related to the economics of the utilization of physician services. Physicians play an important role in a health care system as physicians are a patient's primary point of contact with the health care system and physicians are predominantly responsible for directing how patients use other health care resources. In particular, physicians are at the center of Canada's universal public insurance system with first dollar coverage for medically necessary physician and hospital services.

The thesis comprises three separate essays. The first essay has a methodological focus on statistically modeling and predicting the use of general practitioners (GPs) when use is measured as the number of GP visits. The essay compared a state-of-the-art parametric latent class negative binomial model to a nonparametric kernel conditional density estimator, and evaluated how well each was able to fit the observed data and predict physician use.

The second and third essays look at more substantive policy questions. The second essay investigates how the supply of GPs and specialists affects the mix of physician services received by individuals. A persistent concern in many health care systems is how variations in the supply of physicians will impact the use of physician services. The results suggest concerns about

concerns of patient access and receipt of care in the presence of a shortage of specialists may be mitigated, all else equal, if patients are able to substitute GP services for specialist services.

The third essay examines income-related inequity in the use of physician services by asthmatics and diabetics, relative to the general population, and the contributions of different factors to income-related inequality using the concentration index approach.

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Introduction

This thesis is an empirical exploration into a range of issues related to the economics of the utilization of physician services. Physicians play an important role in a health care system as physicians are a patient's primary point of contact with the health care system and physicians are predominantly responsible for directing how patients use other health care resources. In particular, physicians are at the center of Canada's universal public insurance system with first dollar coverage for medically necessary physician and hospital services.

The stated objective of Canadian health care policy is "*to protect, promote and restore the physical and mental well-being of residents of Canada and to facilitate reasonable access to health services without financial or other barriers*" (Canada Health Act (1984)). In practice, Canadian health care policy is operationalized by each province providing universal public health insurance to all residents for medically necessary physician and hospital services. However, simply removing the financial barriers to physician and hospital services may not result in equal access for all residents.

National health care expenditures in Canada are projected to be nearly $172 billion or roughly 11% of gross domestic product (GDP) in 2008 (CIHI (2008)). Expenditures on physician services represent the third largest category of health care expenditure in Canada, behind hospitals and drugs, accounting for 13.2% of total health care expenditures or roughly 1.4% of GDP in 2008 (CIHI (2008)). However, the 1.4% of GDP spent specifically on physicians understates the importance of physicians given their role in allocating other types of health care resources, such as the 1.8% of GDP spent on prescription drugs (CIHI (2008)).

By understanding the determinants of physician use we can better understand how well the Canadian health care system is performing relative to its stated objective of reasonable access without financial barriers. In addition, a better understanding of how nearly 11% of the Canadian economy is organized, allocated, and distributed can have meaningful implications both for a nation's economy and the health of its residents.

Physician utilization, in an economic sense, is the intersection of the demand for physician services and the supply of physician services. Demand for physician services is a derived demand for health: people demand physician services based on their perceived health care need in order to improve their health (Grossman (1972)).

This thesis comprises three essays that empirically explore different economic aspects of physician services utilization. The first essay has a methodological focus on analyzing physician utilization. There is currently a debate in the literature over how best to model the number of physician visits (a count variable) in the presence of unobserved heterogeneity. The second and third essays make contributions to the physician utilization literature while looking at more substantive policy questions. The second essay explores how variations in physician supply effect the mix of physician services received. The third essay explores income-related inequities in physician utilization using the concentration index approach of Wagstaff and van Doorslaer (2000), while marrying a condition specific approach, focusing on asthmatics and diabetics, with a population based approach using data representative of the entire population.

The first essay tackles issues of statistically modeling and predicting physician use. Modeling and predicting health care utilization are the foundation of many health economics analyses, such as calculating risk-adjustment capitation payments or measuring equity in health care utilization. Being able to do this well can lead to better health economic analyses. The most common models used to analyze the number of physician visits are parametric count data models. Parametric models assume data are generated by a specific probability distribution and make inference based on the assumed distribution. If the distributional assumptions are correct, parametric methods perform very well. However, if the distributional assumptions are incorrect, parametric models can be very misleading. Alternatively, a nonparametric approach makes no prior distributional assumptions about the data generating process and only assumes the existence of a data generating process.

The first essay makes two distinct contributions to the literature using count data models to analyze general practitioner (GP) utilization: (i) it is the first paper to use a nonparametric kernel conditional density estimator to model the number of GP visits and compare the predicted number of GP visits with that from a latent class negative binomial model; and (ii) it uses panel data to control for the potential endogeneity between self-reported health status and the number of GP visits. The first essay also contributes to the literature on the determinants of GP use in a publicly insured health care system with first dollar coverage by showing how different patient characteristics affect the conditional mean number of GP visits.

The first essay uses six cycles of the longitudinal Canadian National Population Health Survey. Eight model specifications are estimated using both a parametric latent class negative binomial model and a nonparametric kernel conditional density estimator: (i) six cross-sectional specifications, one for each cycle in the panel, and (ii) two panel specifications: one without endogeneity correction and one with endogeneity correction. Endogeneity is corrected by including a lagged variable for self-reported health status.

The results also show meaningful differences between the nonparametric and the parametric model in how the predicted number of GP visits changes with a change in an individual's characteristics, called the incremental effect (IE), but no meaningful differences in IEs between the panel models with and without endogeneity correction, or between the cross-section models and the panel model without endogeneity correction. The largest difference is in the right tail of the distribution. This is important as the right tail of the distribution represents high-use individuals whose utilization is often the hardest to predict but represents a disproportionate share of total utilization.

Essays two and three both address policy concerns related to physician utilization by using unique linked survey-administrative data from Ontario. Ontario respondents in the Canadian Community Health Survey 2000/2001

(CCHS 1.1) are linked with their monthly administrative health records from the Ontario Health Insurance Program (OHIP) claims database for three fiscal years (April 1, 1999 to March 31, 2002). The linked survey-administrative data set provides a more complete measure of physician utilization (the actual number of physician visits and the actual dollar value of physician services received) relative to the standard measure provided by survey data alone (the self-reported number of physician visits).

The second essay investigates how the supply of GPs and specialists affects the mix of physician services received by individuals. A persistent concern in many health care systems is how variations in the supply of physicians will impact the use of physician services. For example, physician shortages are often cited by physician groups as a policy concern governments need to address before people lose access to needed physician services. A reduction in the supply of GPs or specialists can impede access to necessary services provided by each type of physician. However, the extent to which the mix of services provided by each physician is responsive to the relative supply of other types of physicians, the supply of physicians themselves may not be an accurate measure of access to necessary services. Therefore, it is important to document whether, and in what way, physician supply affects the mix of physician services received to provide insight into the strength of this particular policy concern.

The analysis uses three different regression methodologies. The number of GP visits and the number of specialist visits is first modeled using a standard single-equation negative binomial model and then using a double-equation simultaneous negative binomial model. Finally, the dollar value of GP services received and specialist services received are modeled using a generalized linear model with a log-link function and gamma family distribution.

Results show two main effects between the supply and utilization of each type of physician. The own-supply effect shows that as the supply of one physician type increases, so does utilization of that physician type. The cross-supply effect shows as the supply of one physician type increases, utilization of the other physician type decreases. At the same time, people exhibit strong 'taste effects' for health care, shown by the positive association between GP use and specialist use. An increase in the use of one physician type is strongly associated with an increase in the other physician type. The supply and taste effects are necessary to differentiate since a decrease in the supply of one physician type appears to induce people to substitute towards the other physician type.

The third essay examines income-related inequity in the use of physician services by asthmatics and diabetics, relative to the general population, and the contributions of different factors to income-related inequality using the concentration index (CI) approach of Wagstaff and van Doorslaer (2000). Income-related horizontal inequity is the extent to which those of the same health care need, but with differing incomes, systematically utilize different amounts of health care. Given the stated objective of Canadian health care policy this is particularly important since a continuing policy concern is whether people with similar health care need use similar quantities of health care services.

All previous work using the CI approach are based on health care use in the general population. There is heterogeneity of health status in the general population and it is unclear how well health status measures included in social surveys fully capture health status. An alternative approach to assessing equity focuses on health care use among groups of people identified as having a particular health condition. It is argued that focusing on a homogenous group (with respect to a particular health condition) is a better control for health care need. A disadvantage of the group specific approach is that it focuses only on people who have received a defined health care service associated with the particular health condition (e.g., admitted to hospital for actute myocardial infarction). The third essay marries the group specific approach with the population based approach by focusing on people with specified health conditions - asthma and diabetes - from a population health survey that includes both users and non-users of physician services.

The results show no meaningful inequity in the probability of GP use in all three groups, but pro-poor inequity in the number of GP visits and the dollar value of GP services received. Conversely, pro-rich inequity is found in the probability of specialist use and conditional specialist use for all respondents; no inequity in specialist use among asthmatics; and only pro-rich inequity in the probability of a specialist visit for diabetics. Decomposing the inequalities in physician use into need and non-need factors shows non-need factors make the inequalities more pro-rich, while the need factors make the inequalities more pro-poor. Interestingly, income has no meaningful contribution to the probability of a GP visits and the conditional number of GP visits for asthmatics and diabetics. However, income has a strong positive contribution for asthmatics and diabetics in the dollar value of GP services received.

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Chapter 1

Nonparametric Versus Latent Class Models of General Practitioner Utilization: Evidence from Canada

1.1 Introduction

Economists have expended great effort developing models of health care utilization to produce more accurate predictions. Predicting health care utilization is the foundation of many health economics analyses. For example, the literature on risk-adjustment uses predicted health care utilization to design more efficient payment systems (Ellis (2008)). And, the concentration-index approach to measuring equity in health care utilization uses a methodology based on predicted health care utilization (Wagstaff and van Doorslaer (2000)). Models of physician utilization are one application commonly found in these literatures. The first point of contact in most health care systems for most people is a general practitioner (GP) who often acts as a gatekeeper to the broader health care system. Thus, being able to predict a patient's use of GP services is critical to understanding the use of a broader range of services, such as, hospital care, prescription drugs and specialist services.

The most common models to analyze physician utilization are parametric count data models, since the most common metric of physician utilization is the number of physician visits. The econometrics literature developing count data methods for studying physician utilization over the past 25 years can be divided into four main strands: (i) developing more flexible parametric models, (ii) developing panel models to explicitly control for unobserved individual heterogeneity, (iii) comparing the performance of different parametric models, and (iv) modeling endogenous variables. The latent class negative binomial (LCNB) model has been shown to be the preferred parametric model when modeling the number of GP visits (Deb and Trivedi (1997), Deb and Trivedi (2002), Jiménez-Martín et al. (2002), and Sarma and Simpson (2006)).[1]

Parametric count data models all assume a functional form for the data generating process of the dependent variable. If a parametric count data model assumes the true data generating process, then the model is efficient and unbiased. However, if a parametric model does not assume the true data generating process, then the model will be misspecified, no longer efficient and unbiased, and will not closely fit the observed distribution. One way to handle issues of model specification is to use a nonparametric model which simply assumes the existence of a differentiable data generating process but does not assume

[1]The literature comparing model performance of parametric models has primarily used measures of a model's log-likelihood and information criterion (Akaike information criterion and Bayesian information criterion). This paper also uses the log-likelihood and information criterion to compare parametric models.

a specific functional form.

This paper answers two questions. Does a nonparametric estimator perform as well or better than a state-of-the-art parametric count data model in predicting GP utilization? And, are the estimated effects of an individual's characteristics on the number of GP visits different in a nonparametric model than the effects from a parametric model?[2]

Models of health care utilization are also central in the evaluation of health care system performance. In many countries, health policy strives to provide all eligible individuals access to medically necessary hospital and physician services based on their need for care and not based on other determinants, such as their sex or socioeconomic status. Determining whether this policy goal is achieved is viewed as a key measure of success for the health care system.

However, just because all eligible individuals have access to a GP does not mean they will all visit the GP equally. The utilization of GP services results from the complex interaction between the preferences and constraints of both individuals and physicians. For example, in a given population, if everyone has the same health status and equal access to a GP we may still observe different patterns of utilization.

Econometric models of physician utilization are also central to estimating the affects of a person's characteristics on their utilization. The affect of certain characteristics - such as need, sex and socioeconomic status - can be thought about in terms of the Grossman model of health human capital (Grossman

[2]The focus of the paper is mainly on estimating the conditional mean function rather than the underlying probability density function.

(1972)), where the demand for health care is derived from the demand for health. Health itself can be viewed as a consumption good (people receive utility from being healthy), an investment good (by investing in better health, people can increase the amount of healthy time available to earn income), or both. The returns from investing in health will depend on the utility a person receives from being healthier and/or the returns from increasing healthy time.

Within the Grossman framework, the expected effect of need is straightforward: all else equal, people with greater need would be expected to make more GP visits because they must invest more to attain the same level of health capital.

The expected effect of a person's sex can be thought of as influencing their need for reproductive and preventative health care. We may expect females of younger ages to make more GP visits because of physiological differences that require more health care (i.e. services related to child birth). Over the life cycle differences by sex in the pattern of health care consumption could be attributed to differences in the need for preventative health care and disease patterns.

A person's household income can influence both their returns from investing in better health and their budget constraint. People with higher income will receive a higher return from investing in health care, since each unit of health produced and allocated to earning income will provide a greater return relative to people with lower income. People with higher income may also consume preventative health care in order to minimize the time lost due to illness in the future. Income can also affect people along two other important margins: (i) the relative monetary cost of making a visit, and (ii) the opportunity cost of time required to make a visit. The relative monetary cost of making a visit is equal to the total monetary cost of making a GP visit - such as the fee charged for a visit and the transportation costs to the visit - relative to total income. Thus a person with higher-income, and thus a smaller relative monetary cost of a visit, may be expected to make more visits to a GP than a person with lower-income.[3] The opportunity cost of time required to make a visit may be higher for a higher-income person, all else equal, than for a lower-income person. The higher cost may cause a higher-income person to make fewer GP visits. The direction of the net effect of household income on the number of GP visits is ambiguous.

People with more education may prefer better health. A person with more education may make more GP visits because they recognize the benefits of improved health or they better understand the need for preventative care (Birch et al. (1993)) or they better understand the benefit of GP services given their current health status. But, if a more educated person is a more efficient producer of health then one may expect them to make fewer GP visits (Grossman (1972)). The direction of the net effect is ambiguous as it is not clear which effect dominates.

This paper answers two questions. Does a nonparametric estimator do as well or better than the state-of-the-art parametric count data model in predicting GP utilization? And, are the estimated effects of an individual's characteristics on the number of GP visits different in a nonparametric model

[3] This effect is not as pronounced in health care systems with first dollar insurance coverage because health care is free to the patient at the point of service.

than the effects from a parametric model?

Two issues arising in the analysis of GP utilization are unobserved individual heterogeneity and the potential endogeneity between health status and the number of GP visits. Controlling for unobserved individual heterogeneity is crucial as it may be the cause of over-dispersion commonly observed in the counts (Cameron and Trivedi (1998)). Correcting endogeneity between health status and the number of GP visits is important because endogenous variables can lead to biased parameter estimates.

To control for unobserved individual heterogeneity and the potential endogeneity between health status and the number of GP visits I use six cycles of panel data from the Canadian National Population Health Survey. I model the number of GP visits using eight different models: (i) six cross-sectional models, one for each cycle in the panel, and (ii) two panel models: one with no endogeneity correction, and one with endogeneity correction. Endogeneity is corrected by including a lagged variable for self-reported health status. The eight models are estimated using both a parametric latent class negative binomial model (LCNB) and a nonparametric kernel conditional density estimator (KCDE). The LCNB and the KCDE are compared to determine which provides a closer fit to the observed distribution and to determine if the estimated incremental effects associated with a change in an individual's characteristics differ substantially across the models.

This paper makes two distinct contributions to the literature using count data models to analyze GP utilization: (i) it is the first to use a nonparametric KCDE to model GP utilization and compare the predicted utilization with that from a state-of-the-art parametric model; and (ii) it uses panel data to control for the potential endogeneity between self-reported health status and the number of GP visits. This paper also contributes to the literature on the determinants of GP use in a publicly insured health care system with first dollar coverage by showing how different patient characteristics affect the conditional mean number of GP visits when modeled using a nonparametric estimator. While dozens of papers have used Canadian cross-sectional data to model physician utilization, most have poor model specifications, only one uses a LCNB (Sarma and Simpson (2006)), and none have used a nonparametric estimator.

1.2 Literature

1.2.1 Econometric modeling of general practitioner utilization

The analysis of GP use generally divides the number of GP visits into two components: the probability of GP use, and the conditional intensity of GP use. The probability of GP use is the likelihood a patient makes at least one visit to a GP. The conditional intensity of GP use is the number of visits a patient makes to a GP, conditional on making at least one GP visit. This division is a natural one for both conceptual and statistical reasons.

Conceptually, the relationship between a patient and a GP is commonly framed as a principal-agent relationship where the patient (principal) contracts with a physician (agent) because the physician has more information than the patient regarding the patient's health and the effects of alternative treatments (McGuire (2000)). Dividing the number of GP visits into probability of use and conditional intensity fits with the principal-agent framework since the probability of use should be influenced primarily by patient factors and conditional intensity should be determined by both the patient and GP.

Statistically, dividing the number of GP visits into the probability of use and conditional intensity is one way of dealing with the skewed distribution of GP visits that contains a large proportion of zeros. The analysis of the probability of use and conditional intensity can be done separately using a methodology called the two-part model. A two-part model estimates two separate and independent models: (i) a binary outcome model for the probability of use; and (ii) a model of the number of GP visits, conditional on making at least one GP visit, for the conditional intensity of use.

An extensive literature developing count data methods has emerged over the past 25 years and can be divided into four main strands: (i) developing more flexible parametric cross-sectional models; (ii) developing panel count data models; (iii) comparing the performance of different models; and (iv) modeling endogeneity.

The development of more flexible cross-sectional models focuses on three types of models: (i) single-distribution models; (ii) two-part models; and (iii) multiple-distribution models. Single-distribution models build on the Poisson model by relaxing the equidispersion property (negative binomial model); accounting for a large proportion of zeros (zero-inflated Poisson and zero-inflated negative binomial models); and accounting for only non-zero counts (zero-truncated Poisson and zero-truncated negative binomial models). The more flexible two-part model can specify different models for each of the two-parts: logit model and a truncated-geometric (Mullahy (1986)), negative binomial distributed (Pohlmeier and Ulrich (1995)), semi-parametric (Gurmu (1997)) or probit-Poisson log-normal (Winkelmann (2004)). Finally, multiple distribution models have extended single distribution models to multiple distributions by using the latent class approach (Deb and Trivedi (1997), and Deb and Trivedi (2002)).

The second strand of the literature has developed models for panel data. Hausman et al. (1984) develops a single distribution Poisson and negative binomial models (both fixed and random effects); Van Ourti (2004) develops a Gaussian random effects two-part panel model; Bago d'Uva (2005) develops a latent class negative binomial panel model; and Bago d'Uva (2006) introduces a latent class two-part panel model. All these papers draw on the developments of cross-sectional models and extend them to a panel setting.

The third strand of the literature compares different models to determine which model best fits the data. The statistics frequently used are in-sample measures of model performance such as the Akaike Information Criterion, Bayesian Information Criterion and the value of the maximized log-likelihood function. The more flexible latent class model performs better than other parametric count data methods when modeling GP use (Deb and Trivedi (1997), Deb and Trivedi (2002), Bago d'Uva (2006), and Sarma and Simpson (2006)).

The fourth strand of the count data literature has explored the potential endogeneity between GP visits and self-reported health. A patient who perceives their own health to be poor tends to have a higher probability of use and conditional intensity. However, by visiting a GP a patient may perceive themselves as having a lower health status. A few methods of dealing with this type of endogeneity have been proposed (see Mullahy (1986) and Windmeijer and Santos Silva (1997)). A simple way to control for the endogeneity between GP visits and self-reported health with panel data is to include last periods self-reported health status as a control variable (Schellhorn et al. (2000)).

In the past 15 years, studies using Canadian health survey data have applied a number of different methodologies to model the probability of use and conditional intensity (see Table 1.1 and Table 1.2).

Models of the probability of use using Canadian Data

The probability of a GP visit is commonly estimated using a binary-outcome model such as a linear probability model, logit model or probit model. All of these models assume there is a continuous unobserved latent variable with an assumed distribution. The linear probability model assumes the latent variable is linear. The logit model assumes the latent variable has a logistic distribution and the probit model assumes the latent variable has a normal distribution. However only two realizations (0 or 1) of the latent variable are observed.

Studies using Canadian data have focused on these three binary-outcome models. Deri (2005) models the probability of use using a linear probability model. Dunlop et al. (2000) and Allin (2006) each model the probability of use using a logit model. Birch et al. (1993), Eyles et al. (1995) and Stabile

(2001) each model the probability of use using a probit model.

Models of Intensity using Canadian Data

Studies using Canadian data have applied a number of econometric methods to model either the unconditional or the conditional number of GP visits. Common approaches use OLS on a log-transformation of the count variable (the log-transformation is one way to account for the skewed distribution of GP visits), a Heckman sample selection model (to account for the propensity for some people choose to visit a GP), a negative binomial model (to account for over-dispersion), or a latent class negative binomial model (to account for unobserved heterogeneity between different groups of people).

Stabile (2001) and Deri (2005) each employ OLS on the log-transformation of the conditional number of GP visits. The logarithmic transformation of the count variable lessens the effect of skewness and the use of OLS provides for an easy interpretation of coefficients. However, other models of GP utilization are generally preferred (Cameron and Trivedi (1998)).

Birch et al. (1993) and Eyles et al. (1995) use a Heckman sample selection method (Heckman (1979)) to model the unconditional number of GP visits. The Heckman sample selection method is a two-stage estimation technique. In the first stage, estimates from a probit model are used to calculate a correction factor, the inverse Mills ratio. In the second stage, the correction factor is included in the OLS regression of the number of GP visits on explanatory variables.

More recently, the more flexible latent class model has been used to model the unconditional number of GP visits in Canada. A latent class model assumes the sample is drawn from a number of unobserved, or latent, 'classes', with each class representing a different distribution. For example, the latent class negative binomial model with two classes assumes each observation in the sample is drawn from one of two different negative binomial distributions. The latent class negative binomial model classifies a heterogeneous sample into more homogeneous classes using observable individual characteristics. This allows for heterogeneity across classes, such as individuals who are 'high-users' or 'low-users' of GP visits, while allowing for unobserved individual heterogeneity within each class.

Sarma and Simpson (2006), to my knowledge, is the only Canadian study to use a latent class negative binomial methodology to model the unconditional number of GP visits. They find the latent class negative binomial model out performs other standard parametric count data models using the log-likelihood, AIC and BIC statistics.

1.2.2 Determinants of general practitioner utilization in Canada

In the past 15 years, studies using Canadian health survey data consistently find certain factors are related to GP utilization. A person's health status and sex are important determinants of the probability of use and intensity of use. A person in poorer health has a higher probability of use and intensity of use relative to a person in better health. At younger ages, males have a lower probability of use and intensity than females, but at older ages males have a higher probability of use and intensity. The evidence is less consistent with respect to other determinants, such as income and education.

Determinants of Probability of Use

Table 1.1 summarizes the findings regarding the determinants of the probability of GP use in Canada. The evidence on the relationship between a person's household income and the probability of GP use is mixed. A number of studies find, after controlling for need, no significant relationship between income and the probability of use (Birch et al. (1993), Eyles et al. (1995) and Dunlop et al. (2000)). Three more recent studies find that a person with low-income has a statistically significant lower probability of use relative to a person with higher income (Stabile (2001), Deri (2005), and van Doorslaer et al. (2006)). Fell et al. (2007) find a person with low-income has a statistically significant higher probability of use relative to a person with higher income. There is some evidence to suggest the degree of income inequity in the probability of a GP visit at the Canada level is a result of differences between provinces (Allin (2006)[4]).

The evidence on the relation between a person's level of education and the probability of GP use is also mixed. A number of studies find, after controlling for need, either a small statistically significant negative relationship or no significant relationship between a person's level of education and their probability of GP use (Birch et al. (1993), Eyles et al. (1995), Deri (2005) and

[4]Allin (2006) finds, after controlling for need, the probability of GP use is pro-rich in all provinces, except Prince Edward Island. British Columbia is less pro-rich relative to the Canadian average, and the three territories, Yukon, Northwest Territories, and Nunavut, are more pro-rich relative to the Canadian average.

Fell et al. (2007)). Two studies find that a person with more education has a higher probability of GP use relative to a person with less education (Dunlop et al. (2000) and Allin (2006)).

The relationship between a person's health status and the probability of GP use is clear and statistically significant: being in poorer health leads to a higher probability of GP use. The most common measures of health status are: self-reported health[5], self-reported number of chronic conditions and self-reported activity limitations[6]. The lower a person's self-reported health, the greater is their probability of GP use (Birch et al. (1993), Eyles et al. (1995), Dunlop et al. (2000), Stabile (2001), Allin (2006), and Fell et al. (2007)). The greater a person's number of chronic conditions, the greater their probability of GP use (Dunlop et al. (2000), Stabile (2001) and Fell et al. (2007)). Finally, having an activity limitation is associated with a higher probability of GP use relative to having no activity limitation (Deri (2005)).

The relationship between a person's sex and the probability of GP use is also clear and statistically significant: males have a lower probability of GP use (Birch et al. (1993), Eyles et al. (1995), and Deri (2005)). While we may expect males to have a lower probability of GP use at younger ages, it is not clear males will have a lower probability of GP use over the life cycle. Interestingly, Deri (2005) is the only paper to include an interaction term between sex and age. She finds a small positive, and statistically significant, coefficient on the interaction term 'age and male' on the probability of GP use of a GP visit.

[5]Self-reported health is measured on a five-level Likert scale: excellent, very good, good, fair, or poor.

[6]Activity limitation indicates whether a person reports a limitation in their activities due to a long-term disability or handicap.

This supports the assertion that as males age their probability of GP use of use surpasses the probability of GP use of females.

A number of other factors - such as immigration status, marital status, the presence of children in the household, and region[7]/province of residence - are common control variables. These characteristics are not the focus of this study, but are included in the analysis to mitigate omitted variable bias since one aim of the paper is to produce good estimates of the effect of income and education.

There is no statistically significant difference in the probability of GP use between immigrants and Canadian-born (Deri (2005)). The effect of a person's marital status on the probability of GP use varies across studies. Birch et al. (1993), Eyles et al. (1995), and Dunlop et al. (2000) find no effect. The presence of children in the household is found to have either no effect (Dunlop et al. (2000)) or a positive effect on the probability of GP use (Deri (2005)). Dunlop et al. (2000) find a person's region/province of residence has no significant effect on the probability of GP use. But, most studies find a statistically significant affect of region/province of residence on the probability of GP use (Birch et al. (1993), Allin (2006), and Fell et al. (2007)).

Determinants of Intensity

Table 1.2 summarizes the findings for select determinants on the intensity of GP use in the Canada.

[7]When there is insufficient sample size or variation within a province, smaller provinces are aggregated into regions: Maritimes (Newfoundland, Nova Scotia, Prince Edward Island and New Brunswick), Quebec, Ontario, Prairies (Manitoba, Saskatchewan and Alberta) and British Columbia.

There are mixed results of the effect of income on intensity. The majority of studies find, after controlling for need, no significant relationship between income and intensity (Birch et al. (1993), Eyles et al. (1995), Dunlop et al. (2000), Deri (2005), Sarma and Simpson (2006)). Stabile (2001) finds, conditional on making at least one visit to a GP, a person with higher income has a lower intensity relative to a person with lower income. van Doorslaer et al. (2006) find that, conditional on making at least one visit to a GP, a person with higher income has a higher intensity relative to a person with lower income.

The evidence is also mixed on the relation between education and intensity. Most studies find, after controlling for need, no significant relationship between education and intensity (Birch et al. (1993)), Eyles et al. (1995), Dunlop et al. (2000), Stabile (2001), Sarma and Simpson (2006)). Deri (2005) finds a person with more education has a lower intensity relative to a person with less education.

The relationship between health status and intensity is clear and significant: people with poorer self-reported health have a higher intensity relative to people with better self-reported health (Birch et al. (1993), Eyles et al. (1995), Stabile (2001), and Sarma and Simpson (2006)). The more chronic conditions a person reports, the greater their intensity (Dunlop et al. (2000), Stabile (2001), Deri (2005), Sarma and Simpson (2006)). A person reporting an activity limitation has higher intensity relative to a person who does not report having an activity limitation (Deri (2005)).

A number of other factors may influence intensity. Males have a lower intensity (Birch et al. (1993), Eyles et al. (1995), and Deri (2005)). There is mixed evidence of the difference in intensity between immigrants and Canadian born. One paper finds immigrants have a higher intensity relative to Canadian born (Sarma and Simpson (2006)), while others find there to be no difference between immigrants and Canadian born (Dunlop et al. (2000) and Deri (2005)).

Evidence of the effect of marital status on intensity varies. One study finds marital status has no effect (Birch et al. (1993)) while other studies find that a person who is married has higher intensity relative to a person who is not married (Deri (2005), Sarma and Simpson (2006)). Another study finds single males have lower intensity than females who are married, separated/widowed or divorced (Dunlop et al. (2000)). Yet another finds a person who is widowed has a higher intensity relative to all other marital statuses (Eyles et al. (1995)). The presence of children in the household has no significant effect on intensity (Deri (2005)).

The region/province of residence has an effect on intensity. Two studies find, all else equal, a person living in Ontario or British Columbia to have a higher intensity relative to a person living in the Maritimes, Quebec or the Prairies (Birch et al. (1993), Eyles et al. (1995)). One study finds no regional variation for males, but females in Ontario have higher intensity relative to all other regions (Dunlop et al. (2000)). Jiménez-Rubio et al. (2008) finds evidence of a pro-poor income inequality in the number of GP visits in all provinces except New Brunswick, Prince Edward Island, and Quebec.

1.3 Data and Methods

1.3.1 National Population Health Survey

This study uses six cycles (1994/1995 - 2004/2005) of the Canadian National Population Health Survey (NPHS). The NPHS has collected health and socio-demographic information every two years since 1994/1995 from the same sample of household residents, age 12 and older, in all ten provinces. The NPHS excludes populations living in the three Territories, residents of health care institutions, those living on Indian Reserves, Canadian Forces Bases and in some remote areas in Quebec and Ontario. The longitudinal sample contains 17,276 persons and is not renewed over time (Statistics Canada (2004)).

The NPHS has a complex survey design based on a two-stage, stratified, cluster design. The sampling frame for all provinces, except Québec, is based on the Labour Force Survey (LFS). The LFS divides each province into three types of geographic areas (major urban, urban towns, and rural). From each area type, separate geographic and socioeconomic strata are defined. From each strata, generally 6 clusters are sampled with probability proportional to the population size of the cluster. From each cluster a sample of dwellings are sampled. From each dwelling, a household member is selected using the rejective method. The rejective method of sampling was used to ensure survey respondents are more representative of the population. If simple random sampling was used to select household members then the chance of a household member being selected would be inversely related to the number of persons in that household. This would then underrepresent people in large households, typically parents and children, and overrepresent people from small households, typically single people or the elderly. The rejective method attempts to select a more representative sample by pre-identifying a portion of the sample of household for screening. Screened households without a household member under 25 years of age are 'rejected' from being surveyed.[8]

The Québec sample was based on the sampling frame of the 1992/1993 Social and Health Survey (ESS) collected by Santé Québec. The sample frame for the ESS is similar to the LFS, except the ESS divides Québec into 15 health areas plus 4 urban intensity classes. Strata are then drawn from the 19 geographic areas (Statistics Canada (2004)).

To account for the NPHS's complex survey design, Statistics Canada produces sample weights and provides them with the micro data. The sample weights are computed using an initial weight representing the inverse probability of selection. The initial weight is then adjusted to account for survey specifics (such as non-response). Adjustments are also made for the longitudinal sample due to attrition. The last adjustment consists of post-stratification within each province to ensure consistency with population estimates based on the 1996 Canadian Census (Statistics Canada (2004)).

The dependent variable in the analysis is the self-reported number of consultations with a family doctor or general practitioner (GP) in the 12 months prior to the survey. The independent variables account for demand and supply side factors affecting utilization.[9] The relevant and desired income concept to

[8]For a more detailed treatment of the rejective method used in the NPHS, please refer to Tambay and Mohl (1995).

[9]For a complete list of independent variables and their definitions, refer to Table 1.A1 in Appendix 1.A1.

capture is a person's permanent income. Measures of current income, such as household income, do not fully capture permanent income. Other variables in addition to household income, such as education, in part capture the impact of permanent income. Again, the main independent variables of interest are household income, level of education, self-reported health status, number of chronic conditions and sex.

Household income is constructed as a continuous variable in real 1994 dollars.[10] Household income is not adjusted for household composition - such as marital status and the number of children living in the household. Rather, household composition variables are included as independent variables in the regression analysis. The level of education is a derived variable indicating the highest level of education attained by the individual: less than high school, high school graduate, some post secondary, and post secondary graduate.

Self-reported health status is based on a respondents answer to the question "*In general, would you say your health is: excellent, very good, good, fair, or poor.*"[11] The number of chronic conditions is self-reported by the respondent. A series of binary variables are constructed indicating the number of reported chronic conditions: zero, one to three, four or five, or six or more.

The analysis sample is restricted to respondents who are: (i) present in all six cycles of the survey, (ii) 18 years of age or older in cycle 1, and (iii) not

[10]Appendix 1.A2 provides more details on how the household income variable is constructed.

[11]It is common in the literature to use current self-reported health status in a model of health care use over the previous 12 months. However, this is an example of prediction after the fact, or postdiction. In the general postdiction case the estimated coefficients of self-reported health status are inconsistent and the direction can not be signed (Manning et al. (1982)).

missing information on the number of GP visits. Respondents who moved to a jurisdiction not surveyed are also removed. The final sample size of 7,334 people.[12]

One concern that may arise from the sample restrictions is how a systematic risk of selection into the sample may affect the results. Since the purpose of the paper is to compare between models, then any possible selection effects should not affect the results as any selection effects should affect each model in the same way.

Weighted descriptive statistics for the number of GP visits are reported in Table 1.3.[13] The overall mean number of GP visits in the sample is 3.26. The mean number of GP visits decreases as household income rises, from 4.11 visits for households earning less than $20,000 to 2.62 visits for households earning more than $80,000. The decrease is less dramatic by level of education, from 3.75 visits for individuals with less than a high-school education to 2.95 visits for individuals with a post-secondary education. The most dramatic differences are seen across health statuses: respondents in excellent health average 1.95 visits, while respondents in poor health average 11.07 visits. The mean number of GP visits also increases with the number of chronic conditions: respondents reporting zero chronic conditions average 1.80 visits, while respondents reporting 6 or more chronic conditions average 8.61 visits.

The overall median number of GP visits is 2. There is no variation in the

[12]The initial sample is 17,276. There were 7,189 observations dropped due to non-response in at least one cycle, 2,211 individuals less than 18 years of age; and 542 observations dropped due to missing information for the number of GP visits

[13]Refer to Table 1.A3 and 1.A4 in Appendix 1.A3 for descriptive statistics for the number of GP visits for each cycle. While there is some variation across cycles in the panel, the main conclusions of Table 1.3 still hold.

median number of GP visits across socioeconomic and immigrant status. The median for males (1) is lower than the median for females (2). The greatest difference in median number of GP visits is observed across health statuses. Respondents in excellent health have a median number of GP visits equal to 1 compared to respondents in poor health have a median number of GP visits equal to 6.

The overall proportion of individuals reporting zero GP visits in a year is 21.1%. There is little variation by income and education. The proportion of individuals reporting zero GP visits in a year decreases across self-reported health categories: excellent (28.7%) to very good (22.5%) to good (16.9%) to fair (10.5%) to poor (4.5%). A similar, yet more pronounced, decrease can be seen across the number of reported chronic conditions: zero (33.4%) to one to three (15.7%) to four or five (6.5%) to six or more (0.0%). Males report zero GP visits nearly twice as often as females (27.7% compared to 14.9%).

The overall proportion of people reporting 5 or fewer GP visits is 84.3%.[14] There an increase between lowest and highest household income (78.1% to 89.0%) and education (79.7% to 86.6%) levels. The increase is more dramatic from poor to excellent self-reported health (40.1% to 93.6%), as well as zero and 6 or more chronic conditions (44.7% to 93.8%). Males have a higher proportion of respondents reporting fewer than 5 GP visits compared to females (79.7% compared to 89.0%). These results suggest the distribution of GP visits in this sample is skewed - given the high proportion of zeros and a low mean -

[14]The threshold of 5 is used to get a sense of the proportion of people reporting a low number of visits. The threshold of 5 was chosen to be consistent with the definition of 'non-frequent user' by Dunlop et al. (2000).

and over-dispersed.

Descriptive statistics for a set of select independent variables are presented in Table 1.4. The average household income in all years for all respondents is just over \$47,000, with the median at just under \$42,000. Changes in the mean between cycles may be a result of the improving economic climate in Canada during the 1990s and the changing age structure of the sample.

By cycle six, just over two in five respondents report having attained a post-secondary education. The proportion of individuals reporting some post-secondary education, high school or less than high school decreases over the panel. The increase in post-secondary is expected since education takes time to complete and given the respondents age over the panel they are able to complete higher levels of education. By the end of the panel, approximately one in five people do not have a high school education.

Overall, the health of the sample declines over time. The decline in health status is most likely due to the increase in age of the sample during the panel (from 41.4 years to 51.4 years). While roughly the same proportion of people report being in very good health (approximately 40% in each year); there is a 36.5% decrease in the proportion of respondents reporting excellent health between 1994 and 2004 (from 27.7% to 17.6%); and a 21% increase in people reporting good health between 1994 and 2004 (from 24.8% to 32.0%). Note while the proportion of individuals in fair or poor health is low in terms of levels (6.4% and 1.1% in cycle 1 respectively), there are large percentage increase (42% and 118% respectively) between cycle 1 and cycle 6.

There is also a notable increase in the number of chronic conditions over the panel. The proportion of people reporting no chronic conditions decreases 38.6% (from 46.4% in 1994 to 28.5% in 2004), while one to three chronic conditions increases 16.9% (from 48.4% in 1994 to 56.6% in 2004). However, the largest relative increases are for four or five chronic conditions (a 166.7% increase from 4.2% in 1994 to 11.2% in 2004) and six or more chronic conditions (a 270.0% increase from 1.0% in 1994 to 3.7% in 2004).

1.3.2 Modeling Strategy

The literature developing more flexible parametric count data models builds on potentially misleading distributional assumptions for the number of GP visits. For example, assuming the number of GP visits is generated from a Poisson distribution or a negative binomial distribution. The assumption is potentially misleading as it may: (i) mask the underlying data structure, or (ii) mis-specify the conditional mean function. Both of these possibilities have motivated this paper to use a nonparametric kernel conditional density estimator to analyze the number of GP visits and to compare the performance of the preferred parametric model to a nonparametric estimator.

Two main modeling approaches are used: one parametric and one non-parametric. The parametric model is a latent class negative binomial (LCNB) model[15]. The nonparametric model is a kernel conditional density estimator (KCDE).

Both models account for unobserved individual heterogeneity, but do so

[15]Consistent with the findings of Sarma and Simpson (2006), I find the LCNB model to be preferred to other cross-sectional parametric models using standard in-sample measures of model performance: $log(L)$, AIC, and BIC. See Appendix 1.A7 for this analysis.

in a different manner. The LCNB model accounts for unobserved individual heterogeneity by assuming the population is generated from two different latent classes, each of which has a different negative binomial distribution as the data generating process. Individuals are assumed heterogeneous between latent classes, but homogeneous within each latent class. The KCDE accounts for unobserved individual heterogeneity by allowing the parameter estimates to vary across individuals.

Three different model specifications are estimated (Table 1.5). The first model specification estimates six cross-sectional models, one from each cycle in the panel. The second model specification uses all six cycles to estimate a panel model with no endogeneity correction. The third approach uses five cycles, cycle two through six, to estimate a panel model that includes a one period lag in self-reported health status to correct for the possible endogeneity between self-reported health status and the number of GP visits.

Survey design effects are ignored in the model comparison as incorporating sample weights into the nonparametric model is not straightforward. To keep the models comparable, sample weights were also not used when estimating the parametric models, but clustering is not accounted for. Again, since the purpose of the paper is to compare models, not using sample weights should affect models in the same way and not contaminate the model comparison exercise. Not accounting for clustering will affect the standard error estimates, which will not affect the model comparison exercise but may affect the inference made from the incremental effects.

Not including sample weights in the models means some caution should be used when interpreting the estimated incremental effects as they are not precise population point estimates. As noted by Deaton (1997), in the presence of heteroskedacitity and its interaction with the complex survey design it is not straightforward whether the use of weights are appropriate. Deaton (1997) does suggest one solution is to use the bootstrap method to produce point estimates and the associated standard errors. However, the bootstrap method requires each bootstrap sample be selected in the same manner as the original sample (i.e. using the sample complex survey design as the NPHS). However, Statistics Canada did not provide variables to identify strata and clusters on the micro data files used.

1.3.3 Latent Class Negative Binomial Model

The latent class negative binomial (LCNB) model, also referred to as a finite mixture model, was first applied to model the number of GP visits by Deb and Trivedi (1997). The LCNB model fits the data on GP visits better than the two-part model (Deb and Trivedi (1997), Deb and Trivedi (2002), Jiménez-Martín et al. (2002), and Sarma and Simpson (2006)).

The latent class approach assumes that the sample of individuals is drawn from a population consisting of C different latent classes and each class has a different underlying distribution. Each person in the sample is assumed to have been drawn from one of the latent classes.

The log-likelihood function is constructed as the sum of the probability of belonging to the j^{th} latent class (π_j) times the negative binomial density for the j^{th} latent class ($f_j(\cdot)$). In the case of only two latent classes ($j = 1$ or 2), the probability of belonging to latent class 1 is π and the probability of belonging to latent class 2 is $1-\pi$. Hence the log-likelihood function is given by:[16]

$$(1.1) \qquad L_{LCNB}(\alpha_j, \beta_j) = \ln\left[\pi f_1(y_i|\mathbf{x}_i, \alpha_1, \beta_1) + (1-\pi) f_2(y_i|\mathbf{x}_i, \alpha_2, \beta_2)\right],$$

where y_i is the number of GP visits, and $\mathbf{x}_i$ is a vector of covariates for individual i, π is the probability of belonging to a latent class one, α_j is the dispersion parameter, and β_j is a vector of parameters for the j^{th} latent class. Each of α_j and β_j are permitted to vary between latent classes. Equation (1.1) is estimated using maximum likelihood. The probability of class membership (π) is estimated simultaneously using a logit specification, based on a person's observable characteristics.

1.3.4 Latent Class Negative Binomial Panel Model

Bago d'Uva (2005) extended the LCNB model to a panel framework (LCNB-Panel). The log-likelihood function for the LCNB-Panel model is constructed in a similar way as the LCNB model, but now the negative binomial density function uses information from all cycles in the panel:[17]

$$(1.2) \quad L_{LCNB-Pan}(\alpha_j, \beta_j) = \ln\left[\pi f_1(y_{it}|\mathbf{x}_{it}, \alpha_1, \beta_1) + (1-\pi) f_2(y_{it}|\mathbf{x}_{it}, \alpha_2, \beta_2)\right],$$

where y_{it} is the number of GP visits, and $\mathbf{x}_{it}$ is a vector of covariates for

[16]Refer to Appendix 1.A4 for a detailed development of equation (1.1). For a more detailed description of latent class models in general, refer to Deb and Trivedi (1997), Deb and Trivedi (2002), or Jones et al. (2007).

[17]Again, refer to Appendix 1.A4 for a detailed development of equation (1.2).

individual i at time t. The probability of belonging to a latent class (π), the dispersion parameter (α_j) and the vector of parameters (β_j) within each latent class are assumed to be constant over time, but are permitted to vary between latent classes.

1.3.5 Nonparametric Kernel Conditional Density Estimator

The nonparametric estimator employed is a kernel conditional density estimator (KCDE) for continuous and categorical variables.[18] The KCDE uses the number of GP visits (y) and explanatory factors ($\mathbf{x}$) to estimate the density of y conditional on $\mathbf{x}$.

The KCDE uses a weighting (or kernel) function to smooth the empirical distribution around each data point. Each variable in the model has its own kernel function, and the choice of kernel function depends on the variable type (continuous, ordered discrete, or unordered discrete). A kernel for a continuous variable provides an estimate of the continuous density function using the information in a neighbourhood around each data point, where the size of the neighbourhood is determined by the smoothing parameter (or bandwidth). A kernel for either an ordered discrete or unordered discrete variable provides an estimate of the density for each outcome of the discrete variable using information from each point of the discrete support.

Since $\mathbf{x}$ is a mixture of continuous ($\mathbf{x}^c$) and discrete ($\mathbf{x}^d$) variables, denote $\mathbf{x} = (\mathbf{x}^c, \mathbf{x}^d)$. The conditional density of y given $\mathbf{x}$ is denoted by $g(y|\mathbf{x})$, which

[18] Refer to Chapter 5 in Li and Racine (2007) for a thorough presentation of the KCDE.

is equal to the ratio of the joint density of $\mathbf{x}$ and y ($f(\mathbf{x}, y)$) to the marginal density of $\mathbf{x}$ ($\mu(\mathbf{x})$):

$$g(y|\mathbf{x}) = \frac{f(\mathbf{x}, y)}{\mu(\mathbf{x})}. \tag{1.3}$$

Since the true functions $g(y|\mathbf{x})$, $f(\mathbf{x}, y)$ and $\mu(\mathbf{x})$ are unknown, each is replaced by the estimates $\hat{g}(y|\mathbf{x})$, $\hat{f}(\mathbf{x}, y)$ and $\hat{\mu}(\mathbf{x})$ respectively:

$$\begin{aligned}
\hat{g}(y|\mathbf{x}) &= \frac{\hat{f}(\mathbf{x}, y)}{\hat{\mu}(\mathbf{x})}, \\
\hat{f}(\mathbf{x}, y) &= \frac{1}{n}\sum_{i=1}^{n} K_{\gamma}(\mathbf{x}, X_i) z(y, Y_i), \\
\hat{\mu}(\mathbf{x}) &= \frac{1}{n}\sum_{i=1}^{n} K_{\gamma}(\mathbf{x}, X_i),
\end{aligned}$$

where n is the sample size, $K_{\gamma}(\cdot)$ is a generalized product kernel for mixed data types, X_i is the i^{th} realization of $\mathbf{x}$, $\gamma = (h, \lambda)$ are the smoothing parameters for the continuous (h) and discrete (λ) variables, $z(\cdot)$ is the kernel for the number of GP visits, and Y_i is the i^{th} realization of y. The kernels are defined as:

$$\begin{aligned}
z(y, Y_i) &= \frac{1}{h_y} k\left(\frac{y - Y_i}{h_y}\right), \\
K_{\gamma}(\mathbf{x}, X_i) &= C(\mathbf{x}^c, X_i^c, h) D(\mathbf{x}^d, X_i^d, \lambda), \\
C(\mathbf{x}^c, X_i^c, h) &= \prod_{r=1}^{p} \frac{1}{h_r} w_g\left(\frac{x_r^c - X_{ir}^c}{h_r}\right), \\
D(\mathbf{x}^d, X_i^d, \lambda) &= \prod_{s=1}^{q} w_{wvr}(\mathbf{x}^d, X_i^d, \lambda) w_{lr}(\mathbf{x}^d, X_i^d, \lambda),
\end{aligned}$$

where p is the number of continuous variables and q is the number of discrete variables. The bandwidth for the r^{th} continuous variable is given by h_r, the bandwidth for the s^{th} discrete variable is given by λ_s. $C(\cdot)$ is a product of second-order Gaussian kernels (w_g). $D(\cdot)$ is the product of Wang-Van Ryzin kernels for the ordered discrete variables (w_{wvr}) and Li-Racine kernels for the unordered discrete variables (w_{lr}). These three kernel functions (w_g, w_{wvr}, and w_{lr}) are given by:

$$\begin{aligned}
w_g &= \frac{e^{-\frac{1}{2}z^2}}{\sqrt{2\pi}}, \text{ where } z = \frac{|X_i^c - \mathbf{x}^c|}{h}, \text{ and } h > 0; \\
w_{wvr} &= \begin{cases} 1-\lambda & \text{if } |\mathbf{x}^d - X_i^d| = 0 \\ \frac{(1-\lambda)\lambda^{|\mathbf{x}^d - X_i^d|}}{2} & \text{if } |\mathbf{x}^d - X_i^d| \geq 1 \end{cases}, \text{ where } \lambda \in [0,1]; \text{ and} \\
w_{lr} &= \begin{cases} 1 & \text{if } \mathbf{x}^d = X_i^d \\ \lambda & \text{if } \mathbf{x}^d \neq X_i^d \end{cases}, \text{ where } \lambda \in [0,1].
\end{aligned}$$

As noted by Li and Racine (2007), nonparametric kernel estimation is relatively insensitive to the choice of kernel but is highly sensitive to the choice of bandwidths. Selecting appropriate bandwidths is critical and non-trivial, especially in the context of multivariate data. Choosing too small a bandwidth will under-smooth the empirical distribution, because less information enters the kernel, decreasing the bias and increasing the variance of the estimates. Choosing too large a bandwidth will over-smooth the empirical distribution, since more information enters the kernel, increasing the bias and decreasing the variance of the estimates. Thus, selecting optimal bandwidths must account for this bias-variance trade off.

The method used to select bandwidths is least squares cross validation, which selects bandwidths (h, λ) by minimizing the weighted integrated square error (see Hall et al. (2004)). One advantage of this method is it automatically removes irrelevant variables by selecting large bandwidths for these variables. One disadvantage of this method is its computationally intensive.

1.4 Results

The presentation of results is organized around three sets of comparisons. The first set compares the two panel models, one without endogeneity correction and one with endogeneity correction. The second set compares the six cross-sectional models to the panel model without endogeneity correction. The third set compares the six cross-sectional and the two panel models, each estimated using a LCNB model and a KCDE.

In each set of comparisons I discuss two aspects of model results: (i) in-sample goodness-of-fit, and (ii) the incremental effect on the predicted conditional mean number of GP visits of a change in a person's observed characteristics. A model's in-sample goodness-of-fit is assessed using three measures: the correct classification ratio (CCR), which is equal to the percentage of correct predictions; the root mean squared prediction error (RMSPE); and the mean absolute prediction error (MAPE). Both the RMSPE and the MAPE quantify the deviation between the predicted number of GP visits and the observed number of GP visits. The RMSPE and MAPE take on values greater than, or equal to, zero with values further from zero signaling a greater deviation in model predictions. Thus, models with a lower RMSPE and MAPE are preferred. Goodness-of-fit measures are presented in Table 1.6 for all six cross-sectional models and both panel models for each of the LCNB model and a KCDE.[19]

The second aspect discussed in each set of comparisons is the incremental effect (IE) of a change in a person's observable characteristics: income, education, self-reported health, number of chronic conditions and sex. The IE is equal to the change in the predicted conditional mean number of GP visits from a change in a given characteristic. The IE is calculated relative to the reference group for each characteristic. Since both the LCNB and the KCDE are non-linear models, the conditional mean, and hence the IE, will depend on the values of the other independent variables. For example, the IE of changing health status from excellent to poor will be different for a person who is older than for a person who is younger, all else equal.[20]

Because the LCNB model and the KCDE are nonlinear models, I compare the IE at three different sets of values for the independent variables. The three sets of values illustrate how the IEs differ for different 'types' of individuals: (i) the median/modal person: the independent variables are set to their median or modal values; (ii) the low-use person: a 25 year-old male with excellent self-reported health, zero chronic conditions, and all other independent variables are set to their median or modal values; and (iii) the high-use person: a 25 year-old male with poor self-reported health and two chronic conditions.

[19]Appendix 1.A5 provides a detailed description of how the CCR, RMSPE and MAPE are calculated.

[20]While the results are presented as incremental effects here, the coefficient estimates from a LCNB and LCNB-Pan models are presented in Appendix 1.A8 for completeness.

The IE for both the LCNB and KCDE are presented in Table 1.7 for the median person, Table 1.8 for the low-use person, and Table 1.9 for the high-use person. Each table presents the conditional mean number of GP visits ($E[y|x]$) for a person with characteristic x_j and the IE of moving to characteristic x_j from the reference group.

1.4.1 Goodness-of-Fit

Endogeneity Correction vs. No Endogeneity Correction

Correcting for endogeneity does not improve the LCNB model predictions. Comparing the CCR, RMSPE, and MAPE between the LCNB panel model with endogeneity correction and without endogeneity correction, both models have nearly identical goodness-of-fit measures (Table 1.6). The CCR of the LCNB panel model without endogeneity correction (15.2%) is nearly identical to that of the LCNB panel model with endogeneity correct (15.7%). The RMSPE is nearly identical for both models (5.45 compared to 5.43), and the MAPE is identical (2.60). A similar comparison for the KCDE panel models is not made, because the KCDE panel model with endogeneity correction under-smooths the data, leading to the model perfectly predicting the observed values.[21]

[21]Cross-validation appears to breaks down, causing a small bandwidth to be selected for a particular variable resulting in under-smoothing of the observed distribution (as shown by CCRs of 100%). The cause of the under-smoothing is the short panel (6 cycles) as it does not provide sufficient variation to optimize bandwidth selection. The specific bandwidth causing problems is for the variable ID. To prevent the model from under-smoothing, I manually set the bandwidth for the ID variable to 0.4 in order to balance the in- and out-of-sample predictions.

Cross-Sectional vs. Panel Model, without Endogeneity Correction

The cross-sectional models predict as well, or better, than the panel model without endogeneity correction. The six LCNB cross-sectional models have a CCR ranging from 13.9% to 16.8%; with the CCR from the LCNB panel model (15.2%) falling in the range of the cross-sectional CCRs. The predicted values from the LCNB cross-sectional models deviate from the observed values, as shown by the RMSPE (ranging from 4.53 to 6.88) and MAPE (ranging from 2.47 to 2.80). The deviation between the predicted and observed number of GP visits in the LCNB panel model, as shown by RMSPE of 5.45 and a MAPE of 2.60, is within the range of RMSPE and MAPE from the six cross-sectional models. The six KCDE cross-sectional models have a CCR ranging from 47.7% to 58.4%; with the CCR from the KCDE panel model (51.9%) falling in the range of the cross-sectional CCRs. The predicted values from the KCDE cross-sectional models deviate from the observed values, as shown by the RMSPE (ranging from 4.07 to 5.34) and MAPE (ranging from 1.63 to 2.04). The deviation between the predicted and observed number of GP visits in the KCDE panel model, as shown by RMSPE of 5.24 and a MAPE of 1.91, is within the range of RMSPE and MAPE from the six cross-sectional models.

Parametric LCNB Model vs. Nonparametric KCDE

The KCDE produces better predictions than the LCNB model.[22] All pairwise comparisons between the LCNB model and KCDE of goodness-of-fit measures

[22]Discussion here of the KCDE models excludes the KCDE panel model with endogeneity correction.

(CCR, RMSPE and MAPE) favor the KCDE. The seven KCDE models have a CCR ranging from 47.7% to 58.4%, compared to the eight LCNB models that have a CCR ranging from 13.9% to 16.8%. The predicted values from the seven KCDE models, as shown by the RMSPE (ranging from 4.07 to 5.80) and MAPE (ranging from 1.63 to 2.04) deviate less from the observed values than the predicted values from the eight LCNB models, as shown by the higher RMSPE (ranging from 4.53 to 6.88) and MAPE (ranging from 2.47 to 2.80).

1.4.2 Incremental Effects

Endogeneity Correction vs. No Endogeneity Correction

The IEs are similar in magnitude and sign between the panel models with and without endogeneity correction. This suggests the endogeneity between self-reported health and the number of GP visits does not meaningfully influence the estimated IE. While the IEs are similar between the two panel models, the conditional mean estimates tend to be smaller with endogeneity correction.

For example, the LCNB panel model without endogeneity correction produces an IE of increasing the median person's household income from $20,000 to $110,000 of -0.12 visits while the panel model with endogeneity correction produces an estimate of -0.10 (Table 1.7). The IEs from both panel models are nearly identical when the median person's household income is increased from $20,000 to $50,000 (-0.05 vs. -0.04) and from $20,000 to $80,000 (-0.09 vs. -0.07). The estimated income-related IEs for the two models are also similar for a person with low-income (Table 1.8). However, the estimated income-related IEs differ in magnitude across the two panel models for the high-use person (Table 1.9). The IE of increasing the high-use person's household income from \$20,000 to \$110,000, is -1.05 without endogeneity correction and -1.37 with endogeneity correction. This larger difference corresponds with the larger conditional mean from both models.

Similar IEs are also found between the two panel models when using the KCDE. For example, the IE of increasing the median person's household income from \$20,000 to \$110,000 is -0.05 visits with no endogeneity correction and -0.01 with endogenity correction (Table 1.7). The estimated IEs are nearly identical from the panel model without endogeneity correction and the panel model with endogeneity correction of increasing the low-use person's household income from \$20,000 to \$50,000 (-0.04 vs. -0.02) and from \$20,000 to \$80,000 (-0.05 vs. -0.04).

Cross-Sectional vs. Panel Model, without Endogeneity Correction

The results from the six cross-sectional models and the panel model without endogeneity correction are consistent with each other in terms of the magnitude and the sign of the IE.

For example, the cross-sectional LCNB models estimate a small IE ranging from -0.25 to 0.00 visits when increasing the median person's household income by \$30,000 (Table 1.7). The IE tends to be larger at lower incomes than at higher incomes. The LCNB panel model also estimates a small IE of -0.05 visits when moving from \$20,000 to \$50,000 of household income, -0.09 visits when moving from \$20,000 to \$80,000, and -0.12 visits when moving from \$20,000 to \$110,000.

An exception to the general finding can be seen for the IE of a change in self-reported health for the median person. The expected conditional mean for all levels of self-reported health are consistent across model specifications, with the exception of poor self-reported health in 1998. In 1998, the IE of moving from excellent to poor health (16.30 visits) is 3-4 times the magnitude of the IE from other years (ranging from 3.57 to 5.92 visits).

The general conclusion also holds for the KCDE: the IEs for the independent variables from the KCDE cross-sectional and panel models are consistent with each other in terms of magnitude of the conditional mean and the sign of the IE. For example, the IE of increasing a person's household income by \$30,000 is, again, consistently near zero or slightly negative. Three cross-sectional KCDE models - 1998, 2000 and 2002 - find a zero IE on the expected conditional mean for every \$30,000 increase in household income. The other three cross-sectional KCDE models - 1994, 1996 and 2004 - find small IEs, between -0.11 and 0.02 visits, for every \$30,000 increase in household income. The KCDE panel model estimates negative IEs of the similar magnitude, between -0.01 and -0.19 visits, for every \$30,000 increase in household income.

Parametric LCNB Model vs. Nonparametric KCDE

The most important finding is the differences between the IEs from the LCNB model and the KCDE are greater for health related variables, such as self-reported health and number of chronic conditions, than for socioeconomic status variables, such as income and education. The differences in IEs depend on both the magnitude and variation of the conditional mean estimates. The magnitude and variation of the conditional mean estimates depend on the segment of the distribution of GP visits under consideration.

The differences in conditional mean estimates from the LCNB model and KCDE are smallest for the low-use person and largest for the high-use person. The LCNB model produces conditional mean estimates that tend to be greater in magnitude and variation. For example, the conditional mean estimates from the panel model without endogeneity correction by self-reported health status for a low-use person have more variation for the LCNB model (range 1.60 to 6.04) than from the KCDE (range 2.05 to 2.40, Table 1.8). However, the conditional mean estimates by self-reported health status for a high-use person are larger in magnitude and variation from the LCNB model (range 10.12 to 23.30) than from the KCDE (range 3.78 to 5.24, Table 1.9).

The larger magnitude and variation of the conditional mean estimates from the LCNB model for changes in self-reported health status results in larger differences in the IEs between the LCNB model and the KCDE. The IEs from the LCNB model range from 0.33 visits (changing from excellent health to very good health) to 4.44 visits (changing from excellent health to poor health). The IEs are smaller from the KCDE ranging from 0.35 visits (changing from excellent health to very good health) to 0.15 visits (changing from excellent health to poor health).

In contrast to the large differences between the IEs from the LCNB model and the KCDE from changes in self-reported health, the differences in IEs are smaller from changes in household income level. The conditional mean estimates from the panel model without endogeneity correction by household income level for a low-use person are of similar magnitude for the LCNB model (range 1.48 to 1.64) than from the KCDE (range 1.45 to 1.53, Table 1.8). While the conditional mean estimates by household income level for a high-use person are larger for the LCNB model (range 9.35 to 10.40) than for the KCDE (range 3.18 to 3.41, Table 1.9), the difference between the small and large estimate is proportionally similar.

The similarity between the LCNB model and the KCDE in the conditional mean estimates for the low-use person result in similar IEs from increasing household income for a low-use person from \$20,000 to \$110,000 produces an IE of -0.15 for the LCNB and -0.08 for the KCDE (Table 1.8). However, the larger conditional mean estimates by household income level for a high-use person from the LCNB model results in much higher IEs than for a low-use person. The IE of increasing income from \$20,000 to \$110,000 for a high-use person is 7.44 for the LCNB and 0.24 for the KCDE (Table 1.9).

1.5 Discussion

The goodness-of-fit results answer the first research question: does the non-parametric estimator out performs the state-of-the-art parametric latent class negative binomial (LCNB) model in predicting the number of GP visits? The pair wise comparisons of the correct classification ratio (CCR), root mean squared prediction error (RMSPE), and the mean absolute prediction error (MAPE) from all eight model specifications (six cross-sectional models and two panel models), each estimated using a LCNB model and KCDE, show the better predictive ability of the KCDE. The LCNB model predicts fewer observed outcomes correctly and the incorrect predictions deviate more from the observed outcomes, relative to the KCDE.

The goodness-of-fit results are interesting since the literature using count data models to analyze GP utilization points to the LCNB model as the preferred parametric model. While it may be the case the LCNB is the preferred model to analyze the number of GP visits among the set of parametric models, it seems that imposing parametric model assumptions about the distribution of the number of GP visits comes at a cost of the models ability to accurately predict the observed number of GP visits. Producing accurate predictions of health care utilization is important, especially in applications such as producing risk-adjusted capitation payments.

The second set of results, the estimated incremental effects (IE) of a change in an individual's characteristics on their conditional mean number of GP visits, draws three main conclusions that helps to answer the second research question: are the estimated effects of an individual's characteristics qualitatively different in a nonparametric model than the effects from a parametric model?

The first conclusion drawn is that there is little meaningful difference in the IEs between a panel model with endogeneity correction and one without endogeneity correction. Neither the ability to accurately predict the observed outcome nor the estimated IEs differ meaningfully between the panel model with endogeneity correction and the panel model without endogeneity correction. This suggests the endogeneity between self-reported health status and the number of GP visits is weak and not correcting for it does not meaningfully bias results.

The second conclusion drawn is that there is little meaningful difference between the cross-sectional models and the panel model without endogeneity correction. Neither the ability to predict the observed outcomes, the estimated conditional means, nor the sign of the IEs differ meaningfully across the two model specifications.

Finally, the third, and the most important, conclusion is that the choice of using a LCNB model or a KCDE is critical to the conditional mean estimates and, ultimately, the IEs. This is demonstrated by the larger estimated IEs from the LCNB model at certain portions of the distribution of GP visits. The differences between the IEs from the LCNB model and the KCDE are relatively small for low-users (i.e the left tail of the distribution); are slightly larger for the median person (i.e the middle of the distribution); and are relatively large for the high-use person (i.e the right tail of the distribution). The magnitude of the IEs is driven by the magnitude of the estimated conditional mean number of GP visits. As expected, the estimated conditional mean is larger the further right in the distribution of GP visits. However, the estimated conditional mean for the high-use person is, on average, 8 times the magnitude for the low-use person when using the LCNB model. By comparison, the estimated conditional mean for the high-use person is, on average, 2.5 times the magnitude for the low-use person when using the KCDE.

The third conclusion suggests imposing parametric assumptions on the distribution of GP visits could be masking the underlying relationship between an individual's characteristics and their number of GP visits due to the non-standard distribution of GP visits as shown by the large proportion of zeros, the large probability mass below five visits, and the long right tail. Analyses of the number of GP visits based on standard parametric models may over predict the number of GP visits, especially for high-users. For example, if the results in this paper from the LCNB model were used to produce risk adjusted capitation payments then the LCNB may over estimate capitation payments made for patients in poorer health.

Overall, the results suggest analyses based on a dependent variable with a non-standard distribution, such as the number of physician visits or health expenditures, lend themselves to nonparametric estimator. The choice of estimation approach is not trivial since the choice of estimator can have meaningful differences in the estimated effect of patient characteristics on their predicted utilization and the accuracy of model predictions. Given the importance of health economic research into areas such as producing capitation finance formulas, forecasting health care expenditure and evaluating health system performance, researchers should be aware of how parametric model assumptions may influence the results of their research.

Table 1.1: Relationship Between Selected Determinants and the Probability of GP Visits

	Data	Methodology	Income	Education	Sex	Self-Reported Health	Chronic Conditions
Birch et al. (1993)	GSS 1	Probit	none	none	M<F ^{**,1}	– **	
Eyles et al. (1995)	GSS 1 & 6	Probit	none	none	M<F ^{**,1}	– **	
Dunlop et al. (2000)	NPHS 1	Logit	none	+ **	M<F	– **	+ **
Stabile (2001)	NPHS L2	Probit	+ **	none		– **	+
Deri (2005)	NPHS L3	Linear Probability	+ + **	none	M<F **		+ **
Allin (2006)	CCHS 2.1	Logit	+	+ **		– **	
Fell et al. (2007)	NPHS 2	Negative Binomial	none	none		– **	+ **

CCHS: Canadian Community Health Survey. 1.1=2000/2001, 2.1=2003
GSS: General Social Survey. 1=1985, 2=1991
NPHS: National Population Health Survey. 1=1994/1995, 2=1996/1997,
L2=1994/1995 to 1996/1997, L3=1994/1995 to 1998/1999
Note: * denotes the 1% level, ** denotes the 5% level, and *** denotes the 10% level.
'+' denotes a positive relationship
'–' denotes a negative relationship.
'none' denotes no statistically significant relationship.
[1] This model does not control for age/sex interactions.

Table 1.2: Relationship Between Selected Determinants and the Intensity of GP Visits

	Data	Methodology	Income	Education	Sex	Self-Reported Health	Chronic Conditions
Models of the Unconditional Number of GP Visits							
Birch et al. (1993)	GSS 1	Sample Selection	none	none	M<F **,[1]	– **	
Eyles et al. (1995)	GSS 1 & 6	Sample Selection	none	none	M<F **,[1]	– **	
Dunlop et al. (2000)	NPHS 1		none	none		– **	+ **
Sarma and Simpson (2006)	NPHS 3	Latent Class Neg. Bin.	none	none	M<F *,[1]	– *	+ *
Jiménez-Rubio et al. (2008)	CCHS 1.1	Generalized Neg. Bin.	– **				
Models of the Conditional Number of GP Visits							
Stabile (2001)	NPHS L2	Log-OLS	– ***	none ***		– **	+ **
Deri (2005)	NPHS L3	Log-OLS	none	– **	M<F ***		+
van Doorslaer et al. (2006)	CCHS 1.1	Generalized Neg. Bin.	– **				

CCHS: Canadian Community Health Survey. 1.1=2000/2001, 2.1=2003
GSS: General Social Survey. 1=1985, 2=1991
NPHS: National Population Health Survey. 1=1994/1995, 2=1996/1997, L2=1994/1995 to 1996/1997, L3=1994/1995 to 1998/1999
Note: * denotes the 1% level, ** denotes the 5% level, and *** denotes the 10% level.
'+' denotes a positive relationship
'–' denotes a negative relationship.
'none' denotes no statistically significant relationship.
[1] This model does not control for age/sex interactions.

Table 1.3: Summary Statistics of annual number of GP Visits (pooled)

	Mean	S.E.(Mean)	Median	0 visits (%)	< 5 visits (%)
Total	3.26	0.03	2	21.1	84.3
Household Income					
Less than $20,000	4.11	0.07	2	19.2	78.1
$20,000 to $50,000	3.37	0.04	2	21.6	83.6
$50,000 to $80,000	2.84	0.05	2	22.1	86.8
More than $80,000	2.62	0.05	2	21.2	89.0
Education					
Less than High School	3.75	0.06	2	20.9	79.7
High School	3.26	0.07	2	20.6	84.6
Some Post-Secondary	3.37	0.06	2	21.3	83.7
Post-Secondary	2.95	0.04	2	21.3	86.6
Self-Reported Health					
Excellent	1.95	0.04	1	28.7	93.6
Very Good	2.56	0.03	2	22.5	88.9
Good	3.88	0.05	2	16.9	79.8
Fair	7.02	0.15	4	10.5	56.8
Poor	11.07	0.51	6	4.5	40.1
Number of Chronic Conditions					
Zero	1.8	0.03	1	33.4	93.8
1 to 3	3.57	0.04	2	15.7	82.9
4 or 5	6.32	0.13	4	6.5	60.3
6 or more	8.61	0.27	6	0.0	44.7
Sex					
Male	2.52	0.03	1	27.7	89.0
Female	3.95	0.04	2	14.9	79.7

Data Source: NPHS, cycle 6, longitudinal file (1994 – 2004)

Table 1.4: Summary Statistics of Independent Variables, by year

	1994	1996	1998	2000	2002	2004	Total
Socioeconomic Status							
Household Income (Real 1994 $)							
Mean	45,780	42,853	47,412	48,780	48,293	52,668	47,631
S.E. (Mean)	347	322	347	347	342	415	145
Median	42,198	40,394	40,471	45,893	44,204	42,959	41,832
5^{th} Percentile	7,630	7,338	7,216	6,881	6,530	6,229	7,120
95^{th} Percentile	105,314	101,029	99,382	95,305	91,007	109,987	103,770
Less than High School	20.1	18.6	18.1	17.8	17.5	17.4	18.3
High School	17.0	16.1	15.5	14.9	14.7	14.3	15.4
Some Post-Secondary	26.7	27.8	26.9	25.8	25.6	25.3	26.3
Post-Secondary	36.3	37.5	39.5	41.5	42.2	43.0	40.0
Health Status							
Excellent	27.7	24.8	24.8	21.5	18.7	17.6	22.5
Very Good	40.0	41.7	42.1	39.9	38.3	38.8	40.1
Good	24.8	26.7	26.1	28.7	32.3	32.0	28.4
Fair	6.4	5.7	6.2	8.2	8.9	9.1	7.4
Poor	1.1	1.1	0.9	1.7	1.9	2.4	1.5
0 CCs	46.4	39.4	38.3	35.7	28.6	28.5	36.2
1 to 3 CCs	48.4	52.9	52.7	55.0	58.8	56.6	54.1
4 or 5 CCs	4.2	6.0	6.9	6.9	9.2	11.2	7.4
6 or more CCs	1.0	1.7	2.2	2.5	3.3	3.7	2.4
Activity Limitation	16.9	16.8	17.1	18.0	23.9	25.4	19.7
Demographics							
Male	48.6	48.6	48.6	48.6	48.6	48.6	48.6
Female	51.4	51.4	51.4	51.4	51.4	51.4	51.4
Recent Immigrant	4.6	4.6	4.6	4.6	4.6	4.6	4.6
Long-Term Immigrant	14.5	14.5	14.5	14.5	14.5	14.5	14.5
Canadian Born	80.9	80.9	80.9	80.9	80.9	80.9	80.9
Age (Mean)	41.4	43.3	45.3	47.4	49.3	51.4	46.4
Single	20.1	19.0	16.4	14.9	13.3	12.1	16.0
Married/Common Law	68.8	68.6	69.6	69.6	69.7	69.8	69.3
Widowed/Divorced	11.1	12.5	14.0	15.4	17.1	18.0	14.7
Child	32.6	31.4	29.8	27.8	25.1	22.9	28.3
Lives Alone	10.9	13.5	14.7	15.5	16.2	16.6	14.6
Currently Working	67.4	69.1	69.0	70.4	68.8	67.6	68.7
Not Currently Working	8.0	6.6	5.6	4.3	4.2	4.0	5.5

Table 1.4, continued

	1994	1996	1998	2000	2002	2004	Total
No Work in the last Year	23.6	22.1	22.1	20.4	20.9	20.5	21.6
Working Not Stated	1.0	2.2	3.3	4.9	6.1	7.9	4.2
Geography							
Newfoundland	2.0	1.9	1.8	1.8	1.8	1.8	1.8
P.E.I.	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Nova Scotia	3.3	3.2	3.2	3.3	3.3	3.3	3.3
New Brunswick	2.6	2.6	2.6	2.7	2.7	2.7	2.7
Quebec	25.7	25.6	25.6	25.6	25.6	25.6	25.6
Ontario	37.4	37.1	37.3	37.2	37.2	37.2	37.2
Manitoba	3.7	3.7	3.6	3.7	3.6	3.6	3.7
Saskatchewan	3.1	3.2	3.2	3.1	3.0	3.0	3.1
Alberta	9.3	9.4	9.5	9.7	9.7	9.8	9.6
British Columbia	12.5	12.8	12.7	12.6	12.5	12.5	12.6
Lives in Urban Area	82.9	82.8	80.2	79.6	79.6	80.0	80.8
Health Behaviour							
Low Weight	1.9	1.5	1.4	1.5	1.5	1.4	1.6
Normal Weight	47.1	45.9	44.2	41.3	37.9	37.9	42.4
Over Weight	35.6	36.8	37.3	37.8	39.4	39.0	37.7
Obese	12.9	13.3	15.6	17.8	19.4	20.2	16.6
BMI Not Stated	2.5	2.4	1.4	1.5	1.9	1.4	1.9

note: All values reported are percentages (%), with the exception of the values for household income which are reported in real 1994 dollars ($).
CCs: stands for '*chronic conditions*'.

Table 1.5: Model Specifications: LCNB and KCDE

Specification	Model Type	Number of Cycles per model	Cycles Included
1	Cross-Section	1	1994-2004
2	Panel	6	1994-2004
3	Panel	5	1996-2004

Note: Specification 3 is the only model to include lagged self-reported health.

Table 1.6: Goodness of Fit Statistics - Cross-Sectional and Panel Models, LCNB and KCDE

LCNB	1994	1996	1998	2000	2002	2004
n	7,334	7,334	7,334	7,334	7,334	7,334
log(L)	-16,248	-15,852	-15,955	-16,021	-16,255	-16,271
CCR	13.9%	14.7%	15.9%	16.8%	14.9%	15.8%
RMSPE	5.49	5.80	6.88	4.53	4.89	4.97
MAPE	2.80	2.58	2.70	2.47	2.57	2.55

LCNB-Panel	No Endogeneity Correction	Endogeneity Correction
n	44,004	36,670
log(L)	-96,916	-80,518
CCR	15.2%	15.7%
RMSPE	5.45	5.43
MAPE	2.60	2.60

KCDE	1994	1996	1998	2000	2002	2004
n	7,334	7,334	7,334	7,334	7,334	7,334
log(L)	-12,008	-11,794	-12,161	-11,937	-11,836	-11,583
CCR	51.7%	50.5%	47.7%	50.1%	54.0%	58.4%
RMSPE	5.10	5.34	4.70	4.36	4.07	4.13
MAPE	2.04	1.83	1.89	1.77	1.71	1.63

KCDE-Panel	No Endogeneity Correction	Endogeneity Correction
n	44,004	36,670
log(L)	-71,037	-20,621
CCR	51.9%	100.0%
RMSPE	5.24	0.10
MAPE	1.91	0.00

LCNB is a latent class negative binomial model.
KCDE is the kernel conditional density estimator.
n is the number of observations.
log(L) is the value of the maximized log-likelihood function.
CCR is the correct classification ratio.
RMSPE is the root mean squared predition error.
MAPE is the mean absolute prediction error.

Table 1.7: Median Person, Conditional Mean and Incremental Effects, Cross-Sectional and Panel, LCNB and KCDE

	LCNB		KCDE		LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	1994				**1996**				**1998**			
<u>Household Income</u>												
\$20,000	2.42	-	3.02	-	1.89	-	2.85	-	1.92	-	2.72	-
\$50,000	2.42	0.00	2.96	-0.06	1.86	-0.03	2.83	-0.01	1.82	-0.10	2.72	0.00
\$80,000	2.42	0.00	2.91	-0.11	1.84	-0.05	2.84	0.00	1.74	-0.18	2.72	0.00
\$110,000	2.43	0.00	2.88	-0.13	1.82	-0.07	2.73	-0.11	1.67	-0.25	2.72	0.00
<u>Education</u>												
LTHS	2.43	0.01	3.02	-0.04	1.95	0.07	2.88	0.09	2.01	0.16	2.81	0.15
HS	2.42	-	3.05	-	1.87	-	2.80	-	1.85	-	2.66	-
Some PS	2.57	0.15	2.99	-0.06	1.92	0.05	2.87	0.07	2.00	0.15	2.63	-0.04
PS	2.55	0.12	2.97	-0.09	1.96	0.09	2.84	0.04	2.03	0.18	2.73	0.07
<u>Chronic Conditions</u>												
Zero	2.42	-	3.64	-	1.87	-	3.12	-	1.85	-	3.84	-
1 to 3 (LCNB) / 2 (KCDE)	3.93	1.51	4.70	1.07	3.09	1.22	3.31	0.19	3.22	1.37	3.16	-0.68
4 to 5 (LCNB) / 4 (KCDE)	6.07	3.65	4.27	0.63	4.56	2.69	3.28	0.15	4.21	2.36	3.08	-0.76
6 or more (LCNB) / 6 (KCDE)	7.31	4.89	5.03	1.40	6.07	4.19	3.36	0.24	5.13	3.28	3.24	-0.60
<u>Self-Reported Health</u>												
Excellent	2.42	-	3.38	-	1.87	-	3.31	-	1.85	-	3.35	-
Very Good	2.97	0.54	3.39	0.01	2.18	0.31	4.77	1.46	2.23	0.38	4.55	1.19
Good	4.01	1.59	3.82	0.44	2.89	1.02	4.31	1.00	2.91	1.06	4.09	0.74
Fair	6.58	4.16	3.84	0.47	4.28	2.41	3.68	0.37	4.65	2.80	4.31	0.96
Poor	8.34	5.92	3.92	0.54	6.95	5.08	3.79	0.48	18.14	16.30	3.88	0.53
<u>Sex</u>												
Male	2.42	-	2.50	-	1.87	-	2.52	-	1.85	-	2.51	-
Female	3.10	0.68	2.81	0.31	2.37	0.50	2.58	0.06	2.22	0.38	2.51	0.00

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Table 1.7, continued

	LCNB		KCDE		LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	2000				**2002**				**2004**			
Household Income												
$20,000	1.73	-	2.54	-	1.81	-	2.45	-	1.83	-	2.57	-
$50,000	1.70	-0.03	2.54	0.00	1.75	-0.06	2.45	0.00	1.81	-0.02	2.54	-0.04
$80,000	1.68	-0.05	2.54	0.00	1.70	-0.11	2.45	0.00	1.80	-0.03	2.50	-0.07
$110,000	1.66	-0.08	2.54	0.00	1.65	-0.16	2.45	0.00	1.78	-0.05	2.52	-0.06
Education												
LTHS	1.78	0.07	2.72	0.10	1.88	0.11	2.49	0.01	1.93	0.11	2.67	0.01
HS	1.71	-	2.62	-	1.77	-	2.48	-	1.82	-	2.65	-
Some PS	1.84	0.13	2.58	-0.05	1.95	0.19	2.45	-0.02	2.03	0.22	2.66	0.00
PS	1.71	0.00	2.52	-0.10	1.85	0.09	2.43	-0.04	1.94	0.12	2.58	-0.07
Chronic Conditions												
Zero	1.71	-	2.82	-	1.77	-	2.68	-	1.82	-	3.15	-
1 to 3 (LCNB) / 2 (KCDE)	2.94	1.23	2.91	0.09	3.10	1.33	2.75	0.07	3.25	1.43	3.07	-0.07
4 to 5 (LCNB) / 4 (KCDE)	4.17	2.46	3.18	0.35	4.45	2.68	3.12	0.44	4.27	2.45	3.25	0.11
6 or more (LCNB) / 6 (KCDE)	4.46	2.75	3.09	0.26	5.57	3.81	3.30	0.62	4.75	2.94	2.92	-0.22
Self-Reported Health												
Excellent	1.71	-	3.30	-	1.77	-	2.89	-	1.82	-	3.14	-
Very Good	2.07	0.36	4.27	0.97	1.97	0.21	4.16	1.27	2.16	0.34	4.37	1.22
Good	2.87	1.16	3.73	0.44	2.67	0.90	4.06	1.17	2.85	1.04	4.60	1.46
Fair	4.03	2.32	3.70	0.40	3.81	2.04	4.08	1.19	4.06	2.24	3.80	0.65
Poor	5.39	3.68	3.33	0.04	6.15	4.38	3.80	0.92	6.11	4.29	3.53	0.39
Sex												
Male	1.71	-	2.26	-	1.77	-	2.32	-	1.82	-	2.31	-
Female	2.05	0.34	2.47	0.21	2.10	0.34	2.36	0.04	2.21	0.40	2.45	0.14

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Table 1.7, continued

	LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	Panel - No Endog. Correction				**Panel - Endog. Correction**			
Household Income								
\$20,000	1.97	-	2.88	-	2.07	-	2.70	-
\$50,000	1.93	-0.05	2.83	-0.05	2.03	-0.04	2.70	-0.01
\$80,000	1.89	-0.09	2.77	-0.11	2.00	-0.07	2.64	-0.07
\$110,000	1.85	-0.12	2.69	-0.19	1.97	-0.10	2.58	-0.12
Education								
LTHS	2.03	0.09	2.92	0.06	2.13	0.09	2.70	0.05
HS	1.94	-	2.86	-	2.04	-	2.65	-
Some PS	2.07	0.13	2.86	0.01	2.19	0.15	2.67	0.02
PS	2.04	0.10	2.84	-0.01	2.15	0.11	2.58	-0.06
Chronic Conditions								
Zero	1.94	-	3.18	-	2.04	-	3.00	-
1 to 3 (LCNB) / 2 (KCDE)	3.27	1.33	3.19	0.01	3.46	1.42	2.99	-0.01
4 to 5 (LCNB) / 4 (KCDE)	4.55	2.61	3.37	0.19	4.71	2.67	3.11	0.10
6 or more (LCNB) / 6 (KCDE)	5.30	3.36	3.35	0.17	5.38	3.34	3.08	0.07
Self-Reported Health								
Excellent	1.94	-	3.23	-	2.04	-	3.07	-
Very Good	2.29	0.35	4.21	0.98	2.36	0.32	4.09	1.01
Good	3.07	1.13	3.95	0.72	3.06	1.02	3.96	0.89
Fair	4.55	2.61	3.92	0.69	4.24	2.20	3.80	0.73
Poor	7.16	5.22	3.74	0.51	6.70	4.66	3.57	0.49
Sex								
Male	1.94	-	2.38	-	2.04	-	2.35	-
Female	2.38	0.44	2.66	0.28	2.49	0.45	2.51	0.16

The incremental effect (I.E.) is equal to the difference in the conditional mean ($E[y|x]$) of characteristic x_j relative to the reference group. The reference group has no reported I.E.
note: The I.E. may not be exactly equal to the difference in conditional means. The difference is only due to rounding errors.

Table 1.8: Low-Use Person, Conditional Mean and Incremental Effects, Cross-Sectional and Panel, LCNB and KCDE

	LCNB		KCDE		LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	1994				**1996**				**1998**			
Household Income												
$20,000	1.84	-	1.53	-	1.47	-	1.48	-	1.44	-	1.42	-
$50,000	1.82	-0.03	1.49	-0.04	1.44	-0.03	1.49	0.00	1.35	-0.09	1.42	0.00
$80,000	1.80	-0.05	1.49	-0.04	1.41	-0.05	1.50	0.01	1.28	-0.17	1.42	0.00
$110,000	1.78	-0.07	1.49	-0.04	1.39	-0.08	1.47	-0.02	1.21	-0.23	1.42	0.00
Education												
LTHS	1.83	0.00	1.61	0.11	1.51	0.07	1.52	0.02	1.51	0.14	1.42	0.01
HS	1.83	-	1.49	-	1.45	-	1.50	-	1.38	-	1.40	-
Some PS	1.88	0.05	1.54	0.04	1.48	0.03	1.50	-0.01	1.49	0.11	1.43	0.03
PS	1.89	0.06	1.48	-0.01	1.52	0.07	1.45	-0.05	1.51	0.14	1.43	0.02
Chronic Conditions												
Zero	1.83	-	1.95	-	1.45	-	2.04	-	1.38	-	1.83	-
1 to 3 (LCNB) / 2 (KCDE)	2.89	1.07	2.01	0.05	2.38	0.93	1.93	-0.11	2.39	1.02	1.77	-0.06
4 to 5 (LCNB) / 4 (KCDE)	4.56	2.73	2.10	0.15	3.39	1.94	1.86	-0.18	3.08	1.70	1.84	0.02
6 or more (LCNB) / 6 (KCDE)	5.39	3.56	2.10	0.15	4.79	3.35	1.90	-0.14	3.81	2.43	1.90	0.08
Self-Reported Health												
Excellent	1.83	-	2.16	-	1.45	-	2.13	-	1.38	-	2.25	-
Very Good	2.32	0.49	2.90	0.74	1.73	0.29	2.79	0.65	1.73	0.35	2.83	0.58
Good	2.98	1.15	2.77	0.61	2.22	0.78	2.56	0.43	2.16	0.78	2.84	0.59
Fair	4.92	3.09	3.40	1.24	3.16	1.71	2.34	0.21	3.47	2.09	2.56	0.31
Poor	5.96	4.13	4.02	1.86	5.35	3.91	2.23	0.10	15.09	13.71	2.52	0.27
Sex												
Male	1.83	-	1.83	-	1.45	-	1.80	-	1.38	-	1.54	-
Female	2.48	0.66	2.02	0.19	1.96	0.52	1.78	-0.03	1.72	0.34	1.72	0.18

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Table 1.8, continued

	LCNB		KCDE		LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	2000				**2002**				**2004**			
Household Income												
$20,000	1.48	-	1.51	-	1.84	-	1.68	-	1.44	-	1.55	-
$50,000	1.44	-0.04	1.51	0.00	1.75	-0.09	1.68	0.00	1.42	-0.02	1.53	-0.02
$80,000	1.40	-0.08	1.51	0.00	1.67	-0.18	1.68	0.00	1.40	-0.05	1.51	-0.04
$110,000	1.37	-0.12	1.51	0.00	1.59	-0.25	1.68	0.00	1.38	-0.07	1.49	-0.06
Education												
LTHS	1.52	0.06	1.59	0.00	1.87	0.10	1.64	-0.04	1.52	0.09	1.49	-0.04
HS	1.45	-	1.59	-	1.77	-	1.68	-	1.43	-	1.53	-
Some PS	1.56	0.10	1.56	-0.03	1.94	0.17	1.60	-0.08	1.54	0.12	1.57	0.04
PS	1.41	-0.04	1.54	-0.05	1.82	0.04	1.65	-0.03	1.50	0.07	1.48	-0.06
Chronic Conditions												
Zero	1.45	-	1.99	-	1.77	-	2.10	-	1.43	-	2.07	-
1 to 3 (LCNB) / 2 (KCDE)	2.54	1.09	2.03	0.04	3.11	1.33	2.14	0.04	2.61	1.18	1.92	-0.15
4 to 5 (LCNB) / 4 (KCDE)	3.67	2.22	2.03	0.04	4.31	2.53	2.17	0.07	3.31	1.89	1.94	-0.14
6 or more (LCNB) / 6 (KCDE)	3.76	2.31	2.23	0.24	5.54	3.76	2.29	0.19	3.65	2.23	2.01	-0.06
Self-Reported Health												
Excellent	1.45	-	2.56	-	1.77	-	2.35	-	1.43	-	2.58	-
Very Good	1.83	0.38	3.02	0.47	1.98	0.20	3.10	0.75	1.73	0.31	3.61	1.02
Good	2.49	1.04	2.50	-0.06	2.69	0.92	2.95	0.60	2.22	0.80	3.63	1.05
Fair	3.42	1.96	2.37	-0.19	3.86	2.08	2.85	0.50	3.15	1.72	2.88	0.30
Poor	4.51	3.06	2.23	-0.33	6.40	4.62	2.72	0.37	4.99	3.56	2.70	0.12
Sex												
Male	1.45	-	1.72	-	1.77	-	1.81	-	1.43	-	1.63	-
Female	1.77	0.31	1.85	0.14	2.18	0.40	1.76	-0.06	1.80	0.37	1.82	0.19

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Table 1.8, continued

	LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	Panel - No Endog. Correction				**Panel - Endog. Correction**			
Household Income								
\$20,000	1.64	-	1.53	-	1.52	-	1.49	-
\$50,000	1.58	-0.06	1.50	-0.04	1.47	-0.05	1.47	-0.02
\$80,000	1.53	-0.11	1.48	-0.05	1.43	-0.09	1.45	-0.04
\$110,000	1.48	-0.15	1.45	-0.08	1.39	-0.13	1.42	-0.07
Education								
LTHS	1.67	0.07	1.55	0.05	1.56	0.07	1.48	0.00
HS	1.60	-	1.50	-	1.48	-	1.48	-
Some PS	1.68	0.08	1.53	0.03	1.58	0.09	1.47	-0.01
PS	1.66	0.06	1.49	-0.01	1.55	0.06	1.46	-0.02
Chronic Conditions								
Zero	1.60	-	1.83	-	1.48	-	1.80	-
1 to 3 (LCNB) / 2 (KCDE)	2.68	1.08	1.86	0.02	2.51	1.03	1.79	0.00
4 to 5 (LCNB) / 4 (KCDE)	3.65	2.05	1.88	0.04	3.33	1.85	1.77	-0.02
6 or more (LCNB) / 6 (KCDE)	4.28	2.69	1.94	0.11	3.85	2.37	1.88	0.08
Self-Reported Health								
Excellent	1.60	-	2.05	-	1.48	-	2.06	-
Very Good	1.93	0.33	2.40	0.35	1.74	0.26	2.46	0.39
Good	2.52	0.93	2.31	0.26	2.23	0.75	2.37	0.31
Fair	3.69	2.09	2.21	0.16	3.04	1.56	2.17	0.11
Poor	6.04	4.44	2.20	0.15	5.11	3.63	2.13	0.07
Sex								
Male	1.60	-	1.83	-	1.48	-	1.75	-
Female	2.03	0.44	2.09	0.26	1.88	0.39	1.86	0.10

The incremental effect (I.E.) is equal to the difference in the conditional mean ($E[y|x]$) of characteristic x_j relative to the reference group. The reference group has no reported I.E.

note: The I.E. may not be exactly equal to the difference in conditional means. The difference is only due to rounding errors.

Table 1.9: High-Use Person, Conditional Mean and Incremental Effects, Cross-Sectional and Panel, LCNB and KCDE

	LCNB		KCDE		LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	1994				**1996**				**1998**			
Household Income												
$20,000	9.61	-	4.89	-	8.93	-	3.77	-	28.18	-	4.08	-
$50,000	9.59	-0.02	4.88	0.00	8.77	-0.16	3.75	-0.02	25.30	-2.88	4.08	0.00
$80,000	9.59	-0.01	4.88	-0.01	8.62	-0.31	3.63	-0.14	22.81	-5.37	4.08	0.00
$110,000	9.62	0.01	4.83	-0.05	8.48	-0.45	3.48	-0.29	20.66	-7.52	4.08	0.00
Education												
LTHS	9.64	0.05	5.02	0.12	9.22	0.41	4.35	0.39	29.48	3.44	4.56	0.32
HS	9.59	-	4.90	-	8.81	-	3.96	-	26.04	-	4.24	-
Some PS	10.18	0.59	5.10	0.20	9.02	0.21	4.09	0.13	28.04	2.00	4.17	-0.07
PS	10.08	0.49	5.15	0.25	9.25	0.44	3.88	-0.08	28.85	2.81	4.25	0.00
Chronic Conditions												
Zero	9.59	-	3.34	-	8.81	-	2.79	-	26.04	-	3.13	-
1 to 3 (LCNB) / 2 (KCDE)	13.23	3.64	3.23	-0.11	12.27	3.46	2.90	0.11	36.99	10.95	3.07	-0.06
4 to 5 (LCNB) / 4 (KCDE)	24.05	14.46	3.73	0.39	20.82	12.01	3.13	0.34	54.69	28.65	3.37	0.24
6 or more (LCNB) / 6 (KCDE)	28.94	19.35	4.71	1.37	29.08	20.27	3.06	0.27	71.29	45.25	3.37	0.24
Self-Reported Health												
Excellent	9.59	-	5.14	-	8.81	-	4.22	-	26.04	-	4.81	-
Very Good	12.42	2.83	7.53	2.39	10.56	1.75	5.86	1.64	32.21	6.17	6.79	1.98
Good	15.90	6.30	10.69	5.55	13.55	4.74	5.63	1.41	39.81	13.77	13.56	8.75
Fair	26.06	16.47	14.51	9.37	19.43	10.62	5.38	1.16	65.63	39.59	9.62	4.81
Poor	16.30	6.70	4.83	-0.31	15.24	6.43	4.63	0.41	49.69	23.65	7.29	2.48
Sex												
Male	9.59	-	5.19	-	8.81	-	4.15	-	26.04	-	4.44	-
Female	13.54	3.95	5.84	0.65	11.98	3.17	4.30	0.14	31.46	5.42	4.39	-0.06

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Table 1.9, continued

	LCNB		KCDE		LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	2000				**2002**				**2004**			
Household Income												
$20,000	8.04	-	4.37	-	11.68	-	4.14	-	9.35	-	4.18	-
$50,000	7.81	-0.24	4.37	0.00	11.03	-0.65	4.14	0.00	9.16	-0.19	4.01	-0.18
$80,000	7.59	-0.45	4.37	0.00	10.45	-1.23	4.14	0.00	8.97	-0.38	3.96	-0.22
$110,000	7.39	-0.65	4.37	0.00	9.93	-1.75	4.14	0.00	8.80	-0.55	3.98	-0.20
Education												
LTHS	8.22	0.35	4.50	0.15	11.79	0.59	4.58	0.36	9.80	0.60	4.29	-0.03
HS	7.87	-	4.35	-	11.20	-	4.22	-	9.21	-	4.32	-
Some PS	8.43	0.56	4.61	0.26	12.23	1.03	4.20	-0.02	9.78	0.57	4.33	0.01
PS	7.62	-0.24	4.32	-0.03	11.38	0.18	4.17	-0.05	9.58	0.37	4.08	-0.24
Chronic Conditions												
Zero	7.87	-	2.99	-	11.20	-	2.85	-	9.21	-	3.27	-
1 to 3 (LCNB) / 2 (KCDE)	11.23	3.36	3.37	0.38	16.00	4.80	3.15	0.30	13.43	4.22	3.05	-0.22
4 to 5 (LCNB) / 4 (KCDE)	19.89	12.02	3.56	0.57	26.89	15.69	3.38	0.53	21.27	12.06	3.42	0.15
6 or more (LCNB) / 6 (KCDE)	20.38	12.51	3.41	0.42	34.84	23.64	3.34	0.49	23.32	14.12	3.18	-0.09
Self-Reported Health												
Excellent	7.87	-	5.18	-	11.20	-	3.97	-	9.21	-	6.70	-
Very Good	9.91	2.05	7.01	1.83	12.40	1.20	6.05	2.08	11.13	1.92	7.60	0.90
Good	13.51	5.64	7.02	1.85	17.02	5.82	6.61	2.63	14.28	5.07	6.65	-0.04
Fair	18.50	10.63	6.83	1.66	24.40	13.20	6.76	2.78	20.22	11.01	5.04	-1.66
Poor	13.20	5.33	6.54	1.36	19.29	8.09	6.11	2.13	15.81	6.60	5.02	-1.68
Sex												
Male	7.87	-	4.33	-	11.20	-	4.17	-	9.21	-	4.16	-
Female	9.56	1.69	4.71	0.38	13.70	2.50	4.65	0.48	11.47	2.26	4.65	0.49

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Table 1.9, continued

	LCNB		KCDE		LCNB		KCDE	
	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.	$E[y\|x]$	I.E.
	Panel - No Endog. Correction				**Panel - Endog. Correction**			
Household Income								
\$20,000	10.40	-	3.41	-	12.80	-	3.48	-
\$50,000	10.02	-0.38	3.29	-0.12	12.31	-0.49	3.30	-0.18
\$80,000	9.67	-0.73	3.26	-0.15	11.85	-0.95	3.24	-0.24
\$110,000	9.35	-1.05	3.18	-0.23	11.43	-1.37	3.16	-0.32
Education								
LTHS	10.59	0.47	3.54	0.14	13.03	0.59	3.64	0.15
HS	10.12	-	3.40	-	12.44	-	3.49	-
Some PS	10.60	0.48	3.51	0.10	13.08	0.65	3.54	0.05
PS	10.50	0.38	3.45	0.05	12.87	0.43	3.45	-0.04
Chronic Conditions								
Zero	10.12	-	2.67	-	12.44	-	2.75	-
1 to 3 (LCNB) / 2 (KCDE)	14.20	4.08	2.73	0.05	17.52	5.08	2.84	0.09
4 to 5 (LCNB) / 4 (KCDE)	23.01	12.89	2.93	0.26	27.37	14.93	2.96	0.21
6 or more (LCNB) / 6 (KCDE)	27.03	16.91	3.05	0.37	31.92	19.49	2.93	0.18
Self-Reported Health								
Excellent	10.12	-	3.78	-	12.44	-	4.49	-
Very Good	12.19	2.07	4.84	1.06	14.49	2.06	5.57	1.09
Good	15.98	5.86	5.21	1.43	18.75	6.31	6.30	1.81
Fair	23.30	13.18	5.24	1.46	25.21	12.78	5.07	0.58
Poor	17.56	7.44	4.02	0.24	21.31	8.87	4.29	-0.20
Sex								
Male	10.12	-	3.78	-	12.44	-	3.63	-
Female	12.84	2.71	4.36	0.59	15.51	3.07	4.13	0.50

The incremental effect (I.E.) is equal to the difference in the conditional mean ($E[y|x]$) of characteristic x_j relative to the reference group. The reference group has no reported I.E.
note: The I.E. may not be exactly equal to the difference in conditional means. The difference is only due to rounding errors.

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1.A1 Appendix: Variable Descriptions

Table 1.A1: Variable Description

Demand Side Variables	
	Socioeconomic
Income	Predicted household income in real 1994 \$'s (modeled household income on cycle 3-6, predicted on all cycles, then converted to real dollars)
Education	High school not completed; high school completed; some post secondary; or post secondary completed
Employment Status	Currently working; not currently working; or did not work in the last year
	Demographic
Age	Persons age in years
Sex	Male (= 0) or Female (= 1)
Immigrant Status	Recent Immigrant (previous 10 years); long-term immigrant (10 or more years); or Canadian born
Marital Status	Married or common law; single; and widowed or divorced
Children	Child under the age of 12 in the household (=1)
Lives Alone	Person lives alone (= 1)
	Health
Self Reported Health Status	Perceived health relative to others of comparable age: excellent, very good, good, fair, or poor
Number of Chronic Conditions	Number of reported chronic health problems
Activity Limitation	Individual reports a health problem that causes them to be limited in their activities / to have a long term disability or handicap (=1)
Body Mass Index	Low weight (BMI$<$ 18.5); Normal Weight (18.5 $\leq$BMI$<$ 25); Over Weight (25 $\leq$BMI$<$ 30); Obese (30 $\geq$BMI)
Supply Side Variables	
Province	Newfoundland; P.E.I.; Nova Scotia; New Brunswick; Quebec; Ontario; Manitoba; Saskatchewan; Alberta; or British Columbia
Urban	Respondent lives in an urban area (= 1)

1.A2 Appendix: Derivation of Income Variable

The NPHS asks survey respondents for a specific value for their household income in cycle 3 through 6. From the value provided, a categorical income variable is constructed. If a respondent chooses not to provide a precise value for their household income, they are asked to indicate what range their household income falls within, with the ranges corresponding to the ranges of the constructed categorical income variable. In cycle 1 and 2, respondents are only asked to indicate what range their household income falls within.

Due to the length of the panel (10 years), it is imperative to account for inflation in the household income variable. To control for inflation, a continuous income variable is necessary and thus must be constructed for cycles 1 and 2.

To construct a continuous income variable for cycle 1 and 2, income from cycle 3 through 6 is modeled and predicted values are generated for all cycles, and then converted to real 1994 dollars using the consumer price index reported on the survey. The log of income ($\ln y$) was modeled using a standard Mincer equation, $\ln y = \mathbf{X}\beta + \epsilon$, estimated using OLS (Mincer (1974)). Predicted income values ($\hat{y}$) are subsequently produced. Four different specifications are used to evaluate the sensitivity of the predicted income variable to the model specification. As shown in Table 1.A2, column (4) has the highest R^2 and CCR.[23] As the purpose of this exercise is to produce accurate predicted values,

[23]The CCR reported is the proportion of predicted income from the model that correspond to the income category reported on in the survey.

and not precise coefficient estimates of the explanatory variables, column (4) is used since it has the greatest predictive power.

Table 1.A2: OLS Regression of $ln(income)$ on $\mathbf{X}$

Controls	(1)	(2)	(3)	(4)
Age (Quadratic)	*	*		
Age (Categorical)			*	*
Immigrant - Flag	*			
Immigrant Status		*	*	*
Reported Income Category				*
n	20,631	20,631	20,631	20,631
R^2	0.342	0.343	0.344	0.907
CCR	20.9%	20.9%	20.9%	91.4%

All models control for sex, province, urban/rural, education, health, employment status and whether the person lives alone.

1.A3 Appendix: Utilization Statistics, by cycle

Table 1.A3: Mean Number of Annual GP Visits, by determinant and year

	1994	1996	1998	2000	2002	2004	Total
Total	3.4	3.1	3.2	3.2	3.3	3.3	3.3
Household Income							
Less than $20,000	4.3	4.0	4.2	3.6	4.3	4.2	4.1
$20,000 to $50,000	3.4	3.2	3.4	3.5	3.4	3.4	3.4
$50,000 to $80,000	3.0	2.7	2.6	2.8	3.0	2.9	2.8
More than $80,000	3.1	2.4	2.3	2.6	2.6	2.8	2.6
Education							
Less than High School	3.5	3.7	3.7	3.7	4.1	3.8	3.8
High School	3.5	3.4	3.0	3.2	3.3	3.1	3.3
Some Post-Secondary	3.8	3.0	3.4	3.2	3.4	3.4	3.4
Post-Secondary	3.1	2.8	2.9	2.9	2.9	3.1	3.0
Self-Reported Health							
Excellent	2.1	1.9	2.0	1.8	2.0	2.0	2.0
Very Good	2.7	2.6	2.6	2.6	2.4	2.5	2.6
Good	4.5	4.0	3.7	3.9	3.6	3.7	3.9
Fair	8.1	7.1	8.3	6.2	6.7	6.4	7.0
Poor	11.6	11.2	14.6	8.8	12.9	9.7	11.1
Number of Chronic Conditions							
Zero	2.1	1.8	1.8	1.7	1.6	1.6	1.8
1-3	4.1	3.5	3.6	3.5	3.4	3.5	3.6
4-5	9.3	6.5	6.0	6.5	5.9	5.6	6.3
6 or More	12.3	10.6	9.1	7.7	8.3	7.3	8.6
Sex							
Male	2.5	2.5	2.5	2.5	2.6	2.6	2.5
Female	4.4	3.8	3.8	3.8	4.0	4.0	4.0

Table 1.A4: Proportion of Zero Annual GP Visits, by determinant and year

	1994	1996	1998	2000	2002	2004	Total
Total	23.4	22.7	21.1	18.7	21.6	19.3	21.1
Household Income							
Less than $20,000	22.9	23.5	18.6	16.7	17.8	15.6	19.2
$20,000 to $50,000	23.9	22.8	22.5	17.8	21.3	21.1	21.6
$50,000 to $80,000	24.6	22	21.6	19.4	23.5	20.5	22.1
More than $80,000	20.5	21.8	19.2	21.3	23.6	20.1	21.2
Education							
Less than High School	26.6	22.1	19.3	16.3	20.1	20.4	20.9
High School	24.8	18.4	20.9	16	21.9	21.1	20.6
Some Post-Secondary	22.3	22.9	23	18.9	21.5	18.8	21.3
Post-Secondary	21.8	24.6	20.6	20.6	22.2	18.7	21.3
Self-Reported Health							
Excellent	30.7	28.8	28	26.8	30.9	26	28.7
Very Good	22.9	23.9	21.8	20.7	24.1	21.7	22.5
Good	19.7	18.2	16.7	13.5	17	16.8	16.9
Fair	12.2	11.3	9.6	9.2	11.6	9.4	10.5
Poor	7.6	3.3	0.2	4.1	4	5.9	4.5
Number of Chronic Conditions							
Zero	33.2	34	33.7	29.9	36.3	33.8	33.4
1-3	15.8	17.8	14.6	13.9	17.7	15.1	15.7
4-5	6.9	5.6	6.2	4.7	6.9	7.7	6.5
6 or More	2.7	2.3	0.01	3.2	4.8	7.4	0
Sex							
Male	29.8	30.8	27.9	24.4	26.9	26.4	27.7
Female	17.3	15	14.6	13.3	16.6	12.6	14.9

1.A4 Appendix: Latent Class Negative Binomial Models

The latent class negative binomial (LCNB) methodology is argued to provide a more flexible parametric approach to modelling utilization (Deb and Trivedi (1997), Deb and Trivedi (2002) and Jiménez-Martín et al. (2002)). The LCNB model is based on the finite mixture models proposed by Aitkin and Rubin (1985) and was more recently applied to models of GP use by Deb and Trivedi (1997).

The latent class approach assumes the sample of individuals are drawn from a population consisting of a finite number of different latent classes. There are assumed to be C latent classes, with each class having a different underlying distribution, and each person in the sample is believed to have been drawn from one of the latent classes.

More formally, a count (y_i) and a vector of covariates $(\mathbf{x}_i)$ are observed for individual i who belongs to latent class j (where $j = 1, \ldots, C$) with probability π_j. It is assumed $0 \leq \pi_j \leq 1$ and $\sum_{j=1}^{C} \pi_j = 1$. Individuals are relatively homogeneous within latent class j, but are heterogeneous between latent classes.

The density function for latent class j is given by $f_j(\cdot)$. Thus, the C-point finite mixture model is given by:

$$f(y_i|\cdot) = \sum_{j=1}^{C} \pi_j f_j(\cdot)$$

In the latent class negative binomial model, $f_j(\cdot)$ is assumed to be a negative binomial distribution. Thus

$$(1.4) \qquad f_j(y_i|\mathbf{x}_i, \theta_j) = \frac{\Gamma(\psi_j + y_i)}{\Gamma(\psi_j)\Gamma(y_i + 1)} \left(\frac{\psi_j}{\mu_{j,i} + \psi_j}\right)^{\psi_j} \left(\frac{\mu_{j,i}}{\mu_{j,i} + \psi_j}\right)^{y_i}$$

where $\Gamma(\cdot)$ is the gamma function, $\mu_{j,i} = e^{\mathbf{x}_i'\beta_j}$, $\psi_j = (1/\alpha_j)$ and $\theta_j = (\alpha_j, \beta_j)$ are vectors of parameters. The parameter $\alpha_j > 0$ is the dispersion parameter for the j^{th} latent class.

In a LCNB model with two latent classes, the probability of belonging to latent class 1 is π. Thus, the log-likelihood function is constructed as the sum of the probability of belonging to the j^{th} latent class times the negative binomial density for the j^{th} latent class:

$$L_{LCNB}(\theta_j) = \pi f_1(y_i|\mathbf{x}_i, \theta_1) + (1 - \pi) f_2(y_i|\mathbf{x}_i, \theta_2)$$

The Latent Class Negative Binomial Panel Model (LCNB-Pan), was first presented by Bago d'Uva (2005). The structure is similar to that of the cross sectional LCNB model, but the specification of $f_j(\cdot)$ accounts for multiple observations on individual i.

Let $y_{it} = [y_{i1}, \ldots, y_{iT_i}]$ be the observed count for individual i, and $\mathbf{x}_{it}$ be a vector of covariates. Conditional on being a member of latent class j, y_{it} has a conditional density function $f_j(y_{it}|\mathbf{x}_{it}, \theta_j)$. As in Bago d'Uva (2005), the conditional density of y_{it} is determined by a negative binomial model:

$$(1.5) \qquad f_j(y_{it}|\mathbf{x}_{it}, \theta_j) = \frac{\Gamma(\psi_j + y_{it})}{\Gamma(\psi_j)\Gamma(y_{it} + 1)} \left(\frac{\psi_j}{\mu_{j,it} + \psi_j}\right)^{\psi_j} \left(\frac{\mu_{j,it}}{\mu_{j,it} + \psi_j}\right)^{y_{it}}$$

where $\mu_{j,it} = e^{\mathbf{x}'_{it}\beta_j}$. θ_j is assumed to be constant across the panel, but can vary between latent classes.

In a LCNB model with two latent classes, the probability of belonging to latent class 1 is π. Thus, using (1.5) the log-likelihood function is given by:

$$L_{LCNB-Pan}(\theta_j) = \ln\left[\pi f_1(y_{it}|\mathbf{x}_{it}, \theta_1) + (1-\pi) f_2(y_{it}|\mathbf{x}_{it}, \theta_2)\right]$$

Both the cross-sectional and panel LCNB models are estimated using maximum likelihood. The probability of class membership (π) is estimated simultaneously using a logit specification, based on an individual's observable characteristics.

1.A5 Appendix: Model Comparison Statistics

Akaike Information Criterion: The Akaike Information Criterion (AIC), first proposed by Akaike (1974), is a measure of model performance that trades off goodness of fit with parsimony.

$$AIC = -2\log L + 2k, \tag{1.6}$$

where $\log L$ is the value of the maximized log-likelihood function, and k is the number of parameters in the model. When comparing between models, those models with smaller AIC values are preferred.

Bayesian Information Criterion: The Bayesian Information Criterion (BIC) is another measure of model performance. It was first proposed by Schwarz (1978), and is also known as the Schwarz Information Criterion (SIC).

$$BIC = -2\log L + k\log(n), \tag{1.7}$$

where $\log L$ is the value of the maximized log-likelihood function, k is the number of parameters in the model and n is the sample size. When comparing between models, those models with smaller BIC values are preferred.

Correct Classification Ratio: The correct classification ratio (CCR) is defined to be the proportion of correctly predicted outcomes from a model. The predicted value for individual i ($\hat{y}_i$) is equal to the modal value. Mathematically, the correct classification ratio is defined as:

$$CCR = \frac{1}{n}\sum_{i=1}^{n} 1\left(\hat{y}_i = y_i\right), \tag{1.8}$$

where $1(\cdot)$ is an indicator function, and y_i is the observed value of the dependent value for individual i. By construction, $0 \leq CCR \leq 1$. A model with stronger predictive power will have a CCR closer to 100%.

Root Mean Squared Prediction Error: The Root Mean Squared Prediction Errors (RMSPE) is defined as the square root of the mean of the sum of squared deviations between the predicted value of the dependent variable for individual i $(\hat{y}_i)$ their observed value (y_i).

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}. \tag{1.9}$$

By construction, $0 \leq RMSPE$. The RMSPE can be thought of as a measure of how far off from the diagonal of the confusion matrix is the model predicting on average. Models better able to predict observed outcomes will have a $RMSPE$ closer to zero.

Mean Absolute Prediction Error: The Mean Absolute Prediction Error (MAPE) is defined as the average deviation of the predicted value of the dependent variable $(\hat{y}_i)$ from the observed value of the dependent variable

(y_i). The MAPE is represented mathematically by:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| . \tag{1.10}$$

By construction, $0 \leq MAPE$. The MAPE can be thought of as a measure of how far off the diagonal of the confusion matrix is the model predicting on average. Models better able to predict observed outcomes will have a $MAPE$ closer to zero.

1.A6 Appendix: Latent Class Negative Binomial model coefficient interpretation

In the case of the standard linear model (with $E[y|\mathbf{x}] = \mathbf{x}'\beta$) the coefficient β_i is interpreted as the change in the conditional mean from a one unit change in x_i.[24] However, for non-linear models (such as the LCNB model, where $E[y|\mathbf{x};c] = exp\left(\mathbf{x}'\beta_c\right)$) the coefficient $\beta_{i,c}$ is interpreted as the percentage change in the conditional mean of class c from a one unit change in x_i. Differentiation of the conditional mean with respect to x_i gives:

$$\frac{\partial E[y|\mathbf{x};c]}{\partial x_i} = \beta_{i,c} exp(\mathbf{x}'\beta_c) \tag{1.11}$$

Hence a one unit change in the x_i in latent class c increases the conditional mean by $\beta_{i,c}exp(\mathbf{x}'\beta_c)$ units. The partial response depends on the conditional mean, which is expected to vary across individuals. When the coefficient $\beta_{i,c}$ is for a binary variable, it can be interpreted as the percentage change in the conditional mean.[25]

[24] This follows given:

$$\frac{\partial E[y|\mathbf{x}]}{\partial x_i} = \beta_i$$

[25] This can be seen by rearranging (1.11) for $\beta_{i,c}$ and noting $x_i = 1$ in the case of a binary variable.

1.A7 Appendix: Cross Section Model Comparison Statistics

Table 1.A5: Comparison of Alternative Parametric Cross-Sectional Models

	Poisson	Negative Binomial	Zero-Inflated Poisson	Hurdle	LCNB
1994					
log(L)	-23,561.3	-16,559.4	-22,207.8	-16,332.8	-16,248.1
k	41	42	82	41	73
AIC	47,204.7	33,202.7	44,579.7	32,831.6	32,642.2
BIC	47,487.6	33,492.5	45,145.5	33,404.3	33,145.9
1996					
log(L)	-22,386.1	-16,188.9	-21,209.3	-15,970.0	-15,851.8
k	41	42	82	41	73
AIC	44,854.3	32,461.7	42,582.5	32,106.0	31,849.5
BIC	45,137.2	32,751.5	43,148.3	32,678.7	32,353.2
1998					
log(L)	-22,811.9	-16,361.5	-21,885.4	-16,116.0	-15,955.3
k	41	42	82	41	73
AIC	45,705.8	32,807.1	43,934.9	32,397.9	32,056.6
BIC	45,988.7	33,096.9	44,500.7	32,970.6	32,560.3
2000					
log(L)	-21,235.7	-16,392.2	-20,493.7	-16,179.1	-16,021.3
k	41	42	82	41	73
AIC	42,553.4	32,868.4	41,151.3	32,524.2	32,188.6
BIC	42,836.3	33,158.2	41,717.1	33,096.9	32,692.4
2002					
log(L)	-21,472.8	-16,506.4	-20,477.4	-16,334.2	-16,254.9
k	41	42	82	41	73
AIC	43,027.5	33,096.8	41,118.7	32,834.4	32,655.8
BIC	43,310.4	33,386.7	41,684.6	33,407.1	33,159.6
2004					
log(L)	-21,607.4	-16,546.5	-20,661.0	-16,360.0	-16,270.8
k	41	42	82	41	73
AIC	43,296.8	33,177.1	41,485.9	32,886.0	32,687.7
BIC	43,579.8	33,466.9	42,051.8	33,458.7	33,191.4

LCNB is a latent class negative binomial model. *Hurdle* is two-stage model with a logit model for the probability of use and a zero truncated negative binomial model of conditional use. *log L* is the value of the maximized log-likelihood function. k is the number of model parameters. *AIC* is the Akaike Information Criterion. *BIC* is the Bayesian Information Criterion.
note: For all models, and all years, $n = 7,334$.
note: Survey design effects are not controlled for. All models are estimated without sample weights.

1.A8 Appendix: LCNB Model Coefficient Estimates

Table 1.A6: Coefficient Estimates, Cross-Section Latent Class NB2 Model (1994–2004)

	1994		1996	
	Low-User	High-User	Low-User	High-User
Household Income	0.013 *	-0.017	0.003	-0.013
(per $10,000)	(0.007)	(0.017)	(0.007)	(0.017)
Very Good Health	0.318 ***	0.178 **	0.357 ***	0.266 ***
	(0.041)	(0.089)	(0.037)	(0.071)
Good Health	0.553 ***	0.439 ***	-0.062 **	-0.007
	(0.047)	(0.102)	(0.031)	(0.068)
Fair Health	1.025 ***	0.965 ***	0.001 *	0.000
	(0.076)	(0.139)	(0.001)	(0.002)
Poor Health	1.386 ***	1.001 ***	0.000 *	0.000
	(0.160)	(0.243)	(0.000)	(0.000)
Less than High School	0.018	-0.012	0.182 ***	0.181 *
	(0.058)	(0.101)	(0.046)	(0.100)
Some Post Secondary	0.152 ***	-0.074	0.453 ***	0.412 ***
	(0.058)	(0.100)	(0.054)	(0.112)
Post Secondary	0.110 **	-0.018	1.021 ***	0.556 ***
	(0.055)	(0.102)	(0.091)	(0.168)
Female	0.456 ***	0.182 **	1.328 ***	1.295 ***
	(0.034)	(0.085)	(0.149)	(0.280)
Age	-0.066 **	0.018	0.003	0.078
	(0.028)	(0.054)	(0.060)	(0.115)
Age^2	0.001 *	-0.001	0.054	-0.001
	(0.001)	(0.001)	(0.050)	(0.109)
Age^3	0.000	0.000	0.029	0.071
	(0.000)	(0.000)	(0.050)	(0.111)
Recent Immigrant	-0.076	-0.308	0.154	0.302
	(0.122)	(0.204)	(0.139)	(0.186)
Long Term Immigrant	0.012	0.049	-0.052	0.145
	(0.056)	(0.127)	(0.055)	(0.107)
Single	-0.250 ***	-0.091	-0.096	-0.252 **
	(0.063)	(0.120)	(0.072)	(0.105)
Widowed or Divorced	-0.089	-0.074	-0.089	-0.060
	(0.057)	(0.135)	(0.060)	(0.108)
Child Present	0.117 **	-0.004	0.100 *	0.131
	(0.047)	(0.093)	(0.053)	(0.095)

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Table 1.A6, continued

	1994		1996	
	Low-User	High-User	Low-User	High-User
Lives Alone	0.078	-0.141	0.061	0.022
	(0.059)	(0.139)	(0.064)	(0.113)
Not Currently Working	0.074	0.192 *	0.000	0.480 **
	(0.068)	(0.108)	(0.083)	(0.201)
No Work, Last 12 Months	0.013	0.202 **	0.082	0.304 ***
	(0.051)	(0.097)	(0.054)	(0.096)
Employment Not Stated	0.222	0.010	0.170	0.340
	(0.156)	(0.257)	(0.156)	(0.321)
Urban	0.079 **	-0.096	0.036	0.020
	(0.040)	(0.090)	(0.041)	(0.079)
Newfoundland	0.106	0.135	0.307 ***	0.097
	(0.072)	(0.191)	(0.076)	(0.147)
P.E.I.	0.114 *	-0.268 *	0.088	0.099
	(0.068)	(0.163)	(0.072)	(0.127)
Nova Scotia	0.127 *	0.053	0.068	0.549 **
	(0.069)	(0.143)	(0.073)	(0.273)
New Brunswick	-0.172 **	-0.209	-0.105	-0.144
	(0.070)	(0.161)	(0.073)	(0.144)
Quebec	-0.333 ***	-0.445 ***	-0.247 ***	-0.292 ***
	(0.054)	(0.131)	(0.054)	(0.111)
Manitoba	-0.123 *	-0.058	-0.062	0.261 **
	(0.068)	(0.148)	(0.075)	(0.131)
Saskatchewan	-0.050	-0.220	-0.076	0.261 **
	(0.070)	(0.149)	(0.077)	(0.130)
Alberta	-0.043	0.041	-0.083	-0.101
	(0.062)	(0.126)	(0.076)	(0.112)
British Columbia	0.027	0.128	0.129 **	0.136
	(0.060)	(0.132)	(0.061)	(0.110)
1 to 3 Chronic Conditions	0.554 ***	0.386 ***	0.527 ***	0.475 ***
	(0.035)	(0.085)	(0.043)	(0.088)
4 or 5 Chronic Conditions	0.931 ***	0.903 ***	1.056 ***	0.667 ***
	(0.072)	(0.163)	(0.072)	(0.172)
6 or more Chronic Conditions	1.171 ***	1.012 ***	1.064 ***	1.288 ***
	(0.100)	(0.318)	(0.162)	(0.215)
Intercept	0.783 *	1.768 **	0.669	-1.494
	(0.413)	(0.745)	(0.468)	(0.408)
α	0.344 ***	0.962 ***	0.224 ***	1.142
	(0.054)	(0.112)	(0.092)	(0.102)
π	0.785 ***	0.215 ***	0.713 ***	0.287
	(0.050)	(0.050)	(0.084)	(0.084)

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Table 1.A6, continued

	1994		1996	
	Low-User	High-User	Low-User	High-User
n		7,334		7,334
log Likelihood		-16,248.10		-15,851.76
Mean Predicted Visits	2.54	8.03	2.39	5.7

	1998		2000	
	Low-User	High-User	Low-User	High-User
Household Income	0.001	-0.049 ***	0.003	-0.023
(per $10,000)	(0.006)	(0.017)	(0.006)	(0.016)
Very Good Health	0.267 ***	0.160 **	0.237 ***	0.225 **
	(0.033)	(0.073)	(0.039)	(0.090)
Good Health	-0.050	-0.062	0.478 ***	0.600 ***
	(0.031)	(0.060)	(0.041)	(0.103)
Fair Health	0.001	0.001	0.861 ***	0.849 ***
	(0.001)	(0.001)	(0.082)	(0.120)
Poor Health	0.000	0.000	1.177 ***	1.086 ***
	(0.000)	(0.000)	(0.129)	(0.196)
Less than High School	0.246 ***	0.201 **	0.031	0.056
	(0.038)	(0.101)	(0.049)	(0.111)
Some Post Secondary	0.482 ***	0.403 ***	0.086 *	0.050
	(0.052)	(0.125)	(0.045)	(0.104)
Post Secondary	0.921 ***	0.926 ***	0.062	-0.117
	(0.063)	(0.171)	(0.044)	(0.102)
Female	1.618 ***	2.913 ***	0.295 ***	0.080
	(0.115)	(0.948)	(0.030)	(0.083)
Age	0.047	0.150	-0.076 **	-0.078
	(0.054)	(0.110)	(0.033)	(0.054)
Age^2	0.083 *	0.071	0.002 **	0.001
	(0.049)	(0.101)	(0.001)	(0.001)
Age^3	0.090 *	0.123	0.000 **	0.000
	(0.046)	(0.107)	(0.000)	(0.000)
Recent Immigrant	0.132	-0.017	0.060	-0.209
	(0.111)	(0.218)	(0.140)	(0.248)
Long Term Immigrant	0.052	0.285 **	-0.022	0.054
	(0.047)	(0.129)	(0.049)	(0.121)
Single	-0.014	0.286 **	0.016	-0.011
	(0.057)	(0.145)	(0.057)	(0.129)
Widowed or Divorced	-0.016	-0.105	0.101 *	-0.203 *
	(0.051)	(0.121)	(0.052)	(0.115)

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Table 1.A6, continued

	1998		2000	
	Low-User	High-User	Low-User	High-User
Child Present	-0.008	0.450 ***	0.058	0.176 *
	(0.046)	(0.099)	(0.040)	(0.093)
Lives Alone	-0.106 *	0.021	-0.131 **	0.044
	(0.056)	(0.139)	(0.051)	(0.123)
Not Currently Working	0.032	0.064	0.132 *	-0.046
	(0.070)	(0.120)	(0.072)	(0.128)
No Work, Last 12 Months	0.095 **	-0.007	0.089 *	-0.052
	(0.046)	(0.107)	(0.048)	(0.093)
Employment Not Stated	0.232 *	-0.176	0.184	-0.364 *
	(0.124)	(0.277)	(0.117)	(0.199)
Urban	0.065 *	0.076	-0.049	0.230 ***
	(0.035)	(0.077)	(0.034)	(0.081)
Newfoundland	0.352 ***	-0.055	0.339 ***	0.335 **
	(0.072)	(0.180)	(0.067)	(0.164)
P.E.I.	0.048	-0.017	-0.139 **	0.178
	(0.063)	(0.148)	(0.061)	(0.170)
Nova Scotia	0.106	0.281 *	0.042	0.394 **
	(0.069)	(0.154)	(0.058)	(0.153)
New Brunswick	-0.116 *	0.058	-0.111 *	0.093
	(0.064)	(0.143)	(0.065)	(0.149)
Quebec	-0.356 ***	-0.206 *	-0.285 ***	-0.101
	(0.052)	(0.109)	(0.044)	(0.108)
Manitoba	0.048	0.071	-0.074	0.086
	(0.063)	(0.164)	(0.062)	(0.125)
Saskatchewan	0.067	0.029	0.031	0.191
	(0.063)	(0.130)	(0.060)	(0.160)
Alberta	-0.037	-0.070	0.008	0.355 **
	(0.053)	(0.126)	(0.052)	(0.148)
British Columbia	0.139 ***	0.042	0.105 **	0.056
	(0.053)	(0.132)	(0.052)	(0.110)
1 to 3 Chronic Conditions	0.564 ***	0.539 ***	0.507 ***	0.609 ***
	(0.036)	(0.078)	(0.034)	(0.079)
4 or 5 Chronic Conditions	0.893 ***	0.683 ***	0.817 ***	1.030 ***
	(0.057)	(0.156)	(0.059)	(0.128)
6 or more Chronic Conditions	1.035 ***	0.997 ***	0.969 ***	0.933 ***
	(0.080)	(0.185)	(0.083)	(0.201)
Intercept	0.531	2.199	0.989 **	-1.505 ***
	(0.493)	(0.876)	(0.503)	(0.197)
α	0.258	0.803	0.222 ***	0.835 ***
	(0.051)	(0.102)	(0.044)	(0.093)

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Table 1.A6, continued

	1998		2000	
	Low-User	High-User	Low-User	High-User
π	0.800	0.200	0.798	0.202
	(0.052)	(0.052)	(0.045)	(0.045)
n		7,334		7,334
log Likelihood		-15,955.28		-16,021.32
Mean Predicted Visits	2.47	8.02	2.56	6.95

	2002		2004	
	Low-User	High-User	Low-User	High-User
Household Income	0.006	-0.031 **	0.003	-0.012
(per $10,000)	(0.006)	(0.014)	(0.006)	(0.012)
Very Good Health	0.177 ***	0.061	0.237 ***	0.161
	(0.043)	(0.119)	(0.043)	(0.113)
Good Health	0.397 ***	0.429 ***	0.471 ***	0.419 ***
	(0.048)	(0.120)	(0.050)	(0.121)
Fair Health	0.749 ***	0.793 ***	0.829 ***	0.761 ***
	(0.071)	(0.140)	(0.077)	(0.150)
Poor Health	1.152 ***	1.357 ***	1.115 ***	1.354 ***
	(0.108)	(0.215)	(0.118)	(0.251)
Less than High School	0.080	0.036	0.058	0.065
	(0.056)	(0.097)	(0.060)	(0.106)
Some Post Secondary	0.124 **	0.068	0.184 ***	-0.017
	(0.051)	(0.095)	(0.056)	(0.100)
Post Secondary	0.124 **	-0.035	0.118 **	-0.001
	(0.049)	(0.088)	(0.053)	(0.095)
Female	0.238 ***	0.181 ***	0.295 ***	0.173 **
	(0.033)	(0.066)	(0.034)	(0.068)
Age	-0.060 *	-0.024	-0.042	-0.082
	(0.033)	(0.052)	(0.043)	(0.053)
Age^2	0.001 *	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age^3	0.000 *	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Recent Immigrant	0.015	-0.172	0.056	-0.099
	(0.112)	(0.170)	(0.109)	(0.251)
Long Term Immigrant	-0.051	0.102	-0.008	-0.022
	(0.057)	(0.093)	(0.053)	(0.092)
Single	0.013	0.007	0.002	-0.177
	(0.059)	(0.116)	(0.070)	(0.127)

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Table 1.A6, continued

	2002		2004	
	Low-User	High-User	Low-User	High-User
Widowed or Divorced	0.074	-0.065	0.063	-0.054
	(0.054)	(0.106)	(0.056)	(0.112)
Child Present	-0.043	0.029	-0.038	0.128
	(0.045)	(0.094)	(0.048)	(0.092)
Lives Alone	-0.118 **	-0.116	-0.135 **	0.033
	(0.055)	(0.108)	(0.059)	(0.110)
Not Currently Working	0.080	0.216 **	0.033	0.515 ***
	(0.071)	(0.101)	(0.079)	(0.124)
Did Not Work in Last 12 Months	0.062	0.029	-0.028	0.042
	(0.054)	(0.087)	(0.057)	(0.095)
Employment Not Stated	0.107	-0.226	-0.020	-0.109
	(0.127)	(0.220)	(0.103)	(0.175)
Urban	-0.002	0.097	0.039	0.151 **
	(0.035)	(0.069)	(0.038)	(0.071)
Newfoundland	0.313 ***	0.119	0.179 **	0.297 **
	(0.068)	(0.136)	(0.072)	(0.123)
P.E.I.	0.079	-0.131	-0.049	0.034
	(0.063)	(0.140)	(0.072)	(0.135)
Nova Scotia	0.203 ***	-0.097	0.011	0.236 *
	(0.070)	(0.124)	(0.067)	(0.131)
New Brunswick	-0.122 *	-0.163	-0.247 ***	-0.057
	(0.065)	(0.150)	(0.069)	(0.144)
Quebec	-0.270 ***	-0.274 ***	-0.381 ***	-0.153
	(0.050)	(0.106)	(0.052)	(0.118)
Manitoba	0.079	-0.307 **	-0.146 **	0.275 **
	(0.063)	(0.136)	(0.064)	(0.133)
Saskatchewan	0.200 ***	-0.089	-0.041	0.103
	(0.064)	(0.148)	(0.073)	(0.115)
Alberta	-0.084	-0.129	-0.100 *	0.128
	(0.053)	(0.114)	(0.059)	(0.133)
British Columbia	0.168 ***	-0.010	0.086	0.126
	(0.057)	(0.123)	(0.061)	(0.106)
1 to 3 Chronic Conditions	0.563 ***	0.559 ***	0.524 ***	0.668 ***
	(0.039)	(0.080)	(0.043)	(0.082)
4 or 5 Chronic Conditions	1.013 ***	0.797 ***	0.881 ***	0.811 ***
	(0.059)	(0.112)	(0.061)	(0.136)
6 or more Chronic Conditions	1.177 ***	1.112 ***	1.008 ***	0.882 ***
	(0.081)	(0.165)	(0.096)	(0.163)

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Table 1.A6, continued

	2002		2004	
	Low-User	High-User	Low-User	High-User
Intercept	0.594	2.398 ***	0.286	2.414 **
	(0.559)	(0.926)	(0.761)	(0.938)
α	0.278 ***	0.693 ***	0.233 ***	0.870 ***
	(0.032)	(0.114)	(0.049)	(0.109)
π	0.779	0.221	0.735 ***	0.265 ***
	(0.039)	(0.039)	(0.056)	(0.056)
n		7,334		7,334
log Likelihood		-16,254.92		-16,270.83
Mean Predicted Visits	2.62	6.79	2.62	6.02

$* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$

Table 1.A7: Coefficient Estimates, Latent Class NB2 Panel Models (1994–2004), with and without endogeneity correction

	No Endog. Corr.		Endog. Corr.	
	Low-User	High-User	Low-User	High-User
Household Income	0.006 **	-0.019 **	0.004	-0.022 **
(per $10,000)	(0.003)	(0.008)	(0.003)	(0.009)
Very Good Health	0.225 ***	0.149 ***	0.193 ***	0.131 **
	(0.020)	(0.055)	(0.021)	(0.064)
Good Health	0.448 ***	0.436 ***	0.396 ***	0.418 ***
	(0.023)	(0.058)	(0.024)	(0.067)
Fair Health	0.874 ***	0.756 ***	0.767 ***	0.673 ***
	(0.036)	(0.077)	(0.037)	(0.088)
Poor Health	1.204 ***	1.354 ***	1.069 ***	1.360 ***
	(0.058)	(0.150)	(0.058)	(0.175)
Lagged Very Good Health			0.068 ***	0.013
			(0.019)	(0.051)
Lagged Good Health			0.115 ***	0.102 **
			(0.022)	(0.050)
Lagged Fair Health			0.252 ***	0.083
			(0.035)	(0.069)
Lagged Poor Health			0.245 ***	0.433 ***
			(0.062)	(0.128)
Less than High School	0.036	0.024	0.043	0.048
	(0.031)	(0.057)	(0.033)	(0.062)
Some Post Secondary	0.116 ***	-0.013	0.101 ***	0.022
	(0.028)	(0.053)	(0.029)	(0.058)

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Table 1.A7, continued

	No Endog. Corr.		**Endog. Corr.**	
	Low-User	High-User	Low-User	High-User
Post Secondary	0.087 ***	0.012	0.078 ***	0.013
	(0.027)	(0.055)	(0.028)	(0.059)
Female	0.321 ***	0.126 ***	0.294 ***	0.179 ***
	(0.020)	(0.043)	(0.020)	(0.043)
Age	-0.067 ***	-0.017	-0.058 ***	-0.042
	(0.015)	(0.026)	(0.017)	(0.028)
Age Squared	0.001 ***	0.000	0.001 ***	0.000
	(0.000)	(0.001)	(0.000)	(0.001)
Age Cubed	0.000 ***	0.000	0.000 ***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Recent Immigrant	0.058	-0.127	0.068	-0.024
	(0.061)	(0.111)	(0.064)	(0.125)
Long Term Immigrant	0.000	0.077	-0.012	0.093
	(0.031)	(0.059)	(0.032)	(0.060)
Single	-0.060 *	-0.013	-0.026	-0.028
	(0.032)	(0.071)	(0.035)	(0.075)
Widowed or Divorced	0.009	-0.070	0.022	-0.099
	(0.028)	(0.058)	(0.030)	(0.062)
Child Present	0.031	0.119 **	0.024	0.148 ***
	(0.023)	(0.053)	(0.024)	(0.056)
Lives Alone	-0.056 *	-0.044	-0.081 ***	-0.003
	(0.029)	(0.060)	(0.031)	(0.065)
Not Currently Working	0.063 *	0.267 ***	0.053	0.305 ***
	(0.033)	(0.089)	(0.034)	(0.106)
No Work, Last 12 Months	0.062 **	0.128 ***	0.058 **	0.082
	(0.025)	(0.049)	(0.028)	(0.054)
Work Not Stated	0.138 **	-0.041	0.116 *	-0.093
	(0.055)	(0.102)	(0.061)	(0.113)
Urban	0.027	0.102 **	0.015	0.122 ***
	(0.019)	(0.042)	(0.020)	(0.046)
Newfoundland	0.270 ***	0.125	0.296 ***	0.179 **
	(0.042)	(0.079)	(0.044)	(0.082)
P.E.I.	0.017	-0.019	0.003	0.059
	(0.040)	(0.083)	(0.042)	(0.092)
Nova Scotia	0.091 **	0.268 ***	0.077 *	0.312 ***
	(0.039)	(0.104)	(0.041)	(0.117)
New Brunswick	-0.157 ***	-0.102	-0.154 ***	-0.050
	(0.039)	(0.082)	(0.040)	(0.084)
Quebec	-0.301 ***	-0.243 ***	-0.311 ***	-0.218 ***
	(0.028)	(0.064)	(0.029)	(0.067)
Manitoba	-0.053	0.065	-0.038	0.080
	(0.036)	(0.071)	(0.038)	(0.075)

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Table 1.A7, continued

	No Endog. Corr.		Endog. Corr.	
	Low-User	High-User	Low-User	High-User
Saskatchewan	0.020	0.040	0.034	0.092
	(0.038)	(0.077)	(0.040)	(0.082)
Alberta	-0.065 **	0.026	-0.070 **	0.024
	(0.033)	(0.061)	(0.034)	(0.066)
British Columbia	0.128 ***	0.074	0.129 ***	0.059
	(0.032)	(0.069)	(0.034)	(0.069)
1 to 3 Conditions	0.533 ***	0.497 ***	0.529 ***	0.523 ***
	(0.019)	(0.044)	(0.040)	(0.082)
4 or 5 Conditions	0.903 ***	0.749 ***	-0.070 **	0.024
	(0.030)	(0.069)	(0.034)	(0.066)
6 or more Conditions	1.029 ***	0.886 ***	0.129 ***	0.059
	(0.044)	(0.099)	(0.034)	(0.069)
Intercept	0.778 ***	1.839 ***	0.618 **	2.062 ***
	(0.237)	(0.384)	(0.270)	(0.443)
α	0.263	0.974	0.248	0.979
	(0.024)	(0.052)	(0.023)	(0.058)
π	0.768	0.232	0.766	0.234
	(0.025)	(0.025)	(0.024)	(0.024)
n		44,004		36,670
log Likelihood		-96,769.19		-80,518.46
Mean Predicted Visits	2.54	6.49	2.57	6.37

No Endog. Corr.: panel model without endogeneity correction. *Endog. Corr.*: panel model with endogeneity correction.
$* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$

Chapter 2

The Effect of Physician Supply on the Mix of Generalist and Specialist Services Used

2.1 Introduction

A continuing policy concern for many health care systems how variations in the supply of physicians will impact access and the use of physician services. For example, in Ontario, Canada, the Ontario Medical Association (OMA) has voiced concerns about the province's physician supply shortage and how this will impact the receipt of needed medical services (Ontario Medical Association. Human Resources Committee (2005)). While it seems evident an adequate supply of physicians would be necessary to maintain the health of a population, it is less evident how the mix of physician services received is affected by variations in physician supply.

This paper asks a series of related questions about the effect of the supply of GPs and specialists on the mix of physician services used. Specifically:

how does the supply of GPs affect the number of GP visits, the number of specialist visits, the dollar value of GP services received, and the dollar value of specialist services received? How does the supply of specialists affect the number of GP visits, the number of specialist visits, the dollar value of GP services received, and the dollar value of specialist services received?

All else equal, people prefer being in better health. In order to maintain or improve health, people must make investments in their health. One such investment is a visit to the physician to seek advice on the type and quantity of health care services to use in order to maintain or improve health. Recent economic research has focused on how the supply of physicians affects people's health status. For example, a 10% increase in the supply of primary care physicians is associated with a 6% increase in the probability of a person reporting very good health (Gravelle et al. (2008)) and a mean reduction in obesity, measured by BMI, of around 4% of mean BMI (Morris and Gravelle (2008)). Recent Canadian evidence also suggests a positive correlation between a higher supply of general practitioners and better health outcomes (measured by self-assessed health status and the Health Utility Index), but a negative correlation between the supply of specialists and health outcomes (Piérard (2009)).

Since evidence suggests the supply of physicians affects health, and since physicians are one input into the production of health, a natural question to ask is: how does physician supply affect the use of physician services? Two possible dimensions of physician use include the quantity of services used from a particular type of physician, and the combination of different types of physician services used. A physician can be broadly classified as either a general practitioner (GP) or a specialist. GPs are the first point of contact with the health care system for most patients, providing advice and services for a broad range of health concerns, and referrals to a specialist. A specialist provides a patient with more specialized advice and services for a narrower range of health concerns. Patients are required to first visit a GP in order to get a referral to a specialist.[1]

Conceptually, the utilization of physician services is the outcome of demand (patient) and supply (physician) behaviour. From the patient's perspective, variations in physician supply may affect four types of physician demand. First, physician supply may affect the probability of a GP visit. For example, if there is a limited supply of GPs then the probability of visiting a GP may decrease because of the increased time cost to a patient of making a visit or the inability to make an appointment. Second, physician supply may affect the intensity demand for GPs. For example, conditional on making at least one GP visit, a limited supply of GPs may delay a patient's next appointment, increasing the time cost to a patient of a GP visit, leading to patients making fewer GP visits. Third, physician supply may affect the probability of specialist use. For example, if there is a greater supply of specialists then GPs may make more referrals because patients may make more requests to be referred given the lower time cost to the patient of making a specialist visit. Finally, physician supply may affect the intensity of demand for specialists. For example, a

[1]Technically, in Canada, a patient can see a specialist without a referral but the fee a specialist can bill the government is lower without a referral. Thus, most specialists tend not to see patients who have not been referred by a GP.

limited supply of specialists may decrease the total number of specialist visits because of longer waiting times.

Variations in aggregate physician supply may also affect an individual physician's treatment decisions. Three possible treatment decisions include whether a physician accepts new patients, whether a physician continues treating an existing patient with a relatively low severity of illness, and whether a GP refers a patient to a specialist. An increase in aggregate physician supply may increase physician use by inducing individual physicians to accept more patients due to their lighter workloads. An increase in physician supply may also induce physicians to continue treating patients with relatively low severities of illness. Finally, an increase in the supply of specialists may induce GPs to refer more patients to specialists, thus increasing specialist use, and accept new patients, leaving GP use unchanged.

To answer the research questions, three separate regression methodologies are employed. A single-equation negative binomial model is used to analyze the number of GP visits and the number of specialist visits. The dollar value of GP services and specialists services received are modeled using a generalized linear model (GLM), with a log-link function and a gamma distribution. Both the negative binomial model and the GLM model assume no simultaneity between GP utilization and specialist utilization. Since simultaneity may bias parameter estimates, a double-equation simultaneous negative binomial model is also used to analyze simultaneously the number of GP visits and the number of specialist visits, and the parameter estimates are compared with the single-equation negative binomial model to see if simultaneity bias is of concern.

The analysis will also focus on three different samples: the general population, asthmatics, and diabetics. It is important to analyze asthmatics and diabetics separately from the general population as both groups are high users of physician services since the proper management of asthma and diabetes involves the regular use of physician service.[2] Without proper management both conditions can become more severe.

Currently, the empirical literature on the interaction between GP and specialist services is based either on administrative data or survey data. Administrative data provides accurate measures of physician utilization, such as the number of visits to a physician or the dollar value of physician services received, but provides limited measures of patient characteristics, such as socioeconomic status or health status. Studies using administrative data often resort to using average neighbourhood socioeconomic status as a proxy for an individual's socioeconomic status. More problematic, studies using administrative data are often unable to control for an individual's health status, a fundamental determinant of physician utilization (see Allin (2006) and references therein). Survey data provide good measures of demographics, socioeconomic status, and health status, but are limited to the self-reported number of physician visits as the only measure of utilization. Having information on the dollar value of physician services received, rather than just the number of physician visits, provides a more complete picture of physician utilization.

[2]One component of Ontario's strategy to reduce the severity of asthma, preventing asthma attacks, and reducing the risk of death or permanent disability from asthma, is through clinical management by an individual's health care team (Ontario Ministry of Health and Long-Term Care (2000)). Diabetes Ontario states by having access to, and using, the diabetes education and management services offered by a qualified team of health care professionals is the key to managing diabetes (Diabetes Ontario (2009)).

This paper makes several contributions to the literature on physician utilization. One contribution is the use of a unique linked survey-administrative data set. The Canadian Community Health Survey, cycle 1.1, (CCHS 1.1) provides measures of an individual's demographic, socioeconomic, and health status. The Ontario Health Insurance Plan (OHIP) claims administrative database provides measures of the number of actual physician visits and the dollar value of physician services received, which provides a measure of the intensity of a physician visit and not simply the number of physician visits. By linking the OHIP administrative data to the CCHS 1.1 the analysis can control for individual level demographics, socioeconomic status, and health status. Physician supply information is derived from the Active Physician Registry (APR). The APR is a registry of all licensed physicians practicing in Ontario, and is provided by the Ontario Physician Human Resources Data Centre. The physician supply measures are based on the number of GPs per 10,000 population and the number of specialists per 10,000 population in a respondents city and account for the distance to other cities. The physician supply measures are then merged with the linked OHIP-CCHS data for each respondent.

A second contribution of this paper is to document how variations in the supply of physicians affects the mix of physician services received. A better understand of this relationship may inform important policy debates. For example, the OMA's concern about physician shortages, may be mitigated if the demanders of physician services simply substitute one physician type for another, and the suppliers of physician services facilitate this substitution.

2.2 Literature

2.2.1 Theoretical Effect of Physician Supply on Utilization

The relationship between a patient and their physician can be framed as a principal-agent relationship. The patient (principal) contracts with a physician (agent) because the physician has more information than the patient regarding the patient's health and the effects of alternative treatments (McGuire (2000)). The agency relationship suggests the demand for health care is a joint decision between patients and their physician.

Standard economic theory assumes the supply curve of physicians and the demand curve for physician services are independent. The total price to a patient of a physician service includes both the monetary price of the service and the time costs associated with search, travel, and waiting. Since the institutional environment in Ontario mandates patients pay a zero monetary price for medically necessary physician services, any increase in physician supply (i.e. a shift of the supply curve to the right) should decrease a patient's time cost of a physician visit, and hence decrease the total price of a physician visit (Fuchs (1978), Wilensky and Rossiter (1983), Escarce (1992)). As the supply of physicians increases, individual physicians may change their behaviour. One behavioural response may be a change a physician's decision threshold. One way a physician may make decisions is to rank patients by severity of illness, and then treat those patients whose severity is greater than the physician's decision threshold. The physician's decision threshold may be formed based on other patient characteristics (i.e. cost of making a visit), the physician's own characteristics (i.e. workload), and the characteristics of the health care system (i.e. the type and quantity of resources available). An increase in physician supply may reduce a physician's workload, leading to a physician to lower their decision threshold for clinical reasons (now there is time for the physician to see patients previous not seen), economic reasons (physicians want to keep their waiting rooms full), or both.

Three treatment decisions a physician may make include: whether the physician accepts new patients, whether the physician continues treating a patient of a given severity of illness, and whether a GP refers a patient to a specialist. A physician's decision threshold to accept a new patient may be lowered with an increase in aggregate physician supply resulting in an increase in physician use. Similarly, a physician's decision threshold to continue care for a particular patient may be lowered with an increase in aggregate physician supply resulting in an increase in physician use. Finally, a GP's decision threshold to refer a patient to a specialist may be lower with an increase in aggregate specialist supply since the time cost to a patient of making a specialist visit is lower inducing GPs to make more referrals to specialists (Cummins et al. (1981)).

Alternatively, the supply curve and the demand curve for physician services may not be independent (Evans (1974), Fuchs (1978), Sloan and Feldman (1978), Reinhardt (1978), Feldman and Sloan (1988), Rice and Labelle (1989)) due to the agency relationship between a patient and their physician. A shift in the physician supply curve to the right may lead physicians to exploit their agency relationship and shift the demand curve for their services to the right in order to avoid lower incomes resulting from increased competition for patients. Given the institutional environment in Ontario, where physicians cannot change the monetary price of their services[3], it may be more likely the supply curve for physicians and the demand curve for physician services are not independent since changing utilization is the main mechanism available to a physician to increase their income.

In general, the independence assumption between the demand and supply curves is not pivotal to the theoretical predictions of how a change in physician supply will affect physician use. Whether or not independence is assumed, the effect of physician supply on the quantity of physician services demanded operates in the same direction: as physician supply increases the quantity demanded increases. Similarly, the effect of physician supply on the quantity of physician services supplied generally operates in the same direction: as physician supply increases the quantity supplied increases. The difference is in the underlying mechanism of how a change in physician supply affects utilization. Since this paper is concerned with the magnitude and direction, rather than the mechanism, of the effect of physician supply on the use of physician services, it is not necessary to make assumptions about the independence of the supply curve and the demand curve.

However, GPs and specialists can have different relationships with each other in different contexts. In some contexts a GP visit and a specialist visit

[3]The fees a physician receives for providing a service are set through negotiations between the Ontario Ministry of Health and Long Term Care and the Ontario Medical Association (OMA).

are complements. For example, in the Ontario health care system a referral from a GP is required for an initial visit to a specialist, making GPs and specialists complements. In other contexts, a GP visit and a specialist visit are substitutes. For example, a specialist with a heavy workload may send a patient with a lower severity of illness back to their GP so the specialist can focus on patients with a higher severity of illness. The demand for one physician type may also be affected by the expectations of patients and physicians about factors affecting demand for the other physician type (Scott (2000)). The nature of the relationship between a GP and specialist results in a simultaneity problem as the demand for each of GPs and specialists may be influenced by the supply of the other. Standard economic theory suggests the demand curve for one physician type will shift with a change in the total price of the other physician type. The direction of the demand curve shift depends on whether GPs and specialists are complements or substitutes. For example, if specialists are a substitute for GPs then a decrease in the total price of a specialist visit will shift the demand curve for GP services to the left. However, if specialists are a complement to GPs, then a decrease in the total price of a specialist visit will shift the demand curve for GP services to the right. Thus, the relationship between GP and specialist services, and the relative total price of each, has implications on their respective demand curves. Table 2.1 summarizes how an increase in the supply of GPs and specialists affects the quantity demanded and the quantity supplied of both physician types.

Demand for a physician's services is often divided into initial demand and intensity demand. Initial demand is the demand for the first physician visit.

Decisions of the patient are believed to be the primary determinant of initial demand. Intensity demand is the demand for physician visits conditional on having made at least one visit. A patient and their physician are believed to jointly determine intensity demand. In this paper, demand refers to intensity demand, since the initial physician visit is not observed in the data.

The utilization of GP services is predicted to increase with the supply of GPs (Phelps and Newhouse (1974), Escarce (1992)). An increase in the supply of GPs may result in greater access to all GPs as patients become aware of alternative GPs (Stano (1985)), possibly due to more aggressive efforts by GPs to promote their services and attract patients (Escarce (1992)). However, it is less clear how the use GP services will respond to an increase in the supply of specialists. A greater supply of specialists may lead GPs to make more referrals to a specialist in order to get a second opinion on a diagnosis, decreasing the quantity demanded of GP services. As the supply of specialists increases the total price of specialist services will decrease. As noted above, the relationship between GPs and specialists will determine how a change in the total price of specialists will affect the utilization of GPs. If specialist visits on net substitute for GP visits, then as the total price of specialist services decreases, the demand curve for GP services will shift to the left, leading to a decrease in the utilization of GPs. However, if specialist visits on net complement GP visits then as the total price of specialist services decreases, the demand curve for GP services will shift to the right, leading to an increase in the utilization of GPs.

Utilization for specialist services will increase with the supply of specialists.

Again, as more specialists are available the total price of specialist services will decrease, increasing utilization of specialist services (Phelps and Newhouse (1974), Escarce (1992)). Again, it is less clear how the utilization of specialist services will respond to an increase in the supply of GPs. As the supply of GPs increases the total price of GP services will decrease. Defining GPs and specialists as complements or substitutes will determine how a change in the total price of GPs will affect the utilization of specialists. If a GP visits is a complement for a specialist visit, then as the total price of GP services decreases, the demand curve for specialist services will shift to the left, leading to a decrease in the utilization of specialists. If GPs are substitutes for specialists, then as the total price of GP services decreases, the demand curve for specialist services will shift to the right, leading to an increase in the utilization of specialists.

2.2.2 Empirical Evidence of Physician Supply on Physician Utilization

The empirical literature focusing on how the supply of physicians affects the use of physician services is built using either survey data or administrative data. The general findings in the literature are: (i) an increase in the supply of GPs is positively associated with the number of GP visits (Jiménez-Martín et al. (2004), Atella and Deb (2008)); (ii) an increase in the supply of GPs has a positive (Jones and Salkever (1995)) or negative association with the use of specialists (Fortney et al. (2005)); (iii) an increase in the supply of specialists has no significant association (Chan and Austin (2003)) or a positive association (O'Donnell (2000)) with the probability of referral by a GP, and (iv) an increase in the supply of specialists has a positive association (Fuchs (1978)), a negative association (Jiménez-Martín et al. (2004)), or no association (Escarce (1992)) with the overall use of specialists.

Two papers (Jiménez-Martín et al. (2004) and Atella and Deb (2008)) look at the effect of physician supply on the use of GP services in Europe. Jiménez-Martín et al. (2004) conduct a comparative analysis of the utilization for physician services across 12 European countries using three cycles (1994-1996) of the European Community Household Panel (ECHP). The supply of physicians is defined as the number of physicians per 1,000 people and physician use is defined as the number of visits to a GP and the number of visits to a specialist during the previous 12 months. The number of visits to a GP is modeled using a latent class negative binomial model with two classes. The number of visits to a specialist is modeled using a two part model where the probability of a specialist visit is modeled using a probit, and the conditional number of specialist visits is modeled using a truncated at zero negative binomial model. The authors find a significant positive effect of an increase in physician supply on the number of GP visits.

Atella and Deb (2008) use Italian survey data from the Italian National Institute of Statistics Multiscopo Survey to examine jointly the utilization of GPs, public specialists, and private specialists, where joint utilization is defined as the number of visits made to each type of physician. Physician supply is defined in two ways: (i) the average number of patients per GP in a region[4], and (ii) the ratio of the total number of specialists in a region to the number of practicing specialists[5]. The authors first estimate a standard single-equation negative binomial model for each type of physician visit. The single-equation negative binomial model assumes any physician-visit variable appearing as a covariate is exogenous. Assuming exogneity, the authors find a statistically significant positive relationship between the number of GP visits and both the number of public specialist visits and the number of private specialist visits. Statistically, the authors reject the exogeneity assumption in favour of assuming the number of visits to different physicians is endogenous.

The authors assume patients engage in a sequential decision-making process where the number of GP visits necessarily affects the number of public specialist visits (but not the reverse), and the number of public specialist visits necessarily affect the number of private specialist visits (but not the reverse). To model the sequential decision making process, the authors develop a simultaneous equation model where the three utilization measures are treated as sequentially endogenous. Once accounting for sequential endogeneity, the authors find a statistically significant negative relationship between the number of GP visits and both the number of public specialist visits and the number of private specialist visits, as well as a positive relationship between GP supply on both the number of public specialist visits and the number of private spe-

[4]Atella and Deb (2008) use the average number of patients per GP in a region as a measure of GP workload, with higher values associated with longer wait times for GP services.

[5]Atella and Deb (2008) use the ratio of the total number of specialists in a region to the number of practicing specialists as a measure of bureaucracy. They argue some specialists are in more bureaucratic positions, and hence non-practicing. The higher this ratio, the greater the size of the bureaucracy.

cialist visits. The marginal effect of an increase of one patient per GP (divided by 1,000) is a 3.8% decrease in the average number of GP visits.

An extensive literature has found evidence of the effect of physician supply on the likelihood of referrals to a specialist by a GP. O'Donnell (2000) conducted a systematic review of the literature focusing on papers looking at GP referral rates, variation in referral rates, possible explanations of those referrals, and decision making in the context of referrals. Of the 91 identified papers in the review, the general consensus is an increase in the availability of specialists increases the referral rates of GPs to specialists.

One of the only studies focusing on a Canadian setting was by Chan and Austin (2003). The authors linked physician information from the physician human resources administrative database and neighbourhood level information derived from the 1996 Canadian census with the Ontario Health Insurance Plan (OHIP) claims database to look at factors affecting patient referral by a GP to a specialist. The authors defined a referral as any consultation (outpatient, limited, or repeat) resulting from a request by the patient's customary physician, where the customary physician is defined as the physician who provided at least 50% of the patient's primary care visits in the last 12 months. The number of referrals was modeled using a multilevel Poisson model with patients (level 1) nested within physicians (level 2), nested within neighbourhoods (level 3). The supply of specialists was defined as the number of specialists per capita. The authors found no significant effect of the supply of specialists on the number of referrals.

Another literature has focused on the effect of specialist supply the use of specialist services. In his seminal paper on the effects of the supply of surgeons on the demand for operations, Fuchs (1978) used utilization information from the US National Health Interview Survey (NIH), for 1963 and 1970, and supply information from the American Medical Association (AMA). The dependent variable was the number of operations per 100,000 in metropolitan and nonmetropolitan areas. Fuchs' regression results showed that an increase of 10% in the surgeon/population ratio leads to a 3% increase in surgeries per capita.

Escarce (1992) focused on the effect of surgeon supply on the demand for surgeon services. The surgical specialties included in the study are ophthalmology, general surgery, orthopedic surgery, and urology. The paper uses data from the Health Care Financing Administration's (HCFA) 1986 Part B Medicare Annual Data Beneficiary File merged with HCFA's 1986 Health Insurance Skeleton Eligibility Write-off File. Information on individuals not enrolled in HMOs was aggregated to obtain information on utilization at the city level. Three measures of utilization were defined: Medicare expenditures per enrollee, the proportion of enrollees who used a specialty service, and Medicare expenditures per user. The surgeon supply variable was defined as the number of surgeons per 100,000 population. The estimation method used is two-stage least squares to account for the endogeneity bias due to the endogenous variable surgeon supply. The characteristics of the non-elderly population, measures of a physician's costs, and measures of amenities were used as instruments. A significant positive effect of surgeon supply on the Medicare expenditures per enrollee was found for certain specialties (ophthalmology) but not for the others. Surgeon supply was found to significantly increase the likelihood of use in all specialties except general surgery. The authors inferred this as evidence of the decrease in the time price of care as physician supply increases. However, surgeon supply is found not to significantly affect the intensity of services used. An increase in the supply of primary care physicians had a negative, but insignificant, effect on the use of surgeons.

Jones and Salkever (1995) looked at how the supply of primary care physicians and general surgeons affects the demand for gallbladder procedures. The focus on gallbladder procedures was due to the higher incidence of these procedures and their often elective status. The analysis was based on four cycles (1976, 1978, 1980, and 1982) of US data, the National Health Interview Survey (NHIS). The determinants of the likelihood of receiving a gallbladder procedure were estimated using a random effects logit model. The authors found the likelihood of receiving a gallbladder procedure is not significantly affected by the supply of general surgeons, but is positively and significantly affected by the supply of primary care physicians. The authors argued their finding was consistent with the hypothesis GPs function as gatekeepers to gallbladder surgery.

A more sophisticated American study, Fortney et al. (2005), used administrative health data from the United States Department of Veteran's Affairs (1995-1999) to see if increasing access to primary care services leads to an increase in the use and costs of other types of health care services by veterans. The authors exploited plausible exogenous variation in the dependent variable from a quasi-natural experiment, where access to primary care services for veterans living in under supplied areas was increased through the introduction of Community-Based Outpatient Clinics (CBOC). The dependent variables were defined as: the difference in the number of clinic encounters made by a veteran before and after the introduction of the CBOC, and the difference in clinical costs before and after the introduction of the CBOC. The change in utilization of health care services by veterans living inside a CBOC catchment area, before and after the introduction of the CBOC, was compared to the change in utilization of health care services by veterans living outside a CBOC catchment area, which were unaffected by the introduction of CBOC. A difference-in-difference instrumental variables (IV) estimator was used to model the change in the number of GP visits after the introduction of a CBOC. The IV estimates showed a statistically significant negative relationship between the number of GP encounters and the use of specialist services. The authors concluded increasing access to a primary care provider resulted in a substitution of GP services for specialist services.

Jiménez-Martín et al. (2004) also look at the effect of supply of specialists on both the probability of a specialist visit and the number of specialist visits, conditional on making at least one specialist visit. The authors find a significant negative effect of an increase in specialist supply on both the probability of a specialist visit and the conditional number of visits.

The empirical literature tells us is the relationship between GP supply, specialist supply and the use of physician services is complicated. Physician supply measures, when used as an explanatory variables, likely proxy for an average physician's workload. There is some ambiguity about whether GPs and specialists are exogenous. If we assume exogeneity, then they are positively related suggesting a complementary relationship between GPs and specialists. If they are endogenous, in the way Atella and Deb (2008) assumed, then the number of GP visits and the number of specialist visits are negatively related suggesting a substitute relationship.

2.3 Data

This paper uses a unique data set that links Ontario respondents in the Canadian Community Health Survey 2000/2001 (CCHS 1.1) with their monthly administrative health records in the Ontario Health Insurance Program (OHIP) claims database. Ontario respondents in the CCHS 1.1 are linked to the OHIP database using a deterministic matching approach based on their unique health card number. A validation procedure was followed to ensure only valid health card numbers are found. A probabilistic match based on birth date, sex, and postal code, resolves any incomplete linkages.

The CCHS 1.1 provides information on socioeconomic, health, and demographic characteristics. The OHIP database provides information on the speciality of the physician providing the service, the fee service code, and the dollar value of the fee service code. The active physician registry (APR) for the year 2000 provides information on the number of licensed GPs and specialists per census subdivision (CSD)[6] who are verified to be actively practicing

[6] A CSD is a geographic area used by Statistics Canada that corresponds to a municipality, or an area deemed to be equivalent to a municipality, defined by law in each province in Canada. The population of a CSD can range from as low as 0 (generally for Indian reserves or Indian Settlements) to as high as 2.4 million (Toronto).

in Ontario.[7]

The total CCHS Ontario sample size is 39,278. However, only Ontario respondents who consented to have their responses linked to administrative health data are included. The linked sample consists of 32,848 respondents, or 83.6% of all Ontario respondents. The analysis sample is restricted to Ontario respondents, 18 years of age or older, with complete information on household income, own level of education, self-reported health status and chronic conditions. The restrictions result in a final sample size is 26,663.[8]

2.3.1 OHIP Database (April 1, 1999 to March 31, 2002)

The OHIP database contains information on physician services received by individuals in Ontario from a fee-for-service physician.[9] It includes information on the number of physician visits, the dollar value of physician services received, and the specialty of the physician who provided the service. Three fiscal years (April 1, 1999 to March 31, 2002) of administrative records are used.

Information from the OHIP database is used to construct two measures

[7]A limitation of these data is the absence of any direct measure of a patient's time cost such as the full cost of a visit (travel time to and from the doctor's office, time in the doctor's office, parking costs, etc.) or the waiting time between the request for a visit and the visit.

[8]As noted above, the linked CCHS-OHIP sample consists of 32,848 respondents. The sample restrictions result in the loss of 3,245 observations less than 18 years of age, 471 who do note report their level of education, 2,247 who do not report their household income and 222 who do not report their marital status, number of chronic conditions or self-reported health status. The descriptive statistics based on the Ontario Sample, Full Linked OHIP Sample, and the Analysis Sample is presented in Appendix 2.A1, Table 2.A1.

[9]According to the Canadian Institute for Health Information (2002), 92.8% of total clinical physician payments in Ontario were fee-for-service (FFS). The Institute for Clinical Evaluative Sciences (2006) notes these rates to be slightly higher for GPs: 95% of GPs in 1999/2000, 96% of GPs in 2000/2001, and 95% of GPs in 2001/2002, were paid by FFS or mainly FFS but with non-FFS involvement.

of physician utilization: the number of physician visits and the dollar value of physician services received. Physician utilization is identified by combining information on the specialty of a physician, the fee service code the physician billed, and the dollar value of the fee service code. Each measure of physician utilization is constructed for two types of physicians: GPs and specialists. These four measures are the main dependent variables in the analysis. A physician service is counted as a GP visit if one of 57 visit related fee-service codes is billed by a physician claiming 'GP' as their specialty. If two or more of the 57 visit related fee service codes are billed on the same day by the same physician then only the first code billed is counted as a GP visit. If two or more of the 57 visit related fee service codes are billed on the same day by two or more physicians claiming 'GP' as their specialty, then two or more GP visits are counted. The dollar value of GP services received is calculated by summing the dollar value for all fee service codes billed between April 1, 1999 to March 31, 2002 by physicians claiming 'GP' as their specialty. A physician service is counted as a specialist visit if a physician claiming one of 28 specialties bills a specialty specific visit related fee service code.[10] As with counting GP visits, if a specialist bills two or more visit related fee service codes corresponding to their specialty on the same day, then only the first fee service code billed is counted as a specialist visit. If two or more specialists bill two or more fee service codes corresponding to their specialty on the same day, then two or more visits are counted. The dollar value of specialist services received is calculated by summing the dollar value for all fee service codes billed between

[10]A complete list of specialties and their specialty specific visit related fee service codes is presented in Appendix 2.A2, Table 2.A2

April 1, 1999 to March 31, 2002 by physicians claiming any one of the 28 specialties.[11]

2.3.2 Canadian Community Health Survey 1.1

The CCHS 1.1 collects socioeconomic, health, and demographic information from household residents, age 12 or older, in all ten provinces and three territories, in 2000/2001. People living on Indian Reserves and on Crown Lands, institutional residents, full-time members of the Canadian Forces, and residents of certain remote regions are excluded from the survey's sampling frame.

The CCHS 1.1 has two different sampling frames: an area frame, and a random-digit dialing (RDD) frame. The area frame is based on the Labour Force Survey's (LFS) two-stage, stratified, cluster design. The LFS divides each province into three types of geographic areas (major urban, urban towns, and rural). From each area type, separate geographic and socioeconomic strata are defined. From each strata, generally 6 clusters are sampled with probability proportional to the population size of the cluster. From each cluster a sample of dwellings are sampled. From each dwelling, a face-to-face interview is conducted with a randomly selected household member. Approximately 88% of the CCHS 1.1 sample was collected using the area frame. In some health regions, an RDD frame was used. The RDD frame constructed banks of phone numbers representing households to form strata that roughly con-

[11] Over the period April 1, 1999 to March 31, 2002 there are some changes to the fee schedule. Any change in the dollar value of a particular fee service code during this period is reflected in the dollar value of services received. There was no attempt made to standardize the dollar value of a particular fee service code across the three year period. Changes to the fee schedule should have no systematic effect on patient behaviour as any fee change affected all patients equally.

form to the health regions boundaries. From each strata, phone numbers were dialed at random until the required sample size for each strata was collected. Approximately 12% of the entire CCHS 1.1 sample was collected using the RDD frame (Béland (2002)).

To account for the CCHS's complex survey design, Statistics Canada produces sample weights that represent a survey respondent's contribution to the total population. The sample weights are computed using an initial weight representing the inverse probability of selection. The initial weight is then adjusted to account for survey specifics (such as non-response). Since the CCHS 1.1 used two overlapping sampling frames with separate sample designs, two weighting strategies were processed side-by-side and integrated using a dual-frame technique. The integrated weights were then calibrated to population projections based on the 2001 Canadian Census within each province (Statistics Canada (Béland (2002)).[12]

The CCHS 1.1 is the source for two measures of socioeconomic status and two proxy measures of health care need.[13] The two measures of socioeconomic status are an individual's household income and their highest level of education. Household income is a continuous variable. People are asked to provide their best estimate of the total income, before taxes and deductions, of all household members from all sources in the past 12 months. Education is defined as the highest level of education attained: less than high school, high

[12]For a more detailed discussion of how the sample weights were generated for the CCHS 1.1, please see Brisebois and Thivierge (2001).

[13]The relevant and desired income concept to capture is a person's permanent income. However, measures of current income, such as household income, do not fully capture permanent income. Other variables in addition to household income, such as education, in part capture the impact of permanent income.

school graduate, some post secondary, and post secondary graduate. The four possible levels of attainment are converted into four binary variables, one for each level of education.

The two proxy measures of an individual's health care need are a respondent's self-reported health status and their self-reported chronic conditions. Self-reported health status asks respondents: "In general, would you say your health is: excellent, very good, good, fair or poor?" The five-level Likert scale variable is converted to five binary variables, one for each health status response. The type of chronic conditions is derived from a series of questions asked to each respondent about specific chronic conditions.[14] Specific chronic conditions are placed into one of three classes as defined by Smith (1999) and Banks et al. (2007): major, medium or minor. Major chronic conditions are heart disease and/or cancer. Medium chronic conditions are diabetes and/or hypertension. Minor conditions are all conditions other than major or medium chronic conditions. A respondent is assigned to the highest class of chronic condition if they have multiple chronic conditions. Three binary variables are constructed, one for each class of chronic conditions.

Demographic variables included in the analysis are: age, sex, age/sex interactions, marital status, children present in the household, employment status, immigration status, an indicator for whether an individual lives alone, and an

[14]The CCHS asks about 23 specific chronic conditions: Alzheimer's disease or other dementia, asthma, arthritis or rheumatism, back problems (excluding fibromyalgia, arthritis or rheumatism), bowel disorder / Crohn's disease or colitis, cancer, cataracts, chronic fatigue syndrome, chronic bronchitis, diabetes, emphysema or chronic obstructive pulmonary disease, epilepsy, fibromyalgia, food allergies, glaucoma, heart disease, high blood pressure, migraine headaches, multiple sclerosis, Parkinson's disease, stomach or intestinal ulcers, thyroid condition, and urinary incontinence.

indicator for whether an individual lives in an urban area.

2.3.3 Active Physician Registry (2000)

The primary independent variables of interest, the supply of GPs and the supply of specialists, comes from the Active Physician Registry (APR). The APR is a registry of all licensed physicians verified to be actively practicing in Ontario and was provided by the Ontario Physician Human Resources Data Centre. The APR provides the number of physicians and the population in each census subdivision (CSD).[15]

However, the physicians to population ratio in the CSD where a respondent lives may not be the best measure of supply. For example, a respondent who lives near the border of two CSDs may be influenced by the physician supply in the adjacent CSD. Recall a CSD is a geographic area corresponding to a municipality, and nearly two-thirds of CSDs have zero physician supply (Table 2.2). Thus, a more complete measure of physician supply would account for the physicians to population ratios in other CSDs in addition to the CSD where a respondent lives. It is also plausible a respondent is more likely to use physicians who are geographically close rather than physicians who are geographically distant.

To account for both the location of physician supply per CSDs and the

[15]Physicians are not randomly distributed geographical. Previous work has the physician's decision of where to locate is consistent with standard location theory (Newhouse et al. (1982)). Factors found to affect a physician's decision where to locate (Dionne et al. (1987), Carpenter and Neun (1999)) can be broken down into factors related to their personal preferences (such as the quality of leisure, the distance to urban amenities, and their average income) and their professional preferences (such as the presence of a hospital, proximity to a large number of other practicing physicians, and proximity to a large population).

distance to other CSDs, the supply ($S_{j,i}$) of physicians of type j available to respondent i is defined as a weighted sum of the physicians to population ratios in all 586 CSDs, where the weight used is a decreasing function of the distance (d_k) between respondent i's home (defined by their postal code) and the centroid of the k^{th} CSD:

$$S_{j,i} = \sum_{k=1}^{586} f(d_k) \times \left(\frac{n_{jk}}{P_k} \times 10000 \right) \qquad (2.1)$$

where $f(d_k)$ is the decay function, n_{jk} is the number of physicians of type j in CSD k, and P_k is the population of the k^{th} CSD.[16]

Three different functional forms for $f(d_k)$ were considered: the inverse of the distance ($1/d_k$), the inverse of the square of the distance ($1/d_k^2$), and the inverse of the square root of the distance ($1/\sqrt{d_k}$). The functional form for $f(d_k)$ was chosen to be the inverse of the distance ($1/d_k$) as it best reflects the magnitude and distribution of the supply of physicians per CSD in Ontario. Table 2.2 presents the mean and the percentiles for the supply of physicians per CSD, and for the three different functional forms considered for $f(d_k)$. Column 1 presents the mean, columns 2-6 present the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles of the distribution of physician supply, and column 7 presents the ratio of the 90^{th} to the 10^{th} percentile. The mean supply of GPs per CSD is

[16] Refer to Appendix 2.A3 for more detail on the construction of the distance variable. However, as defined, S_{ji} may overstate physician supply as it does not adjust for the population in other CSDs. An alternative approach ($S^A_{j,i}$) would be to use a floating catchment methodology similar to Luo (2004). Using a FCM, equation (2.1) could be rewritten as:

$$S^A_{j,i} = \sum_k f(d_k) \times \left(\frac{n_{jk}}{\sum_k f(d_k) P_k} \times 10000 \right)$$

10.7 and specialists per CSD is 10.2. When the functional form is defined as $1/d_k$, the mean supply of GPs (14.8) is slightly higher than the mean supply of GPs per CSD and the mean supply of specialists (7.2) for $1/d_k$ is slightly lower than the mean supply of specialists per CSD. When the functional form is defined as $1/d_k^2$, both the mean supply of GPs (3.1) and the mean supply of specialists (2.7) are notably smaller than the corresponding mean supply of physicians per CSD. Conversely, when the functional form is defined as $1/\sqrt{d_k}$ both the mean supply of GPs (151.8) and the mean supply of specialists (56.4) are both notably larger than the corresponding mean supply of physicians per CSD. Hence, the magnitude of the mean for the decay function $1/d_k$ is closer to the mean of supply per CSD than the other two decay functions. While the magnitude is important, the amount of variation in the distribution is also important. When the functional form is defined as $1/d_k$, the 90^{th} percentile of GP supply is 1.9 times the 10^{th} percentile. This is similar to when the functional form is defined as $1/\sqrt{d_k}$, as the 90^{th} percentile of GP supply is 1.3 times the 10^{th} percentile. However, the magnitude of the $1/\sqrt{d_k}$ relative to the GP supply per CSD is notably larger, suggesting the functional form of $1/\sqrt{d_k}$ provides too much weight to geographically distant CSDs. When the functional form is defined as $1/d_k^2$, the 90^{th} percentile of GP supply is 21.0 times the 10^{th} percentile, suggesting the functional form of $1/d_k^2$ provides too little weight to geographically distant CSDs. The same conclusion would also be drawn by comparing the magnitude and distribution of specialist supply per CSD with the magnitude and distribution of the three different functional forms for $f(d_k)$. Thus, defining $f(d_k) = 1/d_k$ produces a reasonable definition of physician supply, both in terms of the magnitude and the variation of the distribution.

2.4 Methodology

This paper employs three different methodologies. Two different types of negative binomials model are used to analyze the number of GP visits and the number of specialist visits. The first type of negative binomial is the standard single-equation negative binomial model. The second is a double-equation simultaneous negative binomial model. Finally, a generalized linear model is used to analyze the dollar value of GP services received and the dollar value of specialist services received.

To account for survey design effects, the survey sample weight was used to generate the descriptive statistics and to estimate the single-equation negative binomial and the GLM and regression models. Sample weights were not incorporated into the double-equation negative binomial model. Not incorporating sample weights into the double-equation negative binomial model makes a direct comparison of parameter estimates with the single-equation negative binomial model more complicated. Caution should be used when making a direct comparison since the weighted parameter estimates reflect the population while the unweighted parameter estimates reflect the sample. However, since both models have different underlying model assumptions, even if both models were weighted (or unweighted) a comparison of parameter estimates should still be done with caution.

2.4.1 Single- and Double-Equation Negative Binomial Models

The single-equation negative binomial (NB) model is a commonly used method to analyze count data, such as the number of visits to a physician (see Cameron and Trivedi (1998), Greene (2003), Wooldridge (2002) or Cameron and Trivedi (2005)). The NB model allows for over-dispersion, making it less restrictive than the standard Poisson model. However, the NB model assumes all explanatory variables are exogenous. And, as noted above, this may not be the case.

To account for the simultaneity that may arise, Atella and Deb (2008) propose a simultaneous count model to jointly model the number of visits to three types of physicians - GPs, public specialist visits and private specialists. Since only two types of physician visits are modeled in this paper, the three-equation model of Atella and Deb (2008) is modified to a double-equation simultaneous NB model.

The double-equation simultaneous NB model assumes the number of specialist visits and the number of GP visits are sequentially endogenous. This assumption of the double-equation simultaneous NB model is consistent with the institutional relationship of GPs as gatekeepers to specialists in the Canadian health care system.

Let y_{ji} denote the number of visits individual i makes to the j^{th} physician type, where $j = 1$ (GP) or $j = 2$ (specialist). Let z_{ji} denote the physician and individual specific observed exogenous variables. Let μ_{ji} denote the mean number of visits to the j^{th} physician is conditional on z_{ji} and, let l_{ji} be an independent latent variable representing any unobserved physician and individual specific characteristics that may influence the conditional mean number of physician visits. The mean number of visits to a GP is only conditional on z_{ji}, while the mean number of visits to a specialist is also conditional on the number of visits made to the GP:

$$\mu_{1i} = \exp(z_{1i}\beta_1 + l_{1i}), \tag{2.2}$$

$$\mu_{2i} = \exp(y_{1i}\gamma_{21} + z_{2i}\beta_2 + l_{2i}), \tag{2.3}$$

where l_{1i} and l_{2i} are the independent latent variables that influence the conditional mean number of physician visits.[17] The latent variables may be correlated with each other, which is the source of simultaneous equations bias in this setting.

To establish the correlation between l_{1i} and l_{2i}, a common factor specification is used:

$$l_{1i} = h_{1i}, \tag{2.4}$$

$$l_{2i} = \phi_{21}h_{1i} + h_{2i}, \tag{2.5}$$

where h_{ji} are independent latent factors. While h_{1i} and h_{2i} are independent of each other, the covariance between l_{1i} and l_{2i} is ϕ_{21}. The joint density of y_{1i} and y_{2i}, conditional on h_{1i}, h_{2i}, and z_{ji} is a product of two conditional

[17] For example, Atella and Deb (2008) note that unobserved individual characteristics could include family health history, attitudes towards health risk, or lifestyle choices.

densities:

$$L_i(y_{1i}, y_{2i}|z_{1i}, z_{2i}; h_{1i}, h_{2i}) = f_{1i}(y_{1i}|z_{1i}; h_{1i}) f_{2i}(y_{2i}|z_{1i}; h_{1i}, h_{2i}) \tag{2.6}$$

where it is assumed $f_j(\cdot)$ is a negative binomial-2 distribution with mean μ_{ji} and scale α_j:

$$\begin{aligned} f_j(y_i|\mathbf{x}_i; \mu_{ji}, \alpha_j; h_{1i}, h_{2i}) & \\ &= \frac{\Gamma(\psi_j + y_i)}{\Gamma(\psi_j)\Gamma(y_i+1)} \left(\frac{\psi_j}{\mu_{ji}+\psi_j}\right)^{\psi_j} \left(\frac{\mu_{ji}}{\mu_{ji}+\psi_j}\right)^{y_i} \end{aligned} \tag{2.7}$$

and where $\psi_j = 1/\alpha_j$ $(\alpha_j > 0)$, $x_{1i} = [z_{1i}]$ and $x_{2i} = [y_{1i}, z_{2i}]$.

Since the independent latent factors (h_{1i} and h_{2i}) are unknown, equation (2.6) cannot be estimated directly using maximum-likelihood. Instead, a maximum simulated likelihood method is used.

Assume h_{1i} and h_{2i} are drawn from independent and identically distributed unit-normal distributions, n_k, where $k = 1$ or 2, with densities denoted by independent latent factors. The likelihood for an individual conditional only on observables is obtained by integrating out the independent latent factors h_{1i} and h_{2i} from (2.6):

$$\begin{aligned} L_i(y_{1i}, y_{2i}|z_{1i}, z_{2i}; h_{1i}, h_{2i}) &= \int \prod_{j=1}^{2} f_j(y_{ji}|z_{ji}; h_{ji}) n_1(h_{1i}) n_2(h_{2i}) dh_1 dh_2 \\ &= \frac{1}{S} \sum_{s=1}^{S} \left\{ \prod_{j=1}^{2} f_j(y_{ji}|z_{ji}; \mu_{ji}, \alpha_j \tilde{h}_{1i} \tilde{h}_{2i}) \right\} \end{aligned} \tag{2.8}$$

where $\tilde{h}_{1i}$ and $\tilde{h}_{2i}$ are random draws from n_1 and n_2. The maximum simulated likelihood approach maximizes the simulated likelihood (2.8).

2.4.2 The Generalized Linear Model

The dollar value of physician services received is modeled using a generalized linear model (GLM) framework (McCullagh and Nelder (1989)). The GLM framework expresses the relationship between the dollar value of physician services received, d_i, and the independent variables x_i in a general form by writing the relation between the expected value of d_i ($E[d_i|x_i]$) as a linear combination of the x_i variables and their parameters β:

$$g\left(E[d_i|x_i]\right) = x_i\beta, \; d_i \sim F \tag{2.9}$$

where $g(\cdot)$ is called the link function and F is the distributional family.

Various specifications for $g(\cdot)$ and F can be assumed.[18] A common assumption to deal with skewed data, such as health care expenditures, is to define $g(\cdot)$ to be a log function ($g\left(E[d_i|x_i]\right) = ln\left(E[d_i|x_i]\right)$) and F to be a gamma distribution ($F = \Gamma$) (Manning and Mullahy (2001), Manning et al. (2005)). The functional form assumptions can be tested to see if they are reasonable for the data at hand. For example, the link function assumption can be tested using a Box-Cox test (Box and Cox (1964)) and the GLM family assumption can be tested using a modified Park test (Manning and Mullahy (2001)).[19]

[18]For example, the link function can be defined as log, logit, probit, complementary log-log, odds power, power, negative binomial, log-log, log-complement, or an identity function. The family distribution can be defined as normal, inverse gaussian, Bernoulli, Poisson, negative binomial, or gamma distribution.

[19]It has been shown that in the presence of heteroskedacticity, the Box-Cox model can be biased (Manning (1998)).

Using the functional form assumtions of a log-link function and a gamma family distribution, equation (2.9) can be rewritten as:

$$E[d_i|x_i] = e^{x_i\beta},\ d \sim \Gamma. \tag{2.10}$$

The GLM model is defined in this paper to be a one-part model (Mullahy (1998)), although there is some debate in the literature on whether it should be defined as a two-part model (Blough et al. (1999)).

2.5 Results

Two sets of results are presented. The first set of results are the descriptive statistics for the three samples. The second set of results are the marginal effects (MFXs) at the mean from the three different regression models. Using the theoretical predictions of Section 2.2.1 to form expectations on the sign of the MFXs, we would expect the MFXs of GP supply to be positive for GP use, and either negative (if specialists are a substitute for GPs) or positive (if specialists are a complement for GPs) for specialist use. We would also expect the MFXs of specialist use to be either positive (if specialists are a complement for GPs) or negative (if specialists are a substitute for GPs). A similar pattern would be expected for the models of specialist use. We would expect the MFXs of specialist supply to be positive for specialist use, and either negative (if GPs are a substitute for specialists) or positive (if GPs are a complement for specialists) for GP use. We would also expect the MFXs of GP use to be either positive (if GPs are a complement for specialists) or negative (if GPs are a substitute for specialists) for specialist use.

2.5.1 Descriptive Statistics

Descriptive statistics for the number of physician visits and the dollar value of physician services received for a three-year period of utilization (April 1, 1999 to March 31, 2002) are presented in Table 2.3. Column 1 presents descriptive statistics for the number of GP visits and column 2 presents descriptive statistics for the dollar value of GP services received. Among the full sample, the mean number of GP visits in a three-year period is 12.3 (median of 9 and 7.9% of respondents make zero visits) and the mean dollar value of GP services received in a three-year period is \$481 (median of \$310 and 6.3% of respondents have zero dollars received). Column 3 presents descriptive statistics for the number of specialist visits and column 4 presents descriptive statistics for the dollar value of specialist services received. The overall mean number of specialist visits in a three-year period is 4.4 (median of 1 and 38.8% of respondents make zero visits) and the mean dollar value of specialist services received in a three-year period is \$897 (median of \$357 and 13.1% of respondents have zero dollars received). The utilization of GPs and specialists is higher for both asthmatics and diabetics. Relative to the entire sample, asthmatics use just over 40% more GP services (43% more GP visits by asthmatics and 42% more dollars of GP services received) and just over 30% more specialist services (35% more specialist visits by asthmatics and 31% more dollars of specialist services received). Relative to the entire sample, diabetics use approximately 75% more GP services (diabetics make 77% more GP visits and 74% more dollars of GP services received) and approximately 120% more specialist services (diabetics make 121% more specialist visits and 129% more dollars of specialist services received). Clearly, both asthmatics and diabetics use more GP and specialist services suggesting they are more regular users of physicians than the full sample and analyzing these groups separately is prudent.

Descriptive statistics for the independent variables are presented in Table 2.4. The first section of Table 2.4 presents the descriptive statistics for the physician supply variables. Column 1 presents descriptive statistics for the full sample. The mean supply of GPs per 10,000 population is 14.8 (median is 15) and mean supply of specialists per 10,000 population is 7.1 (median is 7). Column 2 presents descriptive statistics for asthmatics and Column 3 presents descriptive statistics for diabetics. The supply of GPs and specialists is nearly identical for asthmatics and diabetics relative to the entire sample. For asthmatics, the mean supply of GPs is 14.7 (median is 15) and the mean and median supply of specialist is 7.0. For diabetics, the mean supply of GPs is 14.7 (median is 15) and mean supply of specialists is 7.1 (median is 7). There does not appear to be any systematic difference in the supply of physicians between the three groups, suggesting asthmatics and diabetics are not more likely than all other respondents to live in a CSD with a greater supply of physicians.

The second section of Table 2.4 presents the descriptive statistics for the socioeconomic status variables. For the full sample, mean household income is just over \$65,000 (median \$58,000); nearly 70% report having attained a post-secondary education, while only 10% of the full sample report having less than a high-school education. Household income is 8% lower for asthmatics (mean of $59,976 and median of $50,000) and 28% lower for diabetics (mean of $47,133 and median of $35,000). Fewer asthmatics (only 65%) and diabetics (only 52%) report having attained a post-secondary education, while 13% of asthmatics and 24% of diabetics report having less than a high-school education. The majority of the full sample (57.8%) and asthmatics (54.1%) report being currently employed, while less than a third (31.5%) of diabetics report being currently employed. Not surprisingly, the majority of diabetics (53.9%) report not currently working or have not worked in the past year, while only 36.8% of the full sample and 40.6% of asthmatics report the same.

The third section of Table 2.4 presents the descriptive statistics for the health status variables. Eight percent of the full sample report having asthma and 5% report having diabetes. Ten percent of asthmatics report also having diabetes. Asthmatics and diabetics report being in worse health relative to the full sample. Nearly 65% of the full sample report being in very good or excellent health, while only 48% of asthmatics and 25% of diabetics do so. Nearly half of respondents report having a minor chronic condition, 15% report having a medium chronic condition, and 7% report having a major chronic condition. There is a notable difference in the BMI of the three groups: 38% of the full sample report having a normal BMI, while 34% of asthmatics and only 4% of diabetics do so; 33% of the full sample report being obese, while 39% of asthmatics and 64% of diabetics report being obese. The proportion of the full sample reporting an activity limitation (24.5%) is less than half the proportion of asthmatics (43.9%) and diabetics (48.2%) reporting an activity limitation.

Finally, the fourth section of Table 2.4 presents the descriptive statistics for the demographic variables. For the full sample, the average age is 44.7 years; 51% are female, 66% are married, 21% are single, 13% are widowed or divorced, 70% are Canadian born, 8% are recent immigrants, 23% are long-term immigrants, and 13.4% live alone. Asthmatics are slightly younger, 42.3 years old, and more likely to be female (63%), single (25%), Canadian born (81%), are less likely to be a recent immigrant (3%) or long-term immigrant (17%), and are as likely to live alone (13.4%). However, diabetics are older, 59.7 years old, more likely to be male (55%), less likely to be single (8%), more likely to be widowed or divorced (24%), less likely to be Canadian born (64%), more likely to be a long-term immigrant (32%), and more likely to live alone (20.5%).

All three groups are similar in terms of the physician supply variables, but asthmatics and diabetics have lower socioeconomic status and are in poorer health.

2.5.2 Mean Utilization by Quintile of GP Supply and Specialist Supply

One way to analyze how a person's use of physician services changes with physician supply is to look at the average physician use for different quintiles in the distribution of GP supply and specialist supply.

Table 2.5 presents the mean number of physician visits, the mean dollar value of physician services received, and the ratio of dollars of physician services to the number of physician visits, for a three-year period (April 1, 1999 and March 31, 2002), by the quintile of GP supply. Overall, the pattern suggests no relationship between GP supply and GP use.

Column 1 presents the mean number of GP visits, column 2 presents the mean dollar value of GP services received, and column 3 presents the ratio of dollars to GP visits. GP utilization is lowest in the bottom 20% of GP supply (mean of 11.8 GP visits, $363 in the dollar value of GP services received, and $37.04 dollars per GP visit) increasing to the fourth quintile (mean of 13.0 GP visits, $518 in the dollar value of GP services received, and $39.13 dollars per GP visit) before decreasing slightly in the top 20% of GP supply.

However, the relationship between GP supply and specialist utilization appears to be a shallow inverted U-shaped. Column 4 presents the mean number of specialist visits, column 5 presents the mean dollar value of specialist services received, and column 6 presents the ratio of dollars of specialist services to the number of specialist visits. Mean specialist visits are low in the first two quintiles (4.2 visits), increasing to 4.7 visits in quintiles 3 and 4 (significant at the 5% level), before decreasing to 4.0 visits in the top 20% of GP supply (significant at the 1% level). The dollar value of specialist services received remains fairly constant across all quintiles (ranging from $856 to $874), with the exception of the fourth quintile where the dollar value of specialist services received spikes at $970 (significant at the 1% level). The shallow inverted U-shaped relationship of specialist visits with GP supply and the relatively stable relationship between the dollar value of specialist services and GP supply results in a relatively flat relationship between GP supply and the ratio of dollars to specialist visits (ranging from \$143.74 to \$162.28), although quintile 3 is statistically lower from quintile 2 and 4 at the 1% level. This pattern of utilization is not entirely consistent with the theoretical predictions of Table 2.1. Assuming GPs and specialists are complements, we would expect to see specialist use increase with GP supply. Overall, Table 2.5 suggests no strong relationship between GP supply and both GP use and specialist use.

Table 2.6 presents the mean number of physician visits, the mean dollar value of physician services received, and the ratio of dollars of physician services to the number of physician visits, for a three-year period (April 1, 1999 and March 31, 2002), by the quintile of specialist supply. Overall, the is no meaningful relationship between specialist supply and GP utilization. Column 1 presents the mean number of GP visits, column 2 presents the mean dollar value of GP services received, and column 3 presents the ratio of dollars of GP services to the number of GP visits. The point estimate is lowest for the bottom 20% (11.7 visits), increases to 12.6 visits by the 3rd quintile, before decreasing slightly to 12.1 visits by the top 20%, although the only statistical difference is between quintile 2 and 3 at the 10% level. A similar relationship is observed between the quintile of specialist supply and the dollar value of GP services received. The point estimate is lowest for the bottom 20% (\$456), increases to \$497 by the 3rd quintile, before decreasing slightly to \$477 visits by the top 20%, although none of the differences are statistically significant. Not surprisingly, there is also a relatively flat relationship between specialist supply and the ratio of dollars to GP visits (ranging from \$36.78 to \$38.91), although the only statistical differences are between quintile 1 and 2 (quintile

2 is statistically higher at the 5% level) and between quintile 2 and 3 (quintile 3 is statistically lower at the 1% level).

Again, there is no meaningful relationship between specialist supply and specialist use. Column 4 presents the mean number of specialist visits, column 5 presents the mean dollar value of specialist services received, and column 6 presents the ratio of dollars of specialist services to the number of specialist visits. The mean number of specialist visits is lowest in the bottom 20% of specialist supply (4.1 specialist visits), increasing slightly to 4.7 visits in quintile 4, before decreasing to 4.2 visits in the top 20% of specialist supply. The relationship between quintile of specialist supply and the dollar value of specialist services received is also fairly flat. The dollar value of specialist services remains fairly constant in the bottom two quintiles ($843 and $797) and the top three quintiles ($903, $939, and $922). There is a statistically significant increase between quintile two and three.

The relationship between specialist supply and the ratio of dollars of specialist services to the number of specialist visits is also fairly flat (ranging from $150.58 to $168.02). Only the top 20% has a significantly higher ratio relative to the other quintiles. The specialist utilization pattern by quintile of specialist supply are, again, not consistent with the theoretical predictions of 2.1.

While the utilization patterns presented in Tables 2.5 and 2.6 generally demonstrate no relationship with physician supply, they do not account for other factors associated with physician use, such as patient income, education and health status. A multivariate analysis is needed to better disentangle the effects of GP supply from the effects of specialist supply while controlling for other observable factors.

2.5.3 Regression Results

Each set of regression results contains three models, one for each sample: the full sample, asthmatics, and diabetics. The first set of regression results is for the single-equation NB model used to analyze the effect of physician supply on the number of physician visits, assuming GP visits and specialist visits are exogenous. The second set of regression results is for the double-equation simultaneous NB model used to analyze the effect of physician supply on the number of physician visits, assuming GP visits and specialist visits are endogenous. Finally, the third set of regression results is for the generalized linear model used to analyze the effect of physician supply on the dollar value of physician services received. Prior to discussing the third set of regression results, model specification tests for the generalized linear models are presented.

Since the single-equation NB model, double-equation simultaneous NB model, and the generalized linear model are nonlinear models, the marginal effects (MFX) rather than the model coefficients are presented. The MFX is equal to the change in the conditional mean resulting from a one-unit change in a particular independent variable. Given the nonlinear nature of the models, the conditional mean and the MFX depend on the values of the other independent variables. For example, the MFX of a change in physician supply will be different for people in areas with a high supply of physicians relative to an area with a low supply of physicians, all else equal. The MFXs are calculated by setting all independent variables to their mean values (for continuous variables) or their modal values (for discrete variables).

Single-Equation Negative Binomial Model

Table 2.7 presents the MFXs at the mean, on the number of GP visits and the number of specialist visits, from a one unit change in GP supply, specialist supply, the interaction between GP and specialist supply, and the number of visits to a specialist or GP.[20] Column 1 presents the MFXs for GP visits for the full sample. The conditional mean number of GP visits is 10.7. The MFX of an increase of 1 GP per 10,000 population (approximately 6.8% of mean GP supply) is predicted to increase the number of GP visits by 0.09 visits or 0.6% and is statistically significant at the 1% level. The MFX of an increase of 1 specialist per 10,000 population (approximately 14.9% of mean specialist supply) is predicted to decrease the number of GP visits by 0.06 visits, or 0.6%, and is statistically significant at the 10% level. There is no meaningful effect from the interaction between GP and specialist supply[21], but an increase of one specialist visit increases the number of GP visits by 0.29, or 2.7%, and is statistically significant at the 1% level. Column 2 presents the MFX for specialist visits for the full sample. The MFXs of a change in

[20] A complete list of MFXs are presented in Appendix 2.A4, Table 2.A3. A complete list of coefficient estimates from the single-equation negative binomial model are presented in Appendix 2.A5, Table 2.A4.

[21] As noted above, the MFXs are evaluated at the mean of each continuous variable. Table 2.2 shows the mean of GP supply is 14.8 and the mean specialist supply is 7.1, which means the interaction term is evaluated at a value of 105. Thus, over most of the distribution of GP supply and specialist supply, the interaction term is going to be small.

the supply of GPs and the supply of specialists on the conditional number of specialist visits are relatively large compared to the MFXs of a change in the supply of GPs and the supply of specialists on the conditional number of GP visits. The conditional mean number of specialist visits is 3.1. The MFX of an increase of 1 GP per 10,000 population is predicted to decrease the number of specialist visits by 0.04 visits, or 1.2%, and is statistically significant at the 1% level. The MFX of an increase of 1 specialist per 10,000 population is predicted to increase the number of specialist visits by 0.07 visits, or 2.1%, and is statistically significant at the 1% level. Again, there is no meaningful effect from the interaction between GP and specialist supply, but an increase of one GP visit is associated with an increase the number of specialist visits by 0.10, or 3.1%, and is significant at the 1% level.

For asthmatics, the MFXs are similar to those obtained for the full sample, but are, in general, statistically insignificant. Column 3 presents the MFX for GP visits for asthmatics. The conditional mean number of GP visits is 15.6. The MFX of an increase of 1 GP per 10,000 population is associated with an increase the number of GP visits by 0.03 visits, or 0.2%, but is not statistically significant. The MFX of an increase of 1 specialist per 10,000 population is associated with an increase the number of GP visits by 0.06 visits, or 0.4%, but is not statistically significant. There is no meaningful effect from the interaction between GP and specialist supply, but an increase of one specialist visit is associated with an increase the number of GP visits by 0.31, or 2.0%, and is significant at the 1% level. Column 4 presents the MFX for specialist visits for asthmatics. The conditional mean number of specialist visits is 4.6. The MFX of an increase of 1 GP per 10,000 population is predicted to decrease the number of GP visits by 0.08 visits, or 1.8%, and is statistically significant at the 5% level. An increase of 1 specialist per 10,000 population is predicted to increase the number of specialist visits by 0.03 visits, or 0.7%, but is statistically insignificant. As before, there is no meaningful effect from the interaction between GP and specialist supply, but an increase of one GP visit is associated with an increase the number of specialist visits by 0.11, or 2.3%, and is significant at the 1% level.

For diabetics, the magnitudes of the MFXs from a change in physician supply are the largest among the three groups. Column 5 presents the MFX for GP visits for diabetics. The conditional mean number of GP visits is 20.3. The MFX of an increase of 1 GP per 10,000 population is predicted to increase the number of GP visits by 0.23 visits, or 1.2%. The MFX of an increase of 1 specialist per 10,000 population is predicted to decrease the number of GP visits by 0.29 visits, or 1.4%. Both of these MFXs are statistically significant at the 5% level. There is no meaningful effect from the interaction between GP and specialist supply, but an increase of one specialist visit is associated with an increase the number of GP visits by 0.23, or 1.1%, and is significant at the 1% level. Column 6 presents the MFX for specialist visits for diabetics. The conditional mean number of specialist visits is 8.6. The MFX of an increase of 1 GP per 10,000 population is predicted to decrease the number of GP visits by 0.22 visits or 2.6%. The MFX of an increase of 1 specialist per 10,000 population is predicted to increase the number of specialist visits by 0.31 visits or 3.6%. Both of these marginal effects are statistically significant at the 1%

level. Again, there is no meaningful effect from the interaction between GP and specialist supply, but an increase of one GP visit is associated with an increase the number of specialist visits by 0.13, or 1.5%, and is significant at the 1% level.

Double-Equation Negative Binomial Model

Table 2.8 presents the MFXs at the mean from a change in GP supply and specialist supply for the double-equation simultaneous negative binomial model.[22] Column 1 presents the MFX for GP visits for the full sample. The conditional mean number of GP visits is 13.1. The MFX of an increase of 1 GP per 10,000 population (approximately 6.8% of mean GP supply) is predicted to increase the number of GP visits by 0.09 visits or 0.7% of the conditional mean number of GP visits. The MFX of an increase of 1 specialist per 10,000 population (approximately 14.9% of mean specialist supply) is predicted to decrease the number of GP visits by 0.09 visits or 0.7%. Both MFXs are significant at the 1% level. Column 2 presents the MFX for specialist visits for the full sample. Again, the MFXs of a change in GP supply and specialist supply on the conditional number of specialist visits are larger than the MFXs of a change in GP supply and specialist supply on the conditional number of GP visits. The conditional mean number of specialist visits is 4.4. The MFX of an increase of 1 GP per 10,000 population is predicted to decrease the number of specialist visits by 0.02 visits or 0.5% of the conditional mean number of specialist visits.

[22] A complete list of the MFXs from the double-equation simultaneous NB model are presented in Appendix 2.A6, Table 2.A5. Coefficients from the double-equation NB model are presented in Appendix 2.A7, Table 2.A6.

The MFX of an increase of 1 specialist per 10,000 population is predicted to increase the number of specialist visits by 0.055 visits or 1.2% of the conditional mean number of specialist visits. The MFX of a change in GP supply is significant at the 5% level and the MFX from a change in specialist supply is significant at the 1% level.

For asthmatics, the MFXs are similar to those obtained for the full sample, but are statistically insignificant. Column 3 presents the MFX of a change in physician supply on the number of GP visits for asthmatics. The conditional mean number of GP visits is 20.0. The MFX of an increase of 1 GP per 10,000 population is associated with an increase the number of GP visits by 0.06 visits or 0.3% of the conditional mean number of GP visits. The MFX of an increase of 1 specialist per 10,000 population is associated with an increase the number of GP visits by 0.01 visits or 0.03%. Column 4 presents the MFXs of a change in physician supply on the number of specialist visits for asthmatics. The conditional mean number of specialist visits is 5.8. The MFX of an increase of 1 GP per 10,000 population is predicted to decrease the number of GP visits by 0.02 visits or 0.4% of the conditional mean number of specialist visits. The MFX of an increase of 1 specialist per 10,000 population is predicted to increase the number of specialist visits by 0.07 visits or 1.2% of the conditional mean number of specialist visits. However, all these marginal effects are not statistically significant.

For diabetics, the magnitudes of the MFXs are the largest among the three groups. Column 5 presents the MFX of a change in physician supply on the number of GP visits for diabetics. The conditional mean number of GP visits is 27.7. The MFX of an increase of 1 GP per 10,000 population is predicted to increase the number of GP visits by 0.266 visits or 1%. The MFX of an increase of 1 specialist per 10,000 population is predicted to decrease the number of GP visits by 0.262 visits or 0.9%. Both of these MFXs are statistically insignificant. Column 6 presents the MFXs of a change in physician supply on the number of specialist visits for diabetics. The conditional mean number of specialist visits is 9.5. The MFX of an increase of 1 GP per 10,000 population is predicted to decrease the number of GP visits by 0.16 visits or 1.7% of the conditional mean number of specialist visits. The MFX of an increase of 1 specialist per 10,000 population is predicted to increase the number of specialist visits by 0.23 visits or 2.4% of the conditional mean number of specialist visits. Both of these marginal effects are statistically significant at the 5% level.

Comparing the results from the double-equation simultaneous NB model (Table 2.8) with the single-equation NB model (Table 2.7) shows the parameter estimates are of the same sign and similar magnitudes. While the single-equation model assumes the number of GP and specialist visits are exogenous and the double-equation simultaneous NB model assumes the number of GP and specialist visits are endogenous, the similar parameter estimates suggest the magnitude of any endogeneity bias is small. In turn, the similarity of parameter estimates between the single-equation NB model and the double-equation simultaneous NB model also suggests the estimates from the generalized linear model - that do not correct for endogeneity bias - are also reliable.

Specification Test for Generalized Linear Models

The assumed functional form of the link function (log) and the family function (gamma) are tested to see if they are appropriate. Table 2.9 presents the results of the GLM functional form tests. A Box-Cox test is used to test the assumed functional form of the link function. A GLM family test is used to test the assumed functional form of the family function. The first four columns of Table 2.9 present the parameter estimates $\hat{\lambda}$, the null hypothesis being tested, the p-value of the test statistic, and the conclusion of the Box-Cox test. A value of $\hat{\lambda}$ close to zero suggests the link function should be specified as a logarithmic (log) function. As shown by column 1, all $\hat{\lambda}$s are close to zero. As shown by column 3, all $\hat{\lambda}$s are statistically different from zero and from one. While all $\hat{\lambda}$s are statistically different from zero, the point estimates are notably closer to zero than to one suggesting the assumption of a log-link function is reasonable.

The last four columns of Table 2.9 presents the parameter estimate $\hat{\gamma}$, the null hypothesis being tested, the p-value of the test statistic, and the conclusion of the GLM family test. To interpret the results: a value of $\hat{\gamma}$ close to 1 suggests the GLM family is correctly specified as a Poisson distribution; a value of $\hat{\gamma}$ close to 2 suggests the GLM family is correctly specified as a Gamma distribution; and a value of $\hat{\gamma}$ close to 3 suggests the GLM family is correctly specified as an inverse Gaussian distribution. As shown by column 5, all $\hat{\gamma}$s for GLM models of the dollar value of GP services received are close to 2, with the exception of the model for asthmatics (3.523). Column 7 shows the $\hat{\gamma}$s are not statistically different from 2 at the 10% level, suggesting the assumption of a gamma distribution is reasonable. Possible other functional form assumptions could be made for the dollar value of GP services received by asthmatics (i.e. inverse Gaussian), but for consistency and simplicity a gamma family function for all three GLM models of the dollar value of GP services received is assumed. Column 5 also presents the point estimates ($\hat{\gamma}$). All three $\hat{\gamma}$s are closest to 2, but are statistically different from 1, 2 and 3 at the 1% level. Since the point estimate of $\hat{\gamma}$'s are closest to 2, this suggests the GLM family is a reasonable specification for all three GLM models of the dollar value of specialist services received.

Marginal Effects on the Dollar Value of Physician Services Received

Table 2.10 presents the MFXs at the mean, on the dollar value of GP services and the dollar value of specialist services, from a one unit change in GP supply, specialist supply, the interaction between GP and specialist supply, and the number of visits to a specialist or GP.[23] Column 1 presents the MFXs for GP visits for the full sample. The conditional mean dollar value of GP services received is \$410. The MFX of an increase of 1 GP per 10,000 population (approximately 6.8% of mean GP supply) is predicted to increase the dollar value of GP services by \$4.51, or 1.1%, and is statistically significant at the 1% level. The MFX of an increase of 1 specialist per 10,000 population (approximately 14.9% of mean specialist supply) is predicted to decrease the dollar value of GP services by \$3.32, or 0.8%, and is statistically significant at the 5% level. There is no meaningful effect from the interaction between GP and special-

[23] A full list of the MFXs from the general linear model are presented in Appendix 2.A8, Table 2.A7. Also, a full list of parameter estimates from the general linear model are presented in Appendix 2.A9, Table 2.A8

ist supply[24], but an increase of \$1 in the dollar value of specialist services is associated with an increase the dollar value of GP services by \$0.10 and is statistically significant at the 1% level. Column 2 presents the MFX for dollar value of specialist services received for the full sample. The conditional mean dollar value of specialist services received is \$618. The MFX of an increase of 1 GP per 10,000 population is predicted to decrease the dollar value of specialist services by \$5.82, or 0.9%. The MFX of an increase of 1 specialist per 10,000 population is predicted to increase the dollar value of specialist services by \$12.91, or 2.1%. Both these MFXs are statistically significant at the 1% level. Again, there is no meaningful effect from the interaction between GP and specialist supply, but an increase of \$1 in the dollar value of GP services received is associated with an increase the dollar value of specialist services by \$0.60 and is statistically significant at the 1% level.

For asthmatics, the coefficients are generally larger than for the full sample, but are generally not statistically significant. Column 3 presents the coefficients of a one unit change in physician supply on the dollar value of GP services received by asthmatics. An increase of 1 GP per 10,000 population or an increase of 1 specialist per 10,000 population is not predicted to have a meaningful effect on the dollar value of GP services used. There is no meaningful effect from the interaction between GP and specialist supply, but an increase of \$1 in the dollar value of specialist services received is associated with an increase the dollar value of specialist services received by \$0.13, and is statistically significant at the 1% level. Column 4 presents the coefficients of a

[24]Again, the interaction term is going to be small and not meaningful over most of the distribution of GP supply and specialist supply.

change in physician supply on the dollar value of specialists services received by asthmatics. An increase of 1 GP per 10,000 population is predicted to decrease the dollar value of specialist services used by $11.93, or 1.4%, and is statistically significant at the 10% level. However, an increase of 1 specialist per 10,000 population is predicted to have no meaningful effect. Again, there is no meaningful effect from the interaction between GP and specialist supply, but an increase of $1 in the dollar value of GP services received will increase the dollar value of specialist services received by $0.65.

The largest effects of physician supply on the dollar value of services used are found for diabetics. Column 5 presents the coefficients of a one-unit change in physician supply on dollar value of GP services received by diabetics. An increase of 1 GP per 10,000 population is predicted to increase the dollar value of GP services by $13.60, or 1.8%, and is statistically significant at the 1% level. An increase of 1 specialist per 10,000 population is predicted to decrease the dollar value of GP services used by $19.49, or 2.6%, and is statistically significant at the 5% level. There is no meaningful effect from the interaction between GP and specialist supply, but an increase of $1 in the dollar value of specialist services received is associated with an increase the dollar value of GP services by $0.07 and is statistically significant at the 1% level. Column 6 presents the coefficients of a change in physician supply on the dollar value of specialist services used by diabetics. An increase of 1 GP per 10,000 population is predicted to decrease the dollar value of specialist services used by $66.26, or 4% of the conditional mean (statistically significant at the 1% level), while an increase of 1 specialist per 10,000 population is predicted to increase the dollar value of specialist services used by \$93.07, or 5.7% (significant at the 1% level). Again, there is no meaningful effect from the interaction between GP and specialist supply, but an increase of \$1 in the dollar value of GP services received is associated with an increase the dollar value of specialist services by \$0.73 and is statistically significant at the 1% level.

Consistent with Table 2.7, Table 2.10 also supports the notion of a substitute relationship between GPs and specialists. The magnitude of the relationship is strongest for people in the greatest health care need (diabetics).

2.6 Discussion

The simple interpretation of the marginal effects (MFXs) from the single-equation NB model and the generalized linear model due to a change in physician supply suggest a substitute relationship between GPs and specialists. Both set of regression results can be easily interpreted as showing an increase in own-physician supply will increase own-physician use and decrease other-physician use. However, the inclusion of both supply and utilization variables as explanatory variables in the model makes for a more complex interpretation. The results can be interpreted as demonstrating two separate effects.

The first effect is the supply effect. The physician supply variables likely proxy for the time costs to patients of making a visit, and the clinical and/or economics incentives shaping a physician's decision threshold. For example, an increase in the supply of GPs will reduce the time it takes a patient to make an appointment for a GP visit, reducing the patients total price of a GP visit, and increasing GP utilization. If a specialist visit substitutes for a GP visit, than a decrease in the total price of a GP visit (the price of a substitute) would result in patients making fewer specialist visits. This substitute relationship is demonstrated by the negative parameter estimates of the specialist supply variable in both the single-equation and double-equation negative binomial models for the number of GP visits, as well as the general linear model for the dollar value of GP services received. A similar result is shown by the negative parameter estimates of the GP supply variable in both the single-equation and double-equation negative binomial models for the number of specialist visits, as well as the general linear model for the dollar value of specialist services received. This interpretation is slightly complicated by the role of the supply side, so it is not a pure demand story. But, it does capture the relationship between the total price of one physician type and the utilization of the other physician type.

The second effect, which I refer to as a 'taste' effect, captures unmeasured causes of utilization. First, people have preferences for consuming health care. The physician utilization variables, when used as explanatory variables in the regression models, may simply proxy for a patient's taste for consuming health care. For example, a patient who uses more GP services may also use more specialist services because they have stronger preferences for obtaining health care when ill or injured. This may simply reflect risk attitudes. Second, people have a need to consume health care due to the complexity of their underlying conditions. In this case, the physician utilization variables may simply proxy for a patient's unobserved need for health care. For example, a patient who uses more GP services may also use more specialist services because they need to given their complex health care need. As these two effects (preferences and unobserved health care need) can not be disentangled, I refer to both as the 'taste' effect. However, the taste effect should not be interpreted as a causal relationship. This is simply a correlation because GP use and specialist use are driven by these more fundamental factors.

While the direction of the supply effects and the taste effects are the same across all three samples, the magnitude of the effects differ. The supply effects are stronger for diabetics, relative to the full sample, and are weaker for asthmatics. The difference in magnitude of the supply effect may be a result of the different natures of the diseases. Diabetics, for example, can have serious complications (such as vision loss, digestive problems, thyroid disease, or kidney disease) affecting a number of different parts of the body, which may require different types of specialists to treat. Complications from asthma can also be serious, but only focus on the respiratory system which requires fewer types of specialists to treat.

The taste effect is stronger for asthmatics and diabetics, relative to the full sample. The larger magnitude of the taste effect may also reflect the complex nature of the chronic conditions. If the utilization variables do proxy for unmeasured health care need, then asthmatics and diabetics are more likely to have unmeasured health care needs given their more complex conditions.

The supply effects are generally consistent with the previous literature that shows an increase in GP (or specialist) supply is positively associated with an increase in the use of GP (or specialist) services.

Interestingly, correcting for sequential endogeneity between GP visits and specialist visits using a double-equation negative binomial model - adapted from the triple-equation negative binomial model proposed by Atella and Deb (2008) - the conclusions of the single-equation negative binomial model are not reversed, unlike in Atella and Deb (2008). Both the single-equation and double-equation models suggest GPs and specialists are substitutes. These contrary findings may be due to the difference between the double-equation and triple-equation models, but are more likely due to the difference in window of utilization studied (three-months vs. three-years). It is likely there is a sequential decision making process during a three-month window, but not during a three year window.

A limitation of the paper is the inability to control for the choice of geographic location by physicians. As noted above, physicians are not randomly distributed geographically across Ontario as a physician's location decision is determined by their preferences, both personal (quality of leisure, the distance to urban amenities, their average income) and professional (close to a hospital, a large number of practicing physicians, and to larger populations).

Since GPs and specialists are found to be substitutes, a shortage in the supply of one physician type would likely result in an increase in the use of the other physician type. However, these results are only suggestive of average behavior.

Table 2.1: Effect of Physician Supply on the Utilization of Physician Services

Increase in GP Supply	Increase in Specialist Supply
Effect on the Quantity of GP Services Demanded	
Increase May decrease total price and increase quantity demanded.	Uncertain May decrease total price of a specialist visit. If specialists are a substitute to GPs, the quantity demanded of GP services may decrease. But, if specialists are a complement to GPs, then the quantity demanded of GP services may increase.
Effect on the Quantity of Specialist Services Demanded	
Uncertain May decrease the total price of a GP visit. If GPs are a substitute to specialists, then the quantity demanded of specialist services may decrease. But, if GPs are a complement to specialists then the quantity demanded of specialist services may increase.	Increase May decrease the total price of a specialist visits and increase the quantity demanded.
Effect on the Quantity of GP Services Supplied	
Increase May decrease a GP's acceptance threshold for new patients and continuation of care threshold, increasing the quantity of GP services supplied.	Decrease May decrease a GP's referral threshold, increasing the number of patients referred to specialists and decreasing the quantity of GP services supplied.
Effect on the Quantity of Specialist Services Supplied	
Increase May decrease a GP's acceptance threshold for new patients, decreasing a specialist's referral threshold and increasing the likelihood a specialist would refer a patient back to a GP, increasing the quantity of GP services supplied.	Increase May decrease a specialist's acceptance threshold for new patients and/or continuation of care threshold, increasing the quantity of specialist services supplied.

Table 2.2: Comparison of Decay Functions from Constructed Physician supply variable, defined using different decay functions, with the Supply of Physicians per CSD

	Mean	10^{th} Percentile	25^{th} Percentile	Median Percentile	75^{th} Percentile	90^{th} Percentile	90 / 10 Percentile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GP Supply							
per CSD	10.7	0.0	0.0	0.0	4.0	19.0	-
$f(d_k) = \frac{1}{d}$	14.8	9.4	12.6	15.0	16.3	18.3	1.9
$f(d_k) = \frac{1}{d^2}$	3.1	0.1	0.2	0.4	0.8	2.1	21.0
$f(d_k) = \frac{1}{\sqrt{d}}$	151.8	128.3	144.5	159.1	162.8	165.2	1.3
Specialist Supply							
per CSD	10.2	0.0	0.0	0.0	0.3	5.0	-
$f(d_k) = \frac{1}{d}$	7.1	3.1	5.2	7.1	7.9	9.5	3.1
$f(d_k) = \frac{1}{d^2}$	2.7	0.1	0.2	0.2	0.6	1.7	17.0
$f(d_k) = \frac{1}{\sqrt{d}}$	56.4	40.7	50.9	61.2	62.7	63.9	1.6

Table 2.3: Mean and Median of Physician Utilization Measures, Number of Visits and Dollar Value of Services Received, for a three-year period (April 1, 1999 to March 31, 2002)

	GP Utilization		Specialist Utilization	
	Visits	Dollar Value	Visits	Dollar Value
	(1)	(2)	(3)	(4)
All				
Mean	12.3	$ 481	4.4	$ 897
S.E.(mean)	0.08	5	0.05	10
Median	9	$ 310	1	$ 357
% 0	7.9%	6.3%	38.8%	13.1%
Asthmatics				
Mean	17.5	$ 683	6	$ 1176
S.E.(mean)	0.34	19	0.21	34
Median	14	$ 495	3	$ 592
% 0	4.6%	3.1%	28.9%	7.8%
Diabetics				
Mean	21.8	$ 836	9.8	$ 2056
S.E.(mean)	0.41	20	0.29	72
Median	18	$ 646	6	$ 1060
% 0	4.4%	1.9%	14.1%	2%
Ratio of Means				
Astmatics / All	1.43	1.42	1.35	1.31
Diabetics / All	1.77	1.74	2.21	2.29

Table 2.4: Descriptive Statistics for Physician Supply, Socioeconomic Status, Health Status, and Demographic Variables

	All	Asthmatics	Diabetics	Ratio of Means (2) / (1)	Ratio of Means (3) / (1)
	(1)	(2)	(3)	(4)	(5)
1. Physician Supply Variables					
GP Supply					
Mean	14.8	14.7	14.7	0.99	0.99
S.E.(mean)	(0.04)	(0.15)	(0.22)		
Median	15	15	15		
Specialist Supply					
Mean	7.1	7	7.1	0.99	0.99
S.E.(mean)	-0.03	-0.1	-0.16		
Median	7	7	7		
2. Socioeconomic Status					
Household Income	$65,077	$59,976	$47,133	0.92	0.72
	(293)	(955)	(1,006)		
Less than High-School	9.5%	12.6%	23.8%	1.33	2.50
	(0.002)	(0.007)	(0.011)		
High-School	14.3%	13.6%	18.5%	0.95	1.30
	(0.002)	(0.007)	(0.010)		
Some Post-Secondary	7.2%	8.6%	6.0%	1.19	0.83
	(0.002)	(0.006)	(0.006)		
Post-Secondary	69.0%	65.3%	51.7%	0.95	0.75
	(0.003)	(0.010)	(0.013)		
Currently Working	57.8%	54.1%	31.5%	0.94	0.55
	(0.003)	(0.010)	(0.012)		
Not Currently Working	16.5%	16.6%	10.6%	1.00	0.64
	(0.002)	(0.008)	(0.008)		
No Work in the last Year	20.3%	24.0%	43.3%	1.18	2.13
	(0.002)	(0.009)	(0.013)		
Working - Not Applicable	5.2%	4.8%	14.6%	0.93	2.83
	(0.001)	(0.004)	(0.009)		
Working - Not Stated	0.2%	x	x		
	(0.000)				
3. Health Status					
Asthma	8.0%	100.0%	10.0%	-	-
	(0.000)	(0.000)	(0.010)		
Diabetes	5.0%	6.0%	100.0%	-	-
	(0.000)	(0.000)	(0.000)		

continued on next page

Table 2.4, continued

	All	Asthmatics	Diabetics	Ratio of Means (2) / (1)	Ratio of Means (3) / (1)
	(1)	(2)	(3)	(4)	(5)
Zero Chronic Conditions	32.0%	0.0%	0.0%	-	-
	(0.000)	(0.000)	(0.000)		
1-3 Chronic Conditions	55.0%	58.0%	53.0%	1.05	0.96
	(0.000)	(0.010)	(0.010)		
4-5 Chronic Conditions	9.0%	24.0%	27.0%	2.67	3.00
	(0.000)	(0.010)	(0.010)		
6 or more Chronic Conditions	4.0%	18.0%	20.0%	4.50	5.00
	(0.000)	(0.010)	(0.010)		
Major Chronic Condition	7.0%	11.0%	23.0%	1.57	3.29
	(0.000)	(0.010)	(0.010)		
Medium Chronic Condition	13.0%	15.0%	77.0%	1.15	5.92
	(0.000)	(0.010)	(0.010)		
Mild Chronic Condition	47.0%	74.0%	0.0%	1.57	-
	(0.000)	(0.010)	(0.000)		
Excellent	27.0%	15.0%	6.0%	0.56	0.22
	(0.000)	(0.010)	(0.010)		
Very Good	37.0%	33.0%	19.0%	0.89	0.51
	(0.000)	(0.010)	(0.010)		
Good	24.0%	28.0%	33.0%	1.17	1.38
	(0.000)	(0.010)	(0.010)		
Fair	9.0%	15.0%	25.0%	1.67	2.78
	(0.000)	(0.010)	(0.010)		
Poor	4.0%	9.0%	16.0%	2.25	4.00
	(0.000)	(0.010)	(0.010)		
Low BMI	2.0%	2.0%	1.0%	1.00	0.50
	(0.000)	(0.000)	(0.010)		
Normal BMI	38.0%	34.0%	14.0%	0.89	0.37
	(0.000)	(0.010)	(0.010)		
Over weight	27.0%	25.0%	21.0%	0.93	0.78
	(0.000)	(0.010)	(0.010)		
Obeses	33.0%	39.0%	64.0%	1.18	1.94
	(0.000)	(0.010)	(0.010)		
Activity Limitation	24.5%	43.9%	48.2%	1.79	1.97
	(0.003)	(0.010)	(0.013)		
4. Demographics					
Age	44.7	42.3	59.7	0.95	1.34
	(0.10)	(0.35)	(0.38)		
Female	51.0%	63.0%	45.0%	1.24	0.88
	(0.000)	(0.010)	(0.010)		
Married / Common Law	66.0%	62.0%	68.0%	0.94	1.03

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Table 2.4, continued

	All	Asthmatics	Diabetics	Ratio of Means (2) / (1)	Ratio of Means (3) / (1)
	(1)	(2)	(3)	(4)	(5)
	(0.000)	(0.010)	(0.010)		
Single	21.0%	25.0%	8.0%	1.19	0.38
	(0.000)	(0.010)	(0.010)		
Widowed / Divorced	13.0%	13.0%	24.0%	1.00	1.85
	(0.000)	(0.010)	(0.010)		
Urban	86.0%	85.0%	86.0%	0.99	1.00
	(0.000)	(0.010)	(0.010)		
Recent Immigrant	8.0%	3.0%	3.0%	0.38	0.38
	(0.000)	(0.000)	(0.000)		
Long Term Immigrant	23.0%	17.0%	32.0%	0.74	1.39
	(0.000)	(0.010)	(0.010)		
Canadian Born	70.0%	81.0%	64.0%	1.16	0.91
	(0.000)	(0.010)	(0.010)		
Lives Alone	13.4%	13.4%	20.5%	1.00	1.53
	(0.007)	(0.007)	(0.010)		

x: cells suppressed due to low cell counts

Table 2.5: Mean number of visits and dollar value of physician services used, for GPs and Specialists, by quintile of GP supply - April 1, 1999 to March 31, 2002

	GP Utilization			Specialist Utilization		
	Visits	Dollars	(2) / (1)	Visits	Dollars	(2) / (1)
GP Supply	(1)	(2)	(3)	(4)	(5)	(6)
Bottom 20%	11.8	\$449	\$37.04	4.2	\$856	\$150.95
	(0.2)	(8)	(0.57)	(0.1)	(21)	(3.08)
2nd (20-40%)	12.0	\$481 **	\$38.22	4.2	\$858	\$160.36 *
	(0.2)	(12)	(0.41)	(0.1)	(21)	(3.23)
3rd (40-60%)	12.0	\$466	\$35.74 ***	4.7 **	\$874	\$143.74 ***
	(0.2)	(13)	(0.40)	(0.1)	(21)	(2.99)
4th (60-80%)	13.0 **	\$518 *	\$39.13 ***	4.7	\$970 **	\$160.53 ***
	(0.2)	(10)	(0.69)	(0.1)	(24)	(3.48)
Top 20%	11.9 *	\$465 *	\$38.27	4.0 ***	\$860 **	\$162.28
	(0.2)	(8)	(0.51)	(0.1)	(21)	(3.46)
Total	12.3	\$481	\$37.70	4.4	\$897	\$155.11
	(0.1)	(5)	(0.24)	(0.1)	(10)	(1.46)

Stars denote statistical significance between quintile q and quintile $q-1$.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Mean number of visits and dollar value of physician services used, for GPs and Specialists, by quintile of specialist supply - April 1, 1999 to March 31, 2002

	GP Utilization			Specialist Utilization		
	Visits	Dollars	(2) / (1)	Visits	Dollars	(2) / (1)
Specialist Supply	(1)	(2)	(3)	(4)	(5)	(6)
Bottom 20%	11.7	\$456	\$37.15	4.1	\$843	\$152.18
	(0.2)	(10)	(0.68)	(0.1)	(21)	(4.09)
2nd (20-40%)	11.9	\$471	\$38.91 **	3.8	\$797	\$151.58
	(0.2)	(9)	(0.48)	(0.1)	(19)	(3.74)
3rd (40-60%)	12.6 *	\$497	\$36.78 ***	4.6 ***	\$903 ***	\$150.58
	(0.2)	(13)	(0.55)	(0.1)	(21)	(4.55)
4th (60-80%)	12.5	\$485	\$37.79	4.7	\$939	\$154.42
	(0.2)	(8)	(0.62)	(0.1)	(22)	(3.69)
Top 20%	12.1	\$477	\$38.51	4.2 ***	\$922	\$168.02 *
	(0.2)	(12)	(1.05)	(0.1)	(26)	(6.75)
Total	12.3	\$481	\$37.70	4.4	\$897	\$155.11
	(0.1)	(5)	(0.24)	(0.1)	(10)	(1.46)

Stars denote statistical significance between quintile q and quintile $q-1$.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Marginal Effects (at the Mean) on the number of GP and Specialist Visits - Single Equation Negative Binomial Model

	Full Sample		Asthmatics		Diabetics	
	General Practitioners	Specialists	General Practitioners	Specialists	General Practitioners	Specialists
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	0.09 ***	-0.04 ***	0.03	-0.08 **	0.23 **	-0.22 ***
(per 10,000 pop.)	[0.8%]	[-1.2%]	[0.2%]	[-1.8%]	[1.2%]	[-2.6%]
SP Supply	-0.06 *	0.07 ***	0.06	0.03	-0.29 **	0.31 ***
(per 10,000 pop.)	[-0.6%]	[2.1%]	[0.4%]	[0.7%]	[-1.4%]	[3.6%]
GP x SP Supply	0 **	0	0	0 *	0	0
	[0.0%]	[0.0%]	[0.0%]	[0.0%]	[0.0%]	[0.0%]
# SP Visits	0.29 ***		0.31 ***		0.23 ***	
	[2.7%]		[2.0%]		[1.1%]	
# GP Visits		0.1 ***		0.11 ***		0.13 ***
		[3.1%]		[2.3%]		[1.5%]
Conditional Mean	10.7	3.1	15.6	4.6	20.3	8.6
n	26,663		2,359		1,507	

The marginal effect at the mean is reported as the absolute change in the number of visits and, in the square brackets below, the percentage change in the conditional mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Marginal Effects (at the Mean) of physician supply on the number of GP and Specialist Visits - Double-Equation Simultaneous Negative Binomial Model

	Full Sample		Asthmatics		Diabetics	
	General Practitioners	Specialists	General Practitioners	Specialists	General Practitioners	Specialists
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	0.09 ***	-0.02 **	0.06	-0.02	0.27	-0.16 **
(per 10,000 pop.)	[0.7%]	[-0.5%]	[0.3%]	[-0.4%]	[1.0%]	[-1.7%]
SP Supply	-0.09 ***	0.06 ***	0.01	0.07	-0.26	0.23 **
(per 10,000 pop.)	[-0.7%]	[1.2%]	[0.0%]	[1.2%]	[-0.9%]	[2.4%]
Conditional Mean	13.1	4.4	20.0	5.8	27.7	9.5
n	26,663		2,359		1,507	

The marginal effect at the mean is reported as the absolute change in the number of visits and, in the square brackets below, the percentage change in the conditional mean.

$* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

Table 2.9: Testing the functional form assumptions of the link-function and the Family-function in the Generalized Linear Model

	Link Specification (Box-Cox Test)				GLM Family Test (Wald Test)			
	$\hat{\lambda}$	H_0	p-value		$\hat{\gamma}$	H_0	p-value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dollar Value of GP Services								
All	0.189	$\hat{\lambda}=0$	0.00	log	1.818	$\hat{\gamma}=0$	0.00	Gamma
	(0.004)	$\hat{\lambda}=1$	0.00		(0.461)	$\hat{\gamma}=1$	0.08	
						$\hat{\gamma}=2$	0.69	
						$\hat{\gamma}=3$	0.01	
Asthmatics	0.181	$\hat{\lambda}=0$	0.00	log	3.523	$\hat{\gamma}=0$	0.00	Gamma or
	(0.012)	$\hat{\lambda}=1$	0.00		(0.899)	$\hat{\gamma}=1$	0.01	inverse
						$\hat{\gamma}=2$	0.09	Gaussian
						$\hat{\gamma}=3$	0.56	
Diabetics	0.314	$\hat{\lambda}=0$	0.00	log	2.071	$\hat{\gamma}=0$	0.00	Gamma
	(0.018)	$\hat{\lambda}=1$	0.00		(0.293)	$\hat{\gamma}=1$	0.00	
						$\hat{\gamma}=2$	0.81	
						$\hat{\gamma}=3$	0.00	
Dollar Value of Specialist Services								
All	0.131	$\hat{\lambda}=0$	0.00	log	1.836	$\hat{\gamma}=0$	0.00	Gamma
	-0.004	$\hat{\lambda}=1$	0.00		-0.034	$\hat{\gamma}=1$	0.00	
						$\hat{\gamma}=2$	0.00	
						$\hat{\gamma}=3$	0.00	
Asthmatics	0.141	$\hat{\lambda}=0$	0.00	log	1.796	$\hat{\gamma}=0$	0.00	Gamma
	-0.013	$\hat{\lambda}=1$	0.00		-0.094	$\hat{\gamma}=1$	0.00	
						$\hat{\gamma}=2$	0.03	
						$\hat{\gamma}=3$	0.00	
Diabetics	0.171	$\hat{\lambda}=0$	0.00	log	1.635	$\hat{\gamma}=0$	0.00	Gamma or
	-0.016	$\hat{\lambda}=1$	0.00		-0.116	$\hat{\gamma}=1$	0.00	Poisson
						$\hat{\gamma}=2$	0.00	
						$\hat{\gamma}=3$	0.00	

Interpretation:
p-value: The null hypothesis ($H_0 : A = B$) is rejected in favor of the alternative hypothesis ($H_a : A \neq B$) at the p-value.
Box-Cox Test: $\hat{\lambda}$ close to zero suggests the link function should be a log specification.
GLM Family Test: $\hat{\gamma}$ close to 1 suggests the GLM family should be a Poisson distribution. $\hat{\gamma}$ close to 2 suggests the GLM family should be a Gamma distribution, $\hat{\gamma}$ close to 3 suggests the GLM family should be an inverse Gaussian distribution.

Table 2.10: Marginal Effects (at the Mean) in Dollar Value of GP Services and Specialists Services from a Change in Physician Supply - Generalized Linear Model

	Full Sample		Asthmatics		Diabetics	
	General Practitioners	Specialists	General Practitioners	Specialists	General Practitioners	Specialists
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	$4.51 ***	-$5.82 ***	$0.41	-$11.93 *	$13.60 ***	-$66.26 ***
(per 10,000 pop.)	[1.1%]	[-0.9%]	[0.1%]	[-1.4%]	[1.8%]	[-4.0%]
Specialist Supply	-$3.32 **	$12.91 ***	$2.21	$6.25	-$19.49 **	$93.07 ***
(per 10,000 pop.)	[-0.8%]	[2.1%]	[0.4%]	[0.7%]	[-2.6%]	[5.7%]
GP x SP Supply	-$0.01 **	-$0.00	-$0.01	$0.07	$0.01	-$0.03
	[0.0%]	[0.0%]	[0.0%]	[0.0%]	[0.0%]	[0.0%]
$ of Specialist Services	$0.10 ***		$0.13 ***		$0.07 ***	
	[0.0%]		[0.0%]		[0.0%]	
$ of GP Services		$0.60 ***		$0.65 ***		$0.73 ***
		[0.1%]		[0.1%]		[0.0%]
Conditional Mean	$410	$618	$583	$864	$759	$1,637
n	26,663		2,359		1,507	

The marginal effect at the mean is reported as the absolute change in the number of visits and, in the square brackets below, the percentage change in the conditional mean.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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2.A1 Appendix: CCHS - OHIP Sample Comparisons

Table 2.A1: Comparison of the CCHS Ontario Sample, Full Linked CCHS-OHIP Sample, and the Full Analysis Sample

	CCHS (Ontario) (1)	CCHS-OHIP (Full) (2)	CCHS-OHIP (Analysis) (3)	Ratio of Means (3)/(1)	(3)/(2)
Demographic					
Age	42.0	42.0	44.7	1.06	1.06
	(0.093)	(0.102)	(0.100)		
Female	50.9%	50.9%	51.0%	1.00	1.00
	(0.003)	(0.003)	(0.000)		
Socioeconomic Status					
Household Income	$64,995	$65,484	$65,077	1.00	0.99
	(258)	(280)	(293)		
Less than High-School	9.4%	9.2%	9.5%	1.01	1.03
	(0.001)	(0.002)	(0.002)		
High-School	14.6%	14.4%	14.3%	0.98	0.99
	(0.002)	(0.002)	(0.002)		
Some Post-Secondary	7.2%	7.3%	7.2%	1.00	0.99
	(0.001)	(0.001)	(0.002)		
Post-Secondary	66.7%	67.2%	69.0%	1.04	1.03
	(0.002)	(0.003)	(0.003)		
Health Status					
Asthma	8.5%	8.6%	8.0%	0.94	0.93
	(0.001)	(0.002)	(0.000)		
Diabetes	4.2%	4.3%	5.0%	1.19	1.15
	(0.001)	(0.001)	(0.000)		
Zero CCs	34.9%	34.3%	32.0%	0.92	0.93
	(0.002)	(0.003)	(0.000)		
Major CC	6.8%	6.9%	7.0%	1.02	1.01
	(0.001)	(0.001)	(0.000)		
Medium CC	12.1%	12.4%	13.0%	1.07	1.05
	(0.002)	(0.002)	(0.000)		
Mild CC	46.1%	46.4%	47.0%	1.02	1.01
	(0.003)	(0.003)	(0.000)		
Excellent	26.5%	26.6%	27.0%	1.02	1.01
	(0.002)	(0.002)	(0.000)		
Very Good	36.6%	36.8%	37.0%	1.01	1.01
	(0.002)	(0.003)	(0.000)		
Good	24.7%	24.4%	24.0%	0.97	0.98
	(0.002)	(0.002)	(0.000)		
Fair	8.6%	8.5%	9.0%	1.04	1.06
	(0.001)	(0.002)	(0.000)		
Poor	3.6%	3.7%	4.0%	1.12	1.08
	(0.001)	(0.001)	(0.000)		
Sample Size	39,278	32,848	26,663		

CC: chronic condition

2.A2 Appendix: OHIP Variables used to define a Physician Visit

Table 2.A2: OHIP variables used to define a physician visit

Physician Type	Specialty Claimed (*sp*)	Fee Schedule Code (*fsc*)
GP	00 GP	A001, A003-008, A100, A110, A112, A115, A813, A815, A888, A901, A903, A905, A933, A945, K004-008, K011-030, K032, K033, K037, K039-041, K399, K623, K624, K629, K887-889
Specialist	02 Anaesthesia	A013-016, A215
	03 Dermatology	A23-26
	03 General Surgery	A033-036, A935
	04 Neurosurgery	A043-046, A935
	06 Orthopaedic Surgery	A063-066, A935
	07 Geriatrics	A071, A073-076, A078, A375, A775
	08 Plastic Surgery	A083-086, A935
	09 Cardiovascular & Thoracic Surgery	A093-096, A935
	13 Internal Medicine	A131, A133-136, A138, A435
	18 Neurology	A181, A183-186, A188, A385
	19 Psychiatry	A193-198, A395, A695, A795, A895, K192, K194-198, K203-206, K208, K209, K620, K623, K624, K629
	20 Obstetrics & Gynaecology	A203-206, A935
	22 Genetics	A221, A225, A226, A325, K16, K44, K222, K223
	23 Ophthalmology	A115, A230, A233-237, A239, A250-252, A254, A935

continued on next page

Table 2.A2, continued

Physician Type	Specialty Claimed (*sp*)	Fee Schedule Code (*fsc*)
	24 Otololaryngology	A243-246, A935
	26 Paediatrics	A263-266, A565, A261, A262, A661, A665, A667, K122, K123, K267, K269
	28 Laboratory Medicine	A283-286, A585, A586
	33 Diagnostic Radiology	A331, A335, A338, A365
	34 Therapeutic Radiology	A340, A341, A343, A345, A346, A348, A745
	35 Urology	A353-356, A935
	41 Gastroenterology	A411, A413-416, A418, A545
	47 Respiratory Disease	A471, A473-476, A478, A575
	48 Rheumatology	A481, A483-486, A488, A595
	60 Cardiology	A601, A603-606, A608, A675, E078
	61 Haematology	A611, A613-616, A618, A655
	62 Clinical Immunology	A525, A621, A623-626, A628
	63 Nuclear Medicine	A635, A636, A638, A735, A835
	64 General Thoracic Surgery	A643-646, A935

2.A3 Appendix: Calculating the distance between a postal code and the centroid of a CSD

To determine the effective supply of physicians, geographic information is combined using the GIS software ArcInfo.[25] The effective supply of physicians is defined as the number of physicians in the province, weighted by the inverse of the linear distance between a respondents home and a physicians census sub-division (CSD).

Since the precise geography of the physician is unknown, the centroid of the census sub-division is used as a proxy for actual location within the CSD. To determine the effective supply of physicians, the distance between a respondents home (geographically defined as their postal code) and the centroid of surrounding CSDs must be determined.

To determine the distance between a postal code and the centroid of a CSD, the GIS software ArcInfo uses: (i) the Ontario Postal code conversion file (PCCF) for September 2002, and (ii) the Ontario CSD cartographic file for 2001. The Ontario PCCF provides the longitude and latitude of each postal code in the province of Ontario, Canada. Since a proportion of postal codes can map to multiple locations, the PCCF provides a single link indicator to designate the most probable geography for a postal code with multiple locations. Postal codes with multiple locations account for approximately 20% of all postal codes. The 2001 CSD cartographic file contains 586 CSDs in

[25]The expertise of Pat DeLuca (School of Geography & Earth Sciences Systems, McMaster University) was enlisted to construct the physician supply variables using ArcInfo.

Ontario. The centroid of each CSD is determined by its latitude and longitude.

ArcInfo combines the latitude and longitude information for the centroid of each of the 586 CSDs in the CSD Cartographic file with the latitude and longitude of each of the n postal codes in the Ontario PCCF to calculate the distance between all CSD centroids and the latitude and longitude of all postal codes. Each cell in the resulting 586 by n matrix contains the distance between each postal code and the centroid of each CSD. The inverse of the distance in each cell is then used to weight the physician to population ratio of each CSDs. The resulting sum of physician to population ratios is a weighted sum of all CSDs in Ontario.

2.A4 Appendix: Single Equation Negative Binomial Model, Marginal Effects

Table 2.A3: Marginal Effects (at the mean), the number of GP and Specialist Visits, Single Equation Negative Binomial Model

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	0.09 ***	-0.04 ***	0.03	-0.08 **	0.23 **	-0.22 ***
SP Supply	-0.06 *	0.07 ***	0.06	0.03	-0.29 **	0.31 ***
GP x SP Supply	0.00 **	0.00	0.00	0.00 *	0.00	0.00
# SP Visits	0.29 ***		0.31 ***		0.23 ***	
# GP Visits		0.10 ***		0.11 ***		0.13 ***
Age	0.15 ***	0.12 ***	0.64 ***	0.22 **	0.57 **	-0.19
Age^2	0.00	0.00 *	-0.01 ***	0.00	0.00	0.00
Female	9.03 ***	2.51 ***	11.53 ***	3.00 ***	23.54 ***	5.73
Female x Age	-0.12 ***	-0.03 ***	-0.18 ***	-0.04 *	-0.31 ***	-0.08 *
Household Income	-0.09 ***	0.07 ***	-0.24 ***	0.05	-0.36 ***	0.11
Urban	1.16 ***	0.61 ***	1.84 **	1.09 **	-0.21	2.02 **
Less Than High-School	0.22	0.16	0.14	-0.91	1.03	-0.64
Some Post-Secondary	-0.06	-0.06	1.17	-0.17	-2.06	1.21
Post-Secondary	-0.55 *	0.32 **	-0.46	0.51	-0.67	0.83
Single	-0.54	0.50 **	0.37	1.14 *	1.57	0.34
Widowed / Divorced	0.78 **	-0.03	2.00	-0.64	4.02 **	-0.52
Not Currently Working	0.85 ***	0.45 **	2.50 **	-0.05	-0.17	0.63
No Work in the Last Year	0.99 ***	0.93 ***	1.15	0.52	1.36	2.57 **
Working - Not Applicable	2.28 ***	0.43	4.04	-0.44	4.38	0.29
Working - Not Stated	0.69	-0.53	-3.02	-0.51	-5.30 ***	-3.20 ***
Recent Immigrant	1.20 *	-0.48 **	-2.57	1.41	5.69	-3.55 *
Long Term Immigrant	0.94 ***	-0.08	-3.08 ***	0.68	1.16	-0.02
Lives Alone	-0.43	0.24	-1.09	0.23	-2.11	0.60
Major CC	5.62 ***	3.21 ***				
Medium CC	7.12 ***	1.24 ***				

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Table 2.A3, continued

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
Minor CC	3.00 ***	1.22 ***				
Very Good (SRH)	1.22 ***	0.52 ***	1.97 *	0.01	7.96 **	-2.01
Good (SRH)	2.08 ***	1.15 ***	4.20 ***	1.15	9.01 **	0.25
Fair (SRH)	3.23 ***	2.16 ***	7.56 ***	2.59 **	8.75 **	2.16
Poor (SRH)	5.48 ***	3.36 ***	10.68 ***	4.47 **	11.94 **	3.68
Activity Limitation	1.78 ***	0.63 ***	1.53 *	-0.07	2.97 ***	1.46 *
Low BMI	-1.24	0.14	0.40	0.24	25.39 *	-4.70 ***
Over Weight	-0.25	-0.20	-1.29	0.30	3.01	-1.65
Obese	0.01	0.10	0.61	0.61	1.64	-1.49
Conditional Mean	10.7	3.1	15.6	4.6	20.3	8.6
n	26,663		23,59		1,507	

GP: General Practitioner. *SP*: Specialist.
$* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$

2.A5 Appendix: Coefficient Estimates, Single Equation Negative Binomial Model

Table 2.A4: Coefficient Estimates, Single-Equation Negative Binomial Model

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	0.008 ***	-0.012 ***	0.002	-0.018 **	0.012 **	-0.026 ***
	(0.002)	(0.003)	(0.005)	(0.009)	(0.005)	(0.009)
SP Supply	-0.006 *	0.021 ***	0.004	0.006	-0.014 **	0.036 ***
	(0.003)	(0.005)	(0.006)	(0.012)	(0.006)	(0.013)
GP x SP Supply	0.000 **	0.000	0.000	0.000 *	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# SP Visits	0.027 ***		0.020 ***		0.011 ***	
	(0.002)		(0.004)		(0.002)	
# GP Visits		0.031 ***		0.023 ***		0.015 ***
		(0.002)		(0.003)		(0.002)
Age	0.014 ***	0.038 ***	0.041 ***	0.047 **	0.028 **	-0.023
	(0.004)	(0.009)	(0.011)	(0.020)	(0.014)	(0.022)
Age^2	0.000	0.000 *	0.000 ***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.824 ***	0.783 ***	0.802 ***	0.705 **	1.050 ***	0.637 *
	(0.056)	(0.099)	(0.134)	(0.288)	(0.227)	(0.365)
Female x Age	-0.011 ***	-0.011 ***	-0.011 ***	-0.010 *	-0.015 ***	-0.009 *
	(0.001)	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)
Household Income	-0.008 ***	0.023 ***	-0.016 ***	0.010	-0.018 ***	0.013
	(0.002)	(0.004)	(0.005)	(0.015)	(0.006)	(0.012)
Urban	0.112 ***	0.210 ***	0.123 **	0.259 **	-0.010	0.258 **
	(0.020)	(0.038)	(0.057)	(0.109)	(0.061)	(0.108)
Less Than High-School	0.021	0.050	0.009	-0.214	0.050	-0.077
	(0.034)	(0.075)	(0.074)	(0.143)	(0.068)	(0.110)
Some Post-Secondary	-0.006	-0.019	0.073	-0.037	-0.106	0.133
	(0.039)	(0.069)	(0.101)	(0.191)	(0.093)	(0.143)
Post-Secondary	-0.051 **	0.104 **	-0.029	0.113	-0.033	0.097
	(0.026)	(0.048)	(0.055)	(0.124)	(0.074)	(0.106)

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Table 2.A4, continued

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
Single	-0.051	0.153 **	0.024	0.235 *	0.075	0.040
	(0.037)	(0.069)	(0.080)	(0.131)	(0.117)	(0.170)
Widowed / Divorced	0.071 **	-0.008	0.123	-0.146	0.189 **	-0.061
	(0.031)	(0.058)	(0.076)	(0.141)	(0.084)	(0.123)
Not Currently Working	0.078 ***	0.135 **	0.152 **	-0.012	-0.008	0.071
	(0.029)	(0.053)	(0.067)	(0.163)	(0.087)	(0.164)
No Work in the Last Year	0.090 ***	0.273 ***	0.072	0.109	0.067	0.294 **
	(0.028)	(0.054)	(0.069)	(0.123)	(0.085)	(0.135)
Working - Not Applicable	0.194 ***	0.127	0.233	-0.101	0.201	0.033
	(0.060)	(0.110)	(0.152)	(0.259)	(0.129)	(0.217)
Working - Not Stated	0.062	-0.184	-0.215	-0.119	-0.303 ***	-0.469 **
	(0.150)	(0.213)	(0.174)	(0.513)	(0.112)	(0.197)
Recent Immigrant	0.107 *	-0.162 **	-0.179	0.269	0.249	-0.523
	(0.055)	(0.079)	(0.156)	(0.278)	(0.214)	(0.351)
Long Term Immigrant	0.086 ***	-0.025	-0.212 ***	0.142	0.057	-0.003
	(0.024)	(0.044)	(0.067)	(0.147)	(0.055)	(0.091)
Lives Alone	-0.040	0.073	-0.071	0.048	-0.108	0.068
	(0.034)	(0.066)	(0.077)	(0.159)	(0.080)	(0.124)
Major CC	0.432 ***	0.730 ***				
	(0.037)	(0.079)				
Medium CC	0.539 ***	0.347 ***				
	(0.031)	(0.059)				
Minor CC	0.277 ***	0.381 ***				
	(0.027)	(0.045)				
Very Good (SRH)	0.112 ***	0.161 ***	0.124 *	0.002	0.351 **	-0.253
	(0.030)	(0.048)	(0.072)	(0.176)	(0.150)	(0.252)
Good (SRH)	0.185 ***	0.333 ***	0.254 ***	0.238	0.412 ***	0.029
	(0.029)	(0.055)	(0.077)	(0.192)	(0.151)	(0.225)
Fair (SRH)	0.269 ***	0.542 ***	0.417 ***	0.475 ***	0.390 **	0.238
	(0.039)	(0.065)	(0.096)	(0.184)	(0.163)	(0.234)

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Table 2.A4, continued

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
Poor (SRH)	0.418 ***	0.741 ***	0.543 ***	0.713 ***	0.494 ***	0.376
	(0.058)	(0.119)	(0.108)	(0.210)	(0.165)	(0.241)
Activity Limitation	0.159 ***	0.189 ***	0.098 *	-0.016	0.146 ***	0.169 *
	(0.024)	(0.039)	(0.051)	(0.098)	(0.054)	(0.098)
Low BMI	-0.123	0.045	0.025	0.051	0.813 **	-0.793 ***
	(0.083)	(0.111)	(0.159)	(0.195)	(0.320)	(0.286)
Over Weight	-0.023	-0.065	-0.084	0.065	0.143	-0.205
	(0.029)	(0.047)	(0.062)	(0.140)	(0.097)	(0.186)
Obese	0.001	0.032	0.039	0.131	0.082	-0.170
	(0.026)	(0.054)	(0.061)	(0.116)	(0.096)	(0.161)
n	26,663		2,359		1,507	

GP: General Practitioner. *SP*: Specialist.
$* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$

2.A6 Appendix: Double Equation Negative Binomial Model, Marginal Effects

Table 2.A5: Marginal Effects (at the Mean) on the number of GP and Specialist Visits - Double-Equation Simultaneous Negative Binomial Model

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	0.10 ***	-0.01	0.03	-0.05	0.43 **	-0.13
	-0.02	-0.01	-0.10	-0.04	-0.18	-0.08
SP Supply	-0.07 ***	0.07 ***	-0.03	0.05	-0.32	0.23 *
	-0.03	-0.01	-0.15	-0.06	-0.28	-0.12
GP x SP Supply	0.00 *	0.00 ***	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.00	0.00
Age	0.09 **	0.11 ***	0.67 ***	0.34 ***	0.76 *	-0.36 *
	-0.04	-0.02	-0.18	-0.09	-0.40	-0.18
Age^2	0.00 *	0.00	0.00 *	0.00	0.00	0.00 **
	0.00	0.00	0.00	0.00	0.00	0.00
Female	15.69 ***	6.29 ***	21.93 ***	7.27 ***	25.06 ***	6.76 **
	-0.57	-0.37	-2.03	-1.13	-6.71	-3.03
Female x Age	-0.21 ***	-0.08 ***	-0.33 ***	-0.11 ***	-0.33 ***	-0.09 **
	-0.01	-0.01	-0.05	-0.03	-0.09	-0.04
Household Income	-0.02	0.11 ***	-0.10	0.06	-0.46 **	0.27 **
	-0.02	-0.01	-0.13	-0.05	-0.23	-0.11
Urban	1.22 ***	0.84 ***	2.45 **	1.25 ***	-1.75	1.72 **
	-0.21	-0.11	-0.98	-0.45	-1.91	-0.72
Less Than High-School	-0.21	-0.50 ***	-0.77	-0.59	0.84	-0.32
	-0.32	-0.16	-1.87	-0.69	-2.01	-0.93
Some Post-Secondary	-0.05	0.18	-0.66	0.42	-0.75	2.13
	-0.39	-0.22	-1.67	-0.83	-2.48	-1.60
Post-Secondary	-0.14	0.39 ***	-1.82	0.74	-0.34	1.31
	-0.25	-0.13	-1.24	-0.55	-2.07	-0.90
Single	-1.00 ***	-0.16	-1.26	0.38	1.42	-0.49
	-0.31	-0.17	-1.27	-0.64	-2.85	-1.41
Widowed / Divorced	0.73 **	0.15	0.14	-0.82	0.60	-1.33
	-0.32	-0.17	-1.45	-0.60	-2.42	-1.14
Not Currently Working	0.91 ***	0.53 ***	0.59	-0.15	2.17	-0.41
	-0.26	-0.15	-1.67	-0.56	-2.94	-1.15
No Work in the Last Year	1.90 ***	1.88 ***	2.78 *	1.18 *	0.88	3.62 ***

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Table 2.A5, continued

	Full Sample GP	Full Sample SP	Asthmatics GP	Asthmatics SP	Diabetics GP	Diabetics SP
	(1)	(2)	(3)	(4)	(5)	(6)
	-0.30	-0.19	-1.43	-0.69	-2.28	-1.07
Working - Not Applicable	1.92 ***	1.37 ***	3.70	0.76	-0.19	0.34
	-0.69	-0.41	-3.53	-1.54	-3.90	-1.74
Working - Not Stated	-0.46	0.63	3.92	2.82	-7.75	-1.39
	-1.97	-1.20	-11.04	-5.72	-16.38	-9.68
Recent Immigrant	0.62	0.15	-0.93	4.91	-5.86 *	-3.56 **
	-0.52	-0.29	-4.00	-3.44	-3.07	-1.56
Long Term Immigrant	0.66 ***	0.40 ***	-1.69	0.57	-0.12	1.20
	-0.25	-0.14	-1.36	-0.66	-1.54	-0.81
Lives Alone	-0.44	0.13	-0.08	0.37	0.27	1.45
	-0.30	-0.17	-1.31	-0.62	-2.29	-1.26
Major CC	13.89 ***	10.31 ***				
	-0.74	-0.69				
Medium CC	13.32 ***	4.78 ***				
	-0.55	-0.34				
Minor CC	5.19 ***	2.69 ***				
	-0.23	-0.15				
Very Good (SRH)	1.22 ***	0.81 ***	1.48	0.32	3.05	1.29
	-0.24	-0.14	-1.56	-0.67	-3.95	-1.68
Good (SRH)	3.11 ***	1.96 ***	4.07 **	2.32 ***	7.18 *	2.56
	-0.30	-0.19	-1.83	-0.83	-3.93	-1.66
Fair (SRH)	5.67 ***	4.38 ***	9.59 ***	5.97 ***	8.96 **	6.92 ***
	-0.49	-0.38	-2.42	-1.45	-4.11	-2.12
Poor (SRH)	9.50 ***	7.91 ***	14.37 ***	11.57 ***	17.87 ***	11.33 ***
	-0.81	-0.74	-3.65	-2.75	-5.72	-3.22
Activity Limitation	3.03 ***	1.98 ***	4.94 ***	2.10 ***	3.66 **	2.70 ***
	-0.24	-0.15	-1.08	-0.50	-1.46	-0.68
Low BMI	-1.37 **	0.07	-2.39	-0.21	22.79 ***	-3.30
	-0.61	-0.38	-2.26	-1.48	-7.68	-3.42
Over Weight	-0.16	-0.25 *	1.41	-0.23	7.84 **	-1.32
	-0.23	-0.13	-1.34	-0.53	-3.44	-1.09
Obese	0.34	0.07	3.33 ***	0.65	4.80 **	-2.01
	-0.25	-0.14	-1.29	-0.54	-2.44	-1.23
GP Visits		-0.04 ***		-0.03		0.09 ***
		-0.01		-0.02		-0.03
Conditional Mean	13.0	4.3	19.8	5.7	27.0	9.4
n	26,663		2,359		1,507	

GP: General Practitioner. *SP*: Specialist. *CC*: chronic condition. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

2.A7 Appendix: Coefficient Estimates, Double Equation Negative Binomial Model

Table 2.A6: Coefficient Estimates, Double-Equation Simultaneous Negative Binomial Model

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	0.007 ***	-0.003	0.002	-0.009	0.016 **	-0.014
	(0.001)	(0.002)	(0.005)	(0.007)	(0.007)	(0.009)
SP Supply	-0.005 ***	0.017 ***	-0.001	0.008	-0.012	0.025 *
	(0.002)	(0.003)	(0.008)	(0.011)	(0.011)	(0.013)
GP x SP Supply	0.000 *	0.000 ***	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.007 **	0.025 ***	0.034 ***	0.060 ***	0.028 *	-0.038 *
	(0.003)	(0.005)	(0.009)	(0.015)	(0.015)	(0.019)
Age^2	0.000 *	0.000	0.000 *	0.000	0.000	0.000 **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	1.193 ***	1.415 ***	1.260 ***	1.464 ***	0.885 ***	0.698 **
	(0.040)	(0.068)	(0.121)	(0.204)	(0.218)	(0.295)
Female x Age	-0.016 ***	-0.019 ***	-0.017 ***	-0.019 ***	-0.012 ***	-0.010 **
	(0.001)	(0.001)	(0.003)	(0.004)	(0.003)	(0.005)
Household Income	-0.001	0.025 ***	-0.005	0.010	-0.017 **	0.029 **
	(0.002)	(0.003)	(0.006)	(0.009)	(0.008)	(0.011)
Urban	0.097 ***	0.206 ***	0.128 **	0.235 ***	-0.063	0.195 **
	(0.017)	(0.029)	(0.053)	(0.088)	(0.068)	(0.087)
Less Than High-School	-0.016	-0.120 ***	-0.040	-0.107	0.031	-0.035
	(0.025)	(0.040)	(0.097)	(0.129)	(0.074)	(0.100)
Some Post-Secondary	-0.004	0.041	-0.033	0.071	-0.028	0.208
	(0.030)	(0.049)	(0.086)	(0.137)	(0.094)	(0.142)
Post-Secondary	-0.011	0.090 ***	-0.091	0.131	-0.013	0.139
	(0.019)	(0.031)	(0.061)	(0.097)	(0.077)	(0.094)
Single	-0.078 ***	-0.037	-0.065	0.066	0.052	-0.053
	(0.025)	(0.040)	(0.066)	(0.108)	(0.101)	(0.158)

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Table 2.A6, continued

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
Widowed / Divorced	0.056 **	0.034	0.007	-0.149	0.022	-0.145
	(0.024)	(0.038)	(0.073)	(0.113)	(0.089)	(0.128)
Not Currently Working	0.068 ***	0.117 ***	0.029	-0.026	0.078	-0.045
	(0.019)	(0.032)	(0.083)	(0.100)	(0.102)	(0.127)
No Work in the Last Year	0.141 ***	0.390 ***	0.136 *	0.198 *	0.033	0.380 ***
	(0.021)	(0.034)	(0.068)	(0.109)	(0.084)	(0.109)
Working - Not Applicable	0.139 ***	0.280 ***	0.173	0.126	-0.007	0.036
	(0.047)	(0.075)	(0.153)	(0.241)	(0.145)	(0.182)
Working - Not Stated	-0.036	0.136	0.180	0.401	-0.339	-0.161
	(0.157)	(0.243)	(0.465)	(0.671)	(0.852)	(1.214)
Recent Immigrant	0.047	0.033	-0.048	0.623	-0.244 *	-0.474 **
	(0.038)	(0.065)	(0.211)	(0.325)	(0.143)	(0.261)
Long Term Immigrant	0.050 ***	0.089 ***	-0.088	0.097	-0.004	0.123
	(0.018)	(0.030)	(0.074)	(0.106)	(0.057)	(0.080)
Lives Alone	-0.034	0.031	-0.004	0.064	0.010	0.151
	(0.023)	(0.038)	(0.066)	(0.105)	(0.085)	(0.128)
Major CC	0.765 ***	1.307 ***				
	(0.030)	(0.048)				
Medium CC	0.767 ***	0.812 ***				
	(0.024)	(0.040)				
Minor CC	0.393 ***	0.602 ***				
	(0.017)	(0.030)				
Very Good (SRH)	0.093 ***	0.183 ***	0.074	0.055	0.109	0.132
	(0.018)	(0.030)	(0.076)	(0.114)	(0.137)	(0.165)
Good (SRH)	0.225 ***	0.405 ***	0.196 **	0.372 ***	0.254 *	0.260
	(0.020)	(0.034)	(0.084)	(0.119)	(0.132)	(0.159)
Fair (SRH)	0.374 ***	0.740 ***	0.418 ***	0.787 ***	0.309 **	0.633 ***
	(0.028)	(0.045)	(0.091)	(0.137)	(0.132)	(0.164)
Poor (SRH)	0.559 ***	1.070 ***	0.568 ***	1.182 ***	0.544 ***	0.872 ***
	(0.037)	(0.060)	(0.113)	(0.165)	(0.145)	(0.180)

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Table 2.A6, continued

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
Activity Limitation	0.222 ***	0.415 ***	0.246 ***	0.362 ***	0.136 **	0.289 ***
	(0.017)	(0.027)	(0.054)	(0.078)	(0.054)	(0.072)
Low BMI	-0.111 **	0.016	-0.128	-0.037	0.614 ***	-0.434
	(0.052)	(0.086)	(0.128)	(0.268)	(0.156)	(0.561)
Over Weight	-0.013	-0.057 *	0.070	-0.040	0.266 **	-0.148
	(0.018)	(0.030)	(0.065)	(0.095)	(0.107)	(0.128)
Obese	0.026	0.016	0.166 ***	0.113	0.186 **	-0.204
	(0.019)	(0.031)	(0.064)	(0.092)	(0.098)	(0.120)
GP Visits		-0.010 ***		-0.004		0.009 ***
		(0.001)		(0.003)		(0.003)
n	26,663		2,359		1,507	

GP: General Practitioner. *SP*: Specialist. *CC*: chronic condition. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$

2.A8 Appendix: Generalized Linear Model, Marginal Effects

Table 2.A7: Marginal Effects (at the mean) on the Dollar Value of GP Services and Specialist Services Received, Generalized Linear Model

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	$5 ***	-$6 ***	$0	-$12 *	$14 ***	-$66 ***
SP Supply	-$3 **	$13 ***	$2	$6	-$19 **	$93 ***
GP x SP Supply	$0 **	$0	$0	$0	$0	$0
$'s of Specialist Services	$0 ***		$0 ***		$0 ***	
$'s of GP Services		$1 ***		$1 ***		$1 ***
Age	$6 **	$25 ***	$23 ***	$39 ***	$11	-$33
Age^2	$0	$0 **	$0 ***	$0	$0	$1 *
Female	$345 ***	$746 ***	$427 ***	$890 ***	$586 ***	$1964 ***
Female x Age	-$5 ***	-$10 ***	-$6 ***	-$14 ***	$8 ***	-$30 ***
Household Income	$3 ***	$10 ***	-$6 **	$5	-$8	$15
Urban	$57 ***	$71 ***	$56 *	$159 **	-$25	$328 **
Less Than High-School	$10	$4	$49	-$14	$37	$205
Some Post-Secondary	$14	$20	$37	$18	$27	$455
Post-Secondary	$11	$11	$5	$148 *	-$7	$303 *
Single	-$58 ***	-$40	-$3	$46	$34	-$202
Widowed / Divorced	$18	-$12	$96	-$69	$173 **	-$189
Not Currently Working	$41 **	$59 **	$112 **	$70	$12	$97
No Work in the Last Year	$32 **	$126 ***	$51	$61	$91	$515 **
Working - Not Applicable	$129 ***	$63	$245 **	-$6	$257 **	-$190
Working - Not Stated	$1	-$19	-$77	-$6	-$13	-$1316 ***
Recent Immigrant	-$3	-$48	-$152 **	$194	$318	-$840 ***
Long Term Immigrant	-$6	$21	-$100 ***	$113	$33	$55
Lives Alone	$3	$20	-$22	-$47	-$68	$318
Major CC	$147 ***	$728 ***				
Medium CC	$183 ***	$297 ***				
Minor CC	$84 ***	$212 ***				
Very Good (SRH)	$73 **	$49 **	$112 **	-$172	$188	-$358
Good (SRH)	$73 ***	$186 ***	$148 ***	$119	$274 **	$44
Fair (SRH)	$112 ***	$314 ***	$234 ***	$334 **	$345 **	$383
Poor (SRH)	$218 ***	$417 ***	$351 ***	$493 **	$530 ***	$835 *

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Table 2.A7, continued

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
Activity Limitation	\$62 ***	\$141 ***	\$49	\$18	\$133 ***	\$569 ***
Low BMI	-\$41	\$4	\$150	-\$81	\$764	\$719
Over Weight	-\$49 *	-\$36	-\$40	-\$78	\$71	-\$72
Obese	-\$22	\$49	\$35	\$50	\$53	-\$360
Conditional Mean	\$410	\$618	\$583	\$864	\$759	\$1637
n	26,663		2,359		1,507	

GP: General Practitioner. *SP*: Specialist. *CC*: chronic condition. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$

2.A9 Appendix: Coefficient Estimates, Generalized Linear Model

Table 2.A8: Coefficient Estimates, Generalized Linear Model, the Dollar Value of GP Services and Specialist Services Received

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
GP Supply	0.011 ***	-0.009 ***	0.001	-0.014 *	0.018 ***	-0.040 ***
	(0.003)	(0.003)	(0.005)	(0.008)	(0.006)	(0.009)
SP Supply	-0.008 **	0.021 ***	0.004	0.007	-0.026 **	0.057 ***
	(0.004)	(0.006)	(0.007)	(0.010)	(0.011)	(0.016)
GP x SP	0.000 **	0.000	0.000	0.000	0.000	0.000
Supply	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$'s of Specia-	0.000 ***		0.000 ***		0.000 ***	
list Services	(0.000)		(0.000)		(0.000)	
$'s of GP		0.001 ***		0.001 ***		0.000 ***
Services		(0.000)		(0.000)		(0.000)
Age	0.015 **	0.040 ***	0.040 ***	0.045 ***	0.014	-0.020
	(0.006)	(0.008)	(0.011)	(0.015)	(0.015)	(0.021)
Age^2	0.000	0.000 **	0.000 ***	0.000	0.000	0.000 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.824 ***	1.154 ***	0.793 ***	1.139 ***	0.727 ***	1.080 ***
	(0.085)	(0.095)	(0.135)	(0.224)	(0.250)	(0.355)
Female x Age	-0.012 ***	-0.016 ***	-0.011 ***	-0.016 ***	-0.011 ***	-0.018 ***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
Household	-0.006 ***	0.016 ***	-0.011 **	0.006	-0.011	0.009
Income	(0.002)	(0.004)	(0.005)	(0.011)	(0.008)	(0.012)
Urban	0.146 ***	0.120 ***	0.100 *	0.197 **	-0.032	0.216 **
	(0.035)	(0.041)	(0.058)	(0.094)	(0.074)	(0.093)
Less Than	0.025	0.007	0.082	-0.016	0.048	0.121
High-School	(0.036)	(0.070)	(0.082)	(0.109)	(0.069)	(0.104)
Some Post-	0.034	0.032	0.062	0.021	0.035	0.248
Secondary	(0.041)	(0.114)	(0.090)	(0.135)	(0.127)	(0.196)
Post-	0.026	0.018	0.008	0.175 *	-0.009	0.186 *
Secondary	(0.037)	(0.047)	(0.059)	(0.100)	(0.076)	(0.100)
Single	-0.146 ***	-0.066	-0.005	0.052	0.044	-0.130
	(0.049)	(0.059)	(0.080)	(0.099)	(0.134)	(0.165)
Widowed	0.043	-0.019	0.155 *	-0.082	0.214 **	-0.119
/ Divorced	(0.035)	(0.056)	(0.092)	(0.103)	(0.095)	(0.131)

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Table 2.A8, continued

	Full Sample		Asthmatics		Diabetics	
	GP	SP	GP	SP	GP	SP
	(1)	(2)	(3)	(4)	(5)	(6)
Not Currently Working	0.097 **	0.092 **	0.180 **	0.079	0.016	0.058
	(0.046)	(0.044)	(0.071)	(0.108)	(0.100)	(0.152)
No Work in the Last Year	0.077 **	0.192 ***	0.086	0.069	0.118	0.307 **
	(0.033)	(0.047)	(0.065)	(0.091)	(0.086)	(0.136)
Working - Not Applicable	0.277 ***	0.098	0.355 **	-0.007	0.303 **	-0.121
	(0.073)	(0.093)	(0.154)	(0.199)	(0.131)	(0.226)
Working - Not Stated	0.002	-0.031	-0.141	-0.007	-0.017	-1.627 ***
	(0.152)	(0.180)	(0.165)	(0.269)	(0.124)	(0.200)
Recent Immigrant	-0.007	-0.081	-0.300 *	0.204	0.353	-0.697 ***
	(0.078)	(0.063)	(0.174)	(0.236)	(0.243)	(0.243)
Long Term Immigrant	-0.015	0.033	-0.182 **	0.126	0.044	0.033
	(0.042)	(0.040)	(0.071)	(0.122)	(0.058)	(0.096)
Lives Alone	0.007	0.032	-0.039	-0.056	-0.092	0.184
	(0.036)	(0.058)	(0.094)	(0.118)	(0.093)	(0.138)
Major CC	0.312 ***	0.810 ***				
	(0.069)	(0.079)				
Medium CC	0.385 ***	0.411 ***				
	(0.062)	(0.049)				
Minor CC	0.204 ***	0.338 ***				
	(0.064)	(0.038)				
Very Good (SRH)	0.173 ***	0.079 **	0.185 ***	-0.206	0.230	-0.234
	(0.067)	(0.038)	(0.072)	(0.144)	(0.154)	(0.197)
Good (SRH)	0.169 ***	0.279 ***	0.239 ***	0.134	0.340 **	0.027
	(0.041)	(0.049)	(0.077)	(0.154)	(0.155)	(0.180)
Fair (SRH)	0.247 ***	0.423 ***	0.353 ***	0.342 **	0.409 **	0.221
	(0.058)	(0.072)	(0.094)	(0.153)	(0.163)	(0.193)
Poor (SRH)	0.433 ***	0.523 ***	0.489 ***	0.468 ***	0.569 ***	0.436 **
	(0.078)	(0.101)	(0.110)	(0.161)	(0.165)	(0.212)
Activity Limitation	0.146 ***	0.216 ***	0.084	0.021	0.175 ***	0.344 ***
	(0.035)	(0.045)	(0.053)	(0.082)	(0.060)	(0.099)
Low BMI	-0.104	0.006	0.229	-0.099	0.697	0.365
	(0.088)	(0.112)	(0.221)	(0.156)	(0.456)	(0.426)
Over Weight	-0.124 *	-0.058	-0.069	-0.093	0.092	-0.044
	(0.064)	(0.040)	(0.060)	(0.101)	(0.102)	(0.172)
Obese	-0.055	0.077	0.060	0.058	0.071	-0.213
	(0.049)	(0.054)	(0.063)	(0.097)	(0.097)	(0.147)
n	26,663		2,359		1,507	

GP: General Practitioner. *SP*: Specialist. *CC*: chronic condition. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

Chapter 3

Income-Related Horizontal Inequities in Physician use by Asthmatics and Diabetics: evidence using linked survey-administrative data from Ontario

3.1 Introduction

The Canadian health care system is built on the premise of reasonable and uniform access to medically necessary physician and hospital services for all Canadian residents. This premise is legislated under the *Canada Health Act* of 1984 which governs Canada's universal single payer public health insurance. Canadians continue to have a strong commitment to an equitable health care system, the premise of equity of access, and hold these values central to their identities as Canadians (Romanow (2002)).

While the *Canada Health Act* is a piece of national legislation, Canada's single payer public health insurance is administered at the provincial level.[1] This paper exploits a unique linked administrative data set from Ontario, the largest of Canada's ten provinces, and the concentration index approach of Wagstaff and van Doorslaer (2000) to quantify and decompose income-related inequalities in the use of GP and specialist services. The specific type of equity of concern is income-related horizontal equity, which asks: are people with the same health care needs treated equally? Income-related horizontal inequity is the extent to which those of same health care need, but differing incomes, systematically utilize different amounts of health care.

This paper asks to what extent are there income-related inequities in the use of physician services? By focusing on different groups of people who each have a common chronic condition, the paper also asks if the general population, asthmatics, and diabetics all experience the same inequities. The paper then goes on to decompose income-related inequalities in physician use into the different contributing factors.

There is a burgeoning literature based on the concentration index approach to quantify the degree of income-related inequity in the use of physician services. In the last 10 years, a number of studies have measured income-related inequity in physician use in Canada at the national level. However, given that the Canadian health care system is administered at the provincial level, it is also interesting to measure income-related inequity in physician use at the provincial level and understanding variations in income-related inequities

[1]There are actually 14 different health care systems in Canada: one for each of the 10 provinces, one for each of the three territories, and one administered by the federal government for the Canadian armed forces and aboriginal communities.

between and within provinces is important.

Allin (2008) used the concentration index approach to look at between-province variation in income-related inequities in the quantity of different health care services used. The two types of physician utilization analyzed were the number of GP visits and the number of specialist visits in the past 12 months. The analysis focused on individuals age 16 and older using the Canadian Community Health Survey 2.1 (2003) public use micro data file. Utilization was defined as the probability of a visit (i.e. whether someone made at least one visit), the conditional number of visits (the number of visits conditional on making at least one visit), and the total number of visits (the unconditional number of visits).[2] Allin (2008) found the income-related inequities in physician visits in Ontario are similar to most other provinces. Ontario, and all other provinces except Prince Edward Island (PEI), were found to have a pro-rich inequity in the probability of a GP visit. However, all provinces were found to have no income-related inequity in the total number of GP visits. Ontario, and all other provinces, were found to have a pro-rich inequity in both the probability of a specialist visit and in the total number of specialist visits.

McGrail (2008) also used the concentration index approach to quantify and decompose income-related inequity in the use of physician services in the Canadian province of British Columbia (BC). Combining data from the BC linked health database on physician use - measured as the dollar value of physician services received - with neighbourhood level income data, McGrail

[2]Results for the conditional number of visits were not included in the paper.

(2008) looked at income-related inequity in physician use at two points in time (1992 and 2002). Consistent with Allin (2008), McGrail (2008) found no inequity in the probability of GP use, but a pro-poor inequity in the dollar value of GP services received, conditional on receiving any GP services. A pro-rich inequity in probability and conditional dollar value of specialist services received was also found. The income-related inequities in physician use were shown not to be meaningfully different between 1992 and 2002.

Jiménez-Rubio et al. (2008) used the concentration index approach to decompose the national estimates of income-related inequity for Canada into between province and within province variation. The authors use the Canadian Community Health Survey 1.1 (2000/2001) and two measures of physician visits in the past 12 months: the number of GP visits and the number of specialist visits. At the national level, the authors find a pro-poor inequity in GP visits and a pro-rich inequity in specialist visits. Ontario, and all other provinces except PEI, New Brunswick, and Quebec, were found to have a pro-rich inequity in the total number of GP visits. Ontario, and all other provinces except Alberta, were found to have a pro-rich inequity in the total number of specialist visits. The decomposition of the concentration index at the Canada level reveals inequity was mainly explained by variation between provinces, rather than within provinces, in income-related inequity. The authors found the contribution of variation between provinces tends to be more pro-rich than the contribution of differences between rich and poor within a province. Ontario was also found to be a large contributor to pro-rich inequities in specialist visits between provinces.

Allin (2008), McGrail (2008), and Jiménez-Rubio et al. (2008) all demonstrate the presence of a pro-poor inequity in the probability of a GP visit; no inequities in the conditional number of GP visits; a pro-rich inequity in the probability of a specialist visit and the conditional number of specialist visits. Ontario is shown to be similar, in most respects, to other provinces in terms of inequities.

Comparing the findings for Canada with other countries provides a sense of how income-related inequities in the Canadian health care system compare to other health care systems. Two prominent studies placing Canada in an international context are van Doorslaer et al. (2002) and van Doorslaer and Masseria (2004).

van Doorslaer et al. (2002) compares income-related inequities in physician use in Canada with 12 European countries and the United States.[3] Canadian data come from the 1996 cross-section of the National Population Health Survey, US data come from the first wave of the Medical Expenditure Panel Survey (MEPS), and European data come from the European Community Household Panel (ECHP).[4] Overall, Canada is similar to most other European countries with respect to income-related inequities in physician visits. Canada is found to have a slightly pro-poor, and not statistically significant, inequity in total GP visits. Six European countries also have a slightly pro-poor, but not statistically significant, inequity in total GP visits; Portugal and Austria have a

[3]The 12 European countries are: Austria, Belgium, Denmark, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, and the United Kingdom.

[4]The US data from the MEPS does not distinguish between GP and specialist visits. As such, the authors compare Canada with the 12 European countries when focusing on income-related inequities in GP and specialist visits.

slightly pro-rich, but not statistically significant, inequity in total GP visits; and Belgium, Ireland, Luxembourg, and Spain, all have a statistically significant pro-poor inequity in total GP visits. Canada is also found to have a pro-rich inequity in total specialist visits, as do nine European countries. Ireland and Portugal show a statistically significant pro-rich inequity in total specialist visits, while Luxembourg shows no income-related inequity in total specialist visits.

van Doorslaer and Masseria (2004) updates van Doorslaer et al. (2002) by using the Canadian Community Health Survey 1.1 (2000/2001) for Canada, and expands on van Doorslaer et al. (2002) by comparing income-related inequity in health care utilization with 20 other countries in the Organization for Economic Cooperation and Development (OECD).[5] Canada is one of only three countries to exhibit a pro-rich inequity in the probability of a GP visit.[6] However, Canada is one of eight countries to exhibit a pro-poor inequity in the total number of GP visits. Canada's pro-rich inequity in the probability of a GP visit and pro-poor inequity in the total number of GP visits must be driven by a pro-poor inequity in the conditional number of GP visits. Again, Canada exhibits a pro-rich inequity in the probability of a specialist visit, as do most other OECD countries. Canada also shows a strong pro-rich inequity in the total number of specialist visits. Overall, the degree of inequity in GP and

[5]The countries included in the study are the 12 contained in the ECHP (Austria, Belgium, Denmark, Finland, Greece, Ireland, Italy, Netherlands, Portugal, and Spain) and 11 non-ECHP countries: Australia, France, Germany, Hungary, Mexico, Norway, Sweden, Switzerland, the UK and the US. Note that surveys from Australia, Germany, Mexico, Sweden, and the US only report total physician visits, but do not distinguish between GP visits and specialist visits.

[6]The other two countries to exhibit a pro-rich inequity in the probability of a GP visit are Finland and Portugal.

specialist visits in Canada is again found to be similar to most other OECD countries.

The above studies all use a population based approach, focusing on the general population, to study income-related inequity in physician use. One inherent problem with simply focusing on the general population is the presence of heterogeneity of health care need in the general population, but limited controls for health care need provided on representative population based social surveys.

A separate, but related, literature takes a more epidemiological approach to study inequities in physician utilization by focusing on groups of people with the same medical condition who use a particular health care service. For example, Alter et al. (1999) and Pilote et al. (2003) focus on people who have suffered an acute myocardial infarction (AMI) to look at socioeconomic factors affecting a patient's post-AMI use of services such as cardiac catheterization, percutaneous coronary intervention (PCI), and coronary artery bypass surgery (CABG). van der Meer and Mackenbach (1999) focus on diabetics in the city of Eindhoven, The Netherlands, to look at socioeconomic differences in the utilization of health care services. Bongers et al. (1997) look at socioeconomic differences in health care utilization among a group of people who tend to use more health care than the general population (people with chronic conditions such as asthma, chronic obstructive pulmonary disease, diabetes, severe back pain, and heart disease). One inherent limitation of the condition specific approach is in their ability to extrapolate the results from the specific group to the general population.

This paper marries the condition specific approach with the population based approach. The analysis uses a representative sample of the general population in Ontario to focus on income-related inequity within two groups of people who have a common chronic condition, asthma or diabetes. Asthmatics and diabetics were chosen because they are both high users of physician services, and for the pragmatic reason that both groups provide a relatively large sample to analyze. The analysis is based on a unique linked survey-administrative data set, not previously used in the literature. The administrative data provides two measures of physician use - the actual number of physician visits and the actual dollar value of physician services received - which provides a more complete picture of physician use. The survey data provides individual level demographic, socioeconomic, and health status information.

3.2 The Concentration Index Approach

Income-related inequality in physician use is analyzed using the concentration index (CI) approach of Wagstaff and van Doorslaer (2000). This approach is built on the concentration curve (CC) which is akin to a Lorenz curve graphing the proportion of physician services used by the cumulative proportion of people, ranked by income, from lowest to highest.[7] If everyone used the same amount of physician services, then the CC would be an upward sloping

[7]Note there is a crucial difference between a CC and a Lorenz cure. The CC is a bivariate curve since it graphs the relationship between two distinct variables: health care use and income. The Lorenz is a univariate curve since it graphs the relationship of only variable: income.

45-degree line running from the origin (0,0) to the top right-hand corner of the graph (1,1), called the line of equality. However, if higher income people use more physician services than lower income people then the CC will lie below the line of equality. Conversely, if lower income people use more physician services than higher income people then the CC will lie above the line of equality. The further the CC lies from the line of equality, the greater the income-related inequality in the use of physician services.

In order to graph the CC, the relative rank of individual i (r_i) in the income distribution must first be determined. Since the analysis is based on survey data, one survey respondent can represent multiple people in the population. To account for the number of people in the population one respondent represents, the survey sampling weights are used to determine r_i. Following the method of Wagstaff and van Doorslaer (2000), the relative rank is equal to a weighted sum of sampling weights:

$$r_i = \sum_{j=1}^{i-1} w_j + \frac{1}{2} w_i, \tag{3.1}$$

where w_i is the sampling weight of individual i, and w_j is the sampling weight of all individuals below i in the income distribution.

The CI is defined as twice the area between the CC and the line of equality. By definition, the CI takes on a value between -1 and 1. A negative CI indicates physician use is concentrated among the poor, while a positive CI indicates physician use is concentrated among the rich. A CI of zero indicates either the CC coincides with the line of equality, or the CC crosses the line of equality and the inequalities among the poor and the rich offset each other. Thus, a CI of zero indicates there is either no income-related inequalities in physician use or the inequalities in physician use at different points in the income distribution offset each other.

Two different CCs of physician use are analyzed: observed physician use and need-standardized physician use. Observed physician use is simply that which is observed in the data. Need-standardized physician use accounts for need using the method of indirect standardization. The CC for observed physician use is denoted by $L_M(r)$, and its CI, denoted by C_M, is the *inequality* index. The CI of need-standardized physician use is denoted by $L_N(r)$, and its CI, denoted by HI, is known as the index of income-related horizontal *inequity*. An example of the relationship between $L_M(r)$ and C_M, and $L_N(r)$ and HI, is presented in Figure 3.1. As shown in Figure 3.1, C_M is equal to twice the light grey area between $L_M(r)$ and 45-degree line, while HI is equal to twice the dark grey area between $L_N(r)$ and the 45-degree line.

Mathematically, C_M is defined by:

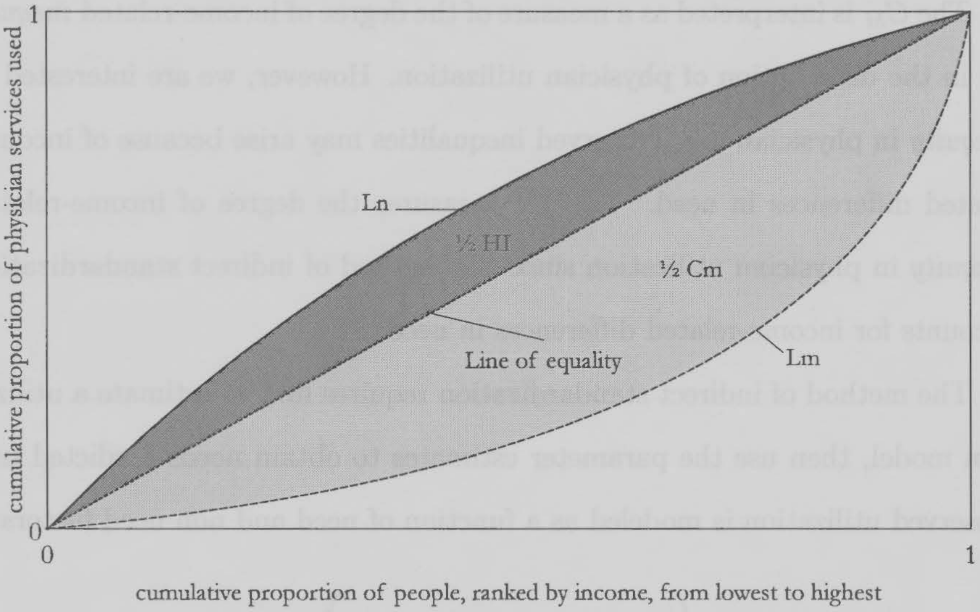
$$C_M = 1 - 2\int_0^1 L_M(r)dr, \tag{3.2}$$

and HI is defined by:

$$HI = 1 - 2\int_0^1 L_N(r)dr. \tag{3.3}$$

Alternatively, both C_M and HI can be computed using the method of

Figure 3.1: Example of Concentration Curve and Concentration Index



Kakwani et al. (1997), where C_M is computed using the convenient regression:

$$2\sigma_r^2\left(\frac{u_i}{\bar{u}}\right) = \gamma + \delta_1 r_i + \varepsilon_{1i}, \tag{3.4}$$

where u_i is observed physician use by individual i, $\bar{u}$ is average physician use in the sample, σ_r^2 is the variance of r_i, and ε_{1i} is a random error term. The estimate $\hat{\delta}_1$ is equal to C_m. HI is computed analogously by replacing u_i and $\bar{u}$ in (3.4) with $\hat{u}_i^{IS}$ with $\bar{\hat{u}}_i^{IS}$:

$$2\sigma_r^2\left(\frac{\hat{u}_i^{IS}}{\bar{\hat{u}}^{IS}}\right) = \gamma + \delta_2 r_i + \varepsilon_{2i}. \tag{3.5}$$

where $\hat{u}_i^{IS}$ is need-standardized physician use, $\bar{\hat{u}}^{IS}$ is the average of need-standardized physician use in the sample, ε_{2i} is a random error term, and the estimate $\hat{\delta}_2$ is equal to HI.

The C_M is interpreted as a measure of the degree of income-related *inequality* in the distribution of physician utilization. However, we are interested in *inequity* in physician use. Observed inequalities may arise because of income-related differences in need. The HI measures the degree of income-related *inequity* in physician utilization since the method of indirect standardization accounts for income-related differences in need.

The method of indirect standardization requires first to estimate a utilization model, then use the parameter estimates to obtain needs-predicted use. Observed utilization is modeled as a function of need and non-need factors:

$$u_i = f\left(\alpha + \sum_j \beta_j x_{ji} + \sum_k \gamma_k z_{ki}\right) + \epsilon_i, \tag{3.6}$$

where u_i is observed physician use (i.e. the number of physician visits or the dollar value of physician services received), α is the intercept, x_{ji} is the j^{th} need variable, z_{ki} is the k^{th} non-need variable, $f(\cdot)$ is the function relating u_i to the linear combination of α, x_{ji}, and z_{ki}, and ϵ_i is the random error term.

Different non-linear models are used to estimate (3.6) depending on the measure of physician use - the number of physician visits or the dollar value of physician services received - and the type of physician use (the probability of use or conditional use). The probability of use is modeled using a logit model for binary outcome data (where the binary variable equals 1 for positive use, zero for no use) for both the number of physician visits and the dollar value of physician services received. The conditional number of physician visits is modeled using a truncated a zero negative binomial model.[8] The conditional dollars of physician services received is modeled using a generalized linear model, with a gamma-family distribution and a log-link function.

Once equation (3.6) has been estimated, need-predicted utilization is generated based on an individual's need factors (x_{ji}) and the average non-need factors in the sample ($\bar{z}_k$):

$$\hat{u}_i^n = f\left(\hat{\alpha} + \sum_j \hat{\beta}_j x_{ji} + \sum_k \hat{\gamma} \bar{z}_k\right). \tag{3.7}$$

The final step of the method of indirect standardization is to calculate need-standardized utilization, which is equal to the difference between an individual's observed utilization (u_i) and their need-predicted utilization ($\hat{u}_i^n$), plus the average need-predicted utilization ($\bar{\hat{u}}$) of the sample:[9]

$$\hat{u}_i^{IS} = u_i - \hat{u}_i^n + \bar{\hat{u}}. \tag{3.8}$$

The distribution of $\hat{u}_i^{IS}$ (across income) can be interpreted as the distribution of physician use we would expect to observe independent of differences in the need variables over the income distribution (O'Donnell et al. (2007)).

[8]The negative binomial model is a standard method used to model count data with a skewed distribution (see Cameron and Trivedi (2005)). The zero-truncated negative binomial model is similar to a negative binomial model except it accounts for the removal of zero counts from the data. The truncation at zero is necessary since the conditional number of physician visits, by definition, is only the positive number of visits.

[9]If equation (3.6) was specified as a linear relationship between u_i and α, x_{ji}, and z_{ki}, then equation (3.8) would use the sample mean ($\bar{u}$) rather than the mean of need-expected utilization ($\bar{\hat{u}}$).

3.2.1 Decomposing of the Concentration Index

The inequality index, C_M, can be decomposed to look at the contribution of each determinant to total inequality in physician use. When a linear model is used, physician utilization is simply a linear combination of j need variables (x_{ji}) and k non-need variables (z_{ki}):

$$u_i = \pi + \sum_j \delta_j x_{ji} + \sum_j \theta_k z_{ki} + \phi_i, \tag{3.9}$$

where π is the intercept term, δ_j is the parameter of the j^{th} need variable, θ_k is parameter of the k^{th} non-need variable, and ϕ_i is the random error term. Using the parameter estimates from (3.9), C_M can be expressed as:

$$C_M = \sum_j \frac{\hat{\delta}_j \bar{x}_j}{\hat{u}} C_j + \sum_k \frac{\hat{\theta}_k \bar{z}_k}{\hat{u}} C_k + \frac{GC_\phi}{\bar{u}}, \tag{3.10}$$

where $\bar{u}$ is the mean of u_i, C_j is the factor-specific CI for x_j, C_k is the factor-specific CI for z_k, and GC_ϕ is the generalized CI for the error term. Note that $\frac{\hat{\delta}_j \bar{x}_j}{\hat{u}}$ is the elasticity of utilization with respect to x_j (η_j), and $\frac{\hat{\theta}_k \bar{z}_k}{\hat{u}}$ is the elasticity of utilization with respect to z_k (η_k). A factor-specific CI measures how the factor is distributed in the population by income. The generalized CI for the error term reflects the income-related inequality in physician use not explained by systematic income-related variations in the regressors.

The HI can be written as C_M minus the sum of the contributions of all need variables (van Doorslaer et al. (2004)):

$$HI = C_M - \sum_j \eta_j C_j. \tag{3.11}$$

However, when a non-linear model is used, the decomposition is not as simple since physician utilization is not simply a linear combination of need and non-need variables. Instead, the decomposition for a non-linear model uses a linear approximation. To make a linear approximation from the non-linear model such as (3.6), the marginal effects at the mean from the non-linear model are used:

$$u_i = \alpha^m + \beta_j^m x_{ji} + \gamma_k^m z_{ki} + \epsilon_i, \tag{3.12}$$

where $\hat{\beta}_j^m$ is the estimated marginal effect at the mean of the jth need variable, $\hat{\gamma}_k^m$ is the estimated marginal effect at the mean of the kth non-need variable, and ϵ_i is the random error term. The marginal effect represents the effect of a change in x_j (or z_k) on predicted physician use.

Since (3.12) is linearly additive, because of the linear approximation, the concentration index can be written as (Wagstaff et al. (2003)):

$$C_M = \sum_j \eta_j \times CI_j + \sum_k \eta_k \times CI_k + GC_\epsilon, \tag{3.13}$$

where η_j is the elasticity of utilization with respect to x_j $\left(\frac{\beta_j^m x_{ji}}{\hat{u}}\right)$, η_k is the elasticity of utilization with respect to z_k $\left(\frac{\gamma_k^m \bar{z}_k}{\hat{u}}\right)$, and GC_ϵ is the generalized CI for the error term. Equation (3.13) can be interpreted as showing C_M is equal to a weighted sum of the factor-specific CIs for the j need variables, the k non-need variables, and the generalized CI for the residual.

3.3 Data

This paper uses a unique linked survey-administrative data set. Ontario respondents in the Canadian Community Health Survey 2000/2001 (CCHS 1.1) are linked with their monthly administrative health records in the Ontario Health Insurance Program (OHIP) claims database. The CCHS 1.1 provides information on socioeconomic, health, and demographic characteristics. The OHIP database provides information on the actual number of physician visits a respondent made and the actual dollar value of services used. The linkage was done using a deterministic matching approach based on a respondent's unique health card number. A validation procedure was used to ensure only valid health card numbers are found. Incomplete linkages were resolved using a probabilistic match based on birth date, sex, and postal code.

The total CCHS 1.1 Ontario sample size is 39,278. However, only Ontario respondents who consented to have their responses linked to administrative health data are included. The linked sample consists of 32,848 respondents, or 83.6% of all Ontario respondents. The analysis sample is restricted to Ontario respondents, 18 years of age or older, with complete information on household income, own level of education, self-reported health status and chronic conditions. The sample restrictions result in a final sample size is 26,663.[10]

[10]Starting with the linked sample size of 32,848, the sample restrictions result in the loss of 3,245 observations less than 18 years of age, 471 who do not report their level of education,

3.3.1 OHIP Database (April 1, 1999 to March 31, 2002)

The OHIP database contains three fiscal years of administrative records (April 1, 1999 to March 31, 2002) on the physician services received by individuals in Ontario from a fee-for-service physician[11], including information on the number of physician visits, the dollar value of physician services received, and the specialty of the physician who provided the service. The OHIP database is used to construct four measures of physician utilization: two different measures of physician use (the number of physician visits and the dollar value of physician services received) for two different types of physicians (GPs and specialists). All four measures are constructed for a three year period (April 1, 1999 to March 31, 2002).

Measures of physician use are identified through a combination of the specialty of a physician, the fee service code the physician billed, and the dollar value of the fee service code. A physician visit is counted as a GP visit if one of 57 visit-related fee service codes is billed by a physician claiming 'GP' as their specialty. If two or more of the 57 visit-related GP fee service codes are billed on the same day by the same physician then only the first fee service code billed is counted as a visit. If two or more of the 57 visit-related GP fee service codes is billed on the same day by two or more physicians claiming 'GP' as their specialty, then two or more visits are counted. The dollar value

2,247 who do not report their household income and 222 who do not report their marital status, number of chronic conditions or self-reported health status.

[11]According to the Canadian Institute for Health Information (CIHI (2002)), 92.8% of total clinical physician payments in Ontario were fee-for-service (FFS). The Institute for Clinical Evaluative Sciences (ICES (2006)) notes these rates are slightly higher for GPs: 95% of GPs in 1999/2000, 96% of GPs in 2000/2001, and 95% of GPs in 2001/2002, were paid by FFS, or mainly FFS but with some non-FFS involvement.

of GP services received is calculated by summing the dollar value for all fee service codes billed by physicians claiming 'GP' as their specialty from April 1, 1999 to March 31, 2002.

A physician visit is counted as a specialist visit if a physician claiming one of 28 specialties bills a visit-related fee service code corresponding with their speciality.[12] As with counting GP visits, if a specialist bills two or more visit-related fee service codes corresponding to their specialty on the same day, then only the first fee service code billed is counted as a visit. If two or more specialists bill two or more visit-related fee service codes corresponding to their specialty on the same day, then two or more visits are counted. The dollar value of specialist services received is calculated by summing the dollar value for all fee service codes billed by physicians claiming any one of the 28 specialties from April 1, 1999 to March 31, 2002.[13]

3.3.2 Canadian Community Health Survey 1.1

The CCHS 1.1 provides information on need and non-need factors from household residents, age 12 or older, in all ten provinces and three territories, in 2000/2001. People living on Indian Reserves and on Crown Lands, institutional residents, full-time members of the Canadian Forces, and residents of certain remote regions are excluded from the survey's sampling frame.

[12]A complete list of 'specialty claimed' and their corresponding visit-related fee service codes is presented in Appendix 3.A1, Table 3.A1.

[13]During the period April 1, 1999 to March 31, 2002 there were some changes to the fee schedule. Any change in the dollar value of a particular fee service code during this period is reflected in the dollar value of services consumed. There was no attempt made to standardize the dollar value of a particular fee service code across the three year period. This is not of concern as any change in the dollar value of a particular fee service code affects all patients in the same manner.

The CCHS 1.1 has two different sampling frames: an area frame, and a random-digit dialing (RDD) frame. The area frame is based on the Labour Force Survey's (LFS) two-stage, stratified, cluster design. The LFS divides each province into three types of geographic areas (major urban, urban towns, and rural). From each area type, separate geographic and socioeconomic strata are defined. From each strata, generally 6 clusters are sampled with probability proportional to the population size of the cluster. From each cluster a sample of dwellings are sampled. From each dwelling, a face-to-face interview is conducted with a randomly selected household member. Approximately 88% of the CCHS 1.1 sample was collected using the area frame. In some health regions, an RDD frame was used. The RDD frame constructed banks of phone numbers representing households to form strata that roughly conform to the health regions boundaries. From each strata, phone numbers were dialed at random until the required sample size for each strata was collected. Approximately 12% of the entire CCHS 1.1 sample was collected using the RDD frame (Béland (2002)).

To account for the CCHS's complex survey design, Statistics Canada produces sample weights that represent a survey respondent's contribution to the total population. The sample weights are computed using an initial weight representing the inverse probability of selection. The initial weight is then adjusted to account for survey specifics (such as non-response). Since the CCHS 1.1 used two overlapping sampling frames with separate sample designs, two weighting strategies were processed side-by-side and integrated using a dual-frame technique. The integrated weights were then calibrated to population projections based on the 2001 Canadian Census within each province (Béland (2002)).[14]

The need factors include: age, sex, age-sex interactions, self-reported health status, severity of chronic conditions, body-mass index, and whether a respondent has an activity limitation. Self-reported health status asks respondents: "In general, would you say your health is: excellent, very good, good, fair or poor?" The five-level Likert scale variable is converted to five binary variables, one for each health status response. The severity of chronic conditions is a derived from a series of questions asked to each respondent about any specific chronic conditions.[15] Specific chronic conditions are placed into one of three classes as defined by Smith (1999) and Banks et al. (2007): major, medium or minor. Major chronic conditions are heart disease and/or cancer. Medium chronic conditions are diabetes and/or hypertension. Minor conditions are all conditions other than major or medium chronic conditions. A respondent is assigned to the highest class of chronic condition if they have multiple chronic conditions. Three binary variables are constructed, one for each class of chronic conditions.[16] A respondent's body mass index (BMI) is classified as either low-BMI ($BMI < 18.5$), normal-BMI ($18.5 \leq BMI < 25$),

[14]For a more detailed discussion of how the sample weights were generated for the CCHS 1.1, please see Brisebois and Thivierge (2001).

[15]The CCHS 1.1 asks about 23 specific chronic conditions: Alzheimer's disease or other dementia, asthma, arthritis or rheumatism, back problems (excluding fibromyalgia, arthritis or rheumatism), bowel disorder / Crohn's disease or colitis, cancer, cataracts, chronic fatigue syndrome, chronic bronchitis, diabetes, emphysema or chronic obstructive pulmonary disease, epilepsy, fibromyalgia, food allergies, glaucoma, heart disease, high blood pressure, migraine headaches, multiple sclerosis, Parkinson's disease, stomach or intestinal ulcers, thyroid condition, and urinary incontinence.

[16]Since asthma is a minor condition and diabetes is a medium condition, by definition, the analyses of asthmatics and diabetics excludes the severity of chronic condition variable from the analysis.

overweight ($25 \leq BMI < 30$), or obese ($30 \leq BMI$). Finally, a binary variable indicating whether a respondent suffers from a limitation in their normal activities is constructed.

The non-need factors[17] include: adjusted household income, highest level of education, marital status, employment status, immigration status, and whether a respondent lives alone. Respondents are asked to provide their best estimate of the total income, before taxes and deductions, of all household members from all sources in the past 12 months. Adjusted household income adjusts total household income using the modified OECD equivalence scale for household size and composition.[18] Education is defined as the highest level of education attained: less than high school, high school graduate, some post secondary, and post secondary graduate. The four possible levels of attainment are converted into four binary variables, one for each level of education. Marital status is classified into three categories: married/common-law, single, or widowed/divorced. Employment status is classified into five categories: currently employed, not currently employed but employed within the past 12 months, not employed in the past 12 months, employment status

[17]A relevant non-need factor to capture would be a person's permanent income. However, measures of current income, such as adjusted household income, do not fully capture permanent income. Other variables in addition to household income, such as education, in part capture the effect of permanent income.

[18]The modified OECD equivalence scale gives a weight of 1.0 to the first adult in the household, 0.3 to the second adult and additional household members 14 years of age and older, and 0.3 to each child in the household:

$$\text{adjusted income} = \frac{\text{household income}}{1 + (0.5 \times (\text{household size} - 1 - \#\ \text{kids})) + 0.3 \times \#\ \text{kids}}$$

not applicable[19], and employment status not stated.[20] Immigration status is defined as either Canadian born, recent immigrant (immigrated within the 10 years of the survey date), or long-term immigrant (immigrated more than 10 years before the survey). Finally, a binary variable indicating whether a respondent lives alone is constructed.

3.3.3 Descriptive Statistics

Descriptive statistics for the number of physician visits and the dollar value of physician services received for the three year period are presented in Table 3.1. Column 1 presents descriptive statistics for the number of GP visits and column 2 presents descriptive statistics for the dollar value of GP services received. In the full sample, the mean number of GP visits in the three year period is 12.3, with 92.1% making at least one GP visit. The mean number of GP visits conditional on making at least one visit during the three year period is 13.3. The mean total dollar value of GP services received is $481, with 93.7% of respondents having received at least one dollar of GP services. The mean total dollar value of GP services received, conditional on receiving at least one dollar of GP services, is $514.[21] Column 3 presents descriptive

[19]The employment status questions are only asked of respondents over the age of 15 and under the age of 75. To ensure respondents are not simply dropped because they are over the age of 75, the flag for employment status not applicable is included in the analysis.

[20]There are very few asthmatic or diabetic respondents who do not report their employment status. For these two groups the 'employment status not stated' variable is dropped from the analysis.

[21]Recall, the number of GP visits are calculated based on the 57 visit-related fee service codes are claimed by a GP, while the dollar value of GP services received is calculated based on all fee service codes claimed by a GP. For example, it is possible for a GP to bill a service that would not be part of a visit such as interpreting test results. Given the difference in how each measure of physician use is calculated, the difference in the proportion of respondents

statistics for the number of specialist visits for a three year period. The overall mean number of specialist visits during a three year period is 4.4 visits, with 61.2% of the full sample made at least one specialist visits. The mean number of specialist visits, conditional on making at least one specialist visit during the three year period, is 7.2 visits. Column 4 presents descriptive statistics for the dollar value of specialist services received. The mean dollar value of specialist services received $897, with 86.9% of the full sample received at least one dollar of specialist services. The mean dollar value of specialist services received, conditional conditional on having more than zero dollars, is $1,032.

The utilization of GPs and specialists during a three year period is higher for both asthmatics and diabetics than for the full sample. Asthmatics use just over 40% more GP services (43% more GP visits and 42% more in the dollar value of GP services received) and just over 30% more specialist services (35% more specialist visits and 31% more in the dollar value of specialist services received). Relative to the full sample, diabetics use approximately 75% more GP services (77% more GP visits and 74% more in the dollar value of GP services received) and approximately 120% more specialist services (121% more specialist visits and 129% more in the dollar value of specialist services received).

Table 3.2 provides information on the income gradient in observed utilization. The first section presents results for the full sample, section two presents results for asthmatics, and section three presents results for diabetics. Again, column 1 presents the mean number of GP visits by income quintile and col-

who made at least one GP visit (92.1%) and the proportion of respondents who received at least one dollar of GP services (93.7%) is expected.

umn 2 presents the mean for the dollar value of GP services received by income quintile. In the full sample, we see a clear inverse relationship between GP use and quintile of adjusted household income. In the bottom 20% of income, the full sample average 16.7 GP visits and $648 in GP services received. Moving up through the income quintiles, the number of visits and the dollar value of GP services received goes down. In the top 20% of income, the average is 9.8 GP visits and $409 in GP services received. A similar pattern can be seen in section 2 for asthmatics and section 3 for diabetics. In the bottom 20% of the income distribution, asthmatics average 25.6 GP visits and $1,028 in GP services, decreasing to 13.8 GP visits and $527 in GP services received in the top 20% of income. Diabetics average 27.0 GP visits and $1,140 in GP services received in the bottom 20% of income, decreasing to 16.4 GP visits and $638 in GP services received in the top 20% of income.

A similar inverse relationship can be seen between quintile of adjusted household income and observed specialist utilization. Column 3 presents the mean number of specialist visits by quintile of adjusted household income and column 4 presents the mean for the dollar value of specialist services received by quintile of adjusted household income. The full sample, in the bottom 20% of income, average 6.3 specialist visits and $1,278 in specialist services received. Rising through the income quintiles, the number of specialist visits and the dollar value of specialist services received goes down. In the top 20% of income, the full sample average 3.7 specialist visits and $722 in specialist services received. Asthmatics average 7.5 specialist visits and $1,632 in specialist services received in the bottom 20% of income, decreasing to

5.4 specialist visits and $1,066 in specialist services received in the top 20% of income. Diabetics average 11.4 specialist visits and $2,404 in specialist services received in the bottom 20% of income, decreasing to 8.2 specialist visits and $1,578 in specialist services received in the top 20% of income. While there these results suggest a clear relationship between income quintile, GP use, and specialist use, Table 3.2 does not account for differences in need and non-need factors across income quintile.

Table 3.3 provides information on the income gradient in need-standardized utilization. The first section presents results for the full sample, section two presents results for asthmatics, and section three presents results for diabetics. Again, column 1 presents the mean number of need-standardized GP visits by quintile of adjusted household income and column 2 presents the mean for the need-standardized dollar value of GP services received by quintile of adjusted household income. In the full sample, we see need-standardized GP use is highest in the bottom income quintile, then decreases and remains flat for the top four quintiles. In the bottom 20% of income, the full sample average 14.3 GP visits and $548 in GP services received. Moving up through the income quintiles, the number of visits and the dollar value of GP services received decreases only slightly. In the top 20% of income, the average is 11.6 GP visits and $480 in GP services received. A similar pattern can be seen in section 2 for asthmatics. In the bottom 20% of the income distribution, asthmatics average 21.9 GP visits and $903 in GP services, decreasing to 16.6 GP visits and $642 in GP services received in the top 20% of income. Diabetics show a more pronounced gradient between need-standardized GP use and income quintile. Diabetics average 25.3 GP visits and $1,074 in GP services received in the bottom 20% of income, decreasing to 19.7 GP visits and $784 in GP services received in the top 20% of income.

Column 3 presents the mean number of specialist visits by quintile of adjusted household income and column 4 presents the mean for the dollar value of specialist services received by quintile of adjusted household income. A flat relationship can be seen in the full sample between quintile of adjusted household income and need-standardized specialist use. In the bottom 20% of income, the full sample averages 4.4 specialist visits and $883 in specialist services received. Rising through the income quintiles, the number of specialist visits and the dollar value of specialist services received is flat until the top 20% of income, when it goes up slightly. In the top 20% of income, the full sample average 4.8 specialist visits and $940 in specialist services received. Asthmatics display an upward sloping gradient between quintile of adjusted household income and need-standardized specialist use. Asthmatics average 4.9 specialist visits and $1,224 in specialist services received in the bottom 20% of income, increasing to 6.8 specialist visits and $1,335 in specialist services received in the top 20% of income. Finally, diabetics display a flat relationship between quintile of adjusted household income and need-standardized specialist use. Diabetics average 10.7 specialist visits and $2,186 in specialist services received in the bottom 20% of income, and 10.4 specialist visits and $2,151 in specialist services received in the top 20% of income. The income gradient in need-standardized utilization suggest a shallower relationship between quintile of adjusted household income, GP use, and specialist use, compared to the income gradient in Table 3.2.

Descriptive statistics for the need and non-need factors are presented in Table 3.4. The first section of Table 3.4 presents the descriptive statistics for the need factors (or the x variables). Column 1 presents descriptive statistics for the full sample. In the full sample, the average age is 44.7 years; 51% are female, 8% have asthma and 5% have diabetes. Ten percent of asthmatics report also having diabetes. Asthmatics are slightly younger, 42.3 years old, and more likely to be female (63%). Diabetics are older, 59.7 years old and more likely to be male (55%). Asthmatics and diabetics report being in worse health relative to the full sample. Nearly 65% of the full sample report being in very good or excellent health, while only 48% of asthmatics and 25% of diabetics do so. Nearly half of respondents report having a minor chronic condition, 15% report having a medium chronic condition, and 7% report having a major chronic condition. There is a notable difference in the BMI of the three groups: 38% of the full sample report having a normal BMI, while 34% of asthmatics and only 4% of diabetics do so; 33% of the full sample report being obese, while 39% of asthmatics and 64% of diabetics report being obese. Just over 24% of the full sample report having an activity limitation, while 43.9% of asthmatics and 48.2% of diabetics report an activity limitation.

The second section of Table 3.4 presents the descriptive statistics for the non-need factors (or the z variables). For the full sample, mean adjusted household income is just over $65,000 (median $58,000); nearly 70% report having attained a post-secondary education, while only 10% of the full sample report having less than a high-school education. Household income is 8%

lower for asthmatics (mean of \$59,976 and median of \$50,000) and 28% lower for diabetics (mean of \$47,133 and median of \$35,000). Fewer asthmatics (only 65%) and diabetics (only 52%) report having attained a post-secondary education, while 13% of asthmatics and 24% of diabetics report having less than a high-school education. For the full sample: 66% are married, 21% are single, 13% are widowed or divorced, 70% are Canadian born, 8% are recent immigrants and 23% are long-term immigrants. Asthmatics are more likely to be single (25%) and to be Canadian born (81%). Diabetics are less likely to be single (8%) or Canadian born (64%), and more likely to be widowed or divorced (24%) or a long-term immigrant (32%).

What needs to be emphasized is the different income distributions between each group. For example, the income distribution for asthmatics is defined over asthmatics only and the income distribution for diabetics is defined over diabetics only. While asthmatics are similar to the full sample in terms of income, diabetics are more concentrated in the lower income brackets of the full sample. This can be seen in Table 3.5, which presents the Gini coefficient of each sample, the proportion of each sample within income quintiles of the full sample, and the proportion of each sample by absolute income cut-offs. The Gini coefficients (section 1, Table 3.5) suggest the income-inequality within each of the three sample is similar (0.353 - 0.371). However, looking at the proportion of each sample by absolute income cut-offs (section 3, Table 3.5) we clearly see the proportion of asthmatics by income category is similar the proportion of the full sample in each income category. For example, 71.0% of the full sample and 71.6% of asthmatics have an adjusted household income less than \$40,000. However, the proportion of diabetics is higher in the lower income categories. For example, 82.2% of diabetics have an adjusted household income less than \$40,000.

The different income distributions of the each sample means their respective income distributions will have a different variance. In particular, since diabetics are concentrated at lower incomes, the income for diabetics will have a lower variance. The difference in variance of income for each sample makes interpretation of between-group inequities difficult. For example, an $HI = 0.05$ is less problematic in the full sample (with a higher variance in income) relative to an $HI = 0.05$ in the sample of diabetics (with a lower variance in income). Thus, the same HI in a population with larger variance in income is less problematic because the absolute income gradient must be smaller (i.e. if you have the same total amount of income-related inequality in utilization, the absolute income-gradient must be smaller in the sample with a larger variance in income).

3.4 Results

The two main sets of results, the concentration indices and the decomposition, are presented in turn. The first set presents the concentration indices for observed utilization (the inequality index, denoted C_M), and the concentration indices for needs-standardized utilization (the income-related horizontal inequity index, denoted HI). The concentration indices are calculated for the probability of use and conditional use, for both measures of physician use (the number of physician visits and the dollar value of physician services received), and for both physician types (GPs and specialists). The second set of results presents the decomposition of the inequality index (C_M) for all three groups. The decomposition results focus on the contribution of need and non-need factors to income related inequity in physician use.

3.4.1 Concentration Indices

Table 3.6 presents the concentration indices for both the probability of physician use and the amount of physician use, conditional on having positive use, for both GPs and specialists. Section one of Table 3.6 presents the concentration indices for GP utilization, while section two presents the concentration indices for specialist utilization.[22]

Concentration Indices for General Practitioner Use

First looking at the concentration indices for GP utilization (section 1), column 1 shows no income-related inequality in the full sample in the probability of using a GP, but pro-poor inequality in conditional GP use - measured by both visits and the dollar value of GP services received. After need-standardizing GP use, column 2 shows no inequity in the full sample in the probability of GP use, measured both by the number of visits ($HI = 0.004$) and the dollar value of GP services received ($HI = 0.002$). However, there is pro-poor inequity in the conditional number of GP visits ($HI = -0.040$) and in the conditional

[22]All concentration curves for the number of GP visits, the dollar value of GP services received, the number of specialist visits, and the dollar value of specialist services received are presented in Appendix 3.A2.

dollar value of GP services received ($HI = -0.019$), both are statistically significant.

Shifting focus to asthmatics, column 3 section 1 indicates poor asthmatics tend to use more GP services than rich asthmatics. Poor asthmatics have a slightly higher probability of a GP visit and are more likely to received a dollar of GP services than rich asthmatics, but the poor clearly use GPs more conditional on using a GP at all. Looking at need-standardized GP use (column 4), there is a slight pro-poor, but not statistically significant, inequity in the probability of GP use (measured by GP visits ($HI = -0.002$) and the dollar value of GP services received ($HI = -0.006$)). However, pro-poor inequity in conditional GP use is seen for both the number of GP visits ($HI = -0.032$) and the dollar value of GP services received ($HI = -0.030$).

Diabetics also exhibit similar patterns of use and inequity, by income, to the full sample. Columns 5 shows no income-related inequality in the probability of GP use, but pro-poor inequality in conditional GP use - measured by both visits and the dollar value of GP services received. The story for diabetics is similar after need-standardizing GP use. Column 6 shows no meaningful income related inequity in the probability of GP visits ($HI = 0.001$) or the probability of a dollar of GP services received ($HI = -0.001$). However, there is statistically significant pro-poor inequity in conditional GP use - measured by the conditional number of GP visits ($HI = -0.048$) and the conditional dollar value of GP services received ($HI = -0.056$).

Differences between the three groups can be seen by comparing the full sample (column 2), asthmatics (column 4), and diabetics (column 6). The income related inequity in the probability of GP use - GP visits and the dollar value of GP services received - is similar across the three groups, close to zero, and statistically significant only for the full sample. The conditional number of GP visits shows a statistically significant pro-poor inequity across the three groups, ranging from -0.032 (asthmatics) to -0.048 (diabetics). However, the conditional dollar value of GP services received also show a pro-poor inequity across the three groups: ranging from -0.019 (the full sample) to -0.056 (diabetics).

Concentration Indices for Specialist Use

Section 2 of Table 3.6 presents the concentration indices for observed specialist use and need-standardized specialist use for both the number of specialist visits and the dollar value of specialist services received.

Column 1 shows observed specialist utilization for the full sample to be distributed fairly evenly across incomes. The probability of a specialist visit is slightly concentrated among the poor ($C_M = -0.007$), while the probability of receiving a dollar of specialist services ($C_M = 0.002$) is slightly concentrated among the rich, although neither is statistically significant. The conditional number of specialist visits is concentrated among the poor ($C_M = -0.039$) as is the conditional dollars of specialist services received ($C_M = -0.071$). After need-standardizing specialist use, column 2 shows a pro-rich inequity in the probability of specialist use - measured both by the number of visits ($HI = 0.025$) and the dollar value of specialist services received ($HI = 0.012$) - and a slight pro-rich inequity in the conditional number of specialist visits

($HI = 0.013$) and in the conditional dollars of specialist services received ($HI = 0.015$).

Asthmatics show a similar pattern of specialist use and inequity as the full sample. Column 3 in section 2 indicates a pro-poor inequality in the probability of a specialist visit ($C_M = -0.021$), as well as the probability of receiving a dollar of specialist services ($C_M = -0.010$). Conditional specialist use is also concentrated among poor-asthmatics. The concentration index for need-standardized specialist use (column 4) indicates the probability of specialist use and the conditional use of specialists by asthmatics generally have a pro-rich inequity, but neither is statistically significant.

Diabetics generally exhibit a pro-rich inequality and inequity in specialist use. Column 5 shows the probability of observed specialist use is evenly distributed across the income distribution. Use of a specialist, conditional on having positive use, is more heavily concentrated among poor-diabetics. After need-standardizing specialist use for diabetics, column 6 of section 2 shows a small pro-rich inequity in the probability of a specialist visit ($HI = 0.018$) and the conditional number of specialist visits ($HI = 0.009$). There is no inequity in the probability of receiving a dollar of specialist services ($HI = 0.003$), but there is pro-poor inequity in the conditional dollars of specialist services received ($HI = -0.015$), although neither is statistically significant.

Differences across the three groups in inequity in specialist use can be seen by comparing the full sample (column 2), asthmatics (column 4), and diabetics (column 6), in section 2 of Table 3.6. The income related inequity in the probability of a specialist visit is similar across the three groups, close to zero, and not statistically significant only for asthmatics. The income related inequity in the probability of receiving a dollar of specialist services is similar between asthmatics and diabetics, both being close to zero and not statistically significant. The full sample shows a statistically significant pro-rich inequity in the the probability of receiving a dollar of specialist services ($HI = 0.012$). All the three groups show a pro-rich inequity in the conditional number of specialist visits and the conditional dollar value of specialist services received, but are generally not statistically significant.

3.4.2 Decomposition of Concentration Index for Unstandardized Utilization

The decomposition of C_M provides insight into the need and non-need variables determining inequality within each group. As described by equation (3.13) in Section 3.2.1, C_M is equal to the sum of the contributions to income-related inequality from the j need variables, the k non-need variables, and the residual. A negative contribution is interpreted as making a pro-poor contribution to inequality, while a positive contribution is interpreted as making a pro-rich contribution to inequality.

Because each variable's contribution is linearly additive, contributions from related variables are aggregated to see how they contribute to inequality. For example, the contribution of self-reported health overall rather than the contributions of the four self-reported health variables (very-good, good, fair, and poor), where excellent health is the omitted category, is reported. The decomposition results present the contributions from the following socioeconomic, demographic, and health factors: age-sex interactions, self-reported health status, severity of chronic conditions[23], activity limitation, household income, urban, education, marital status, immigration status, lives alone, and BMI status.

The decomposition discussions are organized by the contribution of need factors, the contribution of non-need factors, and the contribution of the residual. Table 3.7 presents the decomposition for GP use and Table 3.8 presents the decomposition for specialist use. Section 1 of each table presents the decomposition for the probability of use (i.e., the probability of using a GP or probability of using a specialist), while section 2 of each table presents the decomposition for conditional use (i.e., the quantity of GP use or the quantity of specialist use, conditional on having any use). The decompositions for the number of physician visits are presented in columns 1-3, and the decompositions for the dollar value of physician services used are presented in columns 4-6. Columns 1 and 4 present the decomposition for the full sample. Columns 2 and 5 present the decomposition for asthmatics. And, columns 3 and 6 present the decomposition for diabetics.

Contribution of Need Factors

The contribution of need factors is negative for all three groups, for both measures of use (visits and the dollars of services received), for both the probability of use and conditional use, and for both GPs and specialists. This suggests the contribution of need factors decreases pro-rich inequality in physician use.

[23]Again, the severity of chronic conditions is only used in the analysis of the full sample.

Focusing on the contribution of need factors to the inequalities in the probability of a GP visit and the conditional number of specialist visits (columns 1-3 in Table 3.7), the contribution of need factors is small towards inequalities in the probability of a GP visit for all three groups, ranging from -0.003 to -0.004, and is mainly comprised of the contribution of the age-sex interactions. The contribution of need factors to the conditional number of GP visits is negative for all three groups: full sample (-0.044), asthmatics (-0.064), and diabetics (-0.057). The contribution of need factors is mainly driven by the contribution of self-reported health status.

Shifting focus to the contribution of need factors to the inequalities in the probability of receiving a dollar of GP services and the conditional dollars of GP services received (columns 4-6 in Table 3.7), the contribution of need factors is, again, small towards inequalities in the probability of receiving a dollar of GP services, ranging from -0.002 to -0.004, and is mainly driven by age-sex interactions. The contribution of need factors is relatively small towards inequalities in the conditional dollars of GP services received for all three groups, ranging from -0.002 to -0.045. Again, the contribution of need is mainly driven by self-reported health status for all groups.

The contribution of need to the inequality in the use of specialists is larger than for GPs. First looking at the the contribution of need factors to the inequalities in the probability of a specialist visit and the conditional number of specialist visits (columns 1-3 in Table 3.8), the contribution of need factors is large towards inequalities in the probability of a specialist visit for all three groups, ranging from -0.027 to -0.064, and is driven by the contribution of age-sex interactions and self-reported health status. The contribution of need factors is also large for the conditional number of specialist visits, ranging from -0.042 to -0.067, and is, again, driven primarily by the contribution of self-reported health status.

Shifting focus to the contribution of need factors to the inequalities in the probability of receiving a dollar of specialist services and the conditional dollars of specialist services received (columns 4-6 in Table 3.8), the contribution of need factors is small towards inequalities in the probability of receiving a dollar of specialist services, ranging from -0.003 to -0.011, and is primarily driven by the contribution the age-sex interactions. Need factors make the largest contribution to the inequality in the conditional dollars of specialist services received, ranging from -0.065 (the full sample) to -0.003 (diabetics), and are primarily driven by the contribution of self-reported health status for the full sample, and the contribution of the age-sex interactions among asthmatics and diabetics.

Contribution of Non-Need Factors

The contribution of non-need factors varies across all three groups, for both measures of physician use (the number of visits and the dollars of services received), for both the probability of use and conditional use, and for both GPs and specialists. Not surprisingly, the contribution of non-need factors is driven mainly by the contribution of income.

The contribution of non-need factors towards inequality in the probability of GP use is close to zero for all three groups (section 1, Table 3.7). The contribution of non-need factors is positive for the probability of a GP visit for asthmatics (0.011), but near zero for the full sample (-0.001) and diabetics (0.003). The contribution of non-need factors towards inequality in the probability of receiving a dollar of GP services is near zero for all three groups. The contribution of non-need factors towards inequality in the conditional number of GP visits (section 2, Table 3.7) is slightly negative, but near zero, for all three groups, while the contribution of non-need factors towards inequality in the conditional dollars of GP services received is near zero for asthmatics and diabetics, but small and negative for the full sample (-0.019).

The contribution of non-need factors to the inequalities in the probability of specialist use (section 1, Table 3.8) is close to zero or positive for the full sample and asthmatics, negative for diabetics, and generally determined by the contribution of income. The contribution of non-need factors to the probability of a specialist visit is positive for asthmatics (0.034) and negative for diabetics (-0.053). However, the contribution of non-need factors towards inequality in the probability of receiving a dollar of specialist services is near zero for all three groups. The contribution of non-need factors towards inequality in the conditional number of specialist visits (section 2, Table 3.8) is effectively zero for the full sample (0.001), small and positive for asthmatics (0.017), and negative for diabetics (-0.053). However, the contribution of non-need factors towards inequality in the conditional dollars of specialist services received is near zero for asthmatics (0.003) and diabetics (-0.001), but positive for the full sample (0.022).

Contribution of Residuals

The contribution of the residual reflects the income-related inequality in physician use not explained by systematic differences in variations in need and non-need factors by income.

The contribution of the residual to the inequalities in the probability of a GP visit (section 1, Table 3.7) is small and positive for the full sample (0.005), small and negative for asthmatics (-0.012), and zero for diabetics. The contribution of the residual towards inequality in the probability of receiving a dollar of GP services is also small and positive for the full sample (0.005), again small and negative for asthmatics (-0.007), and near zero for diabetics (-0.002). The contribution of the residual towards inequality in the conditional number of GP visits (section 2, Table 3.7) is larger and negative for all three groups: the full sample (-0.037), asthmatics (-0.021), and diabetics (-0.090). The residual's contribution towards inequality in the conditional dollars of GP services received for all three groups is negative, ranging from -0.002 for the full sample to -0.069 for diabetics.

The contribution of the residual to the inequalities in the probability of a specialist visit (section 1, Table 3.8) is positive for the full sample (0.027), negative for asthmatics (-0.017), and zero for diabetics. The contribution of the residual to income-related inequalities in the probability of receiving a dollar of specialist services is positive for the full sample (0.012), and near zero for asthmatics (-0.004) and diabetics (-0.002). The contribution of the residual towards inequality in the conditional number of specialist visits (section 2, Table 3.8) is near zero for the full sample (0.002), positive for asthmatics

(0.024), and large and negative for diabetics (-0.090). Finally, the contribution of the residual towards inequality in the conditional dollars of specialist services received is negative for the full sample (-0.029) and diabetics (-0.069), but effectively zero for asthmatics (0.003).

3.5 Discussion

The purpose of the paper was to examine income-related inequity in the use of physician services by asthmatics and diabetics, relative to the general population, and see if there are different contributing factors to inequality. To do so, this paper has applied the concentration index approach of Wagstaff and van Doorslaer (2000) to unique linked survey-administrative data set, and married the condition specific approach taken by epidemiologists with the standard population based approach used in the literature.

The Canadian health care system, as with many health care systems, strives to provide health care based on need and not based on non-need factors such as income. The two specific chronic conditions, asthma and diabetes, are two groups of people who are generally higher users of physician services and who are often in greater need than the general population. Income-related inequalities in utilization within these two groups may be higher given both asthma and diabetes are more prevalent in lower-income people.

The general results are consistent with the previous literature showing some income-related inequities in physician use. There is no income-related inequity in the probability of GP use, pro-poor income-related inequity in conditional

GP use, and a slight pro-rich income-related inequity in the probability and conditional use of specialists.

The results of this paper are in line with the literature. For the inequity in the use of GP services, Allin (2008) found an HI of approximately -0.02 for the probability of a GP visit in Ontario (I found an HI of 0.002). Allin (2008) and Jiménez-Rubio et al. (2008) found an HI in the range of -0.01 to -0.03 for the total number of GP visits (I found an HI of -0.04 for the conditional number of GP visits). McGrail (2008) found an HI of -0.015 for the conditional dollar value of GP services received in BC (I found an HI of -0.019 for the conditional dollar value of GP services received in Ontario). Similarly, for the inequity in the use of specialist services, Allin (2008) found an HI of approximately 0.05 for the probability of a specialist visit in Ontario (I found an HI of 0.025), while Allin (2008) and Jiménez-Rubio et al. (2008) found an HI of approximately 0.05 for the total number of specialist visits (I found an HI of 0.013 for the conditional number of specialist visits). McGrail (2008) found an HI of 0.015 for the conditional dollar value of specialist services received in BC (I found an HI of 0.015 for the conditional dollar value of specialist services received in Ontario). The results are also in line with the findings for Canada by van Doorslaer et al. (2002) and van Doorslaer and Masseria (2004).

Differences can be seen across the three groups with different income-related inequities between the full sample and the condition specific groups, but similar income-related inequities between asthmatics and diabetics. All three groups show no income-related inequity in the probability of GP use and pro-poor inequity in conditional GP use, although the pro-poor inequity is stronger for asthmatics than for the full sample, and stronger again for diabetics than asthmatics. The full sample shows pro-rich income-related inequity in the probability of specialist use, while asthmatics show no income-related inequity in the probability of specialist use and diabetics show a slight pro-rich inequity in the probability of specialist use. The full sample shows a slight pro-rich inequity in the conditional use of specialists, while asthmatics and diabetics show no income-related inequity in the use of specialists.

While inequities in the probability of use are similar for asthmatics and diabetics, relative to the general population, the inequities in physician use conditional on making some use are not. The pro-poor inequity in the conditional number of GP visits is similar across the three groups, but the pro-poor inequity is stronger for diabetics than for asthmatics, and the pro-poor inequity is stronger for asthmatics than for all respondents. However, there does not appear to be any meaningful or significant inequity in the conditional use of a specialist between the three groups.

Interpreting income-related inequity for GP use in isolation from income-related inequity for specialists use only paints a partial picture. Inequities in GP and specialist use should be interpreted together to see how income-related inequities in overall physician use manifest. There is horizontal equity in the probability of using a GP, but the poor are more likely to use continue using a GP. The pro-rich inequity in the probability of specialist use suggests there may be differential referrals to a specialist based on income. This may be due to higher income patients being stronger advocates for themselves, or GPs preferentially referring higher income patients to specialists. Although, once contact with a specialist is made there is little income-related inequity in the conditional use of specialists.

The differences in income-related inequities between the full sample and condition specific groups, but similarities income-related inequities between asthmatics and diabetics, suggests the married conditional specific-population based approach taken in this paper may be a better way of controlling for heterogeneity of health care need in the general population when only limited controls for health care need are available.

The decomposition analysis shows is the largest contributor to inequality of physician use among all groups is income. The interesting subtlety is the small role of need for the probability of a GP visit, but the large role of need for the probability of receiving a dollar of GP services for asthmatics and diabetics, but not for all respondents

A limitation of the concentration index approach is that is depends on the gradient between income and physician use, the variation in income, and an individuals relative rank in the income distribution. Since the income distribution is defined only over the relevant group, the income gradient of physician use, the variation in income, and an individuals relative rank in the income distribution are all relative measures. While there is a gradient among asthmatics and diabetics, there is less variation in income than in the full sample. Since asthmatics and diabetics are generally of lower incomes, the variation in income is also lower. The relative rank of an individual in the income distribution will likely differ if the income distribution is for the general population, for asthmatics, or for diabetics. This means, for example, a pro-rich inequity in physician use among the general population is still of concern within the asthmatic or diabetic groups to the extent the poor do not receive the same appropriate care for their conditions as do the rich.

Table 3.1: Descriptive Statistics: GP and Specialist Utilization, Ontario, 3-year period (1999-2002)

	GP Utilization		Specialist Utilization	
	Visits	Dollar Value	Visits	Dollar Value
	(1)	(2)	(3)	(4)
Full Sample				
Mean - Total Use	12.3	$ 481	4.4	$ 897
(s.e.)	(0.1)	(5)	(0.1)	(10)
% with Positive Use	92.1%	93.7%	61.2%	86.9%
Mean - Conditional on Positive Use	13.3	$ 514	7.2	1032
(s.e.)	(0.1)	(5)	(0.1)	(11)
Asthmatics				
Mean - Total Use	17.5	$ 683	6	$ 1176
(s.e.)	(0.3)	(19)	(0.2)	(34)
% with Positive Use	95.4%	96.9%	71.1%	92.2%
Mean - Conditional on Positive Use	18.4	$ 705	8.4	$ 1276
(s.e.)	(0.3)	(19)	(0.3)	(36)
Diabetics				
Mean - Total Use	21.8	$ 836	9.8	$ 2056
(s.e.)	(0.4)	(20)	(0.3)	(72)
% with Positive Use	95.6%	98.1%	85.9%	98.0%
Mean - Conditional on Positive Use	22.8	$ 853	11.4	$ 2099
(s.e.)	(0.4)	(20)	(0.3)	(73)

Table 3.2: Average Physician Utilization (total number of physician visits and the total dollar value of physician services received), by Quintile of Equivalized Household Income

	GP Utilization		Specialist Utilization	
	Visits	Dollar Value	Visits	Dollar Value
	(1)	(2)	(3)	(4)
1. Full Sample				
Bottom 20%	16.7	$648	6.3	$1,278
	(0.4)	(17)	(0.2)	(46)
2nd (20-40%)	13.7 ***	$517 ***	5.2 ***	$1,046 ***
	(0.3)	(11)	(0.2)	(36)
3rd (40-60%)	12.2 ***	$478 **	4.2 ***	$881 ***
	(0.3)	(13)	(0.1)	(34)
4th (60-80%)	10.7 ***	$421 ***	3.5 ***	$708 ***
	(0.3)	(17)	(0.1)	(25)
Top 20%	9.8 **	$409	3.7	$722
	(0.2)	(24)	(0.2)	(27)
Total	12.3	$481	4.4	$897
	(0.1)	(5)	(0.1)	(10)
2. Asthmatics				
Bottom 20%	25.6	$1,028	7.5	$1,632
	(1.4)	(77)	(0.6)	(132)
2nd (20-40%)	20.5 ***	$765 ***	7.4	$1,392
	(1.1)	(41)	(0.6)	(109)
3rd (40-60%)	16.8 ***	$680	5.7 **	$1,127 *
	(0.9)	(51)	(0.6)	(96)
4th (60-80%)	15.5	$601	5.0	$955
	(0.8)	(36)	(0.4)	(70)
Top 20%	13.8	$527	5.4	$1,066
	(1.1)	(37)	(0.9)	(140)
Total	17.5	$683	6.0	$1,176
	(0.3)	(19)	(0.2)	(34)
3. Diabetics				
Bottom 20%	27.0	$1,140	11.4	$2,404
	(1.7)	(90)	(1.0)	(284)
2nd (20-40%)	25.1	$972	10.0	$2,371
	(1.3)	(50)	(0.9)	(216)
3rd (40-60%)	24.4	$864	11.4	$2,520
	(1.6)	(55)	(1.2)	(354)
4th (60-80%)	19.5 **	$729 **	8.8 **	$1,722 **
	(1.1)	(42)	(0.7)	(132)
Top 20%	16.4 **	$638	8.2	$1,578
	(1.0)	(47)	(0.8)	(197)
Total	21.8	$836	9.8	$2,056
	(0.4)	(20)	(0.3)	(72)

Standard errors are reported in brackets. Stars denote statistical significance between quintile q and quintile $q-1$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.3: Average Need-Standardized Physician Utilization (total number of physician visits and the total dollar value of physician services received), by Quintile of Equivalized Household Income

	GP Utilization		Specialist Utilization	
	Visits	Dollar Value	Visits	Dollar Value
	(1)	(2)	(3)	(4)
1. Full Sample				
Bottom 20%	14.3	$548	4.4	$883
	(0.4)	(14)	(0.2)	(42)
2nd (20-40%)	12.9 ***	$484 ***	4.5	$893
	(0.2)	(9)	(0.2)	(32)
3rd (40-60%)	12.8	$504	4.5	$948
	(0.3)	(13)	(0.1)	(32)
4th (60-80%)	12.0 **	$476	4.4	$884
	(0.3)	(16)	(0.1)	(23)
Top 20%	11.6	$480	4.8 **	$940 *
	(0.2)	(24)	(0.2)	(24)
Total	12.6	$495	4.5	$913
	(0.1)	(4)	(0.1)	(9)
2. Asthmatics				
Bottom 20%	21.9	$903	4.9	$1224
	(1.2)	(69)	(0.6)	(116)
2nd (20-40%)	18.7 **	$711 **	5.9	$1187
	(1.1)	(40)	(0.6)	(98)
3rd (40-60%)	16.3 *	$671	5.3	$1093
	(0.9)	(50)	(0.5)	(79)
4th (60-80%)	17.7	$688	6.1	$1181
	(0.8)	(34)	(0.4)	(64)
Top 20%	16.6	$642	6.8	$1335
	(0.9)	(31)	(0.8)	(121)
Total	17.9	$705	5.9	$1202
	(0.3)	(18)	(0.2)	(31)
3. Diabetics				
Bottom 20%	25.3	$1074	10.1	$2186
	(1.5)	(82)	(1.0)	(272)
2nd (20-40%)	23.9	$927	8.7	$2103
	(1.1)	(40)	(0.9)	(215)
3rd (40-60%)	23.3	$831	10.8	$2339
	(1.5)	(54)	(1.1)	(329)
4th (60-80%)	20.9	$808	9.9	$2056
	(1.0)	(38)	(0.7)	(114)
Top 20%	19.7	$784	10.4	$2151
	(0.9)	(45)	(0.7)	(173)
Total	22.3	$867	10.1	$2164
	(0.4)	(18)	(0.3)	(66)

Standard errors are reported in brackets. Stars denote statistical significance between quintile q and quintile $q-1$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.4: Average of Need (x_i) and Non-Need (z_i) Factors, by sample

	All	Asthmatics	Diabetics	Ratio of Means (2) / (1)	Ratio of Means (3) / (1)
	(1)	(2)	(3)	(4)	(5)
Need Factors (x_i)					
Age	44.7	42.3	59.7	0.95	1.34
	(0.100)	(0.350)	(0.380)		
Female	51.0%	63.0%	45.0%	1.24	0.88
	(0.000)	(0.010)	(0.010)		
Asthma	8.0%	100.0%	10.0%	-	-
	(0.000)	(0.000)	(0.010)		
Diabetes	5.0%	6.0%	100.0%	-	-
	(0.000)	(0.000)	(0.000)		
Zero CCs	32.0%	-	-	-	-
	(0.000)	-	-		
1-3 CCs	55.0%	58.0%	53.0%	1.05	0.96
	(0.000)	(0.010)	(0.010)		
4-5 CCs	9.0%	24.0%	27.0%	2.67	3.00
	(0.000)	(0.010)	(0.010)		
6 or more CCs	4.0%	18.0%	20.0%	4.50	5.00
	(0.000)	(0.010)	(0.010)		
Major CC	7.0%	11.0%	23.0%	1.57	3.29
	(0.000)	(0.010)	(0.010)		
Medium CC	13.0%	15.0%	77.0%	1.15	5.92
	(0.000)	(0.010)	(0.010)		
Mild CC	47.0%	74.0%	0.0%	1.57	0.00
	(0.000)	(0.010)	(0.000)		
Excellent	27.0%	15.0%	6.0%	0.56	0.22
	(0.000)	(0.010)	(0.010)		
Very Good	37.0%	33.0%	19.0%	0.89	0.51
	(0.000)	(0.010)	(0.010)		
Good	24.0%	28.0%	33.0%	1.17	1.38
	(0.000)	(0.010)	(0.010)		
Fair	9.0%	15.0%	25.0%	1.67	2.78
	(0.000)	(0.010)	(0.010)		
Poor	4.0%	9.0%	16.0%	2.25	4.00
	(0.000)	(0.010)	(0.010)		
Low BMI	2.0%	2.0%	1.0%	1.00	0.50
	(0.000)	(0.000)	(0.010)		
Normal BMI	38.0%	34.0%	14.0%	0.89	0.37
	(0.000)	(0.010)	(0.010)		

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Table 3.4, continued

	All	Asthmatics	Diabetics	Ratio of Means (2) / (1)	Ratio of Means (3) / (1)
	(1)	(2)	(3)	(4)	(5)
Over weight	27.0%	25.0%	21.0%	0.93	0.78
	(0.000)	(0.010)	(0.010)		
Obeses	33.0%	39.0%	64.0%	1.18	1.94
	(0.000)	(0.010)	(0.010)		
Activity Limitation	24.5%	43.9%	48.2%	1.79	1.97
	(0.003)	(0.010)	(0.013)		
Non-Need Factors (z_i)					
Household Income	$65,077	$59,976	$47,133	0.92	0.72
	(293)	(955)	(1,006)		
Less than High-School	9.5%	12.6%	23.8%	1.33	2.50
	(0.002)	(0.007)	(0.011)		
High-School	14.3%	13.6%	18.5%	0.95	1.30
	(0.002)	(0.007)	(0.010)		
Some Post-Secondary	7.2%	8.6%	6.0%	1.19	0.83
	(0.002)	(0.006)	(0.006)		
Post-Secondary	69.0%	65.3%	51.7%	0.95	0.75
	(0.003)	(0.010)	(0.013)		
Currently Working	57.8%	54.1%	31.5%	0.94	0.55
	(0.003)	(0.010)	(0.012)		
Not Currently Working	16.5%	16.6%	10.6%	1.00	0.64
	(0.002)	(0.008)	(0.008)		
No Work in the last Year	20.3%	24.0%	43.3%	1.18	2.13
	(0.002)	(0.009)	(0.013)		
Working - Not Applicable	5.2%	4.8%	14.6%	0.93	2.83
	(0.001)	(0.004)	(0.009)		
Working - Not Stated	0.2%	x	x	-	-
	(0.000)				
Married / Common Law	66.0%	62.0%	68.0%	0.94	1.03
	(0.000)	(0.010)	(0.010)		
Single	21.0%	25.0%	8.0%	1.19	0.38
	(0.000)	(0.010)	(0.010)		
Widowed / Divorced	13.0%	13.0%	24.0%	1.00	1.85
	(0.000)	(0.010)	(0.010)		
Urban	86.0%	85.0%	86.0%	0.99	1.00
	(0.000)	(0.010)	(0.010)		
Recent Immigrant	8.0%	3.0%	3.0%	0.38	0.38
	(0.000)	(0.000)	(0.000)		
Long Term Immigrant	23.0%	17.0%	32.0%	0.74	1.39
	(0.000)	(0.010)	(0.010)		
Canadian Born	70.0%	81.0%	64.0%	1.16	0.91
	(0.000)	(0.010)	(0.010)		

x: cells were suppressed due to low cell counts. *CC*: chronic condition

3.6 Appendix: Income Distribution Analysis

Table 3.5: Gini Coefficient and Income Distribution Analysis, by sample

	Full Sample (1)	Asthmatics (2)	Diabetics (3)
1. Gini Coefficient			
	0.353	0.371	0.355
2. By Income Quintile of the Full Sample			
Bottom 20%	13.9 %	17.7 %	26.3 %
2nd (20-40%)	20.5 %	23.5 %	30.7 %
3rd (40-60%)	21.4 %	20.5 %	18.2 %
4th (60-80%)	19.4 %	16.2 %	13.2 %
Top 20%	24.8 %	22.2 %	11.7 %
3. By Absolute Income Cut-Offs			
Less than $20,000	30.1 %	36.0 %	46.2 %
$20,001 to $40,000	40.9 %	35.6 %	36.0 %
$40,001 to $60,000	18.6 %	19.1 %	12.9 %
$60,001 to $80,000	6.5 %	5.7 %	3.8 %
$80,001 or more	3.8 %	3.6 %	1.1 %

note: Columns may not sum to 100% due to rounding errors.

Table 3.6: Concentration Indices (C_M and HI), GP and Specialist utilization

	Full Sample		Asthmatics		Diabetics	
	Inequality (C_M)	Inequity (HI)	Inequality (C_M)	Inequity (HI)	Inequality (C_M)	Inequity (HI)
	(1)	(2)	(3)	(4)	(5)	(6)
1. General Practitioner Utilization						
Visits						
Probability of Use	0.000	0.004 **	-0.004	-0.002	-0.003	0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.006)	(0.005)
Conditional Use	-0.090 ***	-0.040 ***	-0.090 ***	-0.032 **	-0.093 ***	-0.048 ***
	(0.006)	(0.005)	(0.016)	(0.013)	(0.015)	(0.013)
Dollar Value of Services Received						
Probability of Use	-0.002	0.002 **	-0.008 *	-0.006	-0.002	-0.001
	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)
Conditional Use	-0.069 ***	-0.019 **	-0.088 ***	-0.030 *	-0.109 ***	-0.056 ***
	(0.010)	(0.009)	(0.018)	(0.016)	(0.019)	(0.017)
2. Specialist Utilization						
Visits						
Probability of Use	-0.007	0.025 ***	-0.021 *	0.012	0.001	0.018 **
	(0.004)	(0.004)	(0.011)	(0.010)	(0.008)	(0.008)
Conditional Use	-0.039 ***	0.013 *	-0.026 ***	0.032	-0.046 ***	0.009
	(0.010)	(0.007)	(0.030)	(0.024)	(0.021)	(0.018)
Dollar Value of Services Received						
Probability of Use	0.002	0.012 ***	-0.010 **	-0.001	0.000	0.003
	(0.002)	(0.002)	(0.005)	(0.004)	(0.003)	(0.003)
Conditional Use	-0.071 ***	0.015	-0.057 ***	0.017	-0.087 ***	-0.015
	(0.010)	(0.009)	(0.027)	(0.023)	(0.029)	(0.025)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Contribution to Income Related Inequality in the use of General Practitioner Services, the Number of GP Visits and the Dollar Value of GP Services Received, 3-year Utilization

	Number of GP Visits			Dollars of GP Services Received		
	Full Sample	Asthmatics	Diabetics	Full Sample	Asthmatics	Diabetics
	(1)	(2)	(3)	(4)	(5)	(6)
1. Probability of GP Use						
Need Factors						
Age-Sex Interactions	-0.003	-0.002	-0.003	-0.003	-0.002	-0.001
Self-Reported Health Status	0.000	0.001	-0.001	-0.001	0.000	-0.001
Severity of Chronic Conditions	-0.001	x	x	0.000	x	x
Activity Limitation	0.000	-0.001	0.000	0.000	0.000	0.000
BMI Status	0.000	-0.001	0.001	0.000	0.000	0.000
SubTotal (Need)	-0.004	-0.003	-0.003	-0.004	-0.003	-0.002
Non-Need Factors						
(ln) Equivalized Household Income	-0.002	0.015	0.002	-0.004	0.004	0.001
Urban	0.000	0.000	0.000	0.000	0.000	0.000
Education	0.001	-0.004	0.001	0.000	-0.002	0.001
Marital Status	0.001	-0.001	0.000	0.000	0.000	0.001
Employment Status	0.000	0.000	-0.001	0.000	0.000	0.000
Immigration Status	-0.001	0.001	0.001	0.000	0.001	0.000
Lives Alone	0.000	0.000	0.000	0.000	0.000	0.000
Sub-Total (Non-Need)	-0.001	0.011	0.003	-0.003	0.003	0.003
Residual	0.005	-0.012	0.000	0.005	-0.007	-0.002
Inequality Index (C_M)	0.000	-0.004	-0.003	-0.002	-0.008	-0.002
Horizontal Inequity Index (HI)	0.004	0.000	0.000	0.002	-0.004	0.000

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Table 3.7, continued

	Number of GP Visits			Dollars of GP Services Received		
	Full Sample	Asthmatics	Diabetics	Full Sample	Asthmatics	Diabetics
	(1)	(2)	(3)	(4)	(5)	(6)
2. Conditional Use of GPs						
Need Factors						
Age-Sex Interactions	-0.007	-0.005	-0.025	-0.006	-0.002	-0.001
Self-Reported Health Status	-0.022	-0.053	-0.020	-0.023	-0.001	-0.001
Severity of Chronic Conditions	-0.009	x	x	-0.009	x	x
Activity Limitation	-0.005	-0.005	-0.012	-0.006	0.000	0.000
BMI Status	-0.001	-0.001	0.000	-0.002	0.000	0.000
SubTotal (Need)	-0.044	-0.064	-0.057	-0.045	-0.003	-0.002
Non-Need Factors						
(ln) Equivalized Household Income	0.008	0.006	0.016	-0.006	0.004	0.001
Urban	0.000	0.000	0.000	0.000	0.000	0.000
Education	-0.005	0.005	-0.010	-0.003	-0.002	0.001
Marital Status	0.000	-0.001	-0.005	0.002	0.000	0.001
Employment Status	-0.009	-0.017	0.000	-0.011	0.000	0.000
Immigration Status	-0.003	0.000	-0.005	-0.001	0.001	0.000
Lives Alone	0.000	0.002	-0.001	0.000	0.000	0.000
Sub-Total (Non-Need)	-0.009	-0.005	-0.005	-0.019	0.003	0.003
Residual	-0.037	-0.021	-0.090	-0.004	-0.031	-0.069
Inequality Index (C_M)	-0.090	-0.090	-0.093	-0.069	-0.088	-0.109
Horizontal Inequity Index (HI)	-0.046	-0.026	-0.035	-0.023	-0.023	-0.047

x: Severity of chronic condition factors are not included in the analysis of asthmatics and diabetics.
note: Contributions may not accurately sum to the sub-total due to rounding errors.

Table 3.8: Contribution to Income-Related Inequality in the use of Specialist Services, the Number of Specialist Visits and the Dollar Value of Specialist Services Received, 3-year Utilization

	Number of Specialist Visits			Dollars of Specialist Services Received		
	Full Sample	Asthmatics	Diabetics	Full Sample	Asthmatics	Diabetics
	(1)	(2)	(3)	(4)	(5)	(6)
1. Probability of Specialist Use						
Need Factors						
Age-Sex Interactions	-0.016	-0.009	-0.013	-0.006	-0.005	-0.003
Self-Reported Health Status	-0.011	-0.009	-0.039	-0.002	-0.003	0.000
Severity of Chronic Conditions	-0.006	x	x	-0.001	x	x
Activity Limitation	-0.005	-0.004	-0.012	-0.001	0.000	0.000
BMI Status	-0.001	-0.004	-0.001	0.000	-0.001	0.000
SubTotal (Need)	-0.038	-0.027	-0.064	-0.011	-0.009	-0.003
Non-Need Factors						
(ln) Equivalized Household Income	0.008	0.046	-0.039	-0.003	0.008	-0.002
Urban	0.000	0.000	0.000	0.000	0.000	0.000
Education	-0.002	-0.007	-0.004	0.000	-0.004	0.001
Marital Status	0.002	-0.002	-0.003	0.001	0.000	0.001
Employment Status	-0.004	-0.002	-0.011	0.000	-0.002	0.000
Immigration Status	0.000	0.000	0.002	0.000	0.000	0.000
Lives Alone	0.000	-0.001	0.003	0.000	0.000	0.000
Sub-Total (Non-Need)	0.003	0.034	-0.053	-0.002	0.003	-0.001
Residual	0.027	-0.017	0.000	0.015	-0.004	-0.002
Inequality Index (C_M)	-0.007	-0.021	-0.046	0.002	-0.010	0.000
Horizontal Inequity Index (HI)	0.031	0.017	0.019	0.012	-0.001	0.004

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Table 3.8, continued

	Number of Specialist Visits			Dollars of Specialist Services Received		
	Full Sample	Asthmatics	Diabetics	Full Sample	Asthmatics	Diabetics
	(1)	(2)	(3)	(4)	(5)	(6)
2. Conditional Use of Specialists						
Need Factors						
Age-Sex Interactions	-0.002	-0.006	-0.013	-0.009	-0.005	-0.003
Self-Reported Health Status	-0.028	-0.059	-0.039	-0.031	-0.003	0.000
Severity of Chronic Conditions	-0.006	x	x	-0.013	x	x
Activity Limitation	-0.004	0.000	-0.012	-0.006	0.000	0.000
BMI Status	-0.002	-0.002	-0.001	-0.004	-0.001	0.000
SubTotal (Need)	-0.042	-0.067	-0.064	-0.065	-0.009	-0.003
Non-Need Factors						
(ln) Equivalized Household Income	0.016	0.028	-0.039	0.035	0.008	-0.002
Urban	0.000	0.000	0.000	0.000	0.000	0.000
Education	-0.005	0.005	-0.004	-0.004	-0.004	0.001
Marital Status	-0.006	-0.007	-0.003	0.001	0.000	0.001
Employment Status	-0.009	-0.003	-0.011	-0.010	-0.002	0.000
Immigration Status	0.006	-0.005	0.002	0.001	0.000	0.000
Lives Alone	0.000	0.000	0.003	0.000	0.000	0.000
Sub-Total (Non-Need)	0.001	0.017	-0.053	0.022	0.003	-0.001
Residual	0.002	0.024	-0.090	-0.029	0.003	-0.069
Inequality Index (C_M)	-0.039	-0.026	-0.045	-0.071	-0.057	-0.087
Horizontal Inequity Index (HI)	0.002	0.041	0.019	-0.006	0.014	-0.010

x: Severity of chronic condition factors are not included in the analysis of asthmatics and diabetics.
note: Contributions may not accurately sum to the sub-total due to rounding errors.

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3.A1 Appendix: CCHS - OHIP Sample Comparisons

Table 3.A1: Variables from the OHIP database used to define a Physician Visit

Physician Type	Specialty Claimed (*sp*)	Fee Schedule Code (*fsc*)
GP	00 GP	A001, A003-008, A100, A110, A112, A115, A813, A815, A888, A901, A903, A905, A933, A945, K004-008, K011-030, K032, K033, K037, K039-041, K399, K623, K624, K629, K887-889
Specialist	02 Anaesthesia	A013-016, A215
	03 Dermatology	A23-26
	03 General Surgery	A033-036, A935
	04 Neurosurgery	A043-046, A935
	06 Orthopaedic Surgery	A063-066, A935
	07 Geriatrics	A071, A073-076, A078, A375, A775
	08 Plastic Surgery	A083-086, A935
	09 Cardiovascular & Thoracic Surgery	A093-096, A935
	13 Internal Medicine	A131, A133-136, A138, A435
	18 Neurology	A181, A183-186, A188, A385
	19 Psychiatry	A193-198, A395, A695, A795, A895, K192, K194-198, K203-206, K208, K209, K620, K623, K624, K629
	20 Obstetrics & Gynaecology	A203-206, A935
	22 Genetics	A221, A225, A226, A325, K16, K44, K222, K223
	23 Ophthalmology	A115, A230, A233-237, A239, A250-252, A254, A935

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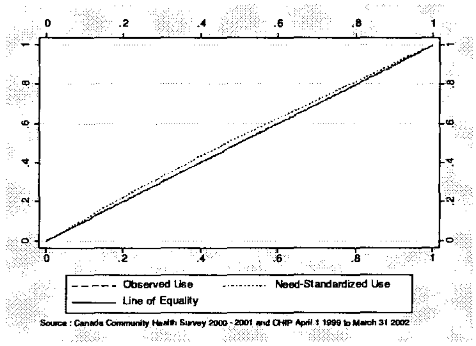
Table 3.A1, continued

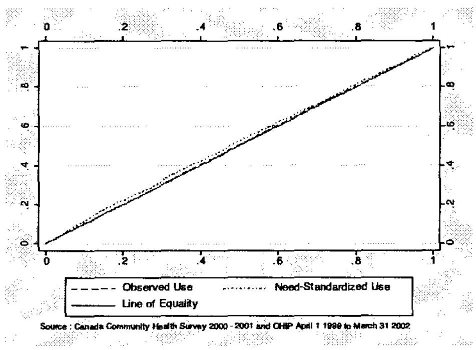
Physician Type	Specialty Claimed (*sp*)	Fee Schedule Code (*fsc*)
	24 Otololaryngology	A243-246, A935
	26 Paediatrics	A263-266, A565, A261, A262, A661, A665, A667, K122, K123, K267, K269
	28 Laboratory Medicine	A283-286, A585, A586
	33 Diagnostic Radiology	A331, A335, A338, A365
	34 Therapeutic Radiology	A340, A341, A343, A345, A346, A348, A745
	35 Urology	A353-356, A935
	41 Gastroenterology	A411, A413-416, A418, A545
	47 Respiratory Disease	A471, A473-476, A478, A575
	48 Rheumatology	A481, A483-486, A488, A595
	60 Cardiology	A601, A603-606, A608, A675, E078
	61 Haematology	A611, A613-616, A618, A655
	62 Clinical Immunology	A525, A621, A623-626, A628
	63 Nuclear Medicine	A635, A636, A638, A735, A835
	64 General Thoracic Surgery	A643-646, A935

3.A2 Appendix: Concentration Curves

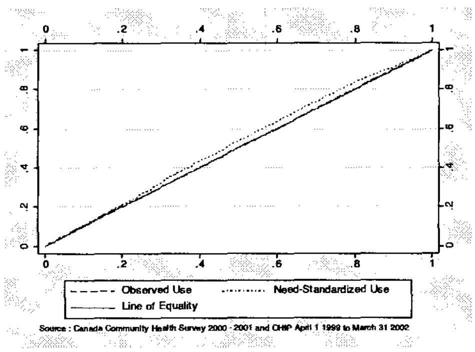
Figure 3.2: Concentration Curves, the Probability of a GP Visit



(a) Full Sample

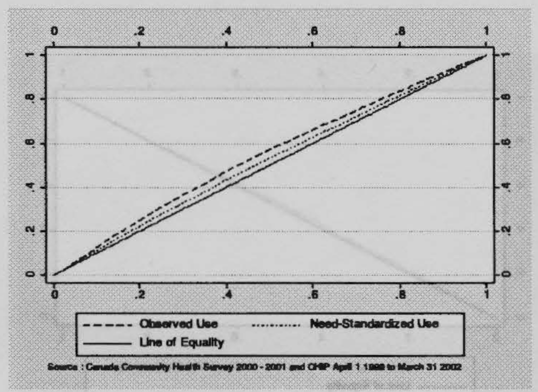


(b) Asthmatics

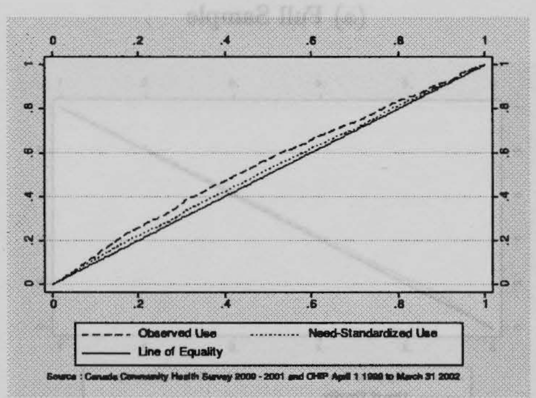


(c) Diabetics

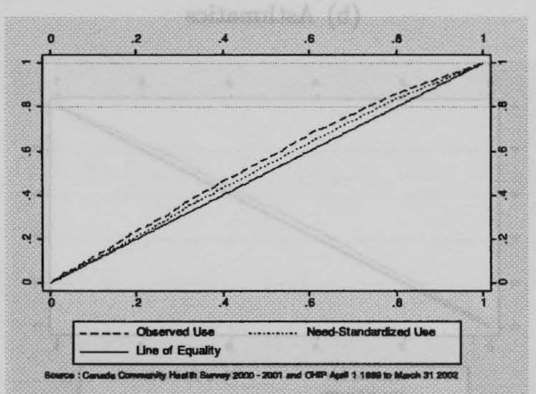
Figure 3.3: Concentration Curves, the Conditional Number of GP Visits



(a) Full Sample

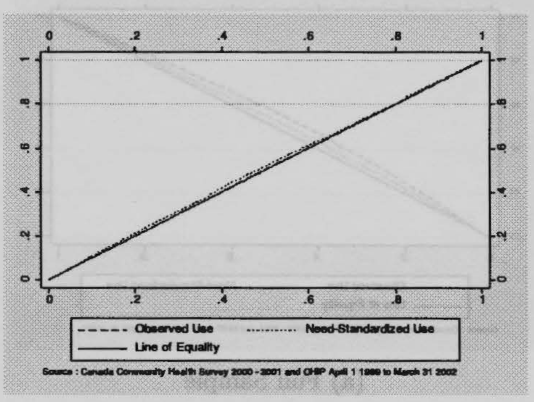


(b) Asthmatics

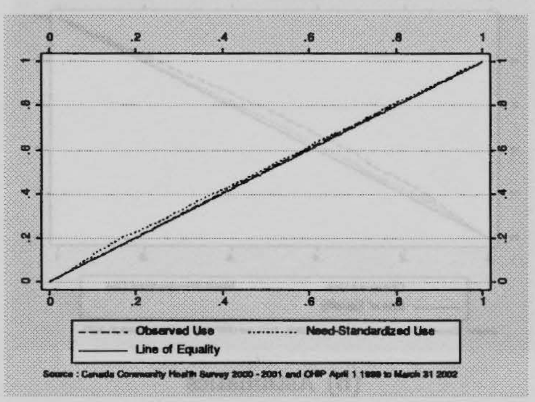


(c) Diabetics

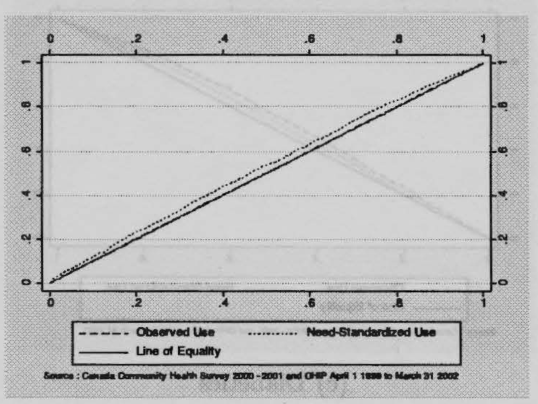
Figure 3.4: Concentration Curves, the Probability of Receiving a Dollar of GP Services



(a) Full Sample

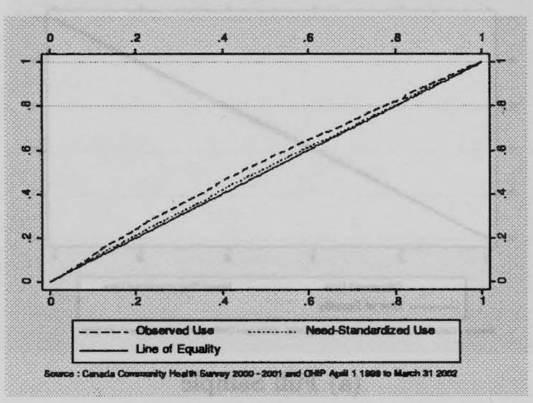


(b) Asthmatics

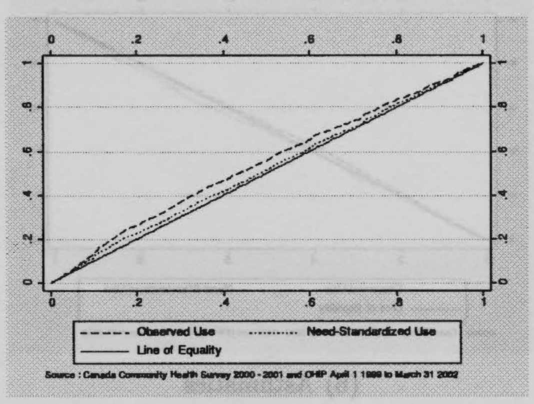


(c) Diabetics

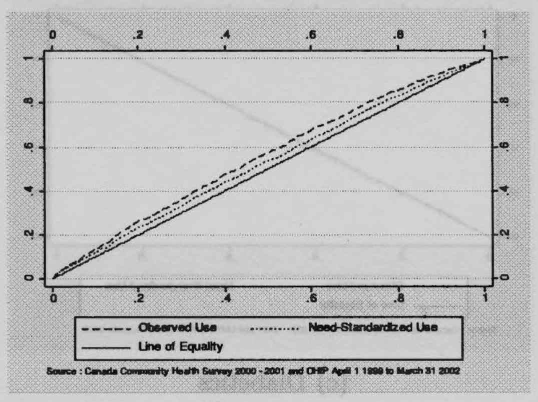
Figure 3.5: Concentration Curves, the Conditional Dollars of GP Services Received



(a) Full Sample

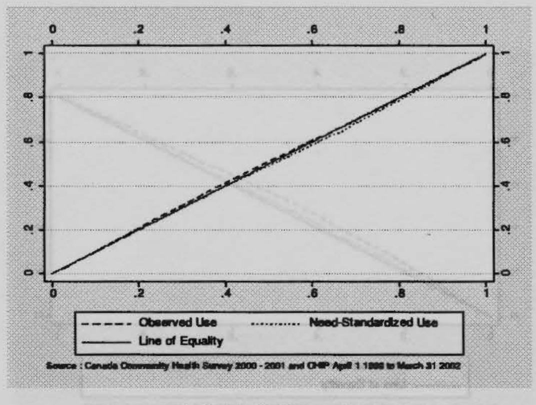


(b) Asthmatics

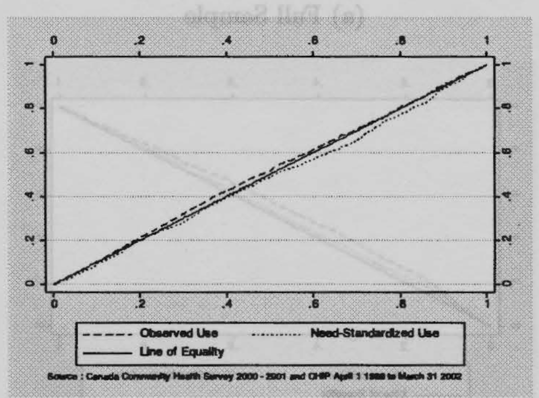


(c) Diabetics

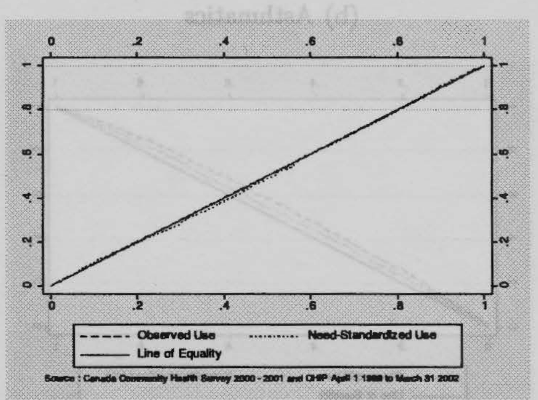
Figure 3.6: Concentration Curves, the Probability of a Specialist Visit



(a) Full Sample

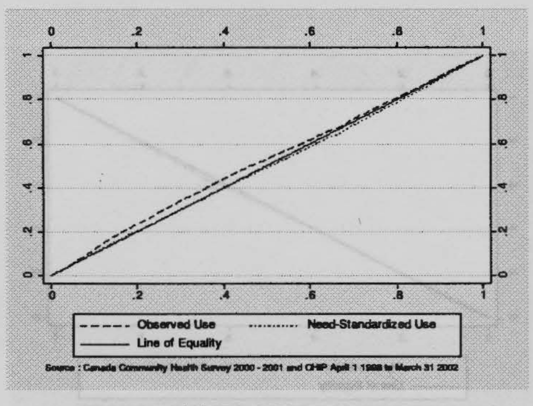


(b) Asthmatics

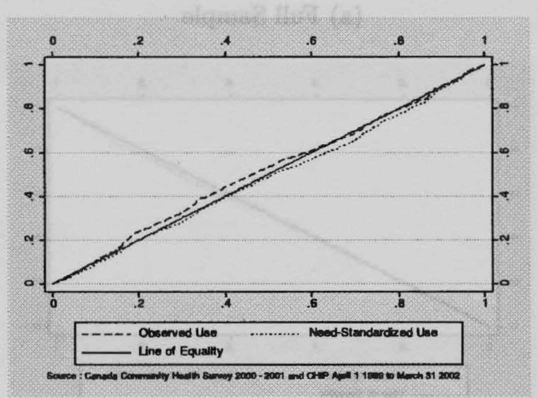


(c) Diabetics

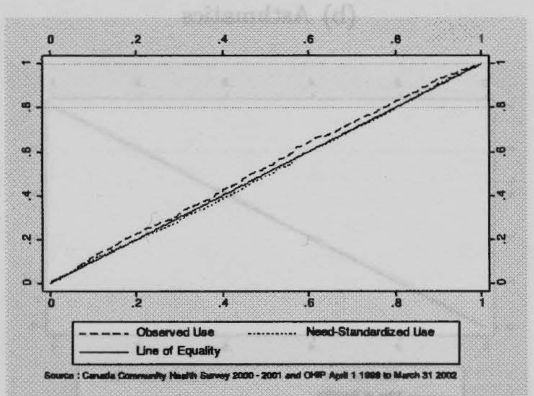
Figure 3.7: Concentration Curves, the Conditional Number of Specialist Visits



(a) Full Sample

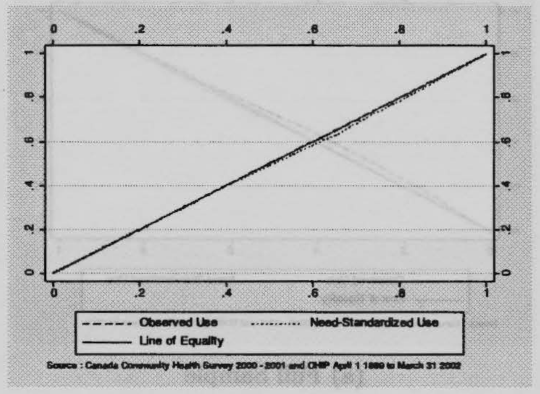


(b) Asthmatics

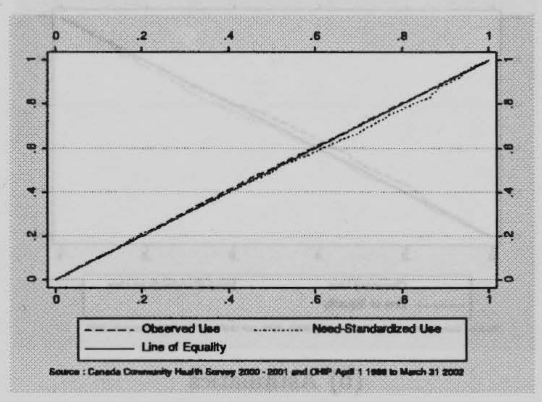


(c) Diabetics

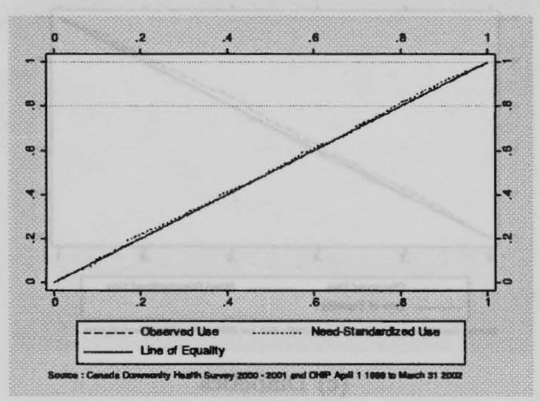
Figure 3.8: Concentration Curves, the Probability of Receiving a Dollar of Specialist Services



(a) Full Sample

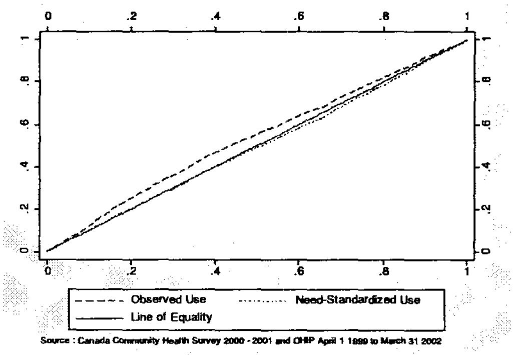


(b) Asthmatics

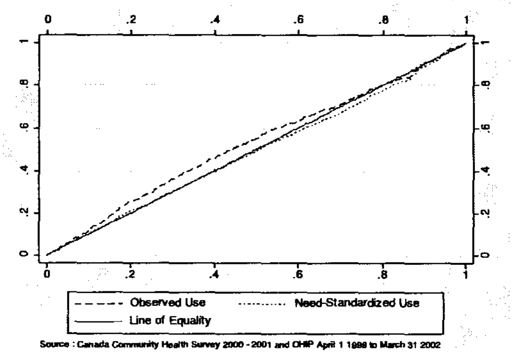


(c) Diabetics

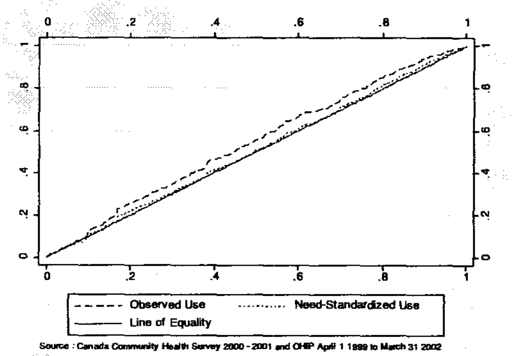
Figure 3.9: Concentration Curves, the Conditional Dollars of Specialist Services Received



(a) Full Sample



(b) Asthmatics



(c) Diabetics

3.A3 Appendix: Coefficient Estimates, Models of GP Use

Table 3.A2: Coefficients Estimates, the Probability of a GP Visits (Logit) and the Conditional Number of GP Visits (TZNB), by Sample

	Full Sample		Asthmatics		Diabetics	
Model:	Logit	TZNB	Logit	TZNB	Logit	TZNB
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.057 ***	0.021 ***	0.086	0.044 ***	-0.378 ***	0.036 ***
	(0.020)	(0.004)	(0.084)	(0.011)	(0.140)	(0.013)
Age^2	0.001 ***	0.000 ***	-0.001	0.000 ***	0.004 ***	0.000 *
	0.000	0.000	(0.001)	0.000	(0.001)	0.000
Female	1.933 ***	0.792 ***	3.611 ***	0.733 ***	-0.779	1.263 ***
	(0.246)	(0.058)	(1.011)	(0.136)	(1.598)	(0.213)
Female x Age	-0.028 ***	-0.011 ***	-0.061 ***	-0.010 ***	0.015	-0.018 ***
	(0.005)	(0.001)	(0.021)	(0.003)	(0.026)	(0.003)
Very Good (SRH)	-0.032	0.150 ***	0.448	0.149 **	0.554	0.245 **
	(0.087)	(0.031)	(0.390)	(0.075)	(0.847)	(0.114)
Good (SRH)	0.061	0.245 ***	-0.305	0.358 ***	0.936	0.319 ***
	(0.108)	(0.030)	(0.434)	(0.080)	(0.854)	(0.112)
Fair (SRH)	-0.147	0.420 ***	-0.303	0.567 ***	0.176	0.380 ***
	(0.174)	(0.038)	(0.534)	(0.095)	(0.851)	(0.118)
Poor (SRH)	0.510 *	0.612 ***	0.627	0.776 ***	2.344 **	0.503 ***
	(0.308)	(0.058)	(0.679)	(0.111)	(1.133)	(0.122)
Major CC	0.938 ***	0.476 ***				
	(0.227)	(0.036)				
Medium CC	1.077 ***	0.501 ***				
	(0.143)	(0.032)				
Minor CC	0.675 ***	0.254 ***				
	(0.079)	(0.029)				
Activity	0.146	0.184 ***	0.445	0.092 *	-0.075	0.197 ***
Limitation	(0.105)	(0.024)	(0.355)	(0.052)	(0.385)	(0.050)
Low BMI	-0.045	-0.094	-0.513	0.069	0.000	0.000
	(0.283)	(0.097)	(0.741)	(0.165)	0.000	0.000
Over Weight	0.027	-0.031	0.623 *	-0.113 *	1.143 **	0.051
	(0.088)	(0.030)	(0.377)	(0.063)	(0.479)	(0.086)
Obese	-0.063	0.019	1.269 ***	0.015	0.149	0.040
	(0.099)	(0.027)	(0.376)	(0.062)	(0.476)	(0.084)
(ln) HH Income	0.066	0.000	-0.042	-0.019	-0.183	-0.042 **
	(0.043)	(0.008)	(0.103)	(0.018)	(0.236)	(0.020)
Urban	0.036	0.140 ***	0.100	0.132 **	-0.375	0.031
	(0.077)	(0.020)	(0.338)	(0.061)	(0.507)	(0.056)
Less Than	-0.121	0.000	-0.699	0.018	0.446	0.019
High-School	(0.140)	(0.033)	(0.471)	(0.072)	(0.482)	(0.064)
Some Post-	0.254 *	-0.010	-1.033 *	0.131	0.387	-0.102
Secondary	(0.151)	(0.042)	(0.545)	(0.105)	(0.614)	(0.088)
Post-Secondary	0.161 *	-0.067 ***	-0.771 **	0.001	0.974 **	-0.084
	(0.097)	(0.026)	(0.385)	(0.057)	(0.467)	(0.064)
Single	-0.348 **	0.003	0.902	0.036	-0.122	0.091
	(0.141)	(0.037)	(0.573)	(0.087)	(0.981)	(0.105)

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Table 3.A2, continued

Model:	Full Sample Logit		Full Sample TZNB		Asthmatics Logit		Asthmatics TZNB		Diabetics Logit		Diabetics TZNB	
	(1)		(2)		(3)		(4)		(5)		(6)	
Widowed /	0.070		0.085	***	1.606	**	0.060		0.659		0.155	*
Divorced	(0.162)		(0.032)		(0.725)		(0.075)		(0.585)		(0.084)	
Not Currently	0.073		0.117	***	0.132		0.185	**	0.476		-0.025	
Working	(0.103)		(0.032)		(0.373)		(0.073)		(0.670)		(0.084)	
No Work in the	0.000		0.147	***	-0.656	*	0.179	***	0.143		0.112	
Last Year	(0.135)		(0.028)		(0.348)		(0.065)		(0.571)		(0.074)	
Working - Not	-0.130		0.253	***	0.169		0.327	**	-1.951		0.248	**
Applicable	(0.344)		(0.058)		(1.341)		(0.140)		(1.093)		(0.121)	
Working - Not	0.689		0.033									
Stated	(0.519)		(0.160)									
Recent Immigrant	-0.249		0.156	***	-1.198	**	0.062		0.395		0.171	
	(0.168)		(0.056)		(0.606)		(0.123)		(0.953)		(0.218)	
Long Term	0.242	**	0.090	***	-0.293		-0.215	***	0.077		0.027	
Immigrant	(0.104)		(0.025)		(0.475)		(0.064)		(0.478)		(0.051)	
Lives Alone	-0.195		0.007		-1.403	**	0.043		-0.081		-0.066	***
	(0.129)		(0.036)		(0.581)		(0.078)		(0.712)		(0.080)	
Constant	2.045	***	0.983	***	0.675		1.064	***	12.469	***	1.491	
	(0.674)		(0.135)		(1.786)		(0.346)		(4.770)		(0.439)	
$\ln(\alpha)$			-0.560	***			-0.846	***			-1.140	***
			(0.029)				(0.059)				(0.067)	
N	26663		24586		2359		2256		1507		1450	

TZNB: truncated at zero, negative binomial model. *CC:* Chronic Condition

A logit model is used for the probability of a GP visit. A TZNB model is used for the conditional number of GP visits.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A3: Coefficients Estimates, the Probability of receiving a dollar of GP services (Logit) and the Conditional Dollars of GP Services Received (GLM), by Sample

	Full Sample		Asthmatics		Diabetics	
Model:	Logit	GLM	Logit	GLM	Logit	GLM
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.082 ***	0.021 ***	0.031	0.046 ***	-0.257 *	0.015
	(0.024)	(0.006)	(0.108)	(0.011)	(0.138)	(0.015)
Age^2	0.001 ***	0.000 *	0.000	0.000 ***	0.002 *	0.000
	0.000	0.000	(0.001)	0.000	(0.001)	0.000
Female	2.125 ***	0.832 ***	4.533 ***	0.848 ***	0.274	0.926 ***
	(0.261)	(0.083)	(1.443)	(0.136)	(1.870)	(0.247)
Female x Age	-0.030 ***	-0.012 ***	-0.067 **	-0.012 ***	0.010	-0.014 ***
	(0.006)	(0.001)	(0.029)	(0.003)	(0.031)	(0.004)
Very Good (SRH)	0.029	0.185 ***	0.178	0.186 **	-2.538 **	0.205
	(0.092)	(0.060)	(0.514)	(0.074)	(1.129)	(0.153)
Good (SRH)	0.218 *	0.222 ***	-0.370	0.353 ***	-2.512 **	0.342 **
	(0.112)	(0.038)	(0.616)	(0.078)	(1.128)	(0.155)
Fair (SRH)	0.172	0.423 ***	0.056	0.536 ***	-2.385 **	0.414 **
	(0.220)	(0.052)	(0.734)	(0.094)	(1.110)	(0.162)
Poor (SRH)	1.447 ***	0.690 ***	2.603 **	0.842 ***	-1.385	0.653 ***
	(0.453)	(0.084)	(1.247)	(0.120)	(1.365)	(0.166)
Major CC	1.038 ***	0.494 ***				
	(0.318)	(0.068)				
Medium CC	1.239 ***	0.346 ***				
	(0.170)	(0.059)				
Minor CC	0.700 ***	0.185 ***				
	(0.085)	(0.060)				
Activity	0.275 **	0.184 ***	0.164	0.105 *	0.511	0.249 ***
Limitation	(0.123)	(0.032)	(0.446)	(0.055)	(0.435)	(0.060)
Low BMI	0.230	-0.107	0.405	0.151	0.000	0.000
	(0.294)	(0.089)	(1.447)	(0.203)	0.000	0.000
Over Weight	-0.063	-0.114 **	0.664	-0.112 *	1.137	0.076
	(0.094)	(0.057)	(0.455)	(0.064)	(0.737)	(0.102)
Obese	-0.154	-0.014	0.690	0.058	0.229	0.025
	(0.109)	(0.045)	(0.471)	(0.066)	(0.723)	(0.094)
(ln) HH Income	0.029	0.010	-0.189	-0.003	0.030	-0.068 **
	(0.031)	(0.010)	(0.263)	(0.017)	(0.144)	(0.031)
Urban	0.257 ***	0.150 ***	0.455	0.104	-0.244	-0.010
	(0.082)	(0.031)	(0.393)	(0.063)	(0.649)	(0.072)
Less Than	-0.175	0.003	-0.519	0.053	0.804	0.075
High-School	(0.160)	(0.035)	(0.594)	(0.085)	(0.651)	(0.071)
Some Post-	0.282 *	0.032	-0.716	0.101	1.127	0.071
Secondary	(0.169)	(0.047)	(0.651)	(0.100)	(1.008)	(0.126)
Post-Secondary	0.259 **	0.009	-0.763 *	0.051	0.977 *	-0.009
	(0.103)	(0.034)	(0.434)	(0.064)	(0.582)	(0.075)
Single	-0.407 ***	-0.108 **	0.545	0.001	-1.501	0.059
	(0.154)	(0.046)	(0.765)	(0.087)	(1.133)	(0.126)
Widowed /	0.129	0.051	1.281	0.102	0.024	0.195 **
Divorced	(0.168)	(0.036)	(0.853)	(0.100)	(0.728)	(0.097)
Not Currently	-0.062	0.156 ***	0.152	0.219 ***	-0.351	0.044

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Table 3.A3, continued

	Full Sample		Asthmatics		Diabetics	
Model:	Logit	GLM	Logit	GLM	Logit	GLM
	(1)	(2)	(3)	(4)	(5)	(6)
Working	(0.109)	(0.043)	(0.451)	(0.077)	(0.642)	(0.102)
No Work in the	-0.005	0.153 ***	-0.743 *	0.244 ***	1.281	0.149 *
Last Year	(0.156)	(0.032)	(0.440)	(0.069)	(0.796)	(0.085)
Working - Not	-0.256	0.325 ***	0.148	0.525 ***	-0.029	0.242 *
Applicable	(0.422)	(0.075)	(1.807)	(0.140)	(1.247)	(0.134)
Working - Not	0.720	0.026				
Stated	(0.590)	(0.167)				
Recent Immigrant	-0.204	0.017	-1.634 **	0.011	0.684	0.172
	(0.181)	(0.070)	(0.757)	(0.139)	(1.184)	(0.229)
Long Term	0.284 **	-0.007	-0.557	-0.156 **	1.461 *	-0.001
Immigrant	(0.120)	(0.040)	(0.549)	(0.076)	(0.757)	(0.059)
Lives Alone	-0.189	0.036	-0.893	0.020	0.022	-0.048
	(0.139)	(0.039)	(0.619)	(0.096)	(0.867)	(0.095)
Constant	2.727 ***	4.628 ***	3.603	4.441 ***	11.426 **	5.919 ***
	(0.647)	(0.158)	(2.823)	(0.343)	(4.683)	(0.531)
N	26663	24968	2359	2291	1507	1476

GLM:generalzed linear model with a log-link function and a gamma family distribution.. *CC*: Chronic Condition

A logit model is used for the probability of receiving a dollar of GP services. A GLM model is used for the conditional dollar value of GP services received.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.A4 Appendix: Coefficient Estimates, Models of Specialist Use

Table 3.A4: Coefficients Estimates, the Probability of a Specialist Visit (Logit) and the Conditional Number of Specialist Visits (TZNB), by Sample

	Full Sample		Asthmatics		Diabetics	
Model:	Logit	TZNB	Logit	TZNB	Logit	TZNB
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.012	0.050 ***	0.073 **	0.042 *	-0.091	0.003
	(0.011)	(0.009)	(0.034)	(0.022)	(0.061)	(0.024)
Age^2	0.000 ***	0.000 ***	0.000	0.000	0.001 *	0.000
	0.000	0.000	0.000	0.000	(0.001)	0.000
Female	1.232 ***	0.514 ***	2.033 ***	0.025	2.577 ***	0.596
	(0.129)	(0.111)	(0.390)	(0.343)	(0.982)	(0.370)
Female x Age	-0.014 ***	-0.007 ***	-0.029 ***	0.000	-0.040 **	-0.009
	(0.003)	(0.002)	(0.009)	(0.006)	(0.016)	(0.006)
Very Good (SRH)	0.119 **	0.231 ***	-0.270	0.277	0.000	-0.199
	(0.053)	(0.058)	(0.196)	(0.190)	(0.381)	(0.283)
Good (SRH)	0.278 ***	0.391 ***	-0.015	0.583 ***	0.235	0.086
	(0.061)	(0.063)	(0.214)	(0.182)	(0.382)	(0.254)
Fair (SRH)	0.626 ***	0.670 ***	0.904 ***	0.657 ***	0.494	0.317
	(0.096)	(0.072)	(0.282)	(0.186)	(0.404)	(0.259)
Poor (SRH)	1.154 ***	0.901 ***	1.586 ***	1.077 ***	0.987 *	0.486 *
	(0.161)	(0.090)	(0.385)	(0.202)	(0.595)	(0.265)
Major CC	1.619 ***	0.563 ***				
	(0.129)	(0.075)				
Medium CC	0.555 ***	0.298 ***				
	(0.074)	(0.070)				
Minor CC	0.473 ***	0.249 ***				
	(0.050)	(0.057)				
Activity Limitation	0.399 ***	0.168 ***	0.271 *	0.003	0.327	0.202 *
	(0.053)	(0.042)	(0.159)	(0.110)	(0.214)	(0.105)
Low BMI	0.022	-0.006	0.053	0.058		
	(0.176)	(0.115)	(0.472)	(0.274)		
Over Weight	-0.048	-0.055	-0.089	0.147	-0.181	-0.165
	(0.054)	(0.056)	(0.183)	(0.164)	(0.377)	(0.194)
Obese	0.043	0.051	0.382 **	0.083	-0.268	-0.102
	(0.057)	(0.062)	(0.173)	(0.120)	(0.344)	(0.167)
(ln) HH Income	0.064 ***	0.021	0.073	0.043	0.061	-0.027
	(0.021)	(0.018)	(0.064)	(0.039)	(0.072)	(0.027)
Urban	0.253 ***	0.209 ***	0.190	0.223 *	0.279	0.307 ***
	(0.047)	(0.043)	(0.168)	(0.119)	(0.243)	(0.109)
Less Than High-School	-0.025	-0.060	0.147	-0.259 *	-0.558 *	-0.022
	(0.085)	(0.063)	(0.267)	(0.145)	(0.335)	(0.115)
Some Post-Secondary	0.084	-0.014	-0.155	0.149	-0.233	0.146
	(0.094)	(0.077)	(0.284)	(0.181)	(0.462)	(0.149)
Post-Secondary	0.122 **	0.087 *	0.273	0.094	0.036	0.068
	(0.060)	(0.050)	(0.211)	(0.127)	(0.332)	(0.115)
Single	-0.239 ***	0.292 ***	0.141	0.239 *	0.286	0.063
	(0.075)	(0.074)	(0.224)	(0.143)	(0.450)	(0.180)

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Table 3.A4, continued

	Full Sample		Asthmatics		Diabetics	
Model:	Logit	TZNB	Logit	TZNB	Logit	TZNB
	(1)	(2)	(3)	(4)	(5)	(6)
Widowed /	-0.138 *	0.106 *	-0.112	-0.139	0.027	0.024
Divorced	(0.074)	(0.064)	(0.233)	(0.143)	(0.459)	(0.140)
Not Currently	0.173 ***	0.140 **	0.113	0.000	-0.103	0.071
Working	(0.058)	(0.059)	(0.177)	(0.166)	(0.325)	(0.174)
No Work in the	0.151 **	0.282 ***	-0.090	0.303 **	0.355	0.256 *
Last Year	(0.072)	(0.057)	(0.214)	(0.134)	(0.304)	(0.142)
Working - Not	0.028	0.274 ***	0.271	0.281	-0.519	0.081
Applicable	(0.173)	(0.103)	(0.633)	(0.266)	(0.615)	(0.239)
Working - Not	0.070	-0.292				
Stated	(0.389)	(0.273)				
Recent Immigrant	-0.088	-0.128	0.042	0.504	-0.795	-0.198
	(0.103)	(0.094)	(0.681)	(0.390)	(0.583)	(0.393)
Long Term	0.115 *	-0.011	0.306	-0.055	0.713 **	-0.115
Immigrant	(0.059)	(0.048)	(0.275)	(0.140)	(0.291)	(0.097)
Lives Alone	0.041	0.027	-0.178	0.202	0.251	-0.015
	(0.070)	(0.069)	(0.230)	(0.162)	(0.425)	(0.140)
Constant	-1.766 ***	-1.248 ***	-3.387 ***	-0.839	1.742	1.518 **
	(0.333)	(0.330)	(1.034)	(0.879)	(1.906)	(0.710)
		0.468 ***		0.319 **		-0.153
		(0.056)		(0.152)		(0.098)
N	26663	16599	2359	1682	1507	1281

TZNB: truncated at zero, negative binomial model. *CC*: Chronic Condition

A logit model is used for the probability of a specialist visit. A TZNB model is used for the conditional number of specialist visits.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A5: Coefficients Estimates, the Probability of receiving a dollar of Specialist services (Logit) and the Conditional Dollars of Specialist Services Received (GLM), by Sample

	Full Sample		Asthmatics		Diabetics	
Model:	Logit	GLM	Logit	GLM	Logit	GLM
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.027	0.035 ***	-0.006	0.057 ***	-0.132	-0.008
	(0.017)	(0.007)	(0.063)	(0.015)	(0.112)	(0.022)
Age^2	0.001 ***	0.000 **	0.001	0.000 **	0.002	0.000
	0.000	0.000	(0.001)	0.000	(0.001)	0.000
Female	2.108 ***	0.972 ***	3.178 ***	0.986 ***	5.224 ***	1.209
	(0.200)	(0.091)	(0.678)	(0.225)	(1.934)	(0.339)
Female x Age	-0.024 ***	-0.014 ***	-0.041 **	-0.014 ***	-0.077 **	-0.021
	(0.004)	(0.002)	(0.017)	(0.004)	(0.031)	(0.005)
Very Good (SRH)	0.009	0.133 ***	-0.082	-0.072	0.021	-0.225
	(0.072)	(0.037)	(0.310)	(0.132)	(0.964)	(0.206)
Good (SRH)	0.138	0.344 ***	0.116	0.329 **	0.045	0.053
	(0.088)	(0.046)	(0.372)	(0.131)	(0.939)	(0.193)
Fair (SRH)	0.312 *	0.614 ***	0.000	0.000	0.000	0.000
	(0.172)	(0.060)	0.000	0.000	0.000	0.000
Poor (SRH)	1.697 ***	0.775 ***	0.000	0.000	0.000	0.000
	(0.379)	(0.074)	0.000	0.000	0.000	0.000
Fair / Poor (SRH)			0.943 *	0.696 ***	0.884	0.374
			(0.527)	(0.133)	(0.983)	(0.204)
Major CC	2.011 ***	0.834 ***				
	(0.384)	(0.069)				
Medium CC	1.298 ***	0.350 ***				
	(0.127)	(0.048)				
Minor CC	0.691 ***	0.253 ***				
	(0.067)	(0.037)				
Activity	0.462 ***	0.232 ***	0.167	0.078	1.010 **	0.476
Limitation	(0.089)	(0.038)	(0.284)	(0.079)	(0.506)	(0.103)
Low BMI	0.381	-0.108	0.000	0.000		
	(0.262)	(0.101)	0.000	0.000		
Over Weight	0.025	-0.072 *	-0.103	-0.069	-0.401	-0.070
	(0.072)	(0.039)	(0.281)	(0.108)	(0.809)	(0.180)
Obese	-0.067	0.090 **	0.420	0.061	-0.803	-0.230
	(0.086)	(0.046)	(0.298)	(0.091)	(0.700)	(0.162)
(ln) HH Income	0.067 ***	-0.016	-0.097	0.019	0.058	-0.018
	(0.023)	(0.028)	(0.084)	(0.029)	(0.190)	(0.028)
Urban	0.264 ***	0.139 ***	0.925 ***	0.115	-0.409	0.277
	(0.066)	(0.037)	(0.252)	(0.087)	(0.636)	(0.095)
Less Than	-0.044	-0.073	-0.051	-0.091	-1.525 **	0.167
High-School	(0.123)	(0.057)	(0.564)	(0.108)	(0.743)	(0.122)
Some Post-	0.147	-0.008	-0.257	0.084	0.989	0.157
Secondary	(0.151)	(0.087)	(0.458)	(0.139)	(1.356)	(0.174)
Post-Secondary	0.240 ***	0.012	0.080	0.165	0.027	0.140
	(0.079)	(0.046)	(0.299)	(0.106)	(0.753)	(0.115)
Single	-0.377 ***	-0.035	-0.290	0.084	-1.451 *	-0.156
	(0.110)	(0.056)	(0.368)	(0.105)	(0.750)	(0.163)
Widowed /	-0.260 **	0.043	0.292	-0.091	-0.695	-0.078

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Table 3.A5, continued

	Full Sample		Asthmatics		Diabetics	
Model:	Logit	GLM	Logit	GLM	Logit	GLM
	(1)	(2)	(3)	(4)	(5)	(6)
Divorced	(0.123)	(0.051)	(0.416)	(0.104)	(0.694)	(0.133)
Not Currently	0.041	0.137 ***	0.585 *	0.074	0.056	0.107
Working	(0.082)	(0.043)	(0.303)	(0.103)	(0.826)	(0.161)
No Work in the	0.089	0.221 ***	-0.080	0.275 ***	0.246	0.414
Last Year	(0.115)	(0.046)	(0.446)	(0.095)	(0.655)	(0.142)
Working - Not	-0.446	0.198 **	-1.490	0.452 **	-0.219	0.062
Applicable	(0.296)	(0.094)	(1.186)	(0.202)	(1.478)	(0.246)
Working - Not	0.119	0.005				
Stated	(0.514)	(0.170)				
Recent Immigrant	-0.195	-0.091	-0.373	0.283	-1.145	-0.469
	(0.134)	(0.065)	(1.167)	(0.273)	(0.849)	(0.250)
Long Term	0.224 **	0.013	-0.175	0.023	1.530 **	0.015
Immigrant	(0.099)	(0.037)	(0.447)	(0.114)	(0.705)	(0.097)
Lives Alone	-0.060	-0.010	-0.324	0.001	0.810	0.152
	(0.104)	(0.055)	(0.420)	(0.114)	(0.781)	(0.136)
Constant	-0.234	4.797 ***	0.848	4.224 ***	5.338	6.521
	(0.466)	(0.398)	(1.543)	(0.568)	(4.454)	(0.689)
N	26663	23276	2359	2190	1507	1475

GLM:generalzed linear model with a log-link function and a gamma family distribution.. *CC*: Chronic Condition

A logit model is used for the probability of receiving a dollar of specialist services. A GLM model is used for the conditional dollar value of specialist services received.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Conclusion

This thesis has investigated empirical issues related to the economics of the utilization of physician services. The broad themes of this thesis have dealt with methodological issues in the statistical modeling of the number of physician visits, as well as addressing policy concerns around access to physician services due to variations in physician supply or financial barriers.

The first essay explores how the choice of statistical model and controlling for unobserved heterogeneity can affect an individual's predicted number of physician visits and the incremental effect (IE) of a change in an individual's characteristics on their predicted number of physician visits. The specific application is to the number of general practitioner (GP) visits.

The results show a nonparametric kernel conditional density estimator provides a better fit to the observed distribution of the number of GP visits than the state-of-the-art parametric latent class negative binomial model. The results also show meaningful differences between the nonparametric and the parametric model in the IEs, but no meaningful differences in the IEs between a panel model with and without endogeneity correction, or between a cross-section model and a panel model without endogeneity correction. The largest difference is in the right tail of the distribution. The IEs from the latent class negative binomial model are up to 190 times the magnitude of the IEs from the kernel conditional density estimator. This is important since the right tail of the distribution represents high-use individuals whose utilization is often the hardest to predict but represents a disproportionate share of total utilization.

The results of the first essay suggest nonparametric kernel methods are well suited to broader applications in the analysis of health care utilization, such as risk-adjusted capitation payments or in measuring income-related inequality in health care use. This is particularly important given the nature of health care utilization data such as over-dispersion, a large proportion of zeros, and long right tails. A pragmatic consideration when using nonparametric kernel methods is their computational intensity. To use nonparametric kernel methods requires sufficient computing power in order to run in a reasonable amount of time. If sufficient computing power is not available then the use of nonparametric kernel methods can be limited.

The second essay addressed the persistent policy concern of how variations in the supply of GPs and specialists may affect the mix of GP and specialist services received. Two main effects between the supply of each type of physician and the use of each type of physician service are discussed: the supply effect, and the taste effect.

The supply effect reveals a substitute relationship between GPs and specialists, since the supply variables proxy for time costs to patients and clinical and/or economic incentives of physicians. The supply effect captures the relationship between the full price (money and time costs) of one physician type and the supply of the other. The supply effect shows a 10% increase in GP supply is associated with a 0.9% increase in the number of GP visits and a 1.2% increase in the dollar value of GP services received, but is associated with a 1.3% decrease in the number of specialist visits and a 1.0% decrease in the dollar value of specialist services received. An increase in specialist supply of 15% is associated with a 0.6% decrease in the number of GP visits and a 0.8% decrease in the dollar value of GP services received, but is associated with a 2.1% increase in the number of specialist visits and the dollar value of specialist services.

The taste effect represents people's preferences for health care, and incorporate their health status and general attitudes towards health care. The taste effect is not a causal relationship and should not be interpreted in the substitute/complement framework. We may expect the use of GPs and specialists to be positively correlated because they are both determined by a patient's fundamental taste for health care. An increase of one GP visit is associated with an increase in the number of specialist visits by 0.1 of a visit while an increase of one specialist visit is associated with an increase in the number of GP visits by almost 0.3 of a visit. An increase in the dollar value of GP services received of $1 is associated with a $0.60 increase the dollar value of specialist services received, while an increase in the dollar value of specialist services received of $1 is associated with a $0.10 increase the dollar value of GP services received.

Results from the second essay suggest concerns around the effect of variations in physician supply on the mix of physician services received may be overstated. For example, concerns of patient access and receipt of care in the presence of a shortage of specialists may be mitigated, all else equal, if patients are able to substitute GP services for specialist services.

Finally, the third essay explored income-related inequities in physician utilization using the concentration index approach, while marrying a condition specific approach, focusing on asthmatics and diabetics, with a population based approach using data representative of the entire population. Income-related inequality in the use of physician services is an important indicator of how the Canadian health care system is doing to meet its objective of facilitating reasonable access without financial barriers to physician services. The results showed non-need factors tend to make income-related inequalities favour the rich, while the need factors tend to make income-related inequalities favour the poor. Interestingly, income had no meaningful contribution to the probability of making a GP visit or the conditional number of GP visits for asthmatics and diabetics. However, income had a strong positive contribution towards the dollar value of GP services received for asthmatics and diabetics.

Both the second and third essays were only possible due to the availability of linked survey-administrative data. Linked survey-administrative data is a invaluable for research, but have been underutilized because of access barriers.