THREE ESSAYS IN HEALTH ECONOMICS

THREE ESSAYS IN HEALTH ECONOMICS

by

TAHA JAMAL, B.A., M.A.

A Thesis submitted to the School of Graduate Studies
in Partial Fulfillment of the Requirements for the Degree
Doctor of Philosophy

McMaster University

DOCTOR OF PHILOSOPHY (2015)	McMaster University
(Economics)	Hamilton, Ontario

Title:	Three essays in health economics
Author:	Taha Jamal, B.A. (Grinnell College), M.A. (Carleton University)
Supervisors:	Professor Jeremiah Hurley Professor Arthur Sweetman Professor Philip DeCicca
Number of Pages:	xiii, 176

Abstract

This thesis comprises three essays that empirically explore two important areas in health economics and policy: the valuation of medical innovations, and access to healthcare.

The first essay explores the role of new medical technologies in improving labor market outcomes by conducting a case study of a class of drugs used in the treatment of arthritis called Cox-2 inhibitors. Cox-2 drugs make an excellent case study for investigating the labor supply effects of medical innovation because the potential labor supply effects are large, and the market introduction of these drugs generates plausibly exogenous variation in their use. Using data from the Health and Retirement Study (HRS) and applying a difference-in-differences approach that compares individuals with arthritis to individuals without arthritis, I find that the introduction of Cox-2 drugs had a positive and significant impact on the probability of working among individuals with long-term arthritis. The effects are stronger among older individuals, the less-educated, and those working in physical occupations. These results highlight the importance of evaluating economic outcomes such as labor supply as part of an assessment of the overall benefits of medical technology.

The second essay builds on work by Allin et al. (2010) and Hurley et

al. (2011) that systematically analyzes the relationship between subjective unmet need and healthcare utilization. However, unlike previous work that uses cross-sectional data, I use panel data from the National Population Health Survey (NPHS) to control for fixed unobserved individual heterogeneity. In addition, healthcare utilization is modeled using latent class models for panel data, which outperform traditional hurdle models. The results of this study confirm previous findings of different patterns of healthcare utilization among individuals with system-related unmet needs, personal-related unmet needs, and no unmet needs. Individuals with personal-related unmet needs tended to use the same amount of services as expected based on their needs. On the other hand, individuals with system-related unmet needs were found to not only be high users of GP and specialist visits, they were also higher-than-expected users.

The third essay examines long-term changes in socioeconomic inequality and inequity in influenza immunization in Canada. The concentration index framework is applied using data from the following two Statistics Canada surveys: the cross-sectional component of the 1996/97 National Population Health Survey (NPHS), and the 2007/08 Canadian Community Health Survey (CCHS). The results show large variations in both coverage and inequity across provinces. In addition, increases in coverage levels across many provinces seem to have drawn disproportionately from those of higher socioeconomic status, contributing to a growing pro-rich inequity in utilization. These results highlight the need for more targeted efforts to help reduce inequities in vaccination.

Contents

List of Tables

List of Figures

Introduction

This thesis consists of three distinct essays that empirically investigate a range of issues in the field of health economics. The research focuses on two economic and policy-relevant themes: the valuation of medical innovations, and access to healthcare. The first essay examines the importance of the non-health benefits of medical innovation. The second essay addresses measurement of access, by examining the use of self-reported unmet needs for healthcare as measures of access. The third essay explores socioeconomic inequalities in access to and uptake of new healthcare technologies, by studying trends in coverage and inequity in influenza immunization in Canada.

Advances in medical technology over the last half century have revolutionized the practice of medicine. Innovative new ways to diagnose and treat illness have led to major improvements in longevity and quality of life (Cutler, 2004; Cutler and McClellan, 2001; Shapiro et al., 2001; Duggan and Garthwaite, 2010). However, technological change is also a major driver of healthcare costs, which have grown nine fold in per-capita terms over this period (Newhouse, 1992; Smith et al., 2009). Given rapidly accelerating trends in the development and diffusion of new medical innovations, the valuation of these innovations is an area of fundamental importance to policy makers.

The costs and health-related benefits of medical innovations are generally well-documented. However, their broader economic benefits are more difficult to measure, and are less well-documented (Duggan and Garthwaite, 2010). These economic benefits could potentially be large, as improvements to peoples health may increase their ability to participate in productive activities such as education, family care-giving, and formal work, and may reduce their reliance on supportive care. Insights into the extent and magnitude of such non-health benefits can help improve assessments of new medical technologies by more comprehensively accounting for all associated costs and benefits.

In the first essay, I provide empirical evidence on the non-health benefits of medical innovations by investigating the impact of a class of anti-arthritic drugs called Cox-2 selective inhibitors on labor supply outcomes. Examining the relationship between medical care use and labor supply outcomes is challenging, as unobserved, time-varying differences across individuals may be correlated with both healthcare use and with labor supply choices. One obvious confounder is disease severity, which is particularly difficult to measure and control for in observational data. Perhaps due to this identification problem, there is a paucity of direct evidence on the effect of medical treatments on economic outcomes.

The main contribution of the first essay is to exploit the introduction of Cox-2 drugs as a natural experiment to identify the causal effect of these drugs on labor supply. Cox-2 drugs make an excellent case study in this context for two important reasons. First, they represent a medical innovation with potentially large labor supply effects. Arthritis affects over 1 in 5 adults in North

America and is among the foremost causes of disability and work limitations. Second, Cox-2 drugs were introduced over a short time period, experienced rapid sales growth, and quickly became "blockbuster" mainstays in the treatment of arthritis. The market introduction of these drugs therefore offers a credible source of exogenous variation in their use, which helps overcome the identification challenge.

Using data from the U.S. Health and Retirement Study (HRS), I employ a difference-in-differences approach comparing individuals with arthritis to individuals without arthritis before and after the introduction of Cox-2 drugs. I find that the introduction of Cox-2 drugs had a positive and economically significant effect on the probability of working among individuals with long-term arthritis. Further analysis by subgroup reveal stronger effects among older individuals, the less-educated, and those working in physical occupations. No effects, however, are observed in the number of hours worked conditional on working. The findings from this study highlight the importance of taking broader economic benefits of medical innovation such as labor supply participation effects into account when evaluating medical technologies.

The second essay of this thesis contributes to the literature on access to healthcare, by investigating the relationship between subjective unmet needs for healthcare and healthcare utilization. Ensuring equity of access to healthcare is a fundamental policy objective and a critical dimension of health system performance in Canada and in most other industrialized countries. However, access is a complex and multi-faceted concept that is usually proxied using either utilization-based measures such as the number of physician visits per year, or self-assessed measures such as subjective unmet needs for healthcare. In comparison to utilization-based measures, subjective unmet needs are a broader measure of access, as they may arise due to features of the healthcare system or from personal circumstances and preferences. However, not all unmet needs represent an access problem as only select reasons for reporting an unmet need may be of policy concern. Insights into the relationship between healthcare utilization and the presence of an unmet need may provide a richer, more comprehensive understanding of the extent and causes of access barriers in the healthcare system.

Building on work by Allin et al. (2010) and Hurley et al. (2011), who systematically examine the relationship between subjective unmet need and healthcare utilization, the second essay makes a number of contributions to the literature. First, unlike previous work that uses cross-sectional data, this study employs panel data to control for unobserved individual heterogeneity. Unobserved individual heterogeneity may arise from unobserved health status, or unobserved personal preferences and attitudes toward health care. Second, healthcare utilization is modelled using latent class panel data models, which have been shown to significantly outperform hurdle models that have been employed in previous studies. As a result, more accurate predictions of the conditional mean of healthcare use can be obtained.

The second essay exploits panel data from the National Population Health Survey. In addition to asking respondents whether they experienced an unmet need, the survey also elicits their reasons for reporting the unmet need. Following Hurley et al. (2011), unmet needs are classified into two types: unmet needs due to reasons over which the individual may be responsible (personal-related unmet need); and unmet needs arising from factors beyond the control of the individual that may be construed as a failure of the healthcare system (system-related unmet need).

Estimating healthcare utilization using latent class panel data models developed by Bago d'Uva and Jones (2009) and using fixed effects methods, I find varying patterns of healthcare utilization among individuals with system-related unmet needs, individuals with personal-related unmet needs, and those with no unmet needs. Individuals with a personal-related unmet need tended to use the same services as expected based on their needs. Individuals with a system-related unmet need, however, were not only high users of GP and specialist visits, they were also higher than expected users. Moreover, the results suggest that this latter finding may be driven by the fact that these individuals may be on waiting lists and incurring additional visits to have their condition monitored.

While ensuring similar use of healthcare by people with similar health needs is a key policy objective, many factors influence whether and how individuals access the healthcare system, and socioeconomic disparities are observed in the utilization of several types of services. In particular, substantial socioeconomic inequalities have been observed in the access to and uptake of new healthcare technologies. For instance, higher educated individuals are more likely to use newer drugs (Lleras-Muney and Lichtenberg, 2005), and to participate in clinical trials to access novel treatments (Sateren et al., 2002). Moreover, given the rapid pace of technological innovation in healthcare, socioeconomic inequalities in access to and uptake of new healthcare technologies may play a mediating role in explaining the socioeconomic gradient in health (Link and Phelan, 1995; Glied and Lleras-Muney, 2008).

The third essay examines long-term trends in both coverage and socioeconomic inequity in influenza vaccination uptake in Canada, in the context of medical technology diffusion. Influenza is a serious public health concern that incurs significant costs to society in terms of excess mortality, morbidity, and lost productivity. Most industrialized countries mitigate the annual impact of influenza through publicly funded influenza vaccination programs, which traditionally target high-risk individuals such as the elderly and those with chronic conditions. The province of Ontario introduced the Universal Influenza Immunization Program (UIIP) in July 2000, and became the first major jurisdiction in the world to offer free flu shots to the entire population. While studies have linked the UIIP to increases in coverage, there is little evidence on its effects on socioeconomic inequity in vaccination.

The study contributes to the literature on preventive care and delivery in two important ways. First, it systematically examines socioeconomic inequity in vaccination uptake across provinces. Influenza vaccination targets and policies have largely focused on average coverage rates for select subpopulations, with little consideration to socioeconomic inequity in vaccination uptake. However, ensuring equity of access is a key policy objective, and average coverage rates can mask underlying socioeconomic inequalities in the uptake of vaccination. A better understanding of socioeconomic disparities in the distribution of flu shots may help identify barriers to vaccination uptake.

Second, this study increases our understanding of the merits of universal versus targeted vaccination programs. Under targeted programs, low coverage rates persist even amongst certain high-risk groups such as healthy seniors and young adults with chronic conditions for whom the vaccine is available free of charge. Whether universal programs are better able to fill such gaps in coverage is an important policy question.

Using data from two large, nationally representative Canadian household surveys - the 1996/97 National Population Health Survey (NPHS) and the 2007/08 Canadian Community Health Survey (CCHS) - I examine coverage and income related horizontal inequity in flu shot use across provinces before and after Ontario's UIIP. Large variations in coverage and inequity trends are observed across provinces, despite most provinces maintaining long-standing influenza immunization programs that offer near identical coverage (with the exception of Ontario). Moreover, increases in coverage levels appear to have drawn disproportionately from those of higher socioeconomic status, contributing to a growing pro-rich inequity in utilization. Despite offering universal vaccination, Ontario's coverage and inequity levels under the UIIP were matched over the long-term by Nova Scotia with a targeted program. The results highlight the need for more targeted efforts to help reduce inequities in vaccination.

References

Allin, S., M. Grignon, and J. LeGrand (2010). Subjective unmet need and utilization of heath care services in Canada: what are the equity implications? *Social Science & Medicine 70*, 465–472.

Bago d'Uva, T. and A. M. Jones (2009). Health care utilisation in Europe: New evidence from the ECHP. *Journal of Health Economics 28*, 265–279.

Cutler, D. M. (2004). *Your Money or Your Life*. Oxford, England: Oxford University Press.

Cutler, D. M. and M. McClellan (2001). Is technological change in medicine worth it? *Health Affairs 20*(5), 11–29.

Duggan, M. and C. Garthwaite (2010). Empirical evidence on the value of pharmaceuticals. In *The Handbook of the Economics of the Biopharmaceutical Industry*, pp. 3309–3416.

Glied, S. and A. Lleras-Muney (2008). Technological innovation and inequality in health. *Demography 45*(3), 741–761.

Hurley, J., T. Jamal, M. Grignon, and S. Allin (2011). The relationship between self-reported unmet need for health care and health care utilization. McMaster Research Data Centre Research Paper No. 23, McMaster University, Hamilton, Ontario, Canada.

Link, B. and J. Phelan (1995). Social conditions as fundamental causes of disease. *Journal of Health & Social Behavior extra issue*, 80–94.

Lleras-Muney, A. and F. Lichtenberg (2005). The effect of education on medical technology adoption: Are the more educated more likely to use new drugs? *Special issue of the Annales d'Economie et de Statistique in memory of Zvi Griliches 79/80*.

Newhouse, J. P. (1992). Medical care costs: How much welfare loss? *The Journal of Economic Perspectives 6*(3), 3–21.

Sateren, W. B., E. L. Trimble, J. Abrams, O. Brawley, N. Breen, L. Ford, M. McCabe, R. Kaplan, M. Smith, R. Ungerleider, and M. C. Christian (2002). How sociodemographics, presence of oncology specialists, and hospital cancer programs affect accrual to cancer treatment trials. *Journal of Clinical Oncology 20*(8), 2109–2117.

Shapiro, I., M. Shapiro, and D.W.Wilcox (2001). Measuring the value of cataract surgery. In D. Cutler and E. Berndt (Eds.), *Medical Care Output and Productivity*, pp. 411–438. Chicago: University of Chicago Press.

Smith, S., J. P. Newhouse, and M. S. Freeland (2009). Income, insurance, and technology: Why does health spending outpace economic growth. *Health Affairs 28*(5), 1276–1284.

Chapter 1

Medical Innovation and Labor Supply: The Impact of Cox-2 Drugs

1.1 Introduction

Substantial advances have occurred in the development and diffusion of new medical technologies over the last half century. Improvements in diagnosis and treatment have increased longevity and quality of life. Cutler and McClellan (2001), for instance, find that treatment advances account for over 40% of the recent reduction in cardiovascular disease mortality, which in turn has been a key determinant of overall mortality reduction over this period. Medical advances have also significantly improved health outcomes in other areas, including the treatment of low-birthweight infants, depression, and cataract surgery (Cutler, 2004; Cutler and McClellan, 2001; Shapiro et al., 2001; Duggan and Garthwaite, 2010). At the same time, healthcare costs grew nine fold in per-capita terms between 1960 and 2007, and technological change has been a major driver of this increase (Newhouse, 1992; Smith et al., 2009). Whether and to what extent the benefits of new medical technologies outweigh their costs are fundamental questions in the assessment of medical technology.

While the costs and health-related benefits of medical innovations are well-documented, their broader economic benefits are less well-documented (Duggan and Garthwaite, 2010). These economic benefits may include reduced reliance on supportive care and increased ability to participate in productive activities such as education, family caregiving, and formal work. The labor market benefits of medical innovations may be particularly important. An extensive literature, for example, has shown the importance of health status and disability in influencing work and retirement decisions of older workers (Currie and Madrian, 1999; McGarry, 2004; Bound et al., 1999; Kapteyn et al., 2008). Improvements to health and functional ability may enable people to join the labor force, work more hours conditional on working, be more productive while working, and work until older ages by deferring retirement.

Disability rates among elderly Americans have declined dramatically — by as much as 1% or more per year in recent decades (Cutler, 2001; Schoeni et al., 2008; Freedman et al., 2007; Costa, 2002). Moreover, labor force participation rates at older ages have risen significantly (Maestas and Zissimopoulos, 2010). This increase is especially notable among older men as labor force participation rates among younger men has fallen over time. While several factors drive these trends, advances in medical technologies may have played an important role.

This study contributes to the literature on the non-health benefits of medical innovations by examining the impact of a class of anti-arthritic drugs called Cox-2 selective inhibitors on labor supply. Cox-2 drugs make an excellent case study for investigating the labor supply effects of medical innovation because the potential labor supply effects are large, and the market introduction of these drugs generates plausibly exogenous variation in their use. Arthritis encompasses several rheumatic conditions and disorders, and is one of the most common chronic conditions worldwide. In the United States alone, 50 million adults have doctor-diagnosed arthritis (1 in 5 adults), and arthritis is one of the leading causes of disability and work limitations among adults (CDC, 2012). It is estimated that in 2003 in the U.S., the total cost of arthritis was $128 billion, including $81 billion in direct medical costs and $47 billion in indirect costs as a result of lost earnings (CDC, 2012). Given the high prevalence of arthritis and the large impact of arthritis on work behavior, medical innovations in the treatment of arthritis have the potential to generate substantial labor market benefits.

Examining the effects of medical care use on outcomes such as labor supply is challenging in the absence of randomization, since this relationship may be confounded by time-varying unobservables such as disease severity. The nature of the introduction of Cox-2 drugs represents plausibly exogenous variation in drug utilization that helps overcome this identification problem. Cox-2 drugs were developed to reduce the risks of side effects associated with traditional arthritis medications while maintaining the same level of efficacy. The class comprised three drugs - Celebrex, Vioxx and Bextra - that were all introduced at about the same time. All three rapidly became "blockbusters", with each exceeding sales of more than US$ 1 billion less than 15 months after launch. At their peak in 2004, Cox-2 drugs had a 38% share of the US$18 billion global market in arthritis treatments (Melnikova, 2005). In 2004, however, after the emergence of safety concerns Vioxx was voluntarily recalled from the market. This was shortly followed by the recall of Bextra in 2005.

Recently, Garthwaite (2012) examined the effect of Cox-2 drugs on labor force participation using the Medical Expenditure Panel Survey (MEPS) by exploiting the withdrawal of Vioxx as a natural experiment. In an initial analysis, he employed a difference-in-differences strategy comparing individuals with joint conditions to those without joint conditions. With data pooled across multiple MEPS panels, he found that the withdrawal decreased the probability of working by 10% among individuals aged 55-75 with joint conditions. The effect was stronger among men, whereas no effect was found for women. Limiting the analysis to only the 2004-2005 MEPS panel and adding individual fixed effects substantially reduced the size of the difference-in-differences estimate, suggesting earlier results may be biased upward due to unobserved time invariant heterogeneity across individuals. In a subsequent analysis, Garthwaite (2012) employed an instrumental variables strategy that treated Cox-2 drug use as endogenous and used the withdrawal of Vioxx as an instrument. The IV estimate, which relies primarily on the reduced form relationship identified by the fixed effect difference-in-differences estimate discussed above, showed Vioxx's removal decreased the probability of working for an affected individual by 54%. Due to small sample sizes arising from the use of the single panel, both the fixed effect difference-in-differences estimate and the corresponding

IV estimate were only marginally significant, and estimates for subgroups were not statistically significant. In addition, the short timeframe covered by the single panel did not allow for the study of longer-term changes in labor supply, which may be more relevant given individuals can adapt or switch to medical alternatives over time.

Building on Garthwaite (2012) whose data did not allow him to analyze the introduction of these drugs, I study the introduction of Cox-2 drugs which offers a cleaner natural experiment than the withdrawal of Vioxx. As noted above, Cox-2 drugs were introduced over a short period of time and their utilization grew rapidly such that they quickly became mainstays in the treatment of arthritis. In contrast, with the withdrawal of Vioxx individuals could switch to another Cox-2 drug such as Celebrex. Huse and Marder (2007), for instance, find that by 2006, 42% of former Vioxx users were prescribed another Cox-2 drug. In addition, the withdrawal also raised safety concerns over traditional arthritis medications as detailed below, which may confound the results.

Using data from the Health and Retirement Study (HRS), an ongoing panel survey designed to capture health and economic transitions of Americans over age 50, I adopt a difference-in-differences approach that compares individuals with arthritis to individuals without arthritis before and after the introduction of Cox-2 drugs. The large number of individuals in the relevant age groups allows me to conduct all the analysis separately for men and women, as the effects of arthritis, medication use, and labor force participation may vary across sexes. Moreover, since the HRS follows individuals across many waves, I can examine work outcomes allowing for a reasonable length of time for the take-up of Cox-2 drugs and for labor supply adjustments. In addition, I can study differences in the effects separately for individuals with long-term and individuals with short-term arthritis. Finally, whereas most studies have focused on labor force participation, I also examine the effect on hours worked.

I find that the introduction of Cox-2 drugs had a positive and economically significant effect on the probability of working among individuals with arthritis. Moreover, these effects are primarily seen among individuals with long-term arthritis. A subgroup analysis reveals stronger effects among older individuals, the less-educated, and those working in physical occupations. No effects, however, are observed in the number of hours worked conditional on working.

The rest of the paper proceeds as follows. The next section provides background information about arthritis medication. Section 3 describes the Health and Retirement Study data used in the study, the construction of the analysis sample and key variables, and presents descriptive statistics. Section 4 discusses the methods including the identification strategy which involves a difference-in-differences approach. Section 5 presents the main results, as well as results from subgroup analysis. Finally, Section 6 concludes the paper.

1.2 Innovation in the treatment of arthritis

Non-steroidal anti-inflammatory drugs (NSAIDs) represent a broad class of medications that are mainstays in the treatment of arthritis, and rank among the most commonly used drugs worldwide. They include "traditional" non-selective NSAIDs (nsNSAIDs) as well as newer Cox-2 selective NSAIDs.

1.2.1 nsNSAIDs: Traditional treatment for arthritis

Traditional nsNSAIDs have been available for decades, and include many over-the-counter drugs such as aspirin and ibuprofen. While effective at reducing pain and inflammation, their chronic use is associated with gastrointestinal (GI) side effects. Approximately 10-30% of chronic users develop ulcer disease, and 2-4% experience serious GI complications (Laine, 1996; Silverstein et al., 1995). nsNSAID-related GI events result in more than 100,000 hospital admissions and 7,000-10,000 deaths annually in the U.S. (Lanza et al., 2009). In addition, up to 60% of chronic users experience minor GI problems such as indigestion that often lead to patients discontinuing therapy (Silverstein et al., 1995). The risk of nsNSAID related GI events is significantly higher for patients above 65 years of age, those with a history of ulcer disease, as well as those taking higher doses of nsNSAIDs or multiple nsNSAIDs (Lanza et al., 2009).

1.2.2 Cox-2 drugs:

Efforts to develop NSAIDs without GI side effects led to the introduction of Cox-2 drugs. While traditional nsNSAIDs work by blocking both the Cox-1 enzyme which protects the stomach and the Cox-2 enzyme that triggers pain and inflammation, Cox-2 drugs were designed to selectively block the Cox-2 enzyme. Studies have consistently found that Cox-2 drugs are associated with lower rates of GI side effects and are better tolerated in patients, whilst offering comparable pain relief relative to nsNSAIDs (Rostom et al., 2007).

The first Cox-2 drug, Celebrex, was introduced in January 1999 followed shortly after by Vioxx in May of the same year, and by Bextra in November 2001. Aided by assertive marketing, utilization of these drugs grew rapidly; each attained blockbuster status with over US$1 billion in sales less than 15 months after launch (Melnikova, 2005). Using nationally representative U.S. survey data on community and hospital outpatient services, Dai et al. (2005) observed a sharp increase in patient visits where a Cox-2 drug was used as a percentage of visits where any NSAID was used, from 35% in 1999 to 55% in 2000, and to 61% in 2001 and 2002. This rapid rise in Cox-2 drug use was due to both a substitution away from traditional NSAIDs, as well as an expansion in total market demand. Those at high risk of GI events were more likely to be prescribed a Cox-2 drug, though increases in Cox-2 drug use were also observed among patients at low risk (Dai et al., 2005).

There were early suspicions that Vioxx was associated with increased cardiovascular (CV) risk. However, the initial evidence was not conclusive and was heavily disputed by the manufacturer, Merck. Nevertheless, in April 2002 the FDA required warning labels on Vioxx to indicate the risk of CV events. Finally, in September 2004, preliminary data from the Adenomatous Polyp Prevention On Vioxx (APPROVe) clinical trial being conducted by Merck showed that long-term use of Vioxx resulted in nearly twice the risk of suffering a heart attack or stroke compared to placebo (Bresalier et al., 2005). The trial was abandoned and Merck voluntarily withdrew Vioxx from the market.

In the months after the withdrawal of Vioxx, concerns were raised over other Cox-2 drugs as well as the entire class of NSAIDs as they share common mechanisms of action. Bextra was subsequently withdrawn in March 2005 on recommendation by the FDA over increased risk of CV events and serious skin reactions. Celebrex was allowed to remain on the market, but was required to carry a FDA warning label for CV and GI risk. In addition, CV risk was recognized as a possible class effect for all NSAIDs and the FDA recommended warning labels indicating CV and GI risk for both prescription and over-the-counter NSAIDs.

These events led to a marked change in prescribing patterns for pain medications. The fall in the use of Cox-2 drugs was only partially offset by an increase in nsNSAID use, such that overall NSAID use declined (Greenberg et al., 2009). Wilson (2009) notes a sharp increase in non-narcotic analgesic use in 2005 indicative of a substitution effect away from NSAIDs. In an analysis of MarketScan Commercial and Medicare Supplemental claims data between 2004 to 2006, Huse and Marder (2007) find that by 2006, 42% of former Vioxx users were prescribed another Cox-2 drug, while 29% were prescribed another prescription-strength NSAID. However, almost a quarter of former Vioxx users were receiving either no prescription pain relievers at all, or had switched to over-the-counter NSAIDs.

1.3 Data

The dataset employed in this paper is the Health and Retirement Study (HRS). The HRS is an ongoing biannual, nationally representative, longitudinal survey of households in the U.S. that is managed jointly by the National Institute on Aging and the Institute for Social Research at the University of Michigan. The survey is designed to capture health and economic transitions of Americans over age 50, and includes detailed information on demographics, physical and mental health, insurance coverage, income and wealth, family support systems, employment, and retirement planning. The HRS began in 1992 and the first cohort consisted of individuals born between 1931 and 1941 and their spouses (regardless of when the spouse was born). New cohorts were added in 1998, 2004, and 2010. Currently the HRS has ten waves from 1992 to 2010, and includes survey responses from over 30,000 individuals. The analysis is conducted using the processed files for the HRS provided by RAND, version J.

Three features of the HRS make it particularly suited to this study. First, the HRS is a panel dataset with several waves over a long timespan. This allows me to study the introduction of Cox-2 drugs allowing for a reasonable length of time for the uptake of these drugs, and it also allows me to identify individuals with long-term versus short-term arthritis. Second, the HRS includes a large number of respondents in the relevant age groups. I can therefore examine the effects of Cox-2 drugs separately for men and women, which is important as there is likely to be substantial heterogeneity in the effects of illness, drug use, and labor force participation across sexes. Finally, the HRS also contains detailed information on key variables related to health, healthcare use, and labor force participation.

The two labor supply outcomes I examine are labor force participation, and the number of hours worked conditional on working. Labor force participation is a binary outcome variable based on the following question: "Are you currently working for pay (1=Yes; 0=No)?" For individuals currently working, hours worked are calculated as the sum of hours worked per week on the respondent's main job as well as those worked per week on any secondary job.

The key variable in the analysis is an indicator of arthritis. This variable is based on the following set of questions. Whenever first interviewed, respondents in the HRS are asked: "Have you ever had, or has a doctor ever told you that you have arthritis or rheumatism?" In subsequent interviews, the question wording depends on whether the individual reported having arthritis in the prior wave. If an individual did not report arthritis in their previous interview, they are asked: "Since we last talked to you, has a doctor told you that you have arthritis or rheumatism?" If a person reported having arthritis in their previous interview, the following statement is read by the interviewer: "Our records from your last interview show that you have had arthritis". A record is made if the statement is disputed. When health conditions are disputed, RAND-HRS files recode all prior wave reports (not just the last wave) to "No".[1] To reduce the tendency for individuals to misreport health as a reason for not working, the health section in the HRS was administered prior to the employment and retirement sections.

The main analysis sample includes persons from the original HRS cohort[2] aged 50-70 years in both 1998 and 2002, with information on work outcomes, health, and demographic variables in both 1998 and 2002 waves, and with non-missing arthritis status in the 1996 wave. The age restriction ensures a sample of individuals at risk of arthritis (incidence rises sharply in the middle-aged) who are also likely to be part of the work force. The last restriction enables me to distinguish between long and short-term arthritis.

1.3.1 Descriptive statistics

Table 1.1 presents descriptive statistics by gender for the main analysis sample at the baseline 1998 wave. The "Arthritis" group includes all individuals who have arthritis at the 1998 wave, including those with short-term arthritis as well as those with long-term arthritis. Individuals with long-term arthritis are those with arthritis at both the 1998 wave and the wave prior (1996 wave), whereas individuals with short-term arthritis are those with arthritis at the 1998 wave but not the wave prior (1996 wave). The "No arthritis" category includes individuals who do not have arthritis in either 1998 or 2002. Indi-

[1] Less than 3% of respondents record disputes of arthritis in any given wave.

[2] Two cohorts participated in the HRS before 1998: the original HRS cohort and the AHEAD cohort. Individuals in the latter cohort are mostly over the age of 70 in 1998 and so are not included.

viduals who do not have arthritis at the 1998 wave, but who later develop it by 2002 are captured in a "latent arthritis" group. The information is first presented for the full sample, and then broken down by arthritis status.

Focusing first on the full sample, both men and women are on average 60 years of age. A larger proportion of men (85%) are married relative to women (70%). Men are also on average more educated than women, with 23% of men having a college degree or more compared to 15% of women. Among both sexes, arthritis is the most prevalent health condition. However, there is a notable gender difference, with a significantly larger proportion of women reporting arthritis (52%) than men (40%). With respect to labor supply measures, a higher proportion of men (64%) than women (51%) report that they are currently working. In addition, conditional on working, men work 7 more hours per week on average than women. A higher proportion of men (59%) than women (39%) report working in a physical occupation, or report that their job of longest tenure was a physical occupation.

This information is also further broken down by arthritis status. Small differences are observed between people with arthritis and people without arthritis in terms of demographics. However, differences in terms of education, health, and labor supply measures are notable and statistically significant. A higher proportion of arthritics (27% of men and 28% of women) report having less than a high-school level of education compared to individuals without arthritis (20% of men and 19% of women). Arthritics are also much more likely to report having comorbidities. In terms of labor supply measures, a smaller proportion of people with arthritis (55% of men and 44% of women) report that they are currently working than do people without arthritis (69% of men and 59% of women). However, conditional on working the difference in hours worked between the two groups is not statistically different for men. On the other hand, women with arthritis work 2.5 fewer hours on average than women without arthritis. In addition, a higher proportion of arthritics (64% of men and 43% of women) report working in a physical occupation, or report that their job of longest tenure was a physical occupation compared to people without arthritis (54% of men and 35% of women).

The HRS does not contain data on prescription drug use, but individuals who report having arthritis are asked the following question: "Are you currently taking any medication or other treatments for your arthritis or rheumatism?"[3] Responses to this question allow me to examine trends in overall arthritis-related drug use. Figure 1.1 plots the proportion of arthritics in the sample taking arthritis medication over time, by sex.[4] The first vertical line on the figure indicates the introduction of Cox-2 drugs, and the second indicates the withdrawal of Vioxx.

A higher proportion of female arthritics report using arthritis medication than do male arthritics. Among both male and female arthritics, there is an uptake in the proportion of individuals taking arthritis medication around the introduction of Cox-2 drugs. Use continues to increase rapidly, and peaks in 2004 for both groups. The increase is larger for women (41% in 1998 to 50%

[3]This variable was extracted from the original HRS data as it is not included in the processed RAND-HRS files.

[4]In 1994, this question was asked only of individuals who newly reported having arthritis and was skipped for everyone who reported arthritis in wave 1. For consistency, this information is therefore not plotted for 1994. In 1992 and from 1996 onwards however, the arthritis medication question was consistently asked of all individuals with arthritis.

in 2004) than for men (36% in 1998 to 42% in 2004). After 2004 however, use falls for both groups. The hump-shape of the lines is broadly consistent with the timeline of events, with use of arthritis medication growing after the introduction of Cox-2 drugs and decreasing after the withdrawals of Vioxx and Bextra. Note that this measure of overall use of arthritis medications does not enable us to observe substitution between older arthritis medications and Cox-2 drugs among those taking arthritis medication.

1.4 Methods

1.4.1 Association between arthritis and work outcomes before the introduction of Cox-2 drugs

I first examine the association between arthritis and work outcomes in the HRS data. The object of this exercise is not to estimate a causal relationship, but to simply document the strong relationship between arthritis and work status and to provide a basis of comparison for the main analysis in the paper. For the four waves of the HRS prior to the introduction of Cox-2 drugs (1992, 1994, 1996, 1998), I estimate simple pooled models where the work outcomes of individuals who transition from not having arthritis to having arthritis are compared to individuals who do not have arthritis over the same two-wave period (observations for individuals who report having arthritis in any base period are dropped). The basic specification is as follows:

$$y_{it} = \beta_0 + \beta_1 arthritis_{it} + \beta_2 X_{it} + \tau_t + \epsilon_{it} \tag{1.1}$$

where, y_{it} is a work status measure (either currently working, or hours conditional on working); X_{it} is a vector of covariates; and τ_t are wave fixed effects. This equation is estimated separately for men and women using a linear probability model when current work status is the dependent variable, and OLS when hours is the dependent variable. Standard errors are clustered at the individual level. In some specifications I also add individual fixed effects. The coefficient of interest β_1 measures the association between getting arthritis and work outcomes (again, this has no causal interpretation; it simply helps to document the strength of the relationship between arthritis and work status).

The vector of covariates includes a range of demographic and health variables, including dummies for each year of age, a dummy for whether the respondent is married, dummies for race (White, Black, Other), a dummy for Hispanic ethnicity, dummies for education (less than high school, high school, some college, college degree), as well as dummies for census division (9 divisions). I control for health status by including dummies for the following health conditions: high blood pressure, diabetes, cancer, lung disease, heart problems, stroke, psychological problems.[5] Detailed variable descriptions are provided in Appendix A.

[5]Variables for these conditions are also taken from the RAND-HRS files, and are constructed and based on questions structured identically to those described above for the arthritis variable.

The relationship between arthritis and work outcomes may change over time given that arthritis often progressively worsens. To check if this is the case, I repeat the above comparison looking at work outcomes both one wave out and two waves out.[6]

1.4.2 Empirical strategy for the main model

The core analysis estimates the causal effect of Cox-2 drugs on labor supply. As alluded to earlier, the major difficulty in estimating such a relationship is that there may be unobserved, time-varying differences across individuals that are correlated with both healthcare use and with labor supply choices. One obvious confounder is disease severity. Individuals with more severe illness are more likely to use healthcare resources, and are less likely to work. Disease severity is closely related to time since diagnosis, since arthritis is known to progressively worsen. Other time-varying unobservables may include factors such as the desire or need to work. These factors may induce people to work more, and at the same time also use more healthcare to enable them to work more. Whereas time-invariant unobserved heterogeneity can be dealt with in panel data using individual fixed-effects, the inability to control for time-varying individual unobserved heterogeneity could lead to omitted variable bias.

Identifying the causal effect of Cox-2 inhibitors on labor supply requires

[6] For the specification examining the effect of getting arthritis on work outcomes two waves out, observations cannot be pooled as only one comparison can be made given four waves of data.

exogenous variation in the use of these drugs. In theory, both the introduction of Cox-2 inhibitors and the withdrawal of Vioxx represent two natural experiments that provide plausibly exogenous variation. However, the withdrawal is problematic in this context for three reasons. First, only Vioxx was initially withdrawn and as seen by Huse and Marder (2007), individuals could substitute towards other alternatives such as Celebrex. This decision to switch to another Cox-2 drug, or to a nsNSAID, or to stop medication altogether would likely be strongly affected by selection bias. Second, the withdrawal raised concerns with respect to the safety of traditional nsNSAIDs as well, which may confound the results. Third, the biannual nature of the HRS data makes it ill-suited to study the impact of the withdrawal, as the post-withdrawal data spans other important events that may have differentially impacted those with and without arthritis and hence may confound the results. These events include the return to active marketing of Celebrex in 2006, and the introduction of Medicare Part D in the same year which reduced the cost of prescription drugs for seniors. For these reasons, I focus on the introduction of Cox-2 drugs.[7]

A difference-in-differences approach is used to estimate the effect of Cox-2 drugs on labor supply. Given the introduction of Cox-2 drugs in 1999, comparisons are made using the 1998 wave as the pre-introduction period and the 2002 wave as the post-introduction period. The treatment group is defined as people with arthritis at baseline; the comparison group is people without

[7] As noted, I focus on the introduction of Cox-2 drugs. I did, however, conduct an analysis of the withdrawal of Vioxx (only one Cox-2 drug). I did not find a statistically significant effect on labor market outcomes, perhaps for the reasons I have noted. The results of this exercise are presented in Appendix B.

arthritis over both periods. Individuals who do not have arthritis at baseline but who develop arthritis between the pre and post periods are included as a "latent arthritis" group. The key assumption underlying the difference-in-differences approach is that in the absence of the introduction of Cox-2 drugs, the labor supply response of the treatment group and the comparison group would have continued to evolve in parallel (parallel trends assumption).

As a sensitivity check, Garthwaite (2012) use people with back problems but without arthritis as a comparison group. However, HRS respondents were only asked questions related to back problems in alternative waves, so a similar analysis is not possible. Moreover, people with back problems but without arthritis may not be a good comparator because these individuals may also use arthritis-related medications. There may also be measurement problems in this variable as reporting back problems is highly correlated with reporting arthritis. To test the parallel trends assumption, a falsification test is conducted. Failure to reject the test suggests that the parallel trends assumption is not violated.

The specification is as follows:

$$\begin{aligned} y_{it} &= \beta_1 + \beta_2 intro_{it} + \beta_3 arthr_i + \beta_4 arthr_i \times intro_{it} \\ &\quad + \beta_5 LAarthr_i + \beta_6 LAarthr_i \times intro_{it} + \beta_7 X_{it} + \epsilon_{it} \end{aligned} \tag{1.2}$$

where i indexes the individual, and t represents the wave of interview; y_{it} is either currently working, or hours conditional on working; $intro_{it}$ is an indicator that takes the value of 1 if the observation for individual i was in the 2002 wave, and 0 if it was in the 1998 wave;[8] *arthr* is an indicator for whether individual i is in the treatment group; *LAarthr* is an indicator for whether individual i is in the latent arthritis group; and X_{it} is a vector of covariates described above. The coefficient of interest is the interaction term β_4, which is the intention-to-treat (ITT) effect; it represents the causal effect of the introduction of Cox-2 drugs on the probability of working among individuals with arthritis at baseline (whether or not they actually took the new drugs).

Labor supply responses may vary among individuals with arthritis depending on their disease severity as well as their propensity to take-up Cox-2 drugs. Given the nature of arthritis as a condition that progressively worsens over time, individuals having arthritis for longer may have more severe arthritis relative to those more recently afflicted. In addition, individuals with long-term arthritis may have a higher likelihood of experiencing the side-effects of traditional nsNSAIDs through prolonged exposure, and such high risk individuals were more likely to be prescribed Cox-2 drugs (Dai et al., 2005).

To take these differences into account, the treatment group *arthr* is split into people with long-term and short-term arthritis. This refinement is specified as follows:

[8] 3% of individuals in the 1998 wave were actually interviewed in the first quarter of 1999 after the introduction of Celebrex in Jan 1999. However, it would have been highly unlikely for these individuals to immediately get access and begin using the new drugs as soon as they were introduced. These observations were therefore treated as having occurred in the pre-period. As a check, I also tried dropping these individuals and it did not change the results.

$$
\begin{aligned}
y_{it} &= \beta_1 + \beta_2 intro_{it} + \beta_3 STarthr_i + \beta_4 STarthr_i \times intro_{it} \\
&\quad +\beta_5 LTarthr_i + \beta_6 LTarthr_i \times intro_{it} \\
&\quad +\beta_7 LAarthr_i + \beta_8 LAarthr_i \times intro_{it} + \beta_9 X_{it} + \epsilon_{it}
\end{aligned} \tag{1.3}
$$

Here, $LTarthr$ is an indicator for whether individual i has long-term arthritis, defined as having arthritis at both the baseline wave and the wave prior to baseline; and $STarthr$ is an indicator for whether individual i has short-term arthritis, defined as having arthritis at the baseline wave but not the wave prior to baseline. All other variables are the same as in equation (1.2). Analogous to specification (1.2), the coefficients of interest are the interaction terms β_4 and β_6.

The analysis is conducted separately for men and women. Where the dependent variable is current work status, both equations (1.2) and (1.3) are estimated using a linear probability model. For hours as the dependent variable, OLS is used. In some specifications individual fixed-effects are also added. Standard errors are clustered at the individual level.

1.5 Results

1.5.1 Effect of arthritis on work outcomes

The association between arthritis and an individual's probability of working is reported in Table 1.2. Estimates from equation (1.1) are presented in column (1); column (2) adds individual fixed effects. Panel (a) reports the contemporaneous effect of a new diagnosis of arthritis on work status. For men, when fixed effects are not included, a new diagnosis of arthritis is associated with a 5.7 percentage point decrease in the probability of working during the same period; when individual fixed effects are included, the size of the coefficient is reduced by more than half and it becomes marginally significant. For women, coefficients both with and without individual fixed effects are not statistically significant.

The effects of a new diagnosis of arthritis on an individual's probability of working two years later (one wave out) are presented in panel (b). A much stronger negative association is observed for both men and women, as all coefficients are negative and statistically significant. For men, the coefficient from the fixed effects specification implies that a new diagnosis of arthritis is associated with a 7.5 percentage point decrease in the probability of working two years later. Based on a mean of 71%, this implies a relative decrease in the probability of working by about 11%. For women, the corresponding coefficient from the fixed effects specification implies that a new diagnosis of arthritis is associated with a 4.3 percentage point decrease in the probability of working two years later. Based on a mean of about 59%, this implies a relative decrease in the probability of working by about 7%.

Results for the effect of a new diagnosis of arthritis on an individual's probability of working four years later (two waves out) are shown in panel (c). Only individuals with new diagnoses in 1994 who were observed in both 1992 and 1998 could be studied given four waves of data, and as a result the sample sizes are notably smaller. For men a negative and statistically significant effect of 6 percentage points is observed when individual fixed effects are not included; when individual fixed effects are added to the specification the coefficient in column (2) is no longer statistically significant. For women, the corresponding coefficients are both negative and statistically significant. The coefficient for the fixed effects specification implies a new diagnosis of arthritis lowers an individual's probability of working four years later by 7.5 percentage points. Based on a mean of about 58% this implies a relative reduction in the probability of working of about 13%.

In similar fashion, Table 1.3 presents the results for the association between arthritis and hours worked conditional on working. The effects of a new diagnosis of arthritis on conditional hours worked are much smaller than the effects on the probability of working. For men, there is no statistically significant effect of arthritis on hours either contemporaneously, two years later, or four years later. For women, when individual fixed effects are not included, a diagnosis of arthritis is associated with a reduction of 1.3 hours during the same period; a reduction of 2.6 hours two years later; and a reduction of 3.3 hours four years later. Adding individual fixed effects decreases the magnitude of the coefficients: a diagnosis of arthritis is associated with a reduction of 1.4

hours during the same period; a reduction of 1.9 hours two years later; and no statistically significant effect four years later.

Taken together, four implications can be drawn from this exercise. First, arthritis is associated with a sizable negative impact on the probability of working. Second, arthritis has a much smaller effect on the number of hours worked conditional on working. Third, there are differences in the effect of arthritis on work outcomes between men and women, suggesting the need for separate analysis. Finally, the effect of arthritis on work outcomes is generally larger when observed over a longer period of time. This could be because individuals are slow to adjust their labor supply, or because arthritis progressively worsens over time.

1.5.2 Main effects

Table 1.4 presents estimates from the difference-in-differences regressions, by sex. For both men and women, results are presented from four specifications. Column (1) presents the results from equation (1.2) with no individual fixed effects; column (2) adds individual fixed effects to this model. Column (3) presents results for equation (1.3) where the treatment group is split into individuals with long and short-term arthritis; and column (4) presents results where individual fixed effects are added to this specification. Results from fixed effects specifications are generally considered more robust than results from pooled specifications, as fixed effects control for time-invariant unobserved heterogeneity. However, the presence of measurement error under fixed effects may lead to coefficients being attenuated towards zero, so it is useful to see both results.

Panel (a) presents results where the dependent variable is whether working for pay. For men, I find consistent evidence that the introduction of Cox-2 drugs increased the probability of working. The coefficient on $arthr \times intro$ reported in column (1) is 0.0476, and is statistically significant at the 5% level. Adding individual fixed effects in column (2) reduces the magnitude of the coefficient to 0.0396, though it remains statistically significant at the 5% level. This coefficient implies that the introduction of Cox-2 drugs increased the probability of working by about 4 percentage points among men with arthritis at baseline relative to men without arthritis. The effect is also economically significant as it implies a relative increase in the probability of working of 7% given 55% of individuals with arthritis were working in the pre-period. Moreover, these results appear to be driven by individuals with long-term arthritis. In column (3), the coefficient for $LTarthr \times intro$ is 0.0519 and is statistically significant. In contrast, the coefficient for $STarthr \times intro$ is small and statistically insignificant. When individual fixed effects are added in column (4), the $LTarthr \times intro$ coefficient remains statistically significant but its magnitude is slightly reduced to 0.0440. The coefficient for $STarthr \times intro$ remains small and statistically insignificant.

The results for women follow a similar pattern to those for men, however, the effects are smaller across all specifications and are statistically insignificant under specifications including individual fixed effects. In column (1) the coefficient on $arthr \times intro$ is 0.0286 and is statistically significant at the 5% level.

This implies that the introduction of Cox-2 drugs increased the probability of working by about 3 percentage points among women with arthritis at baseline relative to women without arthritis. While this effect is smaller in absolute terms compared to the effect for men, the effect is similar in relative terms as it implies a 7% increase in the probability of working since fewer women (44%) work. When individual fixed effects are added, the coefficient becomes less positive and statistically insignificant. The coefficient on $LTarthr \times intro$ reported in column (3) is 0.0309 and is statistically significant at the 5% level. When individual fixed effects are added in column (4), this coefficient becomes smaller and statistically insignificant. The coefficient for $STarthr \times intro$ is small and statistically insignificant under both (3) and (4).

Panel (b) presents results where the dependent variable is the number of hours worked conditional on working in both periods. For both men and women the coefficients are statistically insignificant under all specifications. These results are consistent with the minimal effects of arthritis on hours worked observed in the previous section.

In sum, these results imply that the introduction of Cox-2 drugs had a significant positive impact on the probability of working for men. For women, the results are less consistent. Positive and statistically significant effects are observed under specifications (1) and (3), which are similar in relative terms to those observed for men. However, the coefficients are smaller and become statistically insignificant under fixed effects specifications (2) and (4). In addition, the effects for the probability of working appear to be driven by individuals with long-term arthritis. No statistically significant effects are observed for the number of hours worked conditional on working for either men or women. Given these results, I focus on the extensive margin of labor supply and explore whether there are differences by subgroup in the effects of Cox-2 drugs.

1.5.3 Heterogeneity by age, education and occupation

In Table 1.5, I examine the effect of Cox-2 drugs on labor force participation in subgroups defined by age, education, and occupation. I report results based on equation (1.3). The basic specification is reported in column (1), and the specification augmented with individual fixed effects is reported under column (2).

Compared to younger individuals, older individuals may suffer from more severe arthritis, and may be more likely to take-up Cox-2 drugs. They may also have a lesser attachment to the labor market. I therefore split the sample into a younger subsample aged 50-60 in the 1998 wave who are then under the age of 65 in the 2002 wave, and an older subsample aged 61-66 in the 1998 wave who are aged 65-70 in the 2002 wave. Splitting the sample this way ensures that there are sufficient observations in both subsamples as 60 is the mean age at baseline. Moreover, age 65 is the retirement age, after which individuals may also become eligible for Medicare.

Panel (a) of Table 1.5 presents the subgroup analysis by age. For both men and women, the effect of the introduction of Cox-2 drugs is seen only in the older age group among individuals with long-term arthritis. For older men, the coefficient on $LTarthr \times intro$ with and without individual fixed effects is positive and statistically significant at the 5% level. The coefficient in the fixed effects specification implies that the introduction of Cox-2 drugs increased the probability of working by about 5.8 percentage points among men with long-term arthritis at baseline relative to men without arthritis. Relative to a base of 43%, this translates to a 13% increase in the probability of working. For older women, the corresponding coefficient on $LTarthr \times intro$ is statistically significant at the 10% level, implying that the introduction of Cox-2 drugs increased the probability of working by about 4.3 percentage points among women with long-term arthritis at baseline relative to women without arthritis. This translates to a 13% increase in the probability of working.

Next, I examine heterogeneity by level of educational attainment. Persons with lower levels of education are more likely to work in physically demanding occupations and in jobs that offer less flexibility in terms of their work activities, and may hence derive more benefit from Cox-2 drugs. On the other hand, more educated individuals are more likely to take-up newer medications. I define the less-educated subsample to consist of people whose highest level of education is high-school or below, and the more educated subsample to consist of people whose highest level of education is some college or above.

Panel (b) presents results where the sample is split by education. For men, the effect of the introduction of Cox-2 drugs is much larger among individuals with less education. The coefficient on $LTarthr \times intro$ in the fixed effects specification is statistically significant at the 5% level, and implies that the introduction of Cox-2 drugs increased the probability of working by about 5.9 percentage points among men with long-term arthritis at baseline relative to men without arthritis. Relative to a base of 49%, this translates to a 12% increase in the probability of working. In contrast, among individuals with higher education the coefficient on $LTarthr \times intro$ under both specifications is much smaller in magnitude and is statistically insignificant. The coefficient for $STarthr \times intro$ is statistically insignificant in all cases.

For women, a similar pattern is observed but the coefficients are smaller and statistically less significant. The coefficient on $LTarthr \times intro$ without individual fixed effects is statistically significant at the 10% level, and implies that the introduction of Cox-2 drugs increased the probability of working by about 3.3 percentage points among women with long-term arthritis at baseline relative to women without arthritis. Relative to a base of 40%, this translates to an 8% increase in the probability of working. However, with the addition of individual fixed effects the estimate attenuates and is no longer statistically significant. The corresponding coefficients for more educated women are smaller and statistically insignificant.

Finally, I examine differences by occupation type. Individuals working in physical occupations are more likely to be restricted in their work by arthritis than individuals working in non-physical occupations. As a result, they stand to benefit more from arthritis treatments. Given that occupation choice is endogenous, I characterize individuals as working in a physical occupation if they worked in a physical occupation at baseline or if their job of longest tenure at baseline was a physical occupation. Analogously, individuals who worked in a non-physical occupation at baseline or whose job of longest tenure was a non-physical occupation at baseline, are categorized as working in a non-physical occupation.[9]

These results are reported in Panel (c). For men, a positive and statistically significant effect is observed among those with long-term arthritis working in physical occupations. The coefficient on $LTarthr \times intro$ in the fixed effects specification implies that the introduction of Cox-2 drugs increased the probability of working by about 5.4 percentage points among men with long-term arthritis at baseline relative to men without arthritis. This equates to a relative increase of 10% in the probability of working. For men in non-physical occupations, the coefficients are smaller and statistically insignificant. For women on the other hand, there do not appear to be substantial differences by occupation type. The coefficients on $LTarthr \times intro$ are statistically insignificant among women in physical occupations. Among women in non-physical occupations, the coefficient on $LTarthr \times intro$ when individual fixed effects are not included is statistically significant at the 10% level, but with individual fixed effects the coefficient estimate attenuates and is no longer statistically significant.

1.5.4 Falsification exercise

As a check against spurious inference, I conduct a falsification exercise where I look for policy effects at dates when there should be none, by generating

[9] Physical occupations include mechanical, construction, and precision production; service (includes private household services, protective services, food preparation, health service, and personal service); operators, fabricators, and laborers; and farming, forestry, and fishing. Non-physical occupations include professional and technical support; managerial; clerical and administrative support; sales.

two false policy changes in the pre-introduction period: in the 1994 wave and in the 1996 wave. For the false policy change in the 1994 wave, I use the 1992 wave as the pre-period and the 1996 wave as the post-period. Similarly, for the false policy change in the 1996 wave I use the 1994 wave as the pre-period and the 1998 wave as the post-period. I construct separate treatment and comparison groups for each policy change and run regressions based on equations (1.2) and (1.3).[10] If we were to observe significant effects for these false policy changes, it would cast doubt on the identifying assumption of no unobserved year-group effects that underlies the main analysis.

Table 1.6 reports the difference-in-differences estimates from these regressions. The specification based on equation (1.2) is reported in column (1). Individual fixed effects are added under column (2). Results from the estimation of equation (1.3) are reported under column (3). This specification is augmented with individual fixed effects, and the results are reported under column (4). The analysis is conducted separately by sex. The coefficients on the interaction terms under all specifications are both small and statistically insignificant under both false policy changes. The results from this exercise therefore accord with the causal interpretation of the effects reported in Tables 1.4 and 1.5.

[10] The regression based on equation (1.3) can only be estimated for the policy change in the 1996 wave as it requires information from two waves prior.

1.6 Conclusion

Advances in medical treatment have the potential to significantly improve our quality of life, and to generate important economic benefits such as increased productivity, wages, and labor supply. However, outside of the cost-effectiveness literature, only a small number of studies have examined the effect of medical treatments on economic outcomes. While cost-effectiveness studies make allowances for indirect costs/benefits as part of health technology assessment, these are typically not at a system level for a class of innovation. In a review of the literature on the value of pharmaceutical innovation, Duggan and Garthwaite (2010) find that the majority of studies that examine the effect of medical treatments on broader economic outcomes are set in developing countries. For instance, Fox et al. (2004); Thirumurthy et al. (2008); Habyarimana et al. (2010) study the effects of anti-retroviral treatments for AIDS in Africa on labor supply and productivity. They find positive and significant short, medium, and long-term effects of treatment.

Of the few studies set in developed countries, most focus on treatments related to mental health and rely on data from clinical trials, which may not accurately reflect behavior in the real world. These studies find small positive effects of mental health medication on labor supply and productivity (Timbe et al., 2006; Berndt et al., 1998, 2000). Other studies such as Lichtenberg (2002) estimate the effect of aggregate changes in drug utilization on labor supply. He finds that for conditions with above-average changes in drug utilization there were above-average changes in labor supply. However, the changes in drug utilization are not exogenous, and raise concerns of omitted variables bias.

In this study, I examine the impact of the introduction of Cox-2 drugs - a widely prescribed class of medications used in the treatment of arthritis - on labor supply. I find evidence that the introduction of these drugs had a positive and economically significant impact on the probability of working among individuals with arthritis. Moreover, these effects are seen primarily among individuals with long-term arthritis. In addition, there is substantial heterogeneity in the effects, with stronger effects seen in older individuals, the less-educated, and those working in physical occupations. However, I find no evidence of any impact on the number of hours worked conditional on working. The findings from this study suggest that broader economic benefits, and labor supply effects in particular can be significant, and should be accounted for when evaluating medical technologies.

References

Berndt, E., H. Bailit, M. Keller, J. Verner, and S. Finkelstein (2000). Health care use and at-work productivity among employees with mental disorders. *Health Affairs 19*, 244–256.

Berndt, E., S. Finkelstein, P. Greenberg, R. Howland, A. Keith, A. J. Rush, J. Russell, and M. Keller (1998). Workplace performance effects from chronic depression and its treatment. *Journal of Health Economics 17*, 511–535.

Bound, J., M. Schoenbaum, T. Stinebrinker, and T. Waidmann (1999). The dynamic effects of health on the labor force transitions of older workers. *Labour Economics 6*(2), 179–202.

Bresalier, R. S., R. S. Sandler, H. Quan, J. A. Bolognese, B. Oxenius, K. Horgan, C. Lines, R. Riddell, D. Morton, A. Lanas, M. A. Konstam, and J. A. Baron (2005). Cardiovascular events associated with rofecoxib in a colorectal adenoma chemoprevention trial. *New England Journal of Medicine 352*, 1092–1102.

CDC (2012). Arthritis - meeting the challenge of living well: At a glance. *Centers for Disease Control and Prevention.*

Costa, D. L. (2002). Changing chronic disease rates and longterm declines in functional limitation among older men. *Demography Services 39*(1), 119–137.

Currie, J. and B. Madrian (1999). Health, health insurance and the labor market. In O. C. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 3c, pp. 3309–3416.

Cutler, D. M. (2001). Declining disability among the elderly. *Health Affairs 20*(6), 11–27.

Cutler, D. M. (2004). *Your Money or Your Life*. Oxford, England: Oxford University Press.

Cutler, D. M. and M. McClellan (2001). Is technological change in medicine worth it? *Health Affairs 20*(5), 11–29.

Dai, C., R. S. Stafford, and G. C. Alexander (2005). National trends in cyclooxygenase-2 inhibitor use since market release - nonselective diffusion of a selectively cost-effective innovation. *Arch Intern Med. 165*, 171–177.

Duggan, M. and C. Garthwaite (2010). Empirical evidence on the value of pharmaceuticals. In *The Handbook of the Economics of the Biopharmaceutical Industry*, pp. 3309–3416.

Fox, M. P., S. Rosen, W. B. MacLeod, M. Wasunna, M. Bii, G. Foglia, and J. L. Simon (2004). The impact of HIV/AIDS on labour productivity in kenya. *Tropical Medicine and International Health 9*, 318–324.

Freedman, V. A., R. F. Schoeni, L. G. Martin, and J. C. Cornman (2007). Chronic conditions and the decline in late-life disability. *Demography 44*(3), 459–477.

Garthwaite, C. (2012). Economic benefits of pharmaceutical innovations: The case of Cox-2 inhibitors. *American Economic Journal: Applied Economics 4*(3), 116–137.

Greenberg, J., M. Fisher, J. Kremer, H. Chang, E. Rosenstein, M. Kishimoto, S. Lee, Y. Yazici, A. Kavanaugh, and S. Abramson (2009). The COX-2 inhibitor market withdrawals and prescribing patterns by rheumatologists in patients with gastrointestinal and cardiovascular risk. *Clinical and Experimental Rheumatology 27*, 395–401.

Habyarimana, J., B. Mbakile, and C. Pop-Eleches (2010). The impact of HIV/AIDS and ARV treatment on worker absenteeism: Implications for african firms. *Journal of Human Resources 45*(4), 809–839.

Huse, D. and W. Marder (2007). What happened to vioxx users? *Thomson Reuters October*.

Kapteyn, A., J. Smith, and A. van Soest (2008). Dynamics of work disability and pain. *Journal of Health Economics 27*(2), 496–509.

Laine, L. (1996). Nonsteroidal anti-inflammatory drug gastropathy. *Gastrointestinal Endoscopy Clinics of North America 6*(3), 489–504.

Lanza, F. L., F. K. Chan, and E. M. Quigley (2009). Guidelines for prevention of NSAID-related ulcer complications. *American Journal of Gastroenterology 104*, 728–738.

Lichtenberg, F. (2002). The effect of changes in drug utilization on labor supply and per capita output. *NBER Working Paper 9139*.

Maestas, N. and J. Zissimopoulos (2010). How longer work lives ease the crunch of population aging. *Journal of Economic Perspectives 24*(1), 139–160.

McGarry, K. (2004). Do changes in health affect retirement expectations? *Journal of Human Resources 39*(3), 624–648.

Melnikova, I. (2005). Future of Cox-2 inhibitors. *Nature Reviews 4*, 453–454.

Newhouse, J. P. (1992). Medical care costs: How much welfare loss? *The Journal of Economic Perspectives 6*(3), 3–21.

Rostom, A., K. Muir, C. Dube, E. Jolicoeur, M. Boucher, J. Joyce, P. Tugwell, and G. Wells (2007). Gastrointestinal safety of cyclooxygenase-2 inhibitors: A cochrane collaboration systematic review. *Clinical Gastroenterology and Hepatology 5*(7), 818–828.

Schoeni, R. F., V. A. Freedman, and L. G. Martin (2008). Why is late-life disability declining? *The Milbank Quarterly 86*(1), 47–89.

Shapiro, I., M. Shapiro, and D.W.Wilcox (2001). Measuring the value of cataract surgery. In D. Cutler and E. Berndt (Eds.), *Medical Care Output and Productivity*, pp. 411–438. Chicago: University of Chicago Press.

Silverstein, F. E., D. Y. Graham, J. R. Senior, H. W. Davies, B. J. Struthers, R. M. Bittman, and G. S. Geis (1995). Misoprostol reduces serious gastrointestinal complications in patients with rheumatoid arthritis receiving nonsteroidal anti-inflammatory drugs. A randomized, double-blind, placebo-controlled trial. *Annals of Internal Medicine 123*, 241–249.

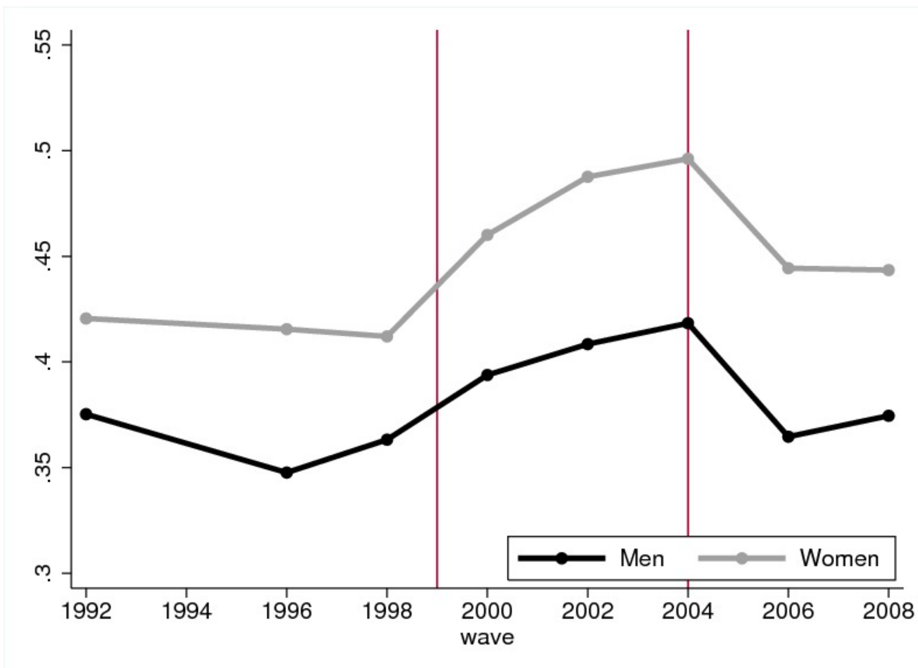
Smith, S., J. P. Newhouse, and M. S. Freeland (2009). Income, insurance, and technology: Why does health spending outpace economic growth. *Health Affairs 28*(5), 1276–1284.

Thirumurthy, H., M. Goldstein, and J. G. Zivin (2008). The economic impact of AIDS treatment: Labor supply in western kenya. *Journal of Human Resources 43*, 511–552.

Timbe, J., M. Horvitz-Lennon, R. Frank, and G. Lewis (2006). A meta-analysis of labor supply effects of interventions for major depressive disorders. *Psychiatric Services 57*, 212–218.

Wilson, R. D. (2009). Analgesic prescribing for musculoskeletal complaints in the ambulatory care setting after the introduction and withdrawal of cyclooxygenase-2 inhibitors. *Archives of Physical Medicine and Rehabilitation 90*, 1147–1151.

Figure 1.1: Proportion of individuals with arthritis taking arthritis medications



Note: Includes individuals aged 50-70 from the original HRS cohort. Question regarding arthritis medication use was not asked in a consistent manner in 1994, so responses are not plotted for that year. See text for details.

Table 1.1: Descriptive statistics: Main analysis sample at baseline

	Men			Women		
Characteristic in 1998 wave	Full sample	No arthritis	Arthritis	Full sample	No arthritis	Arthritis
Arthritis	0.40			0.52		
Short-term	0.05		0.14	0.05		0.09
Long-term	0.34		0.86	0.47		0.91
Latent arthritis	0.10			0.09		
Working for Pay	0.64	0.69	0.55*	0.51	0.59	0.44*
Hours (conditional)	43.11	43.36	42.45	36.28	37.39	34.96*
	(15.59)	(15.62)	(15.08)	(14.21)	(14.27)	(13.83)
Physical occupation	0.59	0.54	0.64*	0.39	0.35	0.43*
Age	60.64	60.32	61.06*	59.49	58.88	60.06*
	(3.32)	(3.34)	(3.23)	(4.09)	(4.20)	(3.92)
White	0.84	0.83	0.85	0.80	0.82	0.78*
Black	0.13	0.13	0.12	0.17	0.13	0.19*
Other race	0.04	0.04	0.03	0.04	0.04	0.03
Hispanic	0.08	0.10	0.06*	0.08	0.09	0.08
Married	0.85	0.85	0.85	0.70	0.72	0.68*
Less than high school	0.23	0.20	0.27*	0.23	0.19	0.28*
High school	0.35	0.34	0.37	0.41	0.41	0.41
Some College	0.19	0.20	0.19	0.21	0.22	0.19
College and above	0.23	0.27	0.18*	0.15	0.19	0.12*
High blood pressure	0.40	0.35	0.47*	0.40	0.29	0.47*
Diabetes	0.13	0.12	0.15*	0.11	0.07	0.13*
Cancer	0.06	0.04	0.08*	0.08	0.07	0.10*
Lung disease	0.05	0.03	0.09*	0.06	0.03	0.09*
Heart problems	0.17	0.14	0.21*	0.11	0.06	0.15*
Stroke	0.04	0.03	0.05	0.03	0.02	0.04*
Psychological problems	0.06	0.04	0.09*	0.13	0.07	0.18*
N	3072	1224	1538	4391	1703	2271

Note: "No arthritis" are individuals who do not have arthritis in either 1998 or in 2002. Physical occupation includes individuals who are currently employed in a physical occupation, as well as individuals whose job of longest tenure was a physical occupation. Indicators for census division are not shown here, but are included in the analysis. For continuous variables, standard deviations are reported in parentheses. * indicates "Arthritis" and "No arthritis" groups are statistically different from each other at the 5% level.

Table 1.2: The association between arthritis and working

	Men (1)	Men (2)	Women (1)	Women (2)
Panel (a): Impact of new diagnosis of arthritis in wave t on probability of working in wave t				
arthritis	-0.0574***	-0.0250*	-0.0171	-0.0208
	(0.0169)	(0.0149)	(0.0156)	(0.0134)
Individual FE	No	Yes	No	Yes
Dependent mean	0.697	0.697	0.574	0.574
N*T	12,802	12,802	12,616	12,616
N		3,761		3,877
Panel (b): Impact of new diagnosis of arthritis in wave t on probability of working in wave t+1				
arthritis	-0.0923***	-0.0749***	-0.0366*	-0.0434**
	(0.0232)	(0.0227)	(0.0211)	(0.0200)
Individual FE	No	Yes	No	Yes
Dependent mean	0.705	0.705	0.585	0.585
N*T	10,576	10,576	9,968	9,968
N		3,148		3,104
Panel (c): Impact of new diagnosis of arthritis in wave t on probability of working in wave t+2				
arthritis	-0.0599*	-0.0387	-0.0646**	-0.0749**
	(0.0329)	(0.0375)	(0.0309)	(0.0345)
Individual FE	No	Yes	No	Yes
Dependent mean	0.712	0.712	0.584	0.584
N*T	4,700	4,700	4,312	4,312
N		2,350		2,156

Note: Regressions are estimated using a linear probability model and include a full set of control variables noted in the text. Standard errors reported in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.3: The association between arthritis and hours worked

	Men (1)	Men (2)	Women (1)	Women (2)
Panel (a): Impact of new diagnosis of arthritis in wave t on hours in wave t				
arthritis	-1.179	-0.870	-1.339*	-1.381**
	(0.755)	(0.643)	(0.709)	(0.613)
Individual FE	No	Yes	No	Yes
Dependent mean	44.95	44.95	38.04	38.04
N*T	8,099	8,099	6,362	6,362
N		2,594		2,128
Panel (b): Impact of new diagnosis of arthritis in wave t on hours in wave t+1				
arthritis	-0.830	0.444	-2.645***	-1.896*
	(1.110)	(0.986)	(1.008)	(1.018)
Individual FE	No	Yes	No	Yes
Dependent mean	45.35	45.35	38.27	38.27
N*T	6,092	6,092	4,552	4,552
N		1,967		1,547
Panel (c): Impact of new diagnosis of arthritis in wave t on hours in wave t+2				
arthritis	-0.578	-1.086	-3.288***	-1.304
	(1.622)	(1.925)	(1.356)	(1.445)
Individual FE	No	Yes	No	Yes
Dependent mean	45.30	45.30	38.18	38.18
N*T	2,614	2,614	1,852	1,852
N		1,307		926

Note: Regressions are estimated using OLS and include a full set of control variables noted in the text. Standard errors reported in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.4: Regression estimates of the effect of the introduction of Cox-2 drugs on labor supply outcomes

	Men				Women			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel (a): Dependent variable: Working for Pay (0/1)								
arthr×intro	0.0476**	0.0396**			0.0286**	0.0159		
	(0.0187)	(0.0187)			(0.0146)	(0.0146)		
STarthr×intro			0.0207	0.0121			0.00345	-0.00234
			(0.0423)	(0.0417)			(0.0321)	(0.0323)
LTarthr×intro			0.0519***	0.0440**			0.0309**	0.0178
			(0.0194)	(0.0194)			(0.0149)	(0.0149)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
N*T	6,144	6,144	6,144	6,144	8,782	8,782	8,782	8,782
N		3,072		3,072		4,391		4,391
Panel (b): Dependent variable: Hours (conditional)								
arthr×intro	-1.378	-1.239			0.750	0.820		
	(0.984)	(0.994)			(0.824)	(0.837)		
STarthr×intro			-1.847	-1.510			0.228	0.238
			(2.321)	(2.374)			(1.432)	(1.450)
LTarthr×intro			-1.297	-1.193			0.814	0.897
			(1.023)	(1.031)			(0.869)	(0.887)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
N*T	2,410	2,410	2,410	2,410	2,838	2,838	2,838	2,838
N		1,205		1,205		1,419		1,419

Note: Regressions are estimated using a linear probability model where working is the dependent variable, and OLS where hours is the dependent variable. All specifications include a full set of control variables noted in the text. Standard errors reported in parentheses are clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1.5: Heterogeneity in the effect of the introduction of Cox-2 drugs on labor force participation

	Men				Women			
Dependent variable: Working for Pay (0/1)								
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel (a): By age								
	Age 50-60 (in 1998)		Age 61-66 (in 1998)		Age 50-60 (in 1998)		Age 61-66 (in 1998)	
STarthr×intro	-0.0207	-0.0264	0.0695	0.0551	-0.0218	-0.0282	0.0362	0.0332
	(0.0584)	(0.0576)	(0.0615)	(0.0608)	(0.0463)	(0.0465)	(0.0443)	(0.0446)
LTarthr×intro	0.0358	0.0267	0.0636**	0.0580**	0.00645	-0.00115	0.0555**	0.0430*
	(0.0281)	(0.0283)	(0.0268)	(0.0269)	(0.0201)	(0.0200)	(0.0226)	(0.0225)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
N*T	2,982	2,982	3,162	3,162	4,894	4,894	3,888	3,888
N		1,491		1,581		2,447		1,944
Panel (b): By level of education								
	High school and below		Some college and above		High school and below		Some college and above	
STarthr×intro	-0.0195	-0.0200	0.0693	0.0655	-0.0364	-0.0395	0.0762	0.0786
	(0.0622)	(0.0607)	(0.0550)	(0.0557)	(0.0400)	(0.0398)	(0.0531)	(0.0547)
LTarthr×intro	0.0650**	0.0586**	0.0204	0.0179	0.0327*	0.0208	0.0284	0.0136
	(0.0253)	(0.0254)	(0.0314)	(0.0312)	(0.0189)	(0.0189)	(0.0249)	(0.0246)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
N*T	3,548	3,548	2,596	2,596	5,626	5,626	3,156	3,156
N		1,774		1,298		2,813		1,578

Continued on Next Page...

Table 1.5 – continued from previous page

	Men				Women			
Dependent variable: Working for Pay (0/1)								
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel (c): By occupation type								
	Physical		Non-physical		Physical		Non-physical	
STarthr×intro	-0.00518	-0.00446	0.0774	0.0503	0.00405	-0.00421	0.00861	-0.00862
	(0.0561)	(0.0559)	(0.0680)	(0.0654)	(0.0599)	(0.0598)	(0.0437)	(0.0441)
LTarthr×intro	0.0598**	0.0540**	0.0457	0.0339	0.0368	0.0219	0.0346*	0.0179
	(0.0258)	(0.0258)	(0.0327)	(0.0326)	(0.0276)	(0.0274)	(0.0204)	(0.0204)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
N*T	3,498	3,498	2,480	2,480	3,030	3,030	4,802	4,802
N		1,749		1,240		1,515		2,401

Note: Regressions are estimated using a linear probability model and include a full set of control variables noted in the text. Standard errors reported in parentheses are clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1.6: Falsification test

	Men				Women			
Dependent variable: Working for Pay (0/1)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel (a): Effect under false policy change in 1994 wave								
arthr×post	-0.00751	-0.0113			-0.00923	-0.0117		
	(0.0149)	(0.0149)			(0.0139)	(0.0138)		
Individual FE	No	Yes			No	Yes		
N*T	8,930	8,930			9,606	9,606		
N		4,803				4,805		
Panel (b): Effect under false policy change in 1996 wave								
arthr×post	-0.0142	-0.0160			0.00243	0.00255		
	(0.0162)	(0.0163)			(0.0139)	(0.0138)		
STarthr×post			-0.0201	-0.0244			-0.0268	-0.0214
			(0.0359)	(0.0356)			(0.0301)	(0.0299)
LTarthr×post			-0.0130	-0.0144			0.00689	0.00631
			(0.0170)	(0.0171)			(0.0144)	(0.0143)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
N*T	7,990	7,990	7,990	7,990	9,754	9,754	9,754	9,754
N		3,995		3,995		4,877		4,877

Note: Regressions are estimated using a linear probability model and include a full set of control variables noted in the text. Standard errors reported in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 1.A: Data and Variable Description

Variable name	Definition
Dependent variables	
Working for Pay	An indicator variable based on the following question: "Are you currently working for pay?"(1=yes, 0=no)
Hours	Sum of the usual number of hours worked per week on the respondent's main job as well as the usual number of hours per week worked on any secondary job. Based on "How many hours a week do you usually work on this job?/How many hours a week do you usually work in this business?"
Arthritis-related variables	
Arthritis	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she has arthritis or rheumatism.
Arthr	An indicator variable taking the value of one if the respondent has arthritis in the baseline wave (1998 wave)
STarthr	An indicator variable taking the value of one if the respondent has short-term arthritis, i.e., has arthritis in the baseline wave (1998 wave), but not the wave prior to baseline (1996 wave).
LTarthr	An indicator variable taking the value of one if the respondent has long-term arthritis, i.e., has arthritis in both the baseline wave (1998 wave), and the wave prior to baseline (1996 wave).
LAarthr	An indicator variable taking the value of one if the respondent has latent arthritis, i.e., does not have arthritis in the baseline wave (1998 wave) but has arthritis in the post period (2002 wave).
Noarthr	An indicator variable taking the value of one if the respondent does not have arthritis in the post period (2002 wave).
Other covariates	
Age50-Age70	Indicator variables taking the value of one for each year of age.
Married	An indicator variable taking the value of one if the respondent's current marital status is married, married with spouse absent, or partnered.
White	An indicator variable taking the value of one if the respondent's race is White/Caucasian.

Continued on Next Page...

Black	An indicator variable taking the value of one if the respondent's race is Black/African American.
Other race	An indicator variable taking the value of one if the respondent's race is other than White or Black.
Hispanic	An indicator variable taking the value of one if the respondent's ethnicity is Hispanic.
Less than high school	An indicator variable taking the value of one if the respondent's highest level of education is less than high school.
High school	An indicator variable taking the value of one if the respondent's highest level of education is high school or GED.
Some College	An indicator variable taking the value of one if the respondent's highest level of education is some college.
College and above	An indicator variable taking the value of one if the respondent's highest level of education is college and above.
High blood pressure	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she has high blood pressure or hypertension.
Diabetes	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she has diabetes or high blood sugar.
Cancer	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she has had cancer or a malignant tumor of any kind, except skin cancer.
Lung disease	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she has chronic lung disease except asthma such as chronic bronchitis or emphysema.
Heart problems	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she had a heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems.
Stroke	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she had a stroke or transient ischemic attack (TIA).
Psychological problems	An indicator variable taking the value of one if the respondent has ever been told by a doctor that he or she had emotional, nervous, or psychiatric problems.
Cendiv1-Cendiv9	Indicator variables taking the value of one for each census division (New England, Mid Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific).

Continued on Next Page…

Physical occupation	An indicator variable taking the value of one if the respondent works in a physical occupation, i.e., works in a physical occupation in the baseline wave (1998 wave), or job of longest tenure at baseline (1998 wave) is a physical occupation. Physical occupations include mechanical, construction, and precision production; service (includes private household services, protective services, food preparation, health service, and personal service); operators, fabricators, and laborers; and farming, forestry, and fishing.
Non-physical occupation	An indicator variable taking the value of one if the respondent works in a non-physical occupation, i.e., works in a non-physical occupation in the baseline wave (1998 wave), or job of longest tenure at baseline (1998 wave) is a non-physical occupation. Non-physical occupations include professional and technical support; managerial; clerical and administrative support; sales.

Appendix 1.B: Withdrawal of Vioxx

Table 1.B1: Effect of withdrawal on probability of work

	Men				Women			
Dependent variable:	Working for Pay (0/1)							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
arthr×withdraw	0.0128	0.00891			-0.00534	-0.0121		
	(0.0184)	(0.0186)			(0.0150)	(0.0150)		
STarthr×withdraw			-0.0208	-0.0297			-0.0333	-0.0336
			(0.0389)	(0.0389)			(0.0317)	(0.0315)
LTarthr×withdraw			0.0182	0.0150			-0.00168	-0.00901
			(0.0191)	(0.0192)			(0.0153)	(0.0153)
Individual FE	No	Yes	No	Yes	No	Yes	No	Yes
N*T	5,602	5,602	5,602	5,602	8,376	8,376	8,376	8,376
N		2,801		2,801		4,188		4,188

Note: For the withdrawal, the pre-period is 2002 whereas the post-period is 2006. Regressions are estimated using a linear probability model and include a full set of control variables noted in the text. Standard errors reported in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 2

Self-reported Unmet Need for Healthcare and Healthcare Utilization in Canada: Evidence using the NPHS

2.1 Introduction

Ensuring equity of access is a critical dimension of health system performance in Canada and in most other industrialized countries. Studies examining socioeconomic inequity in access to healthcare often employ utilization as a proxy for access. However, socioeconomic inequities in healthcare use may arise due to the inequitable treatment of individuals of different socioeconomic status, or may be the result of differences in the preferences of those seeking treatment. Unlike utilization-based measures, subjective unmet needs for healthcare represent a broad measure of access as they are population-based, and are not limited to just those who have had contact with the formal healthcare system. Instead subjective unmet needs are based on an individual's own perception of their healthcare needs, and may be influenced by features of the health-care system as well as by the individual's own personal circumstances and preferences. Studies of subjective unmet needs for healthcare can therefore contribute toward a better understanding of the extent and causes of access problems in the healthcare system.

The literature examining subjective unmet needs for healthcare has largely focused on prevalence rates and associations with individual and healthcare system characteristics. By focusing on unmet needs in isolation from health-care use, the implicit assumption being made is that all unmet needs represent an access problem. However, individuals may have many reasons for reporting an unmet need, only some of which may be of policy concern. It is therefore important to understand the relationship between utilization of healthcare and the presence of an unmet need.

Allin et al. (2010) and Hurley et al. (2011) systematically examine the relationship between subjective unmet need and healthcare utilization using cross-sectional Canadian data. They find that the relationship varies depending on the reasons for reporting the unmet need. Individuals with a personal-related unmet need used the same or slightly less health care than would be predicted based on their needs. In contrast, individuals reporting an unmet need due to system-related reasons (of which wait times make up a significant portion) were not only high users, but they were higher than expected users of healthcare services. Three possible explanations are suggested to explain why those with system-related unmet needs were higher than expected users of healthcare: (1) they may have health care needs that are not well captured by standard survey questions on self-assessed health and chronic conditions, and as a result used more health care than would be predicted; (2) they may be on waiting lists for certain procedures and may require their condition to be monitored, thereby incurring additional visits; or (3) they may have higher preferences for using health care. Determining which explanations is driving these patterns is crucial from a policy perspective, as only the first two represent a genuine system failure that would require a policy response. However, it is not possible to distinguish between them with cross-sectional data.

In this paper, I contribute to the literature on access to healthcare and subjective unmet need by studying the relationship between unmet need and healthcare utilization using panel data from the National Population Health Survey (NPHS). Panel data allows for the control for individual time-invariant unobserved heterogeneity, which may be due to an individual's long-term unobserved health status and/or personal preferences and attitudes toward health care. In addition, this analysis relies on accurately predicting the distribution of utilization adjusted for needs. The empirical literature on modelling healthcare demand has highlighted the importance of accounting for individual unobserved heterogeneity in accurately predicting the conditional mean of healthcare use. Both Allin et al. (2010) and Hurley et al. (2011) employ hurdle model specifications to model healthcare utilization. I model healthcare utilization using latent class hurdle model for panel data developed by Bago d'Uva (2006), which outperforms the traditional hurdle models in most situations.

2.2 Literature on unmet needs

An extensive literature has focused on measuring prevalence and examining individual and health system factors correlated with unmet needs. However, most studies fail to adopt a disaggregated approach to analyzing unmet needs, which limits the policy relevance of their findings (Allin et al., 2010). In addition, direct comparisons between studies are difficult due to differences in survey questions, study populations, and methods.

Significant variations are observed in the prevalence and correlates of unmet needs across healthcare systems. U.S.-based studies, which comprise much of the literature on unmet needs, consistently observe a strong relationship between unmet need and income and insurance status (Allin et al., 2010). This is unsurprising given the U.S. system of healthcare financing and organization. For instance, in a study of working age adults using the 2000 to 2001 Community Tracking Study Household Survey, Pagán and Pauly (2006) find 18% of the uninsured reported unmet needs in comparison to 6.8% of the insured. The role of income and insurance status has also been emphasized in U.S.-Canada comparative studies based on the 2002-2003 Joint Canada United States Survey of Health (JCUSH). For instance, Sanmartin et al. (2006) find higher overall rates of unmet needs among individuals aged 18 or older in the U.S. (13%) than in Canada (11%) driven by the high prevalence of unmet needs among lower income, uninsured Americans. No significant differences are observed in prevalence rates between insured Americans and Canadians, or between Americans and Canadians among higher income groups (Sanmartin et al., 2006).

Even in countries with universal healthcare coverage, prevalence estimates of unmet needs are often large and widely varying. In a comparison across 29 countries using the 2009 European Union Survey on Income and Living Conditions (EU-SILC), Chaupain-Guillot and Guillot (2014) find prevalence of unmet needs for medical examination or treatment during the last year among people aged 16 years and older ranging from less than 1% in Slovenia to over 15% in Bulgaria and Latvia. The most important reasons for reporting unmet needs are cost, followed by watchful waiting, "other reasons", lack of time, and waiting lists. Similar findings are observed in studies using earlier cycles of the EU-SILC (Koolman, 2007; Allin and Masseria, 2009). Chaupain-Guillot and Guillot (2014) find evidence to suggest that some of the observed cross-country variation in unmet needs may be driven by differences in healthcare financing. Applying multilevel logistic regression models controlling for individual and health system characteristics, they find a positive association between the share of household out-of-pocket expenses in total health expenditure and the probability of reporting unmet needs for medical care. However, no effects are observed for other health system characteristics including the density of doctors, method of remuneration, and rules of access (choice of doctor and gate-keeping).

In Canada, early studies documented a growing prevalence of unmet needs among individuals aged 12 and older between 1994-2001, ranging from about 4% in 1994/95 to over 12% in 2000/01 (Sanmartin et al., 2002). Subsequently, Sibley and Glazier (2009) report prevalence rates based on the 2003 Canadian Community Health Survey (CCHS) of about 12% in Canada overall, varying across provinces from under 8% in Prince Edward Island to over 13% in Manitoba. Levesque et al. (2008) report prevalence of unmet needs among adults in 2005 to be as high as 18-19% in parts of Quebec. More recently, Baiden et al. (2014) report prevalence estimates of 10% in Ontario based on the 2012 CCHS. Individual level characteristics that are positively associated with reporting unmet needs include being younger, female, Canadian-born, an urban resident, more highly educated, in poor physical or mental health, without prescription drug insurance, as well as without a regular doctor (Chen and Hou, 2002; Kasman and Badley, 2004; Nelson and Park, 2006; Sanmartin and Ross, 2006; Sibley and Glazier, 2009; Hanley, 2009; Hurley et al., 2011; Ronksley et al., 2012; Sibley and Weiner, 2011)

A small group of studies have explicitly analyzed the relationship between unmet needs and healthcare utilization. However, many of these studies narrowly focus on a single type of healthcare service and/or fail to disaggregate unmet needs. For instance, among U.S.-based studies, Zuckerman and Shen (2004) find a positive association between unmet needs and emergency care use after controlling for health, demographic, socioeconomic and insurance status. Mollborn et al. (2005) find a positive association between prior physician visits and reporting unmet needs, adjusting for health, trust in physicians, demographic, socioeconomic and insurance status. Among Canadian studies, Kasman and Badley (2004) find a positive association between unmet needs and prior consultations with general practitioners, specialists, and physiotherapists controlling for health, demographics, and socioeconomic status . Chen and Hou (2002) disaggregate unmet needs into three types, depending on whether they are due to availability, acceptability, or accessibility. They find a positive association between reporting unmet needs due to availability and acceptability and prior GP or specialist visits adjusting for health, socioeconomic and demographic status. However, no association is found with unmet needs due to accessibility. Nelson and Park (2006) study mental healthcare using a similar disaggregated approach, and find a positive association between all three types of unmet needs and mental healthcare use. Using 2001 and 2003 cycles of the CCHS linked to administrative hospital data, Ronksley et al. (2013) examine the risk of adverse health outcomes among adults with at least one self-reported chronic condition. They find no association between overall unmet needs and all-cause or cause-specific hospitalization after controlling for socioeconomic status, demographics, and health behaviors. After disaggregating unmet needs, a small but statistically significant increased risk of all-cause hospitalization is observed among those with an unmet need due to availability, but not for unmet needs due to accessibility, acceptability, or personal choice. No association is found between unmet needs and other hospitalization-related outcomes including length of stay, subsequent readmission, or in-hospital death.

Only two studies have addressed the question whether individual's with unmet healthcare needs use more or less healthcare than would be expected based on their needs. Allin et al. (2010) examine this issue employing the cross-sectional 2005 Canadian Community Health Survey (CCHS). In their analysis, unmet needs are disaggregated into those due to system barriers, wait times, personal choice and "other" reasons. Healthcare utilization measures include self-reported general practitioner (GP) visits, specialist visits, and inpatient nights in hospital, and each type of utilization is modeled separately using a hurdle model framework. Allin et al. (2010) find that the relationship between unmet need and utilization varies depending on the reasons for reporting the unmet need, as well as by the measure of utilization used. In addition, they find systematic variation between unmet need and residual (actual minus need-predicted) utilization that is positive for those reporting wait times as the reason for an unmet need.

Hurley et al. (2011) build on Allin et al. (2010) in a number of ways, with the most substantial innovation being the measures of utilization analyzed. Whereas Allin et al. (2010) measure utilization using self-reported counts, Hurley et al. (2011) use the CCHS 1.1 linked to administrative data on the actual use of physician and hospital services. Linked data offers them a number of advantages. First, the data is not subject to recall or measurement error. Second, since utilization is measured in terms of the dollar value of services, services can be aggregated to get a more accurate measure of the total volume of care. Finally, the data allow for the study of hospital-based day procedures, which are a growing component of healthcare costs in Canada. Like Allin et al. (2010), Hurley et al. (2011) also use a hurdle framework to model healthcare utilization. They find differing patterns of healthcare utilization with the type of unmet need: based on individual healthcare needs and the provincial norm relationship between those needs and healthcare utilization, those with system-related unmet needs were higher-than-expected users of healthcare services whereas those with personal-related unmet needs use same or less healthcare services than would be expected.

An interesting finding in both Allin et al. (2010) and Hurley et al. (2011) is that individuals reporting an unmet need due to system-related reasons (of which wait times make up a significant portion) were not only high users, but that they were higher than expected users of healthcare services. Hurley et al. (2011) suggest three possible explanations for this finding: First, these individuals may have healthcare needs that are not well captured by the standard survey questions on self-assessed health and chronic conditions, and as a result used more healthcare than would be predicted. Second, these individuals may be on waiting lists for certain procedures and may require their condition to be monitored, thereby incurring additional visits. Third, these individuals may have higher preferences for using healthcare. It is quite likely, however, that a combination of these factors may be at play, and Hurley et al. (2011) find evidence consistent with all three explanations. Distinguishing between these explanations is vital as only the first two represent a genuine system failure and require a policy response.

2.3 Modelling healthcare utilization

Hurdle models (also known as "two part models") have for years been the cornerstone of empirical analysis of healthcare utilization. Under this framework, utilization is modelled as the result of two different decision processes: the first part of the model describes the difference between users and non-users of healthcare, and the second part describes the distribution of conditional utilization. An attractive feature of these models is that they accord with economic intuition underlying the demand for healthcare, whereby the initial contact decision is made independently by the patient, and additional visits and referrals are influenced by the physician. However, the hurdle framework may be incongruous with actual data on healthcare utilization, which is generally measured per period (for instance over a year) rather than per illness episode (Deb and Trivedi, 1997, 2002). Data observed over a period of time may may contain multiple illness episodes per individual. Moreover, the first visit observed in the data may not be the first visit in an episode of care. As a result, a single binary contact decision may not be identifiable, and the principal-agent interpretation ascribed to the hurdle model may be invalid. In addition, it may not be conceptually meaningful to distinguish between users and non-users of healthcare, as even healthy individuals may use healthcare for preventative or precautionary purposes.

Latent class models (also referred to as finite mixture models) have gained in popularity as an alternative way of modelling healthcare utilization. Unlike hurdle models that distinguish between users and non-users of care, latent class models make a distinction between different types of users. If two classes are specified, the different types of users can be thought of as "low users" (with low mean and low variance) and "high users" (with high mean and high variance). The latent class framework offers a flexible way of modelling unobserved individual heterogeneity since no distribution is assumed. It can also be seen as a discrete approximation of an underlying distribution (Heckman and Singer, 1984). Deb and Trivedi (1997) have shown that few points of support are required, usually only two or three. Latent class models for healthcare utilization have mostly been applied to cross-section data, for which Deb and Trivedi (2002) find that they outperform the hurdle model. However, Greene (2001) has argued that the latent class model is only weakly identified at best in a cross-section.

There have been relatively few studies modelling healthcare utilization that apply panel data methods to count data. An early application was Schellhorn et al. (2000) who employ a random effects negative binomial model to estimate the demand for primary physician and specialist visits. Van Ourti (2004) developed a random effects hurdle model with a common random effect in both parts. This model was used to estimate the determinants of physician and hospital visits using data from Belgium, and to calculate horizontal inequity indices. The two-part panel count data model was found to be most appropriate based on several model selection criteria when compared to a one-part panel model, a pooled two-part model, and a pooled one-part model.

Bago d'Uva (2006) brought together the two dominant approaches to modelling healthcare utilization with cross-section data: hurdle models and finite mixture models; and developed a finite mixture hurdle model for panel data. This specification allows for a two-part decision process within each class, and allows for intercept and slope heterogeneity in both parts. This model nests a latent class negative binomial model for panel data that is a panel version of Deb and Trivedi (1997), where both the zeros and the positives are determined by the same negative binomial distribution. The model is used to estimate the number of outpatient visits using data from the Rand Health

Insurance Experiment.

Bago d'Uva and Jones (2009) further extend the model developed by Bago d'Uva (2006), to allow the probabilities of class membership to depend on time invariant individual characteristics. Their approach is analogous to Mundlak (1978) and accounts for possible correlation between observed regressors and unobserved effects. Bago d'Uva and Jones (2009) model GP and specialist visits for twelve EU countries using the European Community Household Panel User Database (ECHP-UDB). When comparing different models, both Bago d'Uva (2006) and Bago d'Uva and Jones (2009) find the panel versions of the latent class models outperform the pooled latent class and hurdle models. Moreover, in most but not all cases, the more flexible latent class hurdle model for panel data offers an improvement over the latent class negative binomial model for panel data. Bago d'Uva et al. (2009) apply the model in Bago d'Uva and Jones (2009) to additional waves of the ECHP-UDB and compute measures of horizontal inequity.

2.4 Methods

Following Hurley et al. (2011), the analysis proceeds in three steps: (1) I estimate separate models of healthcare utilization for each dependent variable; (2) based on the estimated models I predict the distribution of use based on needs and calculate the difference between actual and needs-predicted utilization; and (3) I analyze the relationship between these needs-predicted residuals and unmet need variables.

As mentioned earlier, Hurley et al. (2011) and Allin et al. (2010) find that individuals with system-related unmet need were higher than expected users of healthcare. However, they were unable to distinguish between possible explanations for this finding with cross-sectional data. Using panel data, I make two key improvements over previous work: First, healthcare utilization is modelled in step (1) using latent class panel data models. Latent class models have been shown to outperform traditional hurdle models of healthcare utilization, which allows for more accurate predictions of needs-predicted use. Second, individual fixed effects are added in step (3) to control for individual time-invariant unobserved heterogeneity.

The use of fixed-effects methods improves upon previous cross-sectional studies that fail to account for omitted variable bias when estimating the relationship between needs-predicted residuals and unmet need variables. Omitted variable bias may arise due to the presence of unobservables such as preferences and attitudes towards care or long-term health status, which may be correlated with both needs-predicted residuals and unmet need variables. For instance, individuals with higher preferences for healthcare may be more likely to both report a system-related unmet need and be higher-than-expected users of healthcare. Similarly, those with poor unobserved long-term health may simultaneously be more likely to report a system-related unmet need and be higher-than-expected users of healthcare. Adding individual fixed effects controls for unobserved heterogeneity that is constant over time; however, time-varying individual unobserved heterogeneity cannot be eliminated and remains a source of bias.

In addition, the use of individual fixed effects allows me to indirectly distinguish between possible explanations for why those with system-related unmet need are higher-than-expected users of healthcare services, albeit under strong assumptions. Assuming all heterogeneity due to preferences and long-term health status is constant over time, their impact is eliminated with individual fixed effects. In this case, remaining evidence of a systematic relationship between needs-predicted residuals and unmet need variables after controlling for individual fixed effects in step (3) would suggest that the wait times explanation, specifically, increased visits to monitor people on wait lists, is driving these findings. However, this approach fails if the assumption of time-invariant preferences and unobserved long-term health status is violated. Whether this assumption is reasonable may be debated. For instance, preferences may be state dependent on health shocks, or may depend on information the individual learns about the healthcare system over time. However, there is little evidence on how to model time-varying preferences, and much of the economic literature assumes they are fixed. The constant unobserved health assumption is more questionable, as unobserved health status may change over time, particularly among those with need. However, the inclusion of a rich set of controls for health status may mitigate this effect.

2.4.1 Estimating models of healthcare utilization

The latent class model assumes the population is divided into C distinct classes. The probability that an individual i belongs to class j is π_{ij}, where $0 \leq \pi_{ij} \leq 1, \sum_{j=1}^{C} \pi_{ij} = 1$, and $j = 1, \ldots, C$. Let y_{it} represent the number of visits by individual i in wave t. The number of visits in a given wave conditional on the class that individual i belongs to is distributed according to $f_j\left(y_{it} \mid x_{it}; \theta_j\right)$, where the θ_j are vectors of parameters specific to each class. The joint density of $y_i = [y_{i1}, \ldots, y_{iT}]$ can be written as:

$$g\left(y_i \mid x_i; \pi_{i1}, \ldots, \pi_{iC}; \theta_1, \ldots, \theta_C\right) = \sum_{j=1}^{C} \pi_{ij} \prod_{t=1}^{T} f_j\left(y_{it} \mid x_{it}; \theta_j\right) \tag{2.1}$$

where $x_i = [x_{i1}, \ldots, x_{iT}]$ is a vector of covariates, including a constant.

In most applications of latent class models to healthcare utilization, the class membership probabilities are treated as parameters to be estimated along with $\theta_1, \ldots, \theta_C$, so $\pi_{ij} = \pi_j$ and $j = 1, \ldots, C$ (e.g. Deb and Trivedi (1997), Deb and Trivedi (2002), Bago d'Uva (2006)). This assumes that individual heterogeneity is uncorrelated with the regressors as in a random effects or random parameters specification, such as Van Ourti (2004). A more general approach that accounts for possible correlation between regressors and unobserved effects is to parameterize the heterogeneity as a function of time invariant individual characteristics ($z_i = \bar{x}_i$) analogous to Mundlak (1978). This approach can be implemented within a latent class model by modelling class membership as a multinomial logit (Bago d'Uva et al., 2009). The estimated logit coefficients can be interpreted as long-term associations with being a high user, and differ from the coefficients in the class-conditional distributions that represent short-term effects.

$$\pi_{ij} = \frac{exp(\acute{z}_i \gamma_j)}{\sum_{j=1}^{C} exp(\acute{z}_i \gamma_g)}, \qquad j = 1, \ldots, C; \gamma_C = 0 \tag{2.2}$$

Bago d'Uva (2006) incorporates a hurdle model into the latent class framework by developing a latent class hurdle negative binomial model for panel data (LCH-Pan), which allows for differences across latent classes in both the probability of use and conditional use. In this model, the class specific density $f_j(y_{it} \mid x_{it}; \theta_j)$ is defined as in the standard hurdle model, using a negative binomial model as the underlying distribution. In this case, $\theta_j = (\beta_{j1}, \beta_{j2}, \alpha_j)$, where β_{j1} and β_{j2} are vectors of coefficients in the two hurdle parts, and α_j is the overdispersion parameter. Within class j the determinants of care are allowed to have different effects on the probability of seeking care and on the conditional number of visits (β_{j1} can be different from β_{j2}). In addition, all elements of θ_j are allowed to vary across latent classes.

In this paper, I apply the latent class panel data modelling framework developed by Bago d'Uva (2006) and Bago d'Uva and Jones (2009). In particular, I estimate the LCH-Pan model for GP visits and hospital nights. For specialist visits, the LCH-Pan model failed to converge. The LCH-Pan model estimates a large number of parameters and problems with convergence under this specification have been noted in the literature. Therefore, in the case of specialist visits, I estimate a latent class negative binomial model for panel data (LCNB2-Pan), which is a more restricted version of the LCH-Pan model where $\beta_{j1} = \beta_{j2}$. This assumes that within each class, both the zeros and the positive counts are generated by the same negative binomial distribution.[1] For both the LCNB2-Pan and LCH-Pan models, class membership probabilities are defined as functions of time invariant individual characteristics. As in most other applications of latent class models, I assume that individuals are drawn from two classes ($C = 2$).[2]

2.4.2 Calculating need-predicted utilization

In keeping with the horizontal equity norm of equal treatment for equal need, predictions for need-based utilization must vary only with need. In the literature measuring horizontal inequity, this is done by neutralizing the effects of non-need variables by holding them constant at their mean. However, calculating predictions from highly non-linear latent class models is not straightforward. In particular, it becomes necessary to define whether the individual unobserved heterogeneity represents need, non-need, or a combination of both factors.

Unlike models where class membership probabilities are constant, the more

[1] I tested a number of alternate specifications for specialist visits. I tried using different starting values in the maximization algorithm, restricting a subset of parameters to be equal across latent classes, as well as restricting the overdispersion parameter α_j to zero for the class of low users (this corresponds to a mixture of a hurdle model composed of a logit and truncated negative binomial model for high users, and hurdle model composed of a logit and truncated poisson model for low users). The model failed to converge under these scenarios. A latent class hurdle poisson model ($\alpha_j = 0$ in both classes) was able to converge but performed poorly compared to the LCNB2-Pan model based on log-likelihood and information criteria. Therefore for specialist visits the LCNB2-Pan was the preferred model.

[2] The models with three components failed to converge, and it is widely accepted in the literature that two components are sufficient to capture a substantial portion of individual unobserved heterogeneity when modelling healthcare utilization.

flexible model estimated here specifies class membership probabilities as functions of time invariant covariates that include both need and non-need variables ($z_i = \bar{x}_i$), which allows for individual unobserved heterogeneity to be standardized for need factors. Even using this approach, however, there still remains some variation in the regression that is unexplained. This unexplained portion is assumed to capture non-need factors, which is consistent with the conventional approach to measuring inequity where need-predicted utilization varies only with observable need factors.[3]

Following Bago d'Uva et al. (2009), need-predicted utilization is predicted by holding non-need variables constant at their means as follows:

$$\hat{y}_{it}^{NPRED} = \sum_{j}^{C} \hat{\pi}_j \left(z_i^N, \bar{z}^{NN} \right) E_j \left[y_{it} \mid x_{it}^N, \bar{x}_t^{NN} \right] \tag{2.3}$$

where $\bar{x}_t^{NN}$ and $\bar{z}^{NN}$ are sample averages of non-need variables, x_{it}^N and z_i^N are actual values for need variables and $E_j(.)$ is the expected number of visits conditional on belonging to class j. Based on this approach, individuals with the same need characteristics are allocated to the same latent class regardless of their non-need characteristics. In addition, within each latent class individuals with the same need have the same needs-predicted utilization. Therefore, needs predicted utilization unconditional on the latent class $\hat{y}_{it}^{NPRED}$ varies only with observable need factors.

The needs-predicted residual is then calculated simply as the difference

[3]This assumption may be debatable as part of the unexplained variation may capture unmeasured need. However, assuming the unobserved variation to be need-related did not change the overall findings of this study.

between actual and needs-predicted utilization.

2.4.3 Analyzing the relationship between unmet need and the needs-predicted residuals

In the final stage, fixed effects regressions are run on the needs-predicted residuals using all the non-need variables as regressors. Using a fixed effects estimator allows for control of time-invariant unobserved heterogeneity and obtains consistent estimates. Of particular interest are the coefficients of the unmet need variables. If the coefficient is positive, it indicates that actual utilization is higher than needs-predicted utilization for a person with unmet needs relative to a person without unmet needs, controlling for other non-need variables.

2.5 Data and Variables

This paper draws on the longitudinal Household component of the National Population Health Survey (NPHS) conducted by Statistics Canada. The NPHS was designed to capture information on the health of the Canadian population and related socio-demographic information. It consists of three components: the Households, the Health Institutions, and the North. The Household component uses a complex, stratified two-stage sample design covering household residents in all ten provinces, except persons living on Indian reserves, on Canadian Forces bases, and in some remote areas. Starting in 1994/1995, the survey was conducted every two years until 2010/11 (nine cycles) after which it was discontinued. The first three cycles include both cross-sectional and longitudinal components; from Cycle 4 (2000/01) onwards the survey is strictly longitudinal. The longitudinal sample includes 17,276 persons in 1994/1995 of all ages who were subsequently followed for up to nine waves.

The analysis sample is restricted to (i) Cycles 3 to 9 (seven cycles: 1998/99 – 2010/11) of the NPHS, (ii) respondents aged 18 and above in any given wave, and (iii) observations with non-missing information on any of the variables used in the analysis. The 1994/95 and 1996/97 cycles of the NPHS are excluded because continuous household income is unavailable in both. Income is an important control that is correlated with both unmet need and healthcare utilization. Given the 13 year span of the panel, it is imperative to account for inflation in household income. To do so, the income variable must be continuous. The final sample is an unbalanced panel consisting of 13,549 individuals observed for up to seven waves, for a total of 53,697 observations. The analysis does not use Statistics Canada survey weights.

2.5.1 Dependent variables

I examine three measures of healthcare utilization. Each is a count variable that is modelled separately:

(i) GP visits, based on the following question:

> "Not counting when you were an overnight patient, in the past 12 months, how many times have you seen, or talked on the telephone, about your physical, emotional or mental health with a family doctor or general practitioner?"

(ii) Specialist visits, based on the following question:

> "Not counting when you were an overnight patient, in the past 12 months, how many times have you seen, or talked on the telephone, about your physical, emotional or mental health with an eye specialist or any other medical doctor (such as a surgeon, allergist, orthopedist, gynecologist or psychiatrist)?"

(iii) Inpatient nights, based on the following question:

> "In the past 12 months, Have you been a patient overnight in a hospital, nursing home or convalescent home?...For how many nights?"

2.5.2 Independent variables

Independent variables are included in accordance with studies on modelling the demand for healthcare. To predict needs-predicted utilization, determinants of healthcare must be classified as either "need" or "non-need"; where need adjusters are factors that ought to legitimately affect receipt of healthcare. While any classification ultimately depends on value judgments, I follow the classification used in the extensive literature on equity in health and healthcare.

Need variables

Need variables include a female dummy variable, as well as age, age^2, and an age-female interaction term as continuous variables. Also included are a number of variables to capture health status. These consist of dummies for self-assessed health (excellent, very good, good, fair/poor),[4] a dummy variable for whether the respondent has an activity limitation, as well as dummies indicating the number of chronic conditions (one condition, two or three conditions, three or more conditions, no chronic conditions).

Unmet need variables

The key independent variables in the analysis are those pertaining to unmet need. These are based on the following questions:

> "During the past 12 months, was there ever a time when you felt you needed healthcare but didn't receive it?" (Yes, No, Do not know, Refuse)

If the responded answered "Yes", they were then asked:

> "Thinking of the most recent time, why didn't you get care?"

Respondents were then given a list of 13 possible reasons and could also specify a reason not listed. They were allowed to choose multiple reasons. Following Hurley et al. (2011), I create two dichotomous variables reflecting two types of unmet need: unmet need due to personal reasons, and unmet need due to system-related reasons.[5] Personal reasons are those factors for which the

[4]Self-assessed health in the NPHS is measured in five categories (excellent, very good, good, fair, poor). I combine the "fair" and "poor" categories together as less than 1% of respondents in my sample reported "poor" self-assessed health.

[5]In a few cases (fewer than 350 observations) an unmet need was reported for "other" reasons. These observations were dropped from the analysis as they could not be classified into either personal or system-related unmet need.

individual may reasonably be held responsible. System-related reasons are factors beyond the control of the individual, that may be interpreted as a failure of the healthcare system. The details of this classification are presented in Table 2.1. While most reasons clearly fall into either personal or systemic categories, the classification of a few others such as "didn't know where to go" or "felt it would be inadequate" is less clear cut. For instance, an individual may report feeling services would be inadequate because services are in fact poorly provided (system reason); on the other hand they may have a condition for which there is no treatment or hold unreasonable expectations of what constitutes adequate care (personal reasons).

Table 2.1: Reasons for unmet need

Personal	System-related
Too busy	Not available in area
Didn't get around to it	Not available when required
Didn't know where to go	Wait time too long
Transportation problems	Cost
Personal/family responsibilities	Language problems
Dislikes doctors/afraid	
Decided not to seek care	
Felt it would be inadequate	

Based on the classification in Table 2.1, I create two unmet need variables as follows: I create a binary variable for system-related unmet need that takes a value of 1 if an individual reports an unmet need for any system-related reasons, and a value of 0 if the individual does not have an unmet need or has an unmet need for exclusively personal reasons; similarly, I create a binary variable for personal unmet need that takes a value of 1 if an individual reports an unmet need for any personal reasons, and a value of 0 if the individual does not have an unmet need or has an unmet need for exclusively system-related reasons. A small number of individuals report an unmet need for both personal and system-related reasons. For the purposes of the regression analysis only, these individuals are randomized to make the categories mutually exclusive.

Other non-need variables

Other non-need variables employed in the analysis include controls for socioeconomic status, health behaviours, and demographics. The natural log of equivalized household income is used to capture household income. The NPHS asked individuals their total household income from all sources (in continuous form) and the composition of the household. Household income is deflated by the consumer price index (also included in the survey), and then adjusted for household size and composition using the modified OECD equivalence scale.[6] Also included are four dummies for level of educational attainment (less-than secondary, secondary, some post-secondary, post-secondary graduate). Health behaviours are captured using three dummies for smoking status (smoker, former smoker, non-smoker). Additional variables include dummies for having a regular doctor, being an immigrant, being married, and province of residence.

[6] The modified OECD equivalence scale assigns a weight of 1.0 to the first adult household member, 0.5 to the second adult household member and 0.3 to children.

2.6 Results

2.6.1 Descriptive statistics

Descriptive statistics on all the variables for the pooled sample and by unmet need subsamples are presented in Table 2.2. As expected, individuals reporting unmet needs use more healthcare services than those not reporting unmet needs, with the relative difference largest in hospital nights (76% greater), followed by specialist visits (65% greater), and GP visits (52% greater). Moreover, individuals reporting system-related unmet needs have significantly higher GP visits (16% greater) and specialist visits (19% greater) relative to those reporting personal-related unmet needs. The difference in hospital nights, however, is not statistically different from zero.

Individuals reporting unmet needs also tend to have worse health status than those not reporting unmet needs. The proportion of individuals reporting unmet needs with "fair/poor" health status is double the proportion for those with no unmet needs. A similar pattern can be observed for activity limitations and number of chronic conditions. Moreover, those with a system-related unmet need are in significantly worse health than those reporting a personal-related unmet need. For instance, the proportion of individuals with system-related unmets need reporting "fair/poor" health status is about 18% higher relative to the proportion for those with personal unmet needs.

In terms of demographic characteristics, people reporting unmet needs are more likely to be younger, women, and native born. Moreover, women are also more likely to report a system-related unmet need than a personal unmet need.

There are also some notable differences across provinces, with a smaller proportion of individuals with an unmet need residing in the Atlantic provinces and Ontario. In addition, a higher proportion of individuals with a system-related unmet need reside in Quebec (23%) than those with a personal-related unmet need (17%) and those without an unmet need (20%). On the other hand, a higher proportion of individuals with personal-related unmet needs reside in Ontario and Saskatchewan (26% in Ontario; 7% in Saskatchewan) than those with system-related unmet needs (22% in Ontario; 5% in Saskatchewan).

There also appears to be a relationship between education levels and unmet needs, with those reporting unmet needs more likely to have higher education levels. The proportion of individuals reporting an unmet need with a less-than-secondary education is 17%, whereas the same proportion for those with no unmet needs is almost 20%. Moreover, this gradient appears stronger among those with a system-related unmet need than those with a personal-related unmet need. A smaller proportion of individuals with unmet needs have a regular doctor (83%) compared to those with no unmet needs (88%). In addition, individuals with unmet needs are more likely to be smokers (32%) than those with no unmet needs (24%).

Figure 2.1 displays trends in the unmet variables over time. The overall percentage of individuals with an unmet need rose steeply between 1998/99 and 2002/03 from 6% to over 10%. This is in line with Sanmartin et al. (2002) who report similar changes. Moreover, the rise is steeper for unmet needs due to system-related reasons than for personal-related reasons. Supply side changes resulting from cuts in healthcare budgets during this period may be responsible for this pattern. Since the high in 2002/03, the percentage of individuals with an unmet need declined steadily to a low of about 7% in 2008/09. Both unmet need due to system and personal reasons have dropped during this period, though the drop is slightly more significant for unmet need due to system reasons. In the final 2010/11 wave, however, there is an uptick in the percentage of individuals with an unmet need which rises to 9% driven largely by system-related reasons.

2.6.2 Regression results

Healthcare utilization models

This section presents estimation results from the three utilization models. GP visits and hospital nights are modelled using the LCH-Pan model. Specialist visits are modelled using the LCNB2-Pan model. I first assess the overall performance of the latent-class models relative to traditional pooled hurdle models. Next, I present estimated class probabilities and fitted values, which allow for the two classes to be classified as low and high users. Finally, I discuss the regression coefficients for each model.

Table 2.3 compares the performance of the latent class models to the traditional pooled hurdle model (comprising a logit in the first part and a truncated negative binomial in the second part) according to log-likelihood, AIC, and BIC criteria. For both GP and specialist visits, the latent class model clearly outperforms the hurdle model on all three criteria. For hospital nights, the latent class model is preferred based on the log-likelihood and AIC, while the the hurdle model is marginally preferred based on the BIC. The BIC imposes a heavier penalty on the number of parameters in the model, and therefore the LCH-Pan model does not perform as well under this measure. Overall, the results show that the latent class models are an improvement over the hurdle model for GP and specialist visits. This highlights the importance of taking into account unobserved heterogeneity and the panel nature of the data.

Calculated shares and fitted values for each dependent variable are displayed in Table 2.4. Based on these predictions, the classes can be classified as high and low users. For GP visits, the estimated share of individuals classified as low and high users is 0.650 and 0.350 respectively. The fitted values indicate clear cut differences in average utilization between these two classes, with 2.077 mean visits among low users and 5.55 mean visits among high users. Moreover, significant differences are visible in both the probability and conditional use: low users have a 0.753 probability of use and 2.598 conditional visits on average; in comparison, high users have a 0.896 probability of use and 6.066 conditional visits on average. For specialist visits, the estimated shares for low and high users is 0.774 and 0.226 respectively. There are notable differences in the fitted mean number of visits, with low users having 0.925 visits and high users having 3.050 visits on average.[7] For hospital nights, the estimated shares of low and high users is 0.373 and 0.637 respectively. This implies that the class of high users consists of more individuals than the class of low users. This finding may be due to the fact that latent class panel data models classify individuals as low or high users for the duration of the panel, which in this case spans over 10 years. Given that the data on hospital nights

[7]For specialist visits, fitted values for the probability of use and conditional use are not shown as both the zeros and positive counts are generated by the same distribution.

exhibit substantial variability in the right tail of the distribution even within individuals, the model is unable to distinguish between high users and very high users. This suggests that a model with three classes may be more appropriate; however, such a model failed to converge. The fitted mean number of visits for low users is 0.350 and for high users is 1.401. Moreover, differences in conditional use are more apparent than differences in the probability of use across the two classes.

Tables 2.5-2.7 display the regression coefficients from the healthcare utilization models. Interpreting the regression results of nonlinear latent class models is not straightforward. From the estimated coefficients, it is only possible to qualitatively assess the impact of covariates on healthcare use in terms of significance and sign.

GP visits are modelled using the LCHNB2-Pan model that distinguishes between the probability of use and conditional use across classes. These results are presented in Table 2.5. The first panel corresponds to the class of low users and the second to the class of high users. Estimated coefficients for the probability of use and conditional use are presented for each class.

Results for the probability of use are reported in the first two columns of each panel. For the probability of use in the class of low users, the system-related unmet need coefficient is positive and statistically significant at the 1% level. This implies that among low users, those with a system-related unmet need have a higher probability of GP visits than those without an unmet need. In contrast, no association is observed between personal unmet need and probability of GP visits, as the coefficient for personal unmet need is statistically insignificant. In addition, the coefficients for income and education dummies are also positive and statistically significant consistent with a socioeconomic gradient in the probability of use. There is a strong health gradient with those in poor health having a higher probability of GP visits. Demographic variables are also strongly associated with the probability of use. Moreover, having a regular physician is correlated with higher probability of GP visits, whereas smoking is negatively associated with the probability of GP visits.

For the probability of use among high users, the coefficients for both system-related and personal unmet need are small and insignificant. There is some evidence of a socioeconomic gradient in the probability of use among high users as income is positively associated with the probability of GP visits. However, coefficients for education variables are insignificant. A strong health gradient is observed with those in poor health having a higher probability of GP visits. Demographic variables are also strongly associated with the probability of use. Having a regular physician is also positively associated with the probability of GP visits, whereas smoking is negatively associated with the probability of GP visits.

Results for the conditional use are reported in the last two columns of each panel. For conditional use among low users, the coefficients for both system-related and personal unmet need are positive and statistically significant (system-related at 1% level; personal at 5% level). In terms of socioeconomic status, less-than-secondary level of education is positively associated with conditional visits. There is a strong health gradient with those in poor health having higher conditional GP visits. Demographic variables are also strongly associated with the conditional use. In addition, having a regular physician is associated with higher conditional GP visits, whereas smoking is negatively associated with conditional GP visits.

For conditional use among high users, the coefficient for system-related unmet need is positive and significant at the 1% level, whereas the personal unmet need coefficient is insignificant. There appears to be a negative education gradient, with with lower education levels associated with higher conditional visits. Moreover, there is a strong health gradient with those in poor health having higher conditional GP visits. Demographic variables are also strongly associated with the conditional use. In addition, having a regular physician is associated with higher conditional GP visits.

I employ likelihood-ratio (LR) tests to assess whether differences between the two classes in their response to covariates are statistically significant . For both the probability of use as well as conditional use, coefficients for the two classes are significantly different when tested jointly. When tested individually, significant differences are observed for a number of coefficients. For the probability of use, coefficients for low users are significantly greater in comparison to those for high users at the 1% level for two or three chronic conditions and age^2; at the 5% level for four or more chronic conditions, female, married; and at the 10% level for having one chronic condition. In comparison, coefficients for high users are significantly greater than those for low users at the 1% level for very good self-assessed health, regular doctor, age, and residing in Saskatchewan. Similarly for conditional use, coefficients for low users are significantly greater at the 1% level for very good self-assessed health, good self-assessed health, fair or poor self-assessed health, one chronic condition, two or three chronic conditions, and four or more chronic conditions; at the 5% level system-related unmet need, personal unmet need, age, female; and at the 10% level for residing in Alberta. On the other hand, coefficients for high users are significantly greater at the 1% level for activity limitations, and residing in Saskatchewan. These test results imply that for both the probability of use and conditional use, the two classes differ significantly in their response to health and demographic characteristics. In addition, the classes respond differently to unmet need variables for conditional use only. No significant difference is observed in response to socioeconomic variables across the two classes for both the probability and conditional use. These differences in class response to covariates appear plausible, although there is no apriori information available to validate them.

Specialist visits are modelled using the more restrictive LCNB2-Pan model, where both the zeros and positives are determined by the same distribution. These results are presented in Table 2.6.

Among low users, both system-related and personal unmet need are positively associated with specialist visits (system-related at 1% level; personal at 5% level). In addition, a strong socioeconomic gradient is observed in income and education, as well as a strong health gradient. Demographic variables are strongly associated with specialist visits. Moreover, having a regular doctor and being a former smoker is positively associated with specialist visits, whereas being a current smoker is negatively associated with specialist visits.

In the class of high users, the system-related unmet need coefficient is positive and significant at the 1% level. In comparison, the coefficient for personal unmet need is small and insignificant. There also appears to be strong socioeconomic and health gradients, with the richer and more educated individuals, as well as those in poor health having higher specialist visits. Demographic variables are strongly associated with specialist visits. In addition, being a former smoker is positively associated with specialist visits.

Results from LR tests on the coefficients across the two classes indicate that the coefficients are jointly significantly different. When tested separately, coefficients for low users are significantly greater in comparison to those for high users at the 1% level for ln(income), one chronic condition, two or three chronic conditions, four or more chronic conditions, regular doctor, being female, immigrant, currently smoking, and residing in the Atlantic provinces, Quebec, Manitoba, Saskatchewan, and Alberta; at the 5% level for system-related unmet need and age^2; and at the 10% level for residing in British Columbia. In comparison, coefficients for high users are significantly greater than those for low users at the 1% level for fair self-assessed health, activity limitations; and at the 10% level for the age$\times$female interaction. These results indicate that the two classes significantly differ in their response to demographics, health status, socioeconomic status, as well as system-related unmet need.

Table 2.7 presents the results for the model for hospital nights. Notably, the estimate and associated standard error of the overdispersion parameter (α) in the class of high users are very large in magnitude (α=9.791; S.E = 2.301). This suggests that the model is less precise at estimating the right tail of the distribution, which is not surprising as hospital nights are difficult to model due to their variability. Moreover, large α's have also been observed in a number of other studies, particularly when modelling hospital utilization.[8] The results should therefore be interpreted with caution.

Results for the probability of use are reported in the first two columns of each panel. For the probability of use in the class of low users, the system-related unmet need coefficient is positive and statistically significant at the 1% level, implying that among low users, those with a system-related unmet need have a higher probability of hospital nights than those without an unmet need. In contrast, no association is observed between personal unmet need and probability of hospital nights. Demographic variables are strongly associated with the probability of use. Moreover, activity limitations and having a regular physician are correlated with higher probability of hospital nights, whereas higher income is negatively associated with the probability of hospital nights.

For the probability of use among high users, the system-related unmet need coefficient is positive and marginally significant (statistically significant at the 10% level), and the coefficient for personal unmet need is insignificant. A strong health gradient is observed with those in poor health having a higher probability of hospital nights. Demographic variables are strongly associated with the probability of use. Having a regular physician and less-than-secondary education level are also positively associated with the probability of hospital nights.

Results for the conditional use are reported in the last two columns of each

[8]For instance, in estimation of latent class panel data models for GP and specialist visits (Bago d'Uva and Jones, 2009); hurdle models for hospital stays (Gerdtham, 1997; Gerdtham and Trivedi, 2001); latent class models for hospital outpatient visits (Deb and Trivedi, 1997); and hurdle models for specialist visits (Jiménez-Martín, 2002).

panel. For conditional use among low users, the coefficients for both system-related and personal unmet need are small and insignificant. Demographic variables are strongly associated with conditional use. In addition, fair/poor self-assessed health, activity limitations, and having a regular physician is associated with higher conditional hospital nights, whereas higher income is negatively associated with conditional hospital nights.

For conditional use among high users, the coefficients for both system-related and personal unmet need are small and insignificant. There is a strong health gradient with those in poor health having higher conditional hospital nights. Demographic variables are also strongly associated with the conditional use. In addition, smoking and having a regular physician are positively associated with conditional hospital nights, whereas higher income is negatively associated with hospital nights.

Finally, I assess whether differences between the two classes in their response to covariates are statistically significant using LR tests. For both the probability of use as well as conditional use, coefficients for the two classes are significantly different when tested jointly. Significant differences are also observed for a number of coefficients when tested individually. For the probability of use, coefficients for low users are significantly greater in comparison to those for high users at the 1% level for age, age^2, age$\times$female interaction, and being married; at the 5% level for immigrant status. In comparison, coefficients for high users are significantly greater than those for low users at the 1% level for ln(income), good self-assessed health, fair/poor self-assessed health, one chronic condition, two or three chronic conditions, and four or more chronic conditions; and at the 5% level for very good self-assessed health, activity limitations, and residing in Quebec. Similarly for conditional use, coefficients for low users are significantly greater at the 1% level for age×female interaction, married, residing in Atlantic provinces, Saskatchewan, and British Columbia; and at the 5% level for residing in Manitoba. On the other hand, coefficients for high users are significantly greater at the 1% level for activity limitations; at the 5% level for fair/poor self-assessed health, and residing in Manitoba; and at the 10% level for good self-assessed health, smoking, and female. These test results imply that for both the probability of use and conditional use, the two classes differ significantly in their response to socioeconomic, health, and demographic characteristics.

Table 2.8 presents logit model coefficients for the probability of being a high user for each of the three dependent variables. The first panel presents results for GP visits. Both system and personal unmet need variables are strongly positively associated with being a high user. This is not surprising as individuals with an unmet need are high users of healthcare services. Income on the other hand is negatively associated with being a high user. There is also a strong positive association with poor health status, being a smoker, having a regular doctor. Demographic variables including age, gender, married, residing in Quebec, Saskatchewan, and BC are strongly associated with class membership.

For the specialist visits results presented in the second panel, the system-related unmet need coefficient is positive and large, but statistically insignificant. The personal unmet need variable is marginally significant and positively associated with class membership. A strong positive association is observed with poor health status and having a regular doctor. In addition, demographic variables including age, gender, residing in the Atlantic provinces, and Alberta are strongly associated with class membership.

The third panel presents results for hospital nights. Both the unmet need coefficients are statistically insignificant. The association between socioeconomic variables and being a high user is mixed, with both higher income (significant at 10% level) and having less-than-secondary education (significant at 1% level) being negatively associated with being a high user. Poor health status and having a regular doctor are positively associated with being a high user. Moreover, demographic variables including gender, age×female, residing in Manitoba, and Saskatchewan are strongly associated with class membership.

Estimation results from fixed effects models of needs-predicted residual

Table 2.9 presents the results of fixed effects regressions on the needs-predicted residual. The results for GP visits are presented in the first panel. The coefficient of system-related unmet need is positive and significant at the 1% level and implies that on average, an individual with a system-related unmet need has a residual (actual - needs-predicted GP visits) that is 0.595 visits larger than the residual for an individual with no unmet needs. In other words, individuals reporting a system-related unmet need, on average, use 0.595 more GP services than the provincial norm for someone with their healthcare needs, after accounting for non-need variables as well as unobserved fixed factors. The coefficient for personal unmet need in comparison is small and statistically insignificant. In addition, having a regular doctor and residing in Saskatchewan are also positively associated with the needs-predicted residual.

Similar results are obtained for specialist visits, which are displayed in the second panel. The system-related unmet need coefficient is positive and significant at the 1% level and implies that on average, an individual with a system-related unmet need has a needs-predicted residual that is 0.242 visits larger than the needs-predicted residual for an individual with no unmet needs. In other words, individuals reporting a system-related unmet need, on average, use 0.242 more specialist services than the provincial norm for someone with their healthcare needs, after accounting for non-need variables as well as unobserved fixed factors. The coefficient for personal unmet need in comparison is small and statistically insignificant. In addition, having a regular doctor is positively associated with the needs-predicted residual, whereas having less-than-secondary education and residing in the Atlantic provinces are negatively associated with the needs-predicted residual.

The results for hospital nights are presented in the third panel. There is no association between the unmet need variables and needs-predicted residuals, as the coefficients of both system-related unmet need and personal unmet need are statistically insignificant. However, having less-than-secondary education level is positively associated with the needs-predicted residual, whereas smoking and residing in the Atlantic provinces are negatively associated with the needs-predicted residual.

2.7 Discussion

The main advantage of this study is the use of panel data methods. Latent-class panel data methods are used to model healthcare utilization, which are shown to outperform traditional hurdle models. In addition, the analysis of needs-predicted residuals uses individual fixed effects to control for time-invariant unobserved heterogeneity. Overall findings of this study are consistent with those in Allin et al. (2010) and Hurley et al. (2011). Different patterns of healthcare utilization were observed among individuals with system-related unmet needs, individuals with personal-related unmet needs, and individuals with no unmet needs. Individuals with a personal-related unmet need were high users, but they tended to use the same quantity of services as expected based on their needs. On the other hand, individuals with a system-related unmet need were found to not only be high users of GP and specialist visits, they were also found to be higher-than-expected users.

This study is able to provide additional insights into why those with system-related unmet needs are higher-than-expected users of healthcare services. Three indistinguishable hypotheses were proposed in earlier work to explain this finding: (i) these individuals may have unobserved healthcare needs that are not well captured by standard survey questions; (ii) these individuals may have higher preferences for using healthcare; and (iii) these individuals may be on waiting lists for certain procedures and may require their condition to be monitored, thereby incurring additional visits. Even after controlling for time-invariant heterogeneity using individual fixed effects, which capture both fixed unmeasured health status and fixed unmeasured preferences, a positive relationship is observed between needs-predicted residuals and system-related unmet need. The fixed effects control for the first two explanations assuming individual preferences and long-term health status are time-invariant; this leaves the third explanation suggesting that these individuals may be incurring additional visits to have their condition monitored while on wait lists.

It is important to note that this analysis relies on the assumption that unobserved individual heterogeneity in the form of preferences and long-term health status is constant over time. Fixed individual preferences is a less controversial assumption, and one that is implicit in much of the economic literature. A more controversial assumption is that unobserved long-term health status is constant over time. While there does not appear to be a formal way of testing this assumption, this study includes a rich set of observables to capture health status such as variables for self-assessed health and the number of chronic conditions.

This study may be improved upon in a number of ways in future work. One avenue for improvement may be the inclusion of data on supply side conditions affecting both the reporting of unmet needs and the use of healthcare services. For instance, wait times measures such as data on wait times by region at a sub-provincial level may be included as controls in the regression models. If the coefficient of system-related unmet needs is attenuated in the fixed effects regression models by the inclusion of these wait times measures, this would provide further evidence in support of the wait times explanation. Another avenue for possible improvement would be to use administrative data to directly test the wait times hypothesis. For instance, if rates of visits between a specialist visit and an elective procedure were higher than expected among those with an unmet need this would provide direct evidence in support of the wait times hypothesis.

References

Allin, S., M. Grignon, and J. LeGrand (2010). Subjective unmet need and utilization of heath care services in Canada: what are the equity implications? *Social Science & Medicine 70*, 465–472.

Allin, S. and C. Masseria (2009). Unmet needs as an indicator of health care access. *Eurohealth 15*, 7–14.

Bago d'Uva, T. (2006). Latent class models for utilisation of health care. *Health Economics 1*, 329–343.

Bago d'Uva, T. and A. M. Jones (2009). Health care utilisation in Europe: New evidence from the ECHP. *Journal of Health Economics 28*, 265–279.

Bago d'Uva, T., A. M. Jones, and E. van Doorslaer (2009). Measurement of horizontal inequity in health care utilisation using European panel data. *Journal of Health Economics 28*, 280–289.

Baiden, P., W. den Dunnen, G. Arku, and P. Mkandawire (2014). The role of sense of community belonging on unmet health care needs in Ontario, Canada: findings from the 2012 Canadian community health survey. *J Public Health* (22), 467–478.

Chaupain-Guillot, S. and O. Guillot (2014). Health system characteristics and unmet care needs in Europe: an analysis based on EU-SILC data. *The European Journal of Health Economics*, 1–16.

Chen, J. and F. Hou (2002). Unmet needs for health care. *Health Reports 13*, 23–34.

Deb, P. and P. Trivedi (1997). Demand for medical care by the elderly: a finite mixture approach. *Journal of Applied Econometrics 12*, 313–336.

Deb, P. and P. Trivedi (2002). The structure of demand for health care: latent class versus two-part models. *Journal of Health Economics 21*, 601–625.

Gerdtham, U. (1997). Equity in health care utilization: Further tests based on hurdle models and Swedish micro data. *Health Economics 6*, 303–319.

Gerdtham, U. and P. K. Trivedi (2001). Equity in Swedish health care reconsidered: new results based on the finite mixture model. *Health Economics 10*, 565–572.

Greene, W. (2001). Fixed and random effects in nonlinear models. Working paper 01-01, New York University, Department of Economics, Stern School of Economics.

Hanley, G. (2009). Prescription drug insurance and unmet need for health care: a cross-sectional analysis. *Open Med 3*, 178–183.

Heckman, J. and B. Singer (1984). A method of minimizing the distributional impact in econometric models for duration data. *Econometrica 52*, 271–30.

Hurley, J., T. Jamal, M. Grignon, and S. Allin (2011). The relationship between self-reported unmet need for health care and health care utilization. McMaster Research Data Centre Research Paper No. 23, McMaster University, Hamilton, Ontario, Canada.

Jiménez-Martín, S. (2002). Latent class versus two-part models in the demand for physician services across the European Union. *Health Economics 11*, 301–321.

Kasman, N. and E. Badley (2004). Beyond access: Who reports that health care is not being received when needed in a publicly-funded health care system? *Canadian Journal of Public Health 95*(4), 304–308.

Koolman, X. (2007). Comparative EU statistics on income and living conditions: Issues and challenges. in proceedings of the EU-SILC Conference, Helsinki, Eurostat.

Levesque, J., R. Pineault, L. Robert, M. Hamel, D. Roberge, C. Kapetanakis, B. Simard, and A. Laugraud (2008). Unmet health care needs: A reflection of the accessibility of primary care services? Government of Quebec, Quebec.

Mollborn, S., I. Stepanikova, and K. S. Cook (2005). Delayed care and unmet needs among health care system users: when does fiduciary trust in a physician matter? *Health Services Research* (40), 1898–1917.

Mundlak, Y. (1978). On the pooling of time series and cross-section data. *Econometrica 46*, 69–85.

Nelson, C. and J. Park (2006). The nature and correlates of unmet health care needs in Ontario, Canada. *Social Science & Medicine 62*, 292–300.

Pagán, J. A. and M. V. Pauly (2006). Community-level uninsurance and the unmet medical needs of insured and uninsured adults. *Health Services Research 41*, 788–803.

Ronksley, P., C. Sanmartin, H. Quan, P. Ravani, M. Tonelli, B. Manns, and B. Hemmelgarn (2012). Association between chronic conditions and perceived unmet health care needs. *Open Med 6*, 48–58.

Ronksley, P., C. Sanmartin, H. Quan, P. Ravani, M. Tonelli, B. Manns, and B. Hemmelgarn (2013). Association between perceived unmet health care needs and risk of adverse health outcomes among patients with chronic medical conditions. *Open Med 7*, e21–e30.

Sanmartin, C., J. Berthelot, E. Ng, K. Murphy, D. Blackwell, J. Gentleman, M. Martinez, and C. Simile (2006). Comparing health and health care use in Canada and the United States. *Health Affairs* (25), 1133–1142.

Sanmartin, C., C. Houle, S. Tremblay, and J.-M. Berthelot (2002). Changes in unmet health care needs. *Health Reports 13*, 16–21.

Sanmartin, C. and N. Ross (2006). Experiencing difficulties accessing first-contact health services in Canada. *Healthcare Policy 1*(2), 103–119.

Schellhorn, M., A. E. Stuck, C. E. Minder, and J. C. Beck (2000). Health services utilization of elderly Swiss: Evidence from panel data. *Health Economics 62*, 533–545.

Sibley, L. and R. Glazier (2009). Reasons for self-reported unmet healthcare needs in Canada: A population-based provincial comparison. *Healthcare Policy 5*(1), 87–101.

Sibley, L. and J. Weiner (2011). An evaluation of access to health care services along the rural-urban continuum in Canada. *BMC Health Services Research 11*(20).

Van Ourti, T. (2004). Measuring horizontal inequity in Belgian health care using a gaussian random effects two part count data model. *Health Economics 13*, 705–724.

Zuckerman, S. and Y. C. Shen (2004). Characteristics of occasional and frequent emergency department users: do insurance coverage and access to care matter? *Medical Care* (42), 176–182.

Figure 2.1: Trends in overall, system-related, and personal-related unmet needs over time

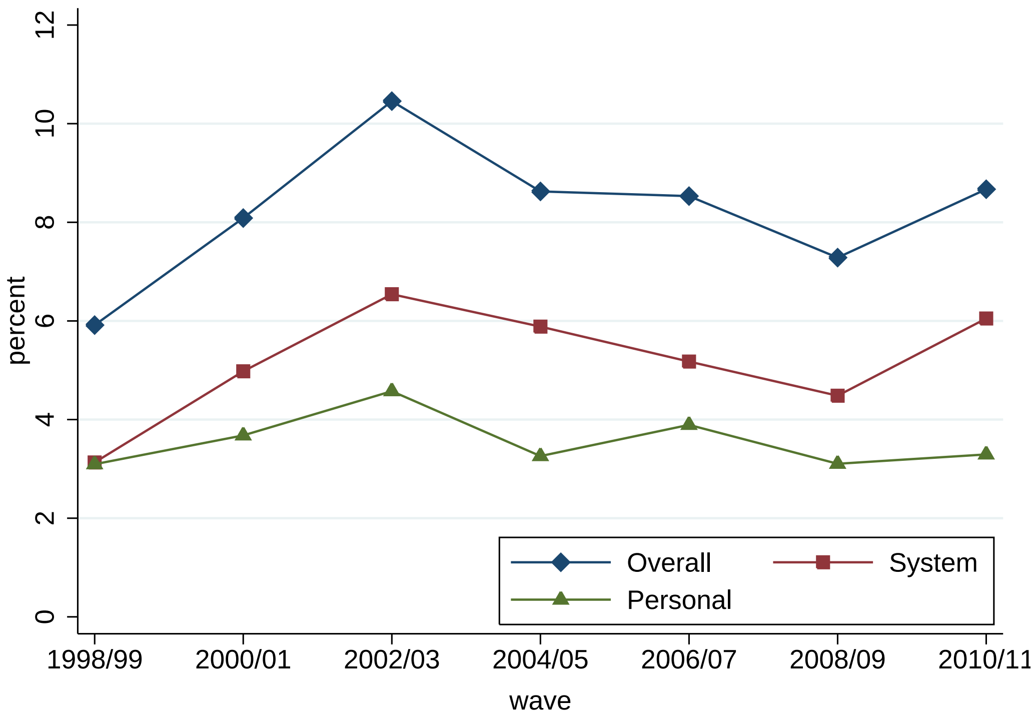


Table 2.2: Descriptive statistics for the pooled full sample, and by unmet need subsample

		Unmet need			
	Total	None	Any	System	Personal
	mean (S.D.)	mean (S.D.)	mean (S.D.)	mean (S.D.)	mean (S.D.)
N	53,697	49,298	4,399	2,813	1,848
Utilization					
GP visits	3.429	3.289	4.994	5.289	4.547
	(5.880)	(5.716)	(7.299)	(7.646)	(6.628)
SP visits	1.473	1.398	2.308	2.488	2.087
	(3.558)	(3.312)	(5.556)	(5.781)	(5.697)
Hospital nights	0.856	0.806	1.419	1.316	1.555
	(7.927)	(7.531)	(11.446)	(8.541)	(14.535)
Need Variables					
Age	48.380	48.702	44.779	45.747	43.343
	(17.023)	(17.104)	(15.648)	(15.416)	(15.810)
Age^2	2630.462	2664.414	2249.979	2330.320	2128.400
	(1775.797)	(1790.280)	(1554.844)	(1542.560)	(1552.281)
Female	0.531	0.527	0.581	0.605	0.545
	(0.499)	(0.499)	(0.494)	(0.489)	(0.498)
Age × Female	25.948	25.916	26.300	27.866	24.012
	(27.479)	(27.649)	(25.494)	(25.615)	(25.097)
Excellent SAH	0.186	0.195	0.094	0.094	0.091
	(0.390)	(0.396)	(0.291)	(0.292)	(0.288)
Very good SAH	0.404	0.412	0.317	0.302	0.335
	(0.491)	(0.492)	(0.465)	(0.459)	(0.472)
Good SAH	0.297	0.291	0.361	0.368	0.349
	(0.457)	(0.454)	(0.480)	(0.482)	(0.477)
Fair/Poor SAH	0.112	0.102	0.228	0.236	0.224
	(0.316)	(0.303)	(0.420)	(0.425)	(0.417)
Activity limitation	0.240	0.222	0.440	0.462	0.407
	(0.427)	(0.416)	(0.496)	(0.499)	(0.491)
Chronic conditions:					
1	0.266	0.269	0.235	0.226	0.248
	(0.442)	(0.443)	(0.424)	(0.418)	(0.432)
2 or 3	0.298	0.294	0.345	0.352	0.333

Continued on Next Page...

Table 2.2 – continued from previous page

		Unmet need			
	Total	None	Any	System	Personal
	mean (S.D.)	mean (S.D.)	mean (S.D.)	mean (S.D.)	mean (S.D.)
	(0.458)	(0.456)	(0.475)	(0.478)	(0.472)
4+	0.136	0.127	0.239	0.258	0.214
	(0.343)	(0.333)	(0.427)	(0.438)	(0.410)
None	0.299	0.310	0.181	0.163	0.205
	(0.458)	(0.462)	(0.385)	(0.370)	(0.404)
Non-need variables					
ln(hincome)	10.230	10.238	10.143	10.144	10.132
	(0.852)	(0.844)	(0.925)	(0.890)	(0.967)
Less-than-secondary	0.195	0.197	0.167	0.157	0.184
	(0.396)	(0.398)	(0.373)	(0.364)	(0.388)
Secondary	0.133	0.135	0.110	0.107	0.113
	(0.339)	(0.341)	(0.314)	(0.309)	(0.316)
Some post-secondary	0.270	0.266	0.307	0.308	0.308
	(0.444)	(0.442)	(0.461)	(0.462)	(0.462)
Post-secondary	0.403	0.402	0.416	0.428	0.396
	(0.491)	(0.490)	(0.493)	(0.495)	(0.489)
Smoker	0.250	0.244	0.316	0.306	0.335
	(0.433)	(0.429)	(0.465)	(0.461)	(0.472)
Former smoker	0.430	0.431	0.414	0.424	0.399
	(0.495)	(0.495)	(0.493)	(0.494)	(0.490)
Non-smoker	0.321	0.325	0.270	0.270	0.266
	(0.467)	(0.468)	(0.444)	(0.444)	(0.442)
Regular MD	0.878	0.883	0.832	0.830	0.820
	(0.327)	(0.322)	(0.374)	(0.376)	(0.384)
Immigrant	0.117	0.119	0.097	0.099	0.094
	(0.322)	(0.324)	(0.296)	(0.298)	(0.291)
Married	0.617	0.622	0.560	0.576	0.539
	(0.486)	(0.485)	(0.496)	(0.494)	(0.499)
ATL	0.232	0.233	0.216	0.216	0.208
	(0.422)	(0.423)	(0.412)	(0.412)	(0.406)
ON	0.249	0.250	0.235	0.222	0.258
	(0.432)	(0.433)	(0.424)	(0.416)	(0.437)
QU	0.188	0.187	0.201	0.225	0.171
	(0.391)	(0.390)	(0.401)	(0.418)	(0.377)

Continued on Next Page…

Table 2.2 – continued from previous page

		Unmet need			
	Total	None	Any	System	Personal
	mean	mean	mean	mean	mean
	(S.D.)	(S.D.)	(S.D.)	(S.D.)	(S.D.)
MB	0.066	0.065	0.069	0.071	0.069
	(0.248)	(0.247)	(0.254)	(0.258)	(0.254)
SA	0.060	0.060	0.057	0.050	0.065
	(0.237)	(0.237)	(0.232)	(0.218)	(0.247)
AB	0.106	0.105	0.115	0.110	0.123
	(0.308)	(0.307)	(0.319)	(0.313)	(0.328)
BC	0.099	0.098	0.107	0.106	0.106
	(0.299)	(0.298)	(0.309)	(0.307)	(0.307)

Table 2.3: Comparison of models

Model N=53,697	log L	AIC	BIC	df
GP visits				
Pooled hurdle model	-117309.1	234736.3	235260.8	59
Panel latent class model	-114430.4	229154.9	230461.9	147
Specialist visits				
Pooled hurdle model	-81701.4	163520.8	164045.4	59
Panel latent class model	-81260.8	162699.7	163491.0	89
Hospital nights				
Pooled hurdle model	-28051.3	56220.5	56745.1	59
Panel latent class model	-27585.9	55467.9	56783.7	147

Note: Regressions are estimated using the full set of covariates as noted in the text. For GP visits and hospital nights, the panel latent class model refers to the LCH-Pan model, whereas for SP visits it refers to the LCNB2-Pan model.

Table 2.4: Expected probability and means, by parts for each latent class

N=53,697	Low users				High users			
	Share	P[y>0]	E[y|y>0]	E[y]	Share	P[y>0]	E[y|y>0]	E[y]
GP visits	0.650	0.753	2.598	2.077	0.350	0.896	6.066	5.550
Specialist visits	0.774			0.925	0.226			3.050
Hospital nights	0.373	0.105	3.485	0.350	0.627	0.115	7.774	1.401

Note: For GP visits and hospital nights, the LCH-Pan model is estimated; whereas for specialist visits the LCNB2-Pan model is estimated. The full set of covariates as noted in the text are used in all the regressions.

Table 2.5: Estimation results for the number of GP visits

N=53,697	Low users				High users			
	P[y>0]		E[y|y>0]		P[y>0]		E[y|y>0]	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Unmet need - system	0.330***	(0.084)	0.217***	(0.033)	0.167	(0.139)	0.095***	(0.034)
Unmet need - personal	-0.018	(0.094)	0.097**	(0.045)	-0.086	(0.159)	-0.044	(0.043)
ln(hincome)	0.086***	(0.019)	-0.008	(0.010)	0.098***	(0.035)	-0.014	(0.013)
Less-than-secondary	-0.042	(0.056)	0.096***	(0.034)	0.020	(0.136)	0.116***	(0.041)
Some post-secondary	0.114**	(0.050)	0.040	(0.032)	0.065	(0.124)	-0.016	(0.038)
Post-secondary	0.181***	(0.048)	-0.008	(0.030)	0.131	(0.118)	-0.068*	(0.037)
Very good SAH	0.144***	(0.037)	0.255***	(0.025)	0.422***	(0.089)	0.048	(0.030)
Good SAH	0.314***	(0.042)	0.482***	(0.027)	0.486***	(0.103)	0.285***	(0.032)
Fair/poor SAH	0.538***	(0.078)	0.808***	(0.035)	0.599***	(0.151)	0.645***	(0.038)
Chronic conditions - 1	0.471***	(0.035)	0.306***	(0.024)	0.289***	(0.088)	0.213***	(0.029)
Chronic conditions - 2 or 3	0.861***	(0.042)	0.551***	(0.024)	0.482***	(0.097)	0.366***	(0.029)
Chronic conditions - 4+	1.242***	(0.076)	0.739***	(0.031)	0.784***	(0.145)	0.496***	(0.035)
Activity limitation	0.247***	(0.047)	0.192***	(0.020)	0.278***	(0.096)	0.329***	(0.023)
Smoker	-0.227***	(0.041)	-0.048*	(0.027)	-0.275***	(0.095)	-0.007	(0.030)
Former smoker	0.025	(0.036)	0.031	(0.021)	-0.080	(0.088)	0.006	(0.026)
Regular MD	1.337***	(0.041)	0.264***	(0.036)	0.970***	(0.092)	0.209***	(0.036)
Age	-0.029***	(0.006)	-0.005	(0.003)	0.026*	(0.014)	-0.013***	(0.004)
Age^2	0.000***	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000***	(0.000)
Female	1.393***	(0.109)	0.528***	(0.065)	0.860***	(0.214)	0.360***	(0.075)
Age × Female	-0.019***	(0.002)	-0.007***	(0.001)	-0.012**	(0.005)	-0.005***	(0.001)
Immigrant	-0.012	(0.051)	0.055*	(0.029)	0.113	(0.141)	0.074*	(0.040)
Married	0.118***	(0.034)	-0.035*	(0.020)	-0.081	(0.077)	-0.023	(0.022)
Atlantic	0.043	(0.046)	-0.007	(0.027)	0.249**	(0.117)	-0.006	(0.034)
QU	-0.194***	(0.048)	-0.422***	(0.035)	-0.390***	(0.110)	-0.386***	(0.038)
MB	0.081	(0.069)	-0.043	(0.043)	0.045	(0.155)	-0.102**	(0.050)
SA	0.008	(0.074)	0.023	(0.046)	0.368**	(0.180)	-0.119***	(0.046)
AB	-0.057	(0.057)	0.031	(0.034)	0.158	(0.142)	-0.050	(0.043)
BC	0.084	(0.061)	0.107***	(0.034)	0.102	(0.142)	0.060	(0.042)
Constant	-1.677***	(0.241)	-0.306**	(0.139)	-1.412***	(0.481)	1.424***	(0.176)
α			0.214***	(0.015)			0.812***	(0.021)

Note: The regression is estimated using the LCNB2hurldle-Pan model. Reference group for dummies are: no unmet need, secondary, Excellent SAH, no chronic conditions. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6: Estimation results for the number of specialist visits

N=53,697	Low users		High users	
	Coef.	S.E.	Coef.	S.E.
Unmet need - system	0.278***	(0.032)	0.138***	(0.054)
Unmet need - personal	0.088**	(0.043)	-0.007	(0.068)
ln(hincome)	0.127***	(0.013)	0.027*	(0.015)
Less-than-secondary	-0.129***	(0.030)	-0.081	(0.066)
Some post-secondary	0.139***	(0.027)	0.101*	(0.058)
Post-secondary	0.171***	(0.026)	0.177***	(0.055)
Very good SAH	0.102***	(0.022)	0.129***	(0.043)
Good SAH	0.192***	(0.024)	0.224***	(0.047)
Fair/poor SAH	0.345***	(0.032)	0.607***	(0.060)
Chronic conditions - 1	0.224***	(0.022)	0.021	(0.042)
Chronic conditions - 2 or 3	0.451***	(0.022)	0.292***	(0.044)
Chronic conditions - 4+	0.725***	(0.028)	0.431***	(0.056)
Activity limitation	0.198***	(0.019)	0.329***	(0.037)
Smoker	-0.206***	(0.024)	0.010	(0.044)
Former smoker	0.036**	(0.018)	0.082**	(0.039)
Regular MD	0.266***	(0.028)	0.069	(0.050)
Age	0.009***	(0.003)	0.012*	(0.007)
Age^2	0.000***	(0.000)	0.000	(0.000)
Female	0.828***	(0.058)	0.521***	(0.111)
Age $\times$ Female	-0.011***	(0.001)	-0.007***	(0.002)
Immigrant	-0.042	(0.026)	-0.233***	(0.058)
Married	0.023	(0.018)	0.053	(0.034)
Atlantic	-0.202***	(0.025)	-0.564***	(0.049)
QU	0.037	(0.024)	-0.333***	(0.053)
MB	-0.204***	(0.037)	-0.439***	(0.076)
SA	-0.118***	(0.036)	-0.487***	(0.082)
AB	-0.237***	(0.032)	-0.430***	(0.060)
BC	-0.233***	(0.031)	-0.342***	(0.062)
Constant	-2.994***	(0.160)	-0.013	(0.227)
α	0.350***	(0.017)	1.461***	(0.036)

Note: The regression is estimated using the LCNB2-Pan model. Reference group for dummies are: no unmet need, secondary, Excellent SAH, no chronic conditions. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7: Estimation results for the number of hospital nights

N=53,697	Low users				High users			
	P[y>0]		E[y|y>0]		P[y>0]		E[y|y>0]	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Unmet need - system	0.481***	(0.136)	0.010	(0.089)	0.170*	(0.102)	-0.199	(0.144)
Unmet need - personal	-0.209	(0.244)	0.046	(0.169)	0.190	(0.121)	-0.158	(0.180)
ln(hincome)	-0.178***	(0.040)	-0.066***	(0.021)	0.020	(0.032)	-0.110*	(0.059)
Less-than-secondary	0.293*	(0.166)	0.206*	(0.117)	0.195**	(0.092)	0.093	(0.122)
Some post-secondary	0.272*	(0.145)	0.090	(0.107)	0.008	(0.092)	0.079	(0.131)
Post-secondary	0.211	(0.147)	0.026	(0.106)	-0.001	(0.089)	0.042	(0.123)
Very good SAH	-0.039	(0.107)	-0.043	(0.073)	0.385***	(0.107)	0.144	(0.161)
Good SAH	0.022	(0.125)	0.123	(0.083)	0.776***	(0.111)	0.448***	(0.161)
Fair/poor SAH	0.297	(0.193)	0.315***	(0.122)	1.513***	(0.124)	0.791***	(0.173)
Chronic conditions - 1	-0.052	(0.099)	0.042	(0.069)	0.597***	(0.112)	0.043	(0.159)
Chronic conditions - 2 or 3	-0.005	(0.109)	-0.016	(0.072)	0.845***	(0.120)	-0.002	(0.151)
Chronic conditions - 4+	0.175	(0.162)	-0.097	(0.113)	1.003***	(0.128)	-0.029	(0.159)
Activity limitation	0.277**	(0.110)	0.152*	(0.089)	0.645***	(0.063)	0.947***	(0.089)
Smoker	-0.112	(0.105)	-0.032	(0.076)	-0.054	(0.078)	0.207*	(0.113)
Former smoker	0.091	(0.091)	0.085	(0.063)	0.051	(0.067)	0.085	(0.089)
Regular MD	0.506***	(0.150)	0.025	(0.138)	0.507***	(0.113)	-0.113	(0.170)
Age	-0.145***	(0.022)	-0.033**	(0.014)	-0.034***	(0.011)	-0.046***	(0.015)
Age^2	0.001***	(0.000)	0.000***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Female	-1.099	(0.746)	0.105	(0.388)	2.561***	(0.276)	1.071***	(0.306)
Age $\times$ Female	0.000	(0.011)	0.005	(0.006)	-0.033***	(0.004)	-0.018***	(0.005)
Immigrant	0.117	(0.136)	-0.021	(0.093)	-0.274***	(0.095)	0.190	(0.140)
Married	1.123***	(0.133)	0.268***	(0.086)	-0.212***	(0.076)	-0.290***	(0.087)
Atlantic	0.256**	(0.122)	0.478***	(0.085)	0.238***	(0.080)	0.035	(0.118)
QU	0.121	(0.131)	0.187**	(0.095)	0.501***	(0.086)	0.110	(0.124)
MB	0.470**	(0.200)	0.323***	(0.122)	0.229**	(0.116)	-0.099	(0.157)
SA	0.218	(0.153)	0.254**	(0.106)	0.343***	(0.126)	-0.303*	(0.173)
AB	0.251*	(0.128)	-0.180	(0.111)	-0.018	(0.107)	-0.032	(0.160)
BC	-0.109	(0.156)	0.248**	(0.113)	0.190*	(0.102)	-0.344**	(0.146)
Constant	2.333**	(0.954)	1.234**	(0.525)	-4.711***	(0.506)	1.754**	(0.894)
α			0.085	(0.069)			9.791***	(2.301)

Note: The regression is estimated using the LCNB2hurldle-Pan model. Reference group for dummies are: no unmet need, secondary, Excellent SAH, no chronic conditions. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8: Estimation results from logit model for probability of being a high user

N=53,697	GP visits		Specialist visits		Hospital nights	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Unmet need - system	0.684***	(0.229)	0.335	(0.223)	0.027	(0.387)
Unmet need - personal	0.791***	(0.266)	0.469*	(0.274)	0.728	(0.452)
ln(hincome)	-0.165***	(0.051)	0.003	(0.055)	-0.203*	(0.110)
Less-than-secondary	-0.016	(0.130)	0.001	(0.149)	-0.760***	(0.241)
Some post-secondary	0.073	(0.122)	0.086	(0.135)	-0.313	(0.241)
Post-secondary	0.161	(0.116)	0.191	(0.127)	-0.235	(0.237)
Very good SAH	0.276**	(0.122)	-0.170	(0.144)	-0.705**	(0.345)
Good SAH	0.005	(0.126)	-0.148	(0.146)	-0.570*	(0.330)
Fair/poor SAH	0.816***	(0.171)	0.381**	(0.191)	0.220	(0.383)
Chronic conditions - 1	0.385***	(0.115)	0.553***	(0.133)	-0.052	(0.320)
Chronic conditions - 2 or 3	0.699***	(0.108)	0.502***	(0.126)	0.248	(0.311)
Chronic conditions - 4+	0.964***	(0.149)	0.689***	(0.168)	0.624*	(0.329)
Activity limitation	0.312***	(0.105)	0.751***	(0.119)	-0.719***	(0.226)
Smoker	0.336***	(0.101)	0.033	(0.108)	0.009	(0.197)
Former smoker	0.109	(0.090)	-0.138	(0.098)	0.069	(0.171)
Regular MD	0.649***	(0.138)	0.332**	(0.151)	0.077	(0.354)
Age	-0.063***	(0.013)	-0.032**	(0.016)	-0.026	(0.033)
Age^2	0.001***	(0.000)	0.000	(0.000)	0.000	(0.000)
Female	1.042***	(0.229)	0.771***	(0.254)	-8.000***	(1.068)
Age $\times$ Female	-0.017***	(0.004)	-0.014***	(0.005)	0.100***	(0.013)
Immigrant	-0.039	(0.123)	0.162	(0.133)	-0.129	(0.233)
Married	0.202**	(0.082)	0.003	(0.092)	0.265	(0.189)
Atlantic	0.084	(0.108)	0.253**	(0.116)	0.068	(0.198)
QU	0.375***	(0.119)	0.070	(0.122)	-0.041	(0.206)
MB	0.269	(0.167)	0.151	(0.177)	0.780**	(0.371)
SA	0.444***	(0.162)	0.046	(0.191)	-0.460*	(0.277)
AB	0.123	(0.141)	0.274**	(0.140)	-0.037	(0.248)
BC	0.290**	(0.137)	0.206	(0.142)	-0.063	(0.252)
Constant	0.465	(0.634)	-1.232*	(0.700)	6.986***	(1.811)

Note: Reference group for dummies are: no unmet need, secondary, Excellent SAH, no chronic conditions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.9: Estimation results from fixed effects regression on (actual - needs predicted use) residuals

	GP visits		Specialist visits		Hospital nights	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Unmet need - system	0.595***	(0.114)	0.242***	(0.077)	0.028	(0.166)
Unmet need - personal	0.109	(0.140)	0.077	(0.095)	0.204	(0.205)
ln(hincome)	-0.018	(0.039)	-0.040	(0.026)	-0.045	(0.057)
Less-than-secondary	0.128	(0.403)	-0.541**	(0.272)	1.185**	(0.589)
Some post-secondary	-0.255	(0.279)	-0.208	(0.188)	0.538	(0.408)
Post-secondary	-0.382	(0.280)	-0.210	(0.190)	0.536	(0.410)
Smoker	-0.252	(0.165)	0.021	(0.112)	-0.469*	(0.242)
Former smoker	-0.047	(0.135)	0.135	(0.091)	-0.192	(0.197)
Regular MD	0.897***	(0.090)	0.179***	(0.061)	0.111	(0.131)
Married	0.004	(0.093)	0.107*	(0.063)	0.024	(0.136)
Atlantic	-0.686*	(0.352)	-0.421*	(0.238)	-1.203**	(0.515)
QU	-0.943*	(0.543)	0.027	(0.367)	0.161	(0.794)
MB	-0.207	(0.543)	-0.333	(0.367)	0.234	(0.794)
SA	1.890***	(0.556)	-0.374	(0.376)	0.089	(0.814)
AB	0.147	(0.372)	-0.227	(0.251)	0.051	(0.544)
BC	0.036	(0.418)	-0.090	(0.283)	-0.235	(0.611)
Constant	-0.016	(0.520)	0.575	(0.351)	0.276	(0.761)
N×T	53697		53697		53697	
N	13549		13549		13549	

Note: Reference group for dummies are: no unmet need, secondary, Excellent SAH, no chronic conditions. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

Changes in Socioeconomic Inequality and Inequity in Influenza Immunization in Canada, 1996/97 to 2007/08

3.1 Introduction

Seasonal influenza is a serious public health concern. Each year 10 to 25% of Canadians catch the flu (Health Canada, 2009). While most people recover quickly, the young, the elderly, and individuals with chronic medical conditions are at high risk of developing serious complications. Flu-related pneumonia alone accounts for 4000-8000 deaths annually, is the leading cause of death from infection and the sixth leading overall cause of death in Canada (Statistics Canada, 1997). Influenza also places a significant burden on the healthcare system via hospitalizations, emergency department crowding and ambulatory visits (Schanzer et al., 2008; Schull et al., 2004). In addition, influenza is associated with substantial economic costs as a result of worker absenteeism and lost productivity (Ryan et al., 2006).

The most effective means of preventing and attenuating the effects of influenza is vaccination. The National Advisory Committee on Immunization (NACI) in Canada recommends vaccination for those at high risk of influenza-related complications, namely individuals with underlying health conditions as well as all individuals 65 years of age and older; those capable of transmitting influenza to individuals at high risk of complications; and those who provide essential community services. NACI also encourages all Canadians over six months of age to get the flu shot (National Advisory Committee on Immunization, 2008).

Publicly funded influenza immunization programs are at the forefront of efforts to mitigate the annual impact of influenza, and Canada represents an interesting context in which to study influenza vaccination program design. Healthcare in Canada falls under provincial/territorial jurisdiction, and vaccine distribution and use is determined by the provinces and territories. However, vaccine purchasing is national to achieve both value and security of supply. Most provinces have maintained long-standing publicly funded influenza vaccination programs since at least the mid-1990s, targeting the elderly and those with chronic conditions. Prince Edward Island and New Brunswick were exceptions and began covering both groups much later (Johansen et al., 2004). Vaccines are delivered in healthcare and community settings, and individuals who do not qualify for a free vaccine can purchase it privately for around $10-15 (Public Health Agency of Canada, 2008).[1]

In July 2000, the province of Ontario became the first major jurisdiction in the world to offer free flu shots to the entire population. The Ontario Universal Influenza Immunization Program (UIIP) was introduced with the goal of reducing the seasonal impact of influenza on the healthcare system, especially, emergency department visits, decreasing the number and severity of influenza cases, reducing the economic impact of influenza, especially in workplaces, and improving pandemic preparedness. The UIIP also expanded vaccine delivery to more accessible settings including local pharmacies, community-based clinics, schools, and workplaces. Mass media advertising and public education campaigns were used to support uptake of the program (Kurji, 2004). Prior to the UIIP, Ontario had a targeted program similar to other provinces in Canada. Studies have linked the UIIP to increases in vaccination rates (Kwong et al., 2006, 2007); and consequently to reductions in influenza-associated mortality, healthcare use, and worker absences (Kwong et al., 2008, 2009; Ward, 2013).

The general framing of vaccination policy and the evaluation of influenza vaccination targets have focused exclusively on average coverage rates for select subpopulations. For instance, the vaccination rate for elderly persons is used as a measure of health system performance (Health Canada, 2008). Yet average coverage rates can mask underlying socioeconomic inequalities in the uptake of vaccination. Socioeconomic disparities have consistently been observed in the use of other forms of preventive care such as cervical cancer

[1] The territories owing to their unique circumstances have offered free flu vaccines to the majority of their populations - Yukon have provided free flu vaccines to all residents aged 18 and older since 1999, and Northwest Territories and Nunavut have offered universal vaccination since 2003 and 2005 respectively.

screening and mammograms, even when these services are universally insured (Gupta et al., 2003; Glazier et al., 2004; Katz et al., 2000; Maxwell et al., 1997). Given that equity in access to healthcare is a fundamental objective of healthcare policy in Canada, policy must focus on both average rates of uptake and inequality in rates of uptake across socioeconomic groups in society. Reducing socioeconomic inequalities in influenza vaccination may also in itself be an effective strategy towards mitigating the severity of influenza, given that individuals with low socioeconomic status are at greater risk of acquiring and transmitting influenza, as well as experiencing worse health outcomes (Lee et al., 2011). It is therefore important to look beyond mean coverage rates to socioeconomic inequality in the distribution of influenza immunization.

This paper contributes to the literature on socioeconomic inequalities in preventive care and delivery by examining long-term trends in both coverage and socioeconomic inequity in influenza immunization in Canada. Given persistently low rates of coverage even amongst certain high-risk groups such as healthy seniors and young adults with chronic conditions, a better understanding of socioeconomic disparities in the distribution of flu shots may help identify barriers to vaccination uptake. In addition, the analysis may help improve our understanding of the merits of universal versus targeted vaccination programs.

Using data from two large, nationally representative Canadian household surveys - the 1996/97 National Population Health Survey (NPHS) and the 2007/08 Canadian Community Health Survey (CCHS) - I initially examine the association between income and flu shot use under various specifications and for several subgroups. In a subsequent analysis, I employ the well-established concentration index framework to explore socioeconomic inequity in flu shot use across provinces over time.

3.2 Literature review

Influenza vaccination uptake can be viewed in the broader context of medical technology diffusion, where numerous studies have documented socioeconomic inequalities in access to and uptake of new healthcare technologies. Lleras-Muney and Lichtenberg (2005), for instance, find that more highly educated people are more likely to use newer drugs after controlling for income, insurance status and other individual characteristics. Sateren et al. (2002) find that the more educated are increasingly likely to participate in clinical trials where they would gain access to the newest treatments. In addition, socioeconomic inequalities in access to and the uptake of new healthcare technologies may play a mediating role in explaining the socioeconomic gradient in health. In their examination of mortality trends for a select set of diseases over the last half of the twentieth century, Link and Phelan (1995) find that educational disparities in mortality widened for conditions that became more preventable or treatable over time relative to conditions where less progress in prevention or treatment was achieved. Glied and Lleras-Muney (2008) studied the relationship between the education gradient in mortality for a comprehensive set of diseases and two measures of innovation: the rate of change in mortality over time and the number of active drugs approved to treat particular diseases.

They find that educational gradients in mortality became larger for diseases where greater innovation had occurred. Jayachandran et al. (2010) study the effect of medical innovation on mortality by examining the introduction of Sulfa drugs in the mid-1930s. The drugs caused significant reductions in mortality; however, the declines were larger among whites than blacks, thereby increasing racial disparities in mortality. Notably, care was not free to all in the settings discussed above, and as a result the gradient in access was explicitly linked to socioeconomic status. Whether such effects arise in a pubic system where care is free for everyone is an important policy question.

Income and educational attainment are important determinants of influenza vaccination (Mullahy, 1999; Endrich et al., 2009). However only two studies have adopted the concentration index approach to systematically examine socioeconomic inequality in influenza immunization uptake: Lorant et al. (2002) and Carrieri and Wuebker (2012). Using 1997 data on individuals aged 25 and over, Lorant et al. (2002) compare socioeconomic inequalities in the use of preventive care with inequities in the use of general healthcare in Belgium. They find that i) standardizing for needs substantially affected the measured inequity in preventive care, particularly flu vaccination; ii) less inequity in the distribution of preventive care obtained in general practice settings (such as flu vaccination) than in specialty settings (such as mammography and pap-tests); and iii) the distribution of preventive care use was more inequitable compared to general healthcare use regardless of healthcare setting.

Carrieri and Wuebker (2012) examine socioeconomic inequalities in preventive care across 13 European countries among individuals aged 50 and over.

After adjusting for need factors, they find large pro-rich inequalities in most forms of preventive care including breast cancer screening, cholesterol and blood sugar tests. However, they do not find substantial income or education-related inequalities in flu vaccination in most countries.

3.3 Data

This study draws from two Statistics Canada surveys: the cross-sectional component of the 1996/97 National Population Health Survey (NPHS), and the 2007/08 Canadian Community Health Survey (CCHS). Both are large, nationally representative household surveys of the non-institutionalized population. The surveys are comparable in terms of design and data collection, and have nearly identical questions and response categories. The advantage of using survey rather than administrative data in this context is that surveys capture flu shots received outside physician offices, which are not recorded in administrative data. The sample sizes for the NPHS and CCHS surveys are 81,804 and 131,959 respectively. To make the analysis comparable, individuals residing in the territories in the CCHS are excluded. Also excluded are individuals under the age of 25, as well as those with missing information on any of the variables used in the analysis (most missing data was due to missing income information). The final sample sizes are 46,572 and 88,926 for the NPHS, CCHS respectively.[2] Sample weights were incorporated in all the statistical analysis.

[2]Further details on the construction of the final estimation samples are provided in Appendix A.

3.3.1 Dependent variables

A binary indicator of whether an individual received a flu shot in the last year is constructed from individual responses to the following two questions: "Have you ever had a flu shot?" Those answering in the affirmative were then asked "When did you have your last flu shot: (less than 1 year ago, 1 year to less than 2 years ago, or 2 years ago or more)?"

3.3.2 Independent variables

Independent variables are included in the model in accordance with the literature on the determinants of influenza immunization (Mullahy, 1999). Under the horizontal equity framework, individuals with equal needs should have equal access to healthcare. Consequently, variables are classified as either "need" or "non-need" based on NACI influenza immunization guidelines.

Need variables

Need variables are defined to capture both age-based and disease-based risk factors. These include age-sex interactions for individuals aged 65 and above with age specified using 3 dummy variables (65-74, 75-84, 85 and over). In addition, a simple binary variable is constructed for the presence of any one or more of the following chronic conditions: cancer, heart disease, diabetes, chronic bronchitis or emphysema, asthma, or suffers effects of stroke.

Non-need variables

The primary non-need variable of interest is predicted equivalized household income. Both surveys asked individuals their total household income from all sources and the composition of the household. Household income was adjusted for household size and composition using the modified OECD equivalence scale.[3] Not all individuals reported their income on a continuous scale; 16% of respondents in the CCHS sample and all respondents in the NPHS sample reported their income in grouped categories only (12 categories in CCHS; 11 categories in NPHS). Continuous income was imputed for all individuals as follows. For the subsample of the CCHS who reported continuous income, a linear regression was estimated by regressing the natural log of household income on household income category, age, age-squared, sex, age-sex interaction, marital status, immigration status, education, household size, and number of children. Based on this auxiliary regression, continuous household income was predicted for all individuals. For the NPHS responders, the auxiliary regression was estimated on the CCHS, from which predictions were made on the NPHS data.[4]

Other non-need variables include additional controls for health status, health behavior, and socio-demographics. Poor health status is an important predictor of vaccination uptake. Controls therefore include an indicator for

[3] The modified OECD equivalence scale assigns a weight of 1.0 to the first adult household member, 0.5 to the second adult household member and 0.3 to children.

[4] Further details of the imputation method as well as sensitivity analysis using the midpoint of each income category as an alternative income measure are provided in Appendix B. The sensitivity analysis shows very similar CI and HI coefficients and rankings using the alternative income measure in comparison to those obtained by imputing income as described above, and confirms the robustness of these results.

the presence of chronic conditions not considered risk factors for influenza, as well as indicators for self-assessed health measured in five categories (excellent, very good, good, fair and poor).[5] Health behaviors are captured by including dummies for smoking status (heavy smoker, occasional smoker, former smoker, non-smoker). A dummy variable indicating whether the individual had a regular family doctor is also included as most individuals obtain flu shots at the doctor's office (Kurji, 2004). Socioeconomic variables include dummies for education (less than high school, high school, some post-secondary, post-secondary). Demographic variables include age-sex interactions for individuals under 65 years of age with age specified using 4 dummy variables (25-34, 35-44, 45-54, 55-64), dummies for marital status (married, formerly married and single), immigration status (recent immigrant, non-recent immigrant, native), and a dummy for whether the respondent resided in a rural or urban area.

3.4 Methods

3.4.1 The association between income and flu shot uptake

I first examine the association between income and flu shot uptake under various empirical specifications. The goal of this exercise is not to estimate a causal relationship, but to examine the strength of the relationship and how it

[5] Although not considered risk factors in NACI recommendations, an argument may be made for classifying poor general health including non-NACI chronic conditions as need-related. Non-NACI health factors are important determinants of inequity, and their contributions vary across provinces. The contribution to inequity of these factors is explicitly presented in the decomposition analysis.

is affected by including exogenous, predetermined, and endogenous covariates in the model.

The basic specification is as follows:

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \gamma ln(income) + \epsilon_i \tag{3.1}$$

where y_i is a flushot outcome variable and x_{ki} is a vector of controls. The coefficient of interest, γ, indicates the approximate percentage point change in flu shot use associated with a one percent change in income.

Three alternate specifications are employed that successively add control variables as follows: (1) includes a dummy for NACI risk factors and only exogenous variables, namely age-sex interactions; (2) adds predetermined variables including education, immigration status, marital status, a dummy for other chronic conditions, a dummy for whether the individual is a former smoker, and a dummy for rural; (3) further adds all other variables including self-assessed health, current smoking status, and a dummy for whether the respondent has a regular family doctor.

In a subsequent analysis, I explore the association between income and flu shot uptake in various subgroups defined by gender and influenza risk status. Here, equation (3.1) is estimated for the various subgroups using a full set of covariates as under specification (3).

3.4.2 Measuring socioeconomic inequality

Income-related inequity in influenza vaccination is examined for each province in 1996/97 and 2007/08. Socioeconomic inequality in influenza immunization is measured using the concentration index. The concentration index is a generalization of the Gini index and is derived from the concentration curve, which compares the cumulative distribution of healthcare use to the cumulative distribution of the population rank ordered by income (Kakwani et al., 1997; O'Donnell et al., 2008). An advantage of the concentration index over other measures such as rank-ratios is that unlike the latter, the concentration index captures the experience of the entire population distribution. In addition, the concentration index can be decomposed in a variety of useful ways to help describe the inequality.

The concentration index is an indicator of the degree of association between an individual's level of health (y_i) and their relative position in the income distribution (r_i) (Kakwani et al., 1997). For any cardinal health variable (y), CI can be calculated using the following "convenient regression" formula (O'Donnell et al., 2008):

$$\frac{2\sigma_r^2}{\bar{y}} y_i = \alpha + \beta r_i + \epsilon_i \tag{3.2}$$

where $\bar{y}$ is the mean health of the sample, r_i is the fractional income rank, and σ_r^2 is the variance of r_i.[6] The OLS estimate of β is by construction equal to

[6]

the concentration index (Kakwani et al. 1997).

The standard concentration index can take values between -1 and +1; a negative value indicates that the distribution of flu shot utilization is concentrated among the poor, i.e. pro-poor inequality; a positive value implies pro-rich inequality; a value of zero implies no inequality. However, when the dependent variable is binary as in this analysis, the standard concentration index presents three methodological problems: i) measured inequality and rankings among provinces may depend on whether the dependent variable is defined in terms of health (getting vaccinated) or ill-health (not getting vaccinated); ii) the bounds of the concentration index are narrower than [-1, 1] and depend on the mean of the dependent variable; and iii) the value of the concentration index depends on the scale of the health variable. To remedy these problems, Wagstaff (2005) and Erreygers (2008) have each proposed alternative corrections to the concentration index for bounded variables.[7] The key difference between them lies in their underlying value judgments of what constitutes the most unequal society.[8] Of the two approaches, the Erreygers concentration index has been applied much more extensively. As a result, I

The fractional rank variable r_i is calculated as:

$$r_i = \frac{1}{N}\sum_{j=1}^{i-1} w_j + \frac{1}{2}w_i \qquad \text{where} \qquad w_0 = 0 \tag{3.3}$$

where w_i is the sampling weight of individual i.

[7]See Wagstaff (2009) and Erreygers (2009) for further debate between the authors on the merits of each approach.

[8]The Erreygers index answers the question of how far the society is from a state where only the upper 50% of the income distribution are using flu shots, independent of flu shot prevalence. The Wagstaff index answers the question of how far the society is, given its overall level of flu shot use, from a state where only the individuals at the top of the income distribution are using flu shots. See Kjellsson and Gerdtham (2012) for more details.

use the Erreygers correction to the concentration index in this analysis.

The concentration index is a measure of socioeconomic inequality. Inequality however, does not necessarily imply inequity. To assess inequity in healthcare utilization one must standardize for need.[9] Need adjusters include those factors that are judged to be legitimate determinants of receipt of care. In general, characterizing the various determinants of healthcare use as need or non-need requires value judgments. In the case of preventive care such as influenza vaccination, however, determination of need is more straightforward because a flu shot is recommended for those with NACI risk factors.

The whole process of calculating an index of horizontal inequity can be described in four steps (O'Donnell et al., 2008):

(1) Estimate a model of healthcare utilization, specifying "need" and "non-need" variables:

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \sum_m \gamma_m z_{mi} + \epsilon_i \tag{3.4}$$

where y_i is a flushot outcome variable, x_{ki} are need-related variables; z_{mi} are non-need variables.

(2) Predict utilization based on needs by using estimates of the model and setting the non-need variables constant at their sample means:

[9] The horizontal inequity approach used here is based on the social choice theory of fair allocation and implies equal allocation for equal need. See Roemer (1998) and Fleurbaey (2008) for a discussion of the philosophical framework behind this approach. The classification of "need" and "non-need" variables ultimately depends on the philosophical framework.

$$\hat{y}_i = \hat{\alpha} + \sum_k \hat{\beta}_k x_{ki} + \sum_m \hat{\gamma_m} \bar{z}_m \tag{3.5}$$

where $\bar{z}_m$ is the mean of z_{mi}

(3) Calculate the indirectly needs-standardized distribution of utilization:

$$y^{IS} = y_i - \hat{y}_i + \bar{y} \tag{3.6}$$

where $\bar{y}$ is the mean of y_i

(4) Calculate the concentration index for the needs-standardized distribution of utilization as described above, to obtain a measure of horizontal inequity, HI.

To further examine the contribution of various factors to income-related inequality in the uptake of flu shots, the concentration index is decomposed using the method developed by Wagstaff et al. (2003):

$$C = \sum_k \left(\frac{\beta_k \bar{x_k}}{\bar{y}} \right) C_k + \frac{GC_\epsilon}{\bar{y}} \tag{3.7}$$

where $\bar{x_k}$ is the mean of x_k, C_k is the concentration index for x_k, and GC_ϵ is the generalized concentration index for ϵ_i. This technique decomposes the concentration index into the weighted sum of the concentration indices of each of its determinants (C_k), where the weights $\left(\frac{\beta_k \bar{x_k}}{\bar{y}}\right)$ are the elasticities of each of the respective determinants. The contribution of each health determinant towards total income related inequality is therefore the product of its impact on the probability of receiving a flu shot (its elasticity term), and the degree to which the determinant is unequally distributed by income (its concentration index) (van Doorslaer and Koolman, 2004; van Doorslaer et al., 2004). The contribution to inequality that cannot be explained by systematic variation in the determinants can be calculated as a residual. This decomposition is exact for linear models. Although the dependent variable in this application is binary, the linear probability model was used for simplicity and ease of decomposition.

3.5 Results

3.5.1 Descriptive results

Table 3.1 presents unadjusted influenza immunization rates by income quartile in 1996/97 and 2007/08 for the following sub-populations: non-seniors without NACI risk, non-seniors with NACI risk factors, and seniors. In both periods, the low risk group comprising non-seniors without NACI risk factors had lower rates than the latter two high risk groups, for whom vaccination is recommended and provided free of charge both before and after the UIIP was introduced. Among the high risk groups, rates were notably higher for seniors than for non-seniors with NACI risk. However, coverage in both high risk groups fell well below the vaccination target of 80% set by a national conference on influenza (Kwong et al., 2007).

Table 3.1 also indicates a notable increase in influenza vaccination rates between 1996/97 and 2007/08, particularly among non-seniors both with and without NACI risk. Coverage increases over this period appear disproportionately higher in high income groups, thereby opening a positive income gradient in 2007/08. Among non-seniors without NACI risk in 1996/97, rates are roughly equal across the bottom three income quartiles. However, the vaccination rate in the highest income quartile is statistically larger, with individuals 36% more likely to be vaccinated than those in the lowest quartile. In 2007/08, a strong income gradient is observed across all income quartiles, with individuals in the highest income quartile 29% more likely to be vaccinated than those in the lowest quartile. Among non-seniors with NACI risk a negative income gradient is observed in 1996/97, with those in the highest income quartile 20% less likely to be vaccinated than those in the lowest quartile. However, by 2007/08 the income gradient is reversed, and individuals in the highest income quartile are 29% more likely to be vaccinated than those in the lowest quartile. In contrast, the income gradient among seniors is almost unchanged: in 1996/97, seniors in the highest income quartile were almost 15% more likely to be vaccinated relative to those in the lowest quartile; whereas in 2007/08, seniors in the highest income quartile are 13% more likely to be vaccinated than those in the lowest quartile.

Coverage rates by province and year are reported Table 3.2, indicating substantial inter-provincial variation in both periods. In 1996/97, Nova Scotia (21.1%), British Columbia (19.5%), and Ontario (19.1%) had among the highest rates of coverage. In comparison, Quebec (9.3%) and Newfoundland and Labrador (13.8%) had among the lowest (the difference between them is statistically significant). Between 1996/97 and 2007/08, coverage doubled in Canada overall from 16.0% to 33.9%. The largest increases were observed in Nova Scotia, Ontario, and Quebec whereas the smallest increases were seen in Newfoundland and Labrador, Alberta, and Manitoba. By 2007/08, Nova Scotia (42.5%) and Ontario (39.0%) ranked highest in terms of coverage (the difference between them is statistically significant), whereas Newfoundland and Labrador (24.9%) and Quebec (28.8%) remained lowest ranked.

3.5.2 Regression results of the association between income and flu shot uptake

Table 3.3 reports the association between ln(income) and an individual's probability of flu shot use under various specifications. For each province, equation (3.1) is estimated separately using three sets of covariates: estimates obtained using only exogenous variables as covariates are presented in column (1); column (2) adds predetermined variables; and column (3) adds all other variables to the model. The reported coefficient estimates indicate the approximate percentage point change in flu shot use associated with a one percent change in income. In 1996/97, the estimates in column (1) are generally small and statistically insignificant. Exceptions are PEI and Alberta, where a one percent change in income is associated with a 3.2 and 1.3 percentage point increase in flu shot uptake respectively. The estimates are almost unchanged under (2) where predetermined variables are added to the model. Adding all other variables under (3) slightly increases the absolute value of the coefficients for PEI and Alberta, although the coefficients are not statistically different. The estimates for all other provinces remain small and statistically insignificant.

In 2007/08, a positive association is observed in Table 3.3 column (1) between ln(income) and an individual's probability of flu shot use for all provinces with the exception of Nova Scotia, where the coefficient is small and statistically insignificant. For instance for Canada, a one percent change in income is associated with a 2.9 percentage point increase in flu shot uptake. With the addition of predetermined variables under (2), estimates for Newfoundland and Labrador, PEI, New Brunswick, Quebec and Saskatchewan are smaller and statistically different. Adding all other variables under (3) does not lead to statistically different estimates.

In summary, the results above indicate: (1) there is almost no association between ln(income) and flu shot uptake in 1996/97; (2) a positive association is observed in almost all provinces in 2007/08; (3) the measured association between ln(income) and flu shot use after controlling for exogenous and predetermined variables is generally not sensitive to the inclusion of additional covariates in the model (namely self-assessed health status, current smoking status, regular doctor).

Table 3.4 reports the association between ln(income) and an individual's probability of overall flu shot use by subgroup in 1996/97. The reported coefficient estimates indicate the approximate percentage point change in flu shot use associated with a one percent change in income. The first panel reports results for men. Most estimates in each of the three subgroups are small and statistically insignificant. Among those aged under 65 and without NACI risk, exceptions are Canada, Newfoundland and Labrador, and Alberta that are significant at the 5% level. For instance, among men aged under 65 without NACI risk in Canada, a one percent change in income is associated with a 0.9 percentage point increase in flu shot uptake. Among men aged under 65 with NACI risk, a large and statistically significant coefficient is observed for New Brunswick, though this is imprecisely estimated. Among seniors, statistically significant estimates at the 5% level are obtained for Alberta, and at the 10% level for Newfoundland and Labrador. The second panel reports results for women. Most estimates for women in each of the three subgroups are also small and statistically insignificant. Among those aged under 65 and without NACI risk, estimates for New Brunswick and Alberta are statistically significant at the 1% level and those for PEI are significant at the 5% level. Among seniors, the estimate for Alberta is statistically significant at the 1% level and that for PEI is significant at the 5% level.

Results for the association between ln(income) and an individual's probability of overall flu shot use by subgroup in 2007/08 are displayed in Table 3.5. The first panel reports estimates for men. Among those aged under 65 and without NACI risk, estimates are positive and statistically significant for Canada, Newfoundland and Labrador, and PEI at the 1% level, and for New Brunswick and Ontario at the 5% level. For instance, among men aged under 65 without NACI risk in Canada, a one percent change in income is associated with a 1.4 percentage point increase in flu shot uptake. Estimates among men aged under 65 with NACI risk in comparison are all small and statistically insignificant except for Quebec. Among seniors, the estimate for Canada is significant at the 1% level; for New Brunswick is significant at the 5% level;

and for Newfoundland and Labrador and Quebec are significant at the 10% level. For instance, among male seniors in Canada, a one percent change in income is associated with a 1.5 percentage point increase in flu shot uptake. The second panel reports results for women. Among those aged under 65 and without NACI risk, most coefficients are positive and statistically significant. Estimates for Canada, New Brunswick, Manitoba and Saskatchewan are statistically significant at the 1% level and those for Newfoundland and Labrador and Quebec are significant at the 5% level. Among those aged under 65 and with NACI risk, estimates for Quebec and Saskatchewan are statistically significant at the 1% level and those for Canada and Manitoba are significant at the 5% level. Among seniors, estimates for Canada, New Brunswick, Quebec, Manitoba and Saskatchewan are statistically significant at the 1% level and those for British Columbia are statistically significant at the 5% level.

In sum, the magnitudes of the estimates of ln(income) are notably larger in 2007/08 than in 1996/97, which is consistent with the trends observed in Table 3.1. Moreover, some gender differences are also observed. Among those under 65 and without NACI risk in 1996/97, positive and significant effects were observed for Canada and Newfoundland and Labrador among men only, for PEI and New Brunswick among women only, and for Alberta among both sexes; whereas in 2007/08 positive and significant effects were observed for PEI, and Ontario among men only, for Quebec, Manitoba, Saskatchewan and British Columbia among women only, and for Canada, Newfoundland and Labrador and New Brunswick among both sexes. Among those under 65 and with NACI risk, positive and statistically significant effects are seen in

1996/97 for New Brunswick among men only; and in 2007/08 for Canada, Manitoba, and Saskatchewan among women only, and for Quebec among both sexes. Among seniors, positive and statistically significant effects are seen in 1996/97 for Newfoundland and Labrador among men only, for PEI among women only, and for Alberta among both sexes; and in 2007/08 for Newfoundland and Labrador among men only, for Manitoba, Saskatchewan, and British Columbia among women only, and for Canada, New Brunswick, and Quebec among both sexes. Notably large positive and statistically significant effects are consistently observed in both periods in only a few instances: for individuals under 65 and without NACI risk in Newfoundland and Labrador among men and in New Brunswick among women; and among male seniors in Newfoundland and Labrador. In contrast, significant effects are seldom observed over both periods and across subgroups in Nova Scotia and Ontario.

3.5.3 Results of the analysis of inequality and inequity in flu shot utilization using the concentration index framework

Results from the analysis of income-related inequality and inequity in flu shot uptake are presented in Table 3.6. The dependent variable is a binary variable indicating whether an individual received a flu shot. The table reports two indicators of income-related inequality and inequity: (1) the Erreygers corrected concentration index (CI) of income-related inequality in the raw distribution of flu shot uptake; (2) horizontal inequity for the distribution of flu shot uptake standardized for NACI risk factors (HI). Finally the last column in each panel presents the provincial rank by HI. A negative value of CI indicates pro-poor inequality in flu shot use, a positive value of CI indicates pro-rich inequality, a value of zero implies equality. The magnitude of the concentration index indicates the strength of the relationship between income and flu shot use, and ranges from -1 to 1.

In 1996/97, the CI estimates generally display substantial pro-poor inequality in the raw distribution of overall flu shots. These estimates are large and statistically significant at the 1% level for Canada (CI=-0.057), Quebec (CI=-0.065), Ontario (CI=-0.078), Manitoba (CI=-0.116) and Alberta (CI=-0.051); at the 5% level for British Columbia (CI=-0.075); and at the 10% level for Newfoundland and Labrador (CI=-0.057) and Saskatchewan (CI=-0.056). Need variables that include NACI defined chronic conditions as well as age-sex interactions for individuals above 65 years of age significantly contribute to income-related inequality, and standardizing for need results in notably more pro-rich/less pro-poor inequality as older, sicker individuals are more likely to both have low income and be immunized. The coefficients of HI are negative and statistically significant at the 5% level for Manitoba (HI=-0.032) implying pro-poor inequity; positive and statistically significant at the 1% level for Alberta (HI=0.030), and at the 5% level for New Brunswick (HI=0.069) implying pro-rich inequity. The coefficient for Canada (HI=0.014), while positive and statistically significant at the 10% level, is small in magnitude and is effectively zero implying near equality .

By 2007/08, the associated coefficients of CI for flu shot use are positive and statistically significant at the 5% level for PEI (CI=0.089) implying pro-rich inequality; and negative and statistically significant at the 1% level for Canada (CI=-0.023), Nova Scotia (CI=-0.074) , Ontario (CI=-0.038), and Alberta (CI=-0.050); and at the 5% level for British Columbia (CI=-0.041) indicating pro-poor inequality. Standardizing for NACI need factors results in notably more pro-rich/less pro-poor inequality, and all HI coefficients are positive and statistically significant. The coefficient of HI for Canada is 0.063 implying strong pro-rich inequity in flu shot use. In comparison, studies have consistently found mildly pro-rich inequity in the probability of GP visits in Canada, and mildly pro-poor inequity in conditional and total number of GP visits (Allin, 2008; Asada and Kephart, 2007; Jiménez-Rubio et al., 2008; Van Doorslaer et al., 2006). Given that the majority of flu shots are received in physician offices and having a regular physician is strongly associated with flu shot receipt, these results imply there is significantly more inequity favoring the rich in flu shot uptake than in the use of general healthcare, a finding consistent with Lorant et al. (2002). The magnitude of some estimates such as those for PEI (HI=0.212), Saskatchewan (HI=0.145), and New Brunswick (HI=0.123) is very large, implying much larger inequity in flu shot use than that observed for even specialist services in Canada. In addition, inequity in flu shot use varies significantly across provinces, with the coefficients of HI ranging from 0.041 (significant at 10% level) for Nova Scotia to 0.212 (significant at 1% level) for PEI.

To illustrate trends in coverage and inequity, both mean coverage and the HI index are plotted jointly in Figure 3.1. Overall, the figure indicates little uniformity in influenza program performance across provinces, with almost no correlation between changes in coverage vs. changes in HI (correlation=-0.01). Among a number of provinces, increases in coverage have come at a cost of greater pro-rich inequity, suggesting that as these programs expanded, they were more likely to attract higher income and more educated individuals. However, even among these provinces there is substantial variation in changes in inequity. For instance, Ontario and Quebec experienced among the largest increases in coverage of around 19 percentage points each. While Ontario (HI=-0.002 in 1996/97 to HI=0.044 in 2007/08; difference is statistically significant) moved from having no inequity to slightly pro-rich inequity, Quebec in comparison experienced a large increase in inequity, moving from having no inequity to strongly pro-rich inequity (HI=-0.009 in 1996/97 to HI=0.094 in 2007/08; difference is statistically significant). Moreover, Manitoba and Newfoundland and Labrador experienced among the smallest increases in coverage (13.0 percentage points for Manitoba; 11.1 percentage points for Newfoundland and Labrador), but substantial increases in pro-rich inequity (HI=-0. 032 in 1996/97 to HI=0.091 in 2007/08 for Manitoba, difference is statistically significant; HI=-0.002 in 1996/97 to HI=0.064 in 2007/08 for Newfoundland and Labrador, difference is statistically significant). In contrast, Nova Scotia both increased coverage (21.3 percentage points) and maintained inequity levels (HI=0. 023 in 1996/97 to HI=0.041 in 2007/08, difference is not statistically significant).

To better understand the main drivers of income-related inequity in flu shot use, Figure 2 presents the decomposition of the HI index for the distribution of flu shot use by province and year. Non-need contributors to horizontal inequity include income, education, non-NACI health (self-assessed health, other non-NACI chronic conditions), and other (marital status, immigration status, rural, regular MD, smoking status, and non-need age-sex interactions). The unexplained category captures the portion of the HI that is not explained by the decomposition (the difference between the HI and the contribution of all factors in the decomposition).

The direct impact of income is the largest contributor to pro-rich inequity, explaining between 30% and 50% of total income-related inequity. It is notable that despite a universal vaccination program, the contribution of income in Ontario is significantly greater in 2007/08 than in 1996/97, when it was almost negligible. Moreover, the contribution of income in Ontario in 2007/08 is larger than that in Alberta, and is similar to that in British Columbia and Nova Scotia. Another significant contributor to pro-rich inequality is education, which explains a further 10-30% of inequity. The remaining contribution to pro-rich inequity under "other" largely consists of the contributions of demographics. Non-NACI defined need variables contribute to pro-poor inequity, as those in poor health are more likely to both have low income and be immunized. Unexplained inequity is generally small and positive, indicating some systematic determinants of flu shot use that are positively correlated with income are not captured in the model.

3.6 Discussion

This study examined long-term trends in uptake and inequity in flu shot utilization in Canada between 1996/97 and 2007/08. Despite most provinces having long-established influenza immunization programs that offer near identical coverage (with the exception of Ontario), large variations in coverage and inequity trends are observed across provinces and there is no evidence of convergence. Among a number of provinces, increases in coverage levels appear to have drawn disproportionately from those of higher socioeconomic status, contributing to a growing pro-rich inequity in utilization.

Ontario's experience with the UIIP over the long-term appears mixed. Between 1996/97 and 2007/08, Ontario achieved one of the highest increases in coverage with one of the smallest amounts of inequity among Canadian provinces. However, Nova Scotia was able to achieve similar or better outcomes without a universal program. Recently, in response to the 2009 H1N1 pandemic influenza episode, a number of provinces including Alberta, Saskatchewan, Manitoba, Nova Scotia, and Prince Edward Island have followed Ontario in adopting universal immunization programs. However, Ontario was the only jurisdiction with a universal influenza immunization program for the period covered in this study.

There may be several different pathways through which high socioeconomic status individuals have disproportionately higher take-up of flu shots. These may include system access barriers, individual information and beliefs, and patient motivation. While direct system access barriers to vaccination in Canada such as cost may not be significant particularly among those at high risk, this may not necessarily translate to equality in vaccination uptake across socioeconomic groups if influenza vaccination is often received in conjunction with other medical services for which there may be underlying access problems. However, there is little inequity in GP visits in Canada where the majority of flu shots are received. Moreover, in their examination of self-reported reasons for not receiving a flu shot in the 2007/08 CCHS, Chen et al. (2012) find up to 70% of those not getting a flu shot cited that they did not feel it was necessary, 18% reported that had not gotten around to it, 5% reported that they had a bad reaction to a previous shot, and 4% cited fear. Only a combined 3% of respondents cited any reasons that would imply system-related access barriers to vaccination including cost, unavailability of the vaccine, respondent did not know where to go, waiting times, transportation barriers, or language problems. Moreover, Ontarians were less likely to think it was not necessary relative to those residing in other provinces, although they were more likely to report that they did not get around to it. These results suggest that system access problems may not be significant barriers to influenza vaccination, and that attitudes and beliefs may play a more significant role.

In terms of policy, programs may be designed to target specific groups with low socioeconomic status and to provide services in ways that mitigate socioeconomic inequalities in uptake. Gupta et al. (2003) argue that shifting the burden of activity from the individual to an organized program is important for the success of any prevention program in reaching disadvantaged populations. Their study finds that the active recruitment strategies of the Manitoba Breast Screening Program for mammography screening were instrumental in both raising coverage rates and lowered inequalities. However, influenza immunization programs in Canada remain passive in terms of recruitment and sending out vaccination reminders.

Another policy option may involve expanding vaccine delivery to settings outside physician offices as a means of reaching disadvantaged individuals. For instance, allowing pharmacists who are the most accessible healthcare providers to administer vaccinations is a policy that has been initiated in a number of provinces including British Columbia, Alberta, Ontario and New Brunswick. However, there may be additional scope of expansion to include schools, malls, workplaces, etc.

References

Allin, S. (2008). Does equity in healthcare use vary across canadian provinces. *Healthcare Policy 3*(4), 83–99.

Asada, Y. and G. Kephart (2007). Equity in health services use and intensity of use in Canada. *BMC Health Services Research 7*(41).

Carrieri, V. and A. Wuebker (2012). Assessing inequalities in preventative care use in europe: A special case of health-care inequalities? *Health, Econometrics and Data Group (HEDG) Working Papers 12/25*.

Chen, Y., J. Wu, Q. Yi, J. Laroche, and T. Wong (2012). Reasons for not having received influenza vaccination and its predictors in canadians. *Vaccine: Development and Therapy 2*, 23–33.

Endrich, M. M., P. R. Blank, and T. D. Szucs (2009). Influenza vaccination uptake and socioeconomic determinants in 11 European countries. *Vaccine 27*(30), 4018–4024.

Erreygers, G. (2008). Correcting the concentration index. *Journal of Health Economics 28*(2), 504–515.

Erreygers, G. (2009). Correcting the concentration index: a reply to wagstaff. *Journal of Health Economics 28*, 521–524.

Fleurbaey, M. (2008). In *Fairness, Responsibility, and Welfare*. Oxford: Oxford University Press.

Glazier, R. H., M. I. Creatore, P. Gozdyra, F. I. Matheson, L. S. Steele, E. Boyle, , and R. Moineddin (2004). Geographic methods for understanding and responding to disparities in mammography use in Toronto, Canada. *JGIM 19*, 952–961.

Glied, S. and A. Lleras-Muney (2008). Technological innovation and inequality in health. *Demography 45*(3), 741–761.

Gupta, S., L. L. Roos, R. Walld, D. Traverse, and M. Dahl (2003). Delivering equitable care: Comparing preventive services in Manitoba. *American Journal of Public Health 93*, 2086–2092.

Health Canada (2008). A federal report on comparable health indicators. Healthy Canadians.

Health Canada (2009). It's your health: Influenza (the "flu").

Jayachandran, S., A. Lleras-Muney, and K. V. Smith (2010). Modern medicine and the twentieth century decline in mortality: Evidence on the impact of sulfa drugs. *American Economic Journal: Applied Economics 2*(2), 118–146.

Jiménez-Rubio, D., P. C. Smith, and E. V. Doorslaer (2008). Equity in health and health care in a decentralised context: evidence from Canada. *Health economics 17*(3), 377–392.

Johansen, H., K. Nguyen, L. Mao, R. Marcoux, R. N. Gao, and C. Nair (2004). Influenza vaccination. *Health Reports 15*(2), 33–43.

Kakwani, N. C., A. Wagstaff, and E. van Doorslaer (1997). Socioeconomic inequalities in health: measurement, computation and statistical inference. *Journal of Econometrics 77*, 87–104.

Katz, S. J., J. K. Zemencuk, and T. P. Hofer (2000). Breast cancer screening in the United States and Canada, 1994: Socioeconomic gradients persist. *American Journal of Public Health 90*, 799–803.

Kjellsson, G. and U.-G. Gerdtham (2012). On correcting the concentration index for binary variables. *Journal of Health Economics 32*(3), 659–670.

Kurji, K. (2004). The Ontario experience with universal vaccination. *Presentation to The National Influenza Vaccine Summit, Atlanta, U.S.A.*.

Kwong, J., S. Maaten, R.E.G.Upshur, D. Patrick, and F. Marra (2009). The effect of universal influenza immunization on antibiotic prescriptions: An ecological study. *Clinical Infectious Diseases 49*, 750–756.

Kwong, J., T. A. Stukel, J. Lim, A. J. McGeer, R. E. G. Upshur, H. Johansen, C. Sambell, W. W. Thompson, D. Thiruchelvam, F. Marra, L. W. Svenson, and D. G. Manuel (2008). The effect of universal influenza immunization on mortality and health care use. *PLoS Med 5*(10), e211.

Kwong, J. C., L. C. Rosella, and H. Johansen (2007). Trends in influenza vaccination in Canada, 1996/1997 to 2005. *Health Reports 18*, 9–19.

Kwong, J. C., C. Sambell, H. Johansen, T. A. Stukel, and D. G. Manuel (2006). The effect of universal influenza immunization on vaccination rates in Ontario. *Health Reports 17*, 31–40.

Lee, B. Y., S. T. Brown, R. R. Bailey, R. K. Zimmerman, M. A. Potter, S. M. McGlone, P. C. Cooley, J. J. Grefenstette, S. M. Zimmer, W. D. Wheaton, et al. (2011). The benefits to all of ensuring equal and timely access to influenza vaccines in poor communities. *Health affairs 30*(6), 1141–1150.

Link, B. and J. Phelan (1995). Social conditions as fundamental causes of disease. *Journal of Health & Social Behavior extra issue*, 80–94.

Lleras-Muney, A. and F. Lichtenberg (2005). The effect of education on medical technology adoption: Are the more educated more likely to use new drugs? *Special issue of the Annales d'Economie et de Statistique in memory of Zvi Griliches 79/80*.

Lorant, V., B. Boland, P. Humblet, and D. Delige (2002). Equity in prevention and health care. *Journal of Epidemiology & Community Health 56*, 510–516.

Maxwell, C., J. F. Kozak, S. D. Desjardins-Denault, and J. Parboosingh (1997). Factors important in promoting mammography screening among Canadian women. *Canadian Journal of Public Health 88*, 346–350.

Mullahy, J. (1999). It'll only hurt a second? Microeconomic determinants of who gets flu shots. *Health Economics 8*(1), 9–24.

National Advisory Committee on Immunization (2008). Statement on influenza vaccination for the 2008-2009 season. Canada Communicable Disease Report 34.

O'Donnell, O., E. van Doorslaer, A. Wagstaff, and M. Lindelow (2008). In *Analyzing health equity using household survey data: a guide to techniques and their implementation*. Washington, DC: World Bank.

Public Health Agency of Canada (2008). Getting ready for flu season. Public Health Agency of Canada.

Roemer, J. (1998). In *Equality of opportunity*. Cambridge, Mass: Harvard University Press.

Ryan, J., Y. Zoellner, B. Gradl, B. Palache, and J. Medema (2006). Establishing the health and economic impact of influenza vaccination within the european union 25 countries. *Vaccine 24*, 6812–6822.

Sateren, W. B., E. L. Trimble, J. Abrams, O. Brawley, N. Breen, L. Ford, M. McCabe, R. Kaplan, M. Smith, R. Ungerleider, and M. C. Christian

(2002). How sociodemographics, presence of oncology specialists, and hospital cancer programs affect accrual to cancer treatment trials. *Journal of Clinical Oncology 20*(8), 2109–2117.

Schanzer, D. L., J. M. Langley, and T. W. Tam (2008). Role of influenza and other respiratory viruses in admissions of adults to canadian hospitals. *Influenza and Other Respiratory Viruses 2*(18).

Schull, M. J., M. M. Mamdani, and J. Fang (2004). Community influenza outbreaks and emergency department ambulance diversion. *Annals of Emergency Medicine 44*(1), 61–67.

Statistics Canada (1997). Selected leading causes of death, by sex.

van Doorslaer, E. and X. Koolman (2004). Explaining income-related inequalities in doctor utilization in europe. *Health Economics 13*, 609–628.

van Doorslaer, E., X. Koolman, and A. M. Jones (2004). Explaining income-related inequalities in doctor utilization in europe. *Health Economics 13*, 629–647.

Van Doorslaer, E., C. Masseria, and X. Koolman (2006). Inequalities in access to medical care by income in developed countries. *Canadian Medical Association Journal 174*(2), 177–183.

Wagstaff, A. (2005). The bounds of the concentration index when the variable of interest is binary, with an application to immunization inequality. *Health Economics 14*, 429–432.

Wagstaff, A. (2009). Correcting the concentration index: a comment. *Journal of Health Economics 28*, 516–520.

Wagstaff, A., E. van Doorslaer, and N. Watanabe (2003). On decomposing the causes of health sector inequalities with an application to malnutrition inequalities in Vietnam. *Journal of Econometrics 112*, 207–223.

Ward, C. (2013). Influenza immunization campaigns: Is an ounce of prevention worth a pound of cure? *American Economic Journal: Applied Economics Forthcoming.*

Figure 3.1: Trends in coverage and inequity

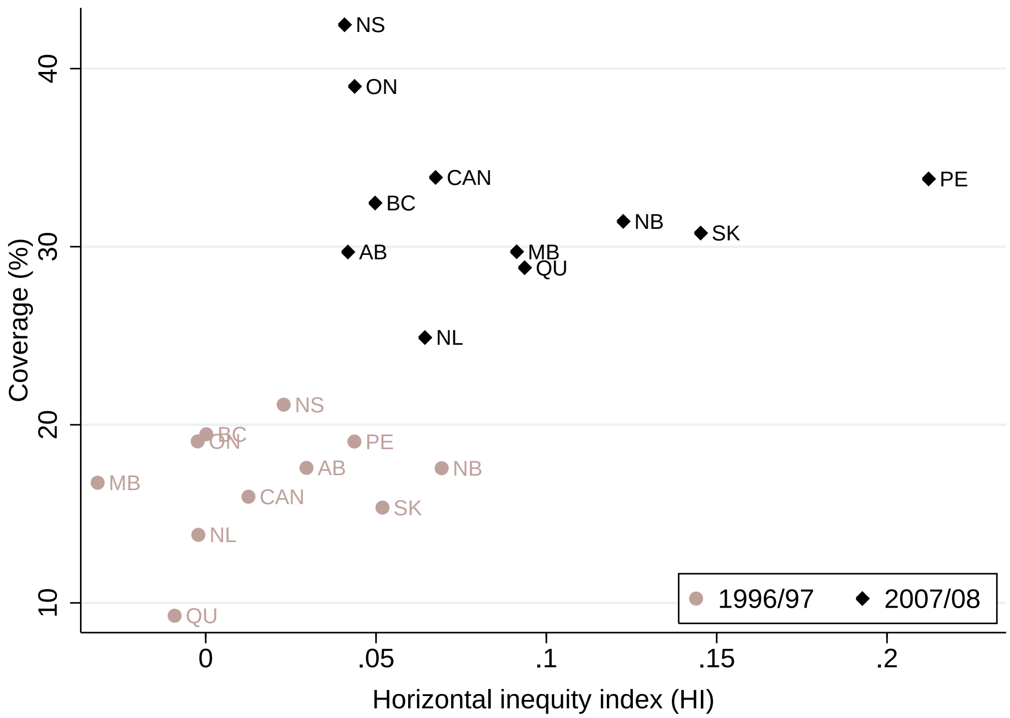
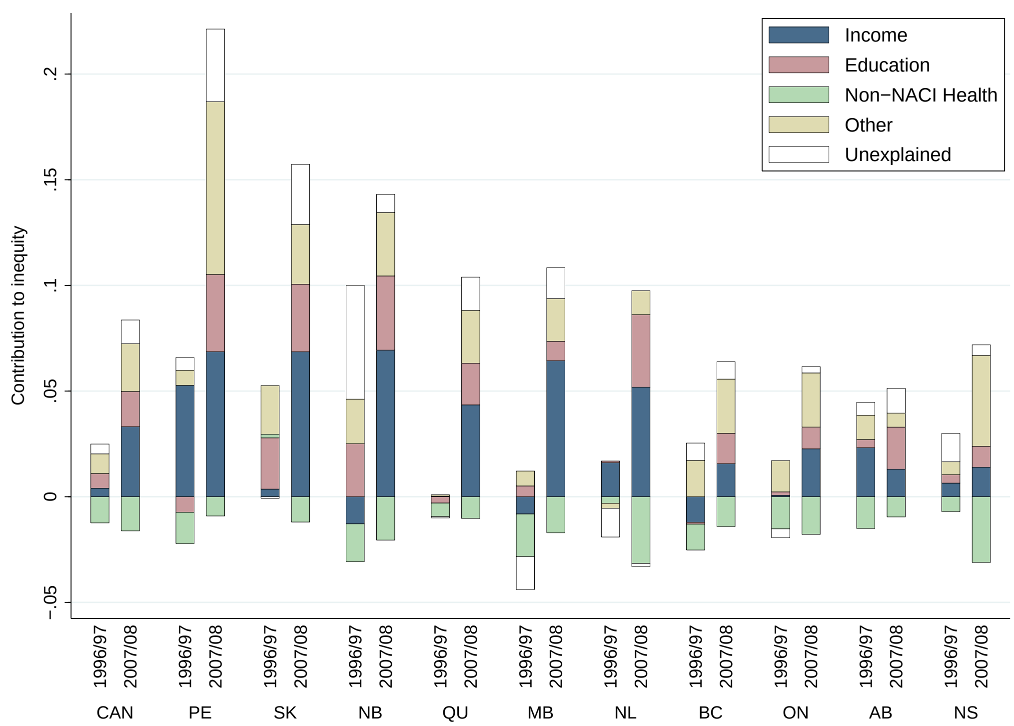


Figure 3.2: Decomposition of the horizontal inequity index, (ranked by 2007/08 HI)



Note: "Non-NACI health" includes non-NACI chronic conditions and self-assessed health; "Other" includes marital status, immigration status, rural, regular MD, smoking status, and non-need age-sex interactions.

Table 3.1: Influenza immunization rates for Canada, by income quartile

	1996/97			2007/08		
	Age < 65 no risk	Age < 65 and risk	Age 65+	Age < 65 no risk	Age < 65 and risk	Age 65+
Q1 (Lowest)	6.6	23.9	47.9	21.1	39.2	63.8
	(24.9)	(42.6)	(50.0)	(40.8)	(48.8)	(48.1)
Q2	6.8	25.9	50.8	22.4	42.2	69.4
	(25.3)	(43.8)	(50.0)	(41.7)	(49.4)	(46.1)
Q3	6.6	20.9	53.0	24.2	44.3	72.4
	(24.9)	(40.7)	(49.9)	(43.1)	(49.7)	(44.7)
Q4 (Highest)	9.0	19.2	55.3	27.2	45.6	72.0
	(28.6)	(39.4)	(49.7)	(44.5)	(49.8)	(44.9)

Note: Standard errors are reported in parentheses.

Table 3.2: Influenza immunization rates, by province and year

	1996/97			2007/08			Change	
	N	Coverage (%)	Rank	N	Coverage (%)	Rank	(%)	Rank
CAN	46,572	16.0		88,926	33.9		17.9	
NL	625	13.8	9	2,941	24.9	10	11.1	10
PE	646	19.1	4	1,666	33.8	3	14.7	5
NS	676	21.1	1	3,736	42.5	1	21.3	1
NB	724	17.6	6	3,936	31.4	5	13.9	6
QU	1,870	9.3	10	17,453	28.8	9	19.5	3
ON	23,371	19.1	3	30,471	39.0	2	19.9	2
MB	8,140	16.8	7	5,087	29.7	7	13.0	8
SK	694	15.4	8	5,151	30.8	6	15.4	4
AB	8,728	17.6	5	7,800	29.7	8	12.1	9
BC	1,098	19.5	2	10,685	32.5	4	13.0	7

Table 3.3: The association between income and flu shot uptake

Dependent variable: Flu shot use [0/1]						
	1996/97			2007/08		
	(1)	(2)	(3)	(1)	(2)	(3)
CAN	0.005	0.001	0.003	0.029***	0.021***	0.021***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
NL	0.010	0.007	0.010	0.041***	0.028**	0.031**
	(0.013)	(0.014)	(0.014)	(0.012)	(0.013)	(0.013)
PE	0.032*	0.034**	0.037**	0.075***	0.052**	0.045*
	(0.017)	(0.017)	(0.017)	(0.024)	(0.023)	(0.023)
NS	0.007	0.004	0.004	0.018	0.010	0.009
	(0.020)	(0.020)	(0.020)	(0.013)	(0.014)	(0.014)
NB	-0.009	-0.013	-0.009	0.063***	0.045***	0.043***
	(0.025)	(0.023)	(0.023)	(0.010)	(0.010)	(0.010)
QU	-0.002	0.001	0.000	0.044***	0.029***	0.027***
	(0.010)	(0.010)	(0.011)	(0.006)	(0.007)	(0.007)
ON	0.000	-0.003	0.000	0.016***	0.014**	0.014**
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
MB	-0.006	-0.010	-0.006	0.044***	0.037***	0.040***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
SK	0.012	0.004	0.002	0.058***	0.044***	0.043***
	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)
AB	0.013***	0.011**	0.015***	0.019*	0.009	0.009
	(0.004)	(0.004)	(0.004)	(0.010)	(0.010)	(0.010)
BC	-0.002	-0.007	-0.007	0.017**	0.010	0.010
	(0.012)	(0.012)	(0.013)	(0.007)	(0.007)	(0.007)

Note: Regressions are estimated using OLS. The columns represent alternate specifications that successively add control variables as follows: (1) includes a dummy for NACI risk factors and only exogenous variables, namely age-sex interactions; (2) adds predetermined variables including education, immigration status, marital status, a dummy for other chronic conditions, a dummy for whether the individual is a former smoker, and a dummy for rural; (3) further adds all other variables including self-assessed health, current smoking status, and a dummy for whether the respondent has a regular family doctor. Coefficient estimates indicate the approximate percentage point change in flu shot use associated with a one percent change in income. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4: The association between income and flu shot uptake in 1996/97, by subgroup

Dependent variable: Flu shot use [0/1]						
	Male			Female		
	Age < 65 no risk	Age < 65 and risk	Age 65+	Age < 65 no risk	Age < 65 and risk	Age 65+
CAN	0.009**	0.000	0.007	0.008	-0.019	0.004
	(0.004)	(0.013)	(0.004)	(0.005)	(0.016)	(0.005)
NL	0.025**	-0.679	0.025*	-0.022	0.023	-0.003
	(0.012)	(0.677)	(0.014)	(0.028)	(0.220)	(0.028)
PE	0.006	0.369	0.005	0.063**	0.094	0.062**
	(0.024)	(0.297)	(0.024)	(0.032)	(0.161)	(0.031)
NS	0.010	-0.045	0.015	0.002	-0.035	-0.001
	(0.021)	(0.231)	(0.024)	(0.021)	(0.118)	(0.026)
NB	0.024	0.499***	0.017	0.071***	-0.030	0.015
	(0.032)	(0.183)	(0.031)	(0.026)	(0.044)	(0.032)
QU	0.008	-0.035	0.001	0.014	0.014	0.016
	(0.013)	(0.055)	(0.012)	(0.015)	(0.059)	(0.014)
ON	0.003	-0.016	-0.001	-0.002	0.005	-0.001
	(0.004)	(0.016)	(0.004)	(0.004)	(0.013)	(0.004)
MB	-0.003	-0.037	-0.008	-0.001	-0.016	-0.001
	(0.008)	(0.049)	(0.009)	(0.011)	(0.050)	(0.012)
SK	0.003	0.066	0.022	0.002	0.031	-0.003
	(0.016)	(0.068)	(0.016)	(0.008)	(0.210)	(0.008)
AB	0.013**	0.007	0.011**	0.030***	-0.039	0.021***
	(0.004)	(0.024)	(0.005)	(0.007)	(0.025)	(0.007)
BC	0.011	0.103	0.015	-0.005	-0.028	-0.010
	(0.014)	(0.086)	(0.014)	(0.024)	(0.062)	(0.022)

Note: Regressions are estimated using OLS and include a full set of covariates as noted in the text. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: The association between income and flu shot uptake in 2007/08, by subgroup

Dependent variable: Flu shot use [0/1]						
	Male			Female		
	Age < 65 no risk	Age < 65 and risk	Age 65+	Age < 65 no risk	Age < 65 and risk	Age 65+
CAN	0.014***	0.014	0.015***	0.022***	0.028**	0.023***
	(0.005)	(0.013)	(0.005)	(0.005)	(0.012)	(0.005)
NL	0.045***	-0.048	0.032*	0.035**	-0.003	0.020
	(0.017)	(0.069)	(0.017)	(0.018)	(0.059)	(0.019)
PE	0.108***	0.031	0.057	0.015	0.030	0.026
	(0.037)	(0.032)	(0.045)	(0.028)	(0.072)	(0.025)
NS	0.020	0.045	0.024	-0.004	0.002	0.000
	(0.023)	(0.054)	(0.021)	(0.025)	(0.039)	(0.021)
NB	0.039**	0.035	0.037**	0.050***	0.018	0.046***
	(0.018)	(0.036)	(0.017)	(0.016)	(0.047)	(0.016)
QU	0.009	0.040*	0.018*	0.028**	0.091***	0.040***
	(0.011)	(0.021)	(0.009)	(0.011)	(0.027)	(0.011)
ON	0.017**	0.005	0.014	0.007	-0.005	0.005
	(0.008)	(0.020)	(0.009)	(0.010)	(0.018)	(0.008)
MB	0.018	-0.058	0.011	0.068***	0.086**	0.072***
	(0.013)	(0.037)	(0.012)	(0.014)	(0.036)	(0.014)
SK	0.012	0.009	0.012	0.069***	0.092***	0.078***
	(0.019)	(0.039)	(0.016)	(0.020)	(0.028)	(0.017)
AB	-0.003	-0.013	-0.001	0.023	0.021	0.021
	(0.017)	(0.033)	(0.015)	(0.016)	(0.042)	(0.015)
BC	-0.005	0.003	-0.003	0.019*	0.048	0.022**
	(0.014)	(0.026)	(0.012)	(0.011)	(0.034)	(0.010)

Note: Regressions are estimated using OLS and include a full set of covariates as noted in the text. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6: Inequality and inequity in flu shot use, by province and year

	1996/97			2007/08		
	CI (S.E.)	HI (S.E.)	Rank (HI)	CI (S.E.)	HI (S.E.)	Rank (HI)
CAN	-0.057***	0.013*		-0.023***	0.067***	
	(0.008)	(0.007)		(0.006)	(0.006)	
NL	-0.057*	-0.002	4	-0.028	0.064***	5
	(0.032)	(0.030)		(0.025)	(0.024)	
PE	-0.028	0.044	8	0.089**	0.212***	10
	(0.040)	(0.037)		(0.036)	(0.035)	
NS	-0.027	0.023	6	-0.074***	0.041*	1
	(0.045)	(0.041)		(0.026)	(0.024)	
NB	-0.002	0.069**	10	0.006	0.123***	8
	(0.035)	(0.033)		(0.022)	(0.020)	
QU	-0.065***	-0.009	2	0.002	0.094***	7
	(0.019)	(0.018)		(0.012)	(0.011)	
ON	-0.078***	-0.002	3	-0.038***	0.044***	3
	(0.007)	(0.006)		(0.011)	(0.011)	
MB	-0.116***	-0.032**	1	-0.001	0.091***	6
	(0.018)	(0.016)		(0.023)	(0.021)	
SK	-0.056*	0.052*	9	0.013	0.145***	9
	(0.032)	(0.027)		(0.020)	(0.019)	
AB	-0.051***	0.030***	7	-0.050***	0.042**	2
	(0.011)	(0.010)		(0.017)	(0.017)	
BC	-0.075**	0.000	5	-0.041**	0.050***	4
	(0.030)	(0.027)		(0.016)	(0.015)	

Note: Regressions are estimated using OLS and include a full set of covariates as noted in the text. Standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix 3.A: Construction of the analysis sample

	NPHS	CCHS
Initial sample size	81,804	131,959
Individuals dropped due to:		
residing in Territories		3,265
under 25 years of age	20,522	20,633
missing flu shot	1,823	2,834
missing income	12,333	14,995
missing other variables	554	1,306
Final sample	46,572	88,926

Appendix 3.B: Construction of the income variable in the NPHS and sensitivity analysis

Construction of the income variable

Step 1: For the subsample of the CCHS who reported continuous income, the following equation was estimated using OLS:

$$ln(income) = \sum_{j=1}^{10} \delta_j income\_category_j + \beta X + \epsilon \tag{3.8}$$

where $ln(income)$ is the natural log of continuous household income; $income\_category_j$ is an indicator that takes the value of 1 if the individual's household income falls within household income category j and 0 otherwise (there are 10 income categories: \$0 to \$5,000; \$5,000 to \$9,000; \$10,000 to \$14,999; \$15,000 to \$19,999; \$20,000 to \$29,999; \$30,000 to \$39,999; \$40,000 to \$49,999; \$50,000 to \$59,999; \$60,000 to \$79,999; over \$80,000); and X is a vector of covariates including age, age-squared, sex, age-sex interaction, dummies for marital status (married, formerly married, single), dummies for immigration status (recent immigrant, non-recent immigrant, native), dummies for education (less than high school, high school, some college, college degree), household size, and number of children in the household.

Step 2: Based on the estimation results of auxilliary equation 3.8 above, continuous household income was predicted for the NPHS sample.

Table 3.B1: Comparison of actual vs. predicted household income in the NPHS.

	Predicted Income									
Actual Income	0-4,999	5,000-9,999	10,000-14,999	15,000-19,999	20,000-29,999	30,000-39,999	40,000-49,999	50,000-59,999	60,000-79,999	Over 80,000
0-4,999	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%
5,000-9,999	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%
10,000-14,999	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%
15,000-19,999	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%
20,000-29,999	0%	0%	0%	0%	100%	0%	0%	0%	0%	0%
30,000-39,999	0%	0%	0%	0%	0.03%	99.97%	0%	0%	0%	0%
40,000-49,999	0%	0%	0%	0%	0%	0.92%	99.08%	0%	0%	0%
50,000-59,999	0%	0%	0%	0%	0%	0%	9.7%	90.3%	0%	0%
60,000-79,999	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%
Over 80,000	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%

Step 3: Predicted household income was adjusted for household size and composition using the modified OECD equivalence scale, which assigns a weight of 1.0 to the first adult household member, 0.5 to the second adult household member and 0.3 to children.

(3.9)

$$equivalent\_income = \frac{predicted\_household\_income}{(1 + 0.5 * (householdsize - 1 - children) + 0.3 * children)}$$

Sensitivity analysis

In this section, the main analysis is replicated using an alternative method of constructing the income variable. Specifically, instead of steps 1 and 2 above, the mean value of income in each income category is assigned to each individual in that category. Individuals in the highest income category earning above \$80,000 are assigned an income of \$87,500. Finally, household income is adjusted for household size and composition as described in step 3.

Table 3.B2: Comparing results from the analysis of inequality and inequity in flu shot use in the NPHS using predicted household income vs. using the midpoint of each household income category.

Dependent variable: Flu shot use [0/1]						
	Predicted income			Midpoint income		
	CI (S.E.)	HI (S.E.)	Rank(HI)	CI (S.E.)	HI (S.E.)	Rank(HI)
CAN	-0.057***	0.013*		-0.054***	0.012*	
	(0.008)	(0.007)		(0.008)	(0.007)	
NL	-0.057*	-0.002	4	-0.054*	0.001	5
	(0.032)	(0.030)		(0.032)	(0.030)	
PE	-0.028	0.044	8	-0.024	0.048	8
	(0.040)	(0.037)		(0.041)	(0.038)	
NS	-0.027	0.023	6	-0.023	0.023	6
	(0.045)	(0.041)		(0.045)	(0.040)	
NB	-0.002	0.069**	10	0.001	0.075**	10
	(0.035)	(0.033)		(0.036)	(0.033)	
QU	-0.065***	-0.009	2	-0.066***	-0.011	2
	(0.019)	(0.018)		(0.019)	(0.018)	
ON	-0.078***	-0.002	3	-0.069***	-0.001	4
	(0.007)	(0.006)		(0.007)	(0.006)	
MB	-0.116***	-0.032**	1	-0.113***	-0.032**	1
	(0.018)	(0.016)		(0.017)	(0.015)	
SK	-0.056*	0.052*	9	-0.051	0.054**	9
	(0.032)	(0.027)		(0.032)	(0.027)	
AB	-0.051***	0.030***	7	-0.050***	0.027***	7
	(0.011)	(0.010)		(0.011)	(0.010)	
BC	-0.075**	0.000	5	-0.078***	-0.010	3
	(0.030)	(0.027)		(0.030)	(0.026)	

Note: Regressions are estimated using OLS and include need and non-need variables as noted in the text. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 3.C: Full regression results of the association between income and flu shot uptake

Table 3.C1: Canada

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.003	(0.003)	0.021***	(0.003)
m35-44	0.006	(0.009)	0.023**	(0.010)
m45-54	0.021*	(0.011)	0.058***	(0.011)
m55-64	0.082***	(0.014)	0.146***	(0.012)
m65-74	0.355***	(0.022)	0.376***	(0.013)
m75-84	0.492***	(0.033)	0.509***	(0.014)
m85plus	0.282**	(0.111)	0.518***	(0.032)
f25-34	-0.013	(0.008)	0.041***	(0.010)
f35-44	0.013	(0.009)	0.067***	(0.010)
f45-54	0.051***	(0.012)	0.103***	(0.011)
f55-64	0.132***	(0.016)	0.226***	(0.011)
f65-74	0.367***	(0.021)	0.423***	(0.012)
f75-84	0.470***	(0.028)	0.482***	(0.014)
f85plus	0.436***	(0.054)	0.506***	(0.021)
NACI chronic conditions	0.106***	(0.011)	0.122***	(0.007)
Non-NACI chronic conditions	0.034***	(0.006)	0.062***	(0.006)
Very good SAH	0.009	(0.007)	0.015**	(0.007)
Good SAH	0.020**	(0.008)	0.021***	(0.007)
Fair SAH	0.080***	(0.015)	0.059***	(0.011)
Poor SAH	0.058**	(0.023)	0.081***	(0.022)
Less-than-secondary	-0.017	(0.011)	-0.020**	(0.009)
Some post-secondary	0.013	(0.009)	-0.003	(0.011)
Post-secondary	0.005	(0.008)	0.035***	(0.007)
Recent Immigrant	-0.009	(0.015)	0.015	(0.014)
Non-recent Immigrant	0.035***	(0.011)	0.017**	(0.008)
Married	-0.009	(0.008)	0.010	(0.007)
Former Married	-0.029**	(0.012)	-0.015*	(0.009)
Rural	-0.014*	(0.007)	-0.030***	(0.005)
Heavy smoker	-0.028***	(0.007)	-0.062***	(0.007)
Occasional smoker	-0.002	(0.016)	-0.039***	(0.013)
Former smoker	0.017**	(0.008)	-0.006	(0.006)
Regular MD	0.058***	(0.007)	0.098***	(0.007)
Constant	-0.047	(0.037)	-0.181***	(0.037)
R^2	0.224		0.166	
N	46,472		88,926	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C2: Newfoundland and Labrador

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.010	(0.014)	0.031**	(0.013)
m35-44	-0.028	(0.051)	0.007	(0.039)
m45-54	-0.026	(0.054)	-0.016	(0.037)
m55-64	0.068	(0.077)	0.057	(0.043)
m65-74	0.296**	(0.131)	0.315***	(0.056)
m75-84	0.305*	(0.162)	0.399***	(0.070)
m85plus	0.813***	(0.090)	0.502***	(0.176)
f25-34	-0.045	(0.048)	0.118**	(0.050)
f35-44	0.023	(0.066)	0.080*	(0.041)
f45-54	0.073	(0.065)	0.054	(0.040)
f55-64	0.056	(0.080)	0.180***	(0.043)
f65-74	0.249**	(0.108)	0.304***	(0.055)
f75-84	0.425***	(0.163)	0.431***	(0.066)
f85plus	0.570***	(0.194)	0.327***	(0.106)
NACI chronic conditions	0.129*	(0.071)	0.144***	(0.030)
Non-NACI chronic conditions	0.032	(0.030)	0.038*	(0.022)
Very good SAH	-0.052	(0.033)	0.021	(0.027)
Good SAH	-0.046	(0.046)	0.037	(0.030)
Fair SAH	0.017	(0.067)	0.139***	(0.047)
Poor SAH	0.274	(0.261)	0.178***	(0.067)
Less-than-secondary	0.000	(0.045)	-0.050	(0.033)
Some post-secondary	0.000	(0.041)	-0.024	(0.040)
Post-secondary	0.001	(0.042)	0.028	(0.029)
Recent Immigrant	-0.206***	(0.057)	-0.116***	(0.030)
Non-recent Immigrant	0.038	(0.116)	0.154*	(0.087)
Married	-0.011	(0.042)	0.009	(0.030)
Former Married	-0.001	(0.063)	-0.028	(0.039)
Rural	-0.004	(0.028)	0.020	(0.022)
Heavy smoker	-0.019	(0.040)	-0.053*	(0.028)
Occasional smoker	-0.059	(0.059)	-0.019	(0.051)
Former smoker	-0.015	(0.039)	0.011	(0.025)
Regular MD	0.024	(0.033)	0.059**	(0.025)
Constant	-0.019	(0.145)	-0.319**	(0.133)
R^2	0.223		0.157	
N	625		2,941	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C3: PEI

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.037**	(0.017)	0.045*	(0.023)
m35-44	0.003	(0.044)	0.152***	(0.050)
m45-54	-0.011	(0.049)	0.255***	(0.061)
m55-64	0.188**	(0.085)	0.335***	(0.057)
m65-74	0.368***	(0.101)	0.483***	(0.069)
m75-84	0.610***	(0.110)	0.461***	(0.102)
m85plus	-0.133*	(0.077)	0.587***	(0.159)
f25-34	0.013	(0.052)	0.137***	(0.044)
f35-44	-0.017	(0.038)	0.153***	(0.048)
f45-54	0.113*	(0.064)	0.275***	(0.071)
f55-64	-0.010	(0.075)	0.399***	(0.060)
f65-74	0.416***	(0.102)	0.468***	(0.068)
f75-84	0.223*	(0.113)	0.676***	(0.073)
f85plus	0.370**	(0.143)	0.631***	(0.106)
NACI chronic conditions	0.091*	(0.048)	0.116***	(0.038)
Non-NACI chronic conditions	0.053*	(0.032)	0.051	(0.033)
Very good SAH	0.027	(0.034)	0.034	(0.040)
Good SAH	0.015	(0.044)	-0.027	(0.039)
Fair SAH	0.078	(0.070)	0.090	(0.060)
Poor SAH	0.019	(0.099)	0.018	(0.100)
Less-than-secondary	0.004	(0.050)	-0.121**	(0.048)
Some post-secondary	0.022	(0.047)	-0.113**	(0.055)
Post-secondary	-0.020	(0.042)	-0.009	(0.041)
Recent Immigrant	-0.107*	(0.055)	0.098	(0.133)
Non-recent Immigrant	-0.003	(0.081)	-0.032	(0.079)
Married	0.007	(0.045)	-0.033	(0.037)
Former Married	0.049	(0.061)	-0.107**	(0.044)
Rural	-0.062**	(0.031)	-0.068**	(0.030)
Heavy smoker	-0.078**	(0.037)	-0.065	(0.044)
Occasional smoker	-0.022	(0.087)	0.043	(0.091)
Former smoker	-0.002	(0.039)	-0.040	(0.036)
Regular MD	0.062	(0.039)	0.091***	(0.034)
Constant	-0.351*	(0.182)	-0.406*	(0.242)
R^2	0.277		0.172	
N	646		1,666	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C4: Nova Scotia

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.004	(0.020)	0.009	(0.014)
m35-44	-0.063	(0.046)	0.076*	(0.042)
m45-54	-0.102**	(0.049)	0.108**	(0.047)
m55-64	0.242***	(0.086)	0.194***	(0.049)
m65-74	0.254***	(0.090)	0.438***	(0.047)
m75-84	0.449***	(0.133)	0.550***	(0.049)
m85plus	0.338	(0.222)	0.277***	(0.103)
f25-34	-0.024	(0.054)	0.154***	(0.043)
f35-44	-0.043	(0.055)	0.097**	(0.040)
f45-54	0.008	(0.053)	0.225***	(0.047)
f55-64	0.201***	(0.075)	0.305***	(0.044)
f65-74	0.448***	(0.095)	0.431***	(0.048)
f75-84	0.638***	(0.094)	0.524***	(0.047)
f85plus	0.435**	(0.216)	0.425***	(0.070)
NACI chronic conditions	0.204***	(0.050)	0.146***	(0.026)
Non-NACI chronic conditions	0.017	(0.029)	0.056**	(0.024)
Very good SAH	0.039	(0.034)	0.015	(0.031)
Good SAH	0.078*	(0.045)	-0.012	(0.034)
Fair SAH	0.043	(0.055)	0.115***	(0.041)
Poor SAH	-0.016	(0.112)	0.139**	(0.057)
Less-than-secondary	-0.019	(0.046)	0.008	(0.034)
Some post-secondary	0.081*	(0.046)	0.006	(0.046)
Post-secondary	-0.013	(0.038)	0.031	(0.029)
Recent Immigrant	-0.034	(0.149)	-0.047	(0.105)
Non-recent Immigrant	0.115	(0.088)	0.074	(0.052)
Married	-0.082*	(0.048)	0.043*	(0.026)
Former Married	-0.070	(0.074)	0.042	(0.035)
Rural	0.019	(0.030)	-0.027	(0.021)
Heavy smoker	-0.047	(0.036)	-0.120***	(0.030)
Occasional smoker	0.167	(0.102)	-0.052	(0.066)
Former smoker	0.039	(0.037)	-0.040	(0.027)
Regular MD	-0.005	(0.062)	0.127***	(0.031)
Constant	0.044	(0.204)	-0.083	(0.150)
R^2	0.350		0.192	
N	676		3,736	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C5: New Brunswick

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	-0.009	(0.023)	0.043***	(0.010)
m35-44	0.076*	(0.043)	0.030	(0.040)
m45-54	0.079	(0.049)	0.043	(0.039)
m55-64	0.159**	(0.064)	0.091**	(0.041)
m65-74	0.472***	(0.097)	0.396***	(0.048)
m75-84	0.613***	(0.105)	0.496***	(0.056)
m85plus	-0.022	(0.055)	0.448***	(0.108)
f25-34	0.021	(0.039)	0.066*	(0.037)
f35-44	0.063	(0.045)	0.082**	(0.039)
f45-54	0.153***	(0.052)	0.198***	(0.042)
f55-64	0.220***	(0.081)	0.228***	(0.041)
f65-74	0.351***	(0.084)	0.424***	(0.048)
f75-84	0.304***	(0.092)	0.501***	(0.049)
f85plus	0.427***	(0.143)	0.435***	(0.076)
NACI chronic conditions	0.084*	(0.049)	0.165***	(0.024)
Non-NACI chronic conditions	0.046*	(0.028)	0.060***	(0.020)
Very good SAH	0.028	(0.036)	0.013	(0.028)
Good SAH	-0.019	(0.037)	0.032	(0.030)
Fair SAH	0.074	(0.063)	0.038	(0.035)
Poor SAH	0.135	(0.095)	0.047	(0.050)
Less-than-secondary	-0.086**	(0.042)	-0.031	(0.028)
Some post-secondary	-0.017	(0.040)	-0.015	(0.037)
Post-secondary	-0.005	(0.041)	0.051**	(0.024)
Recent Immigrant	-0.107**	(0.046)	0.048	(0.093)
Non-recent Immigrant	0.124	(0.076)	0.010	(0.054)
Married	-0.055	(0.044)	0.014	(0.024)
Former Married	-0.053	(0.057)	-0.016	(0.030)
Rural	-0.031	(0.029)	-0.018	(0.018)
Heavy smoker	-0.015	(0.034)	-0.072***	(0.024)
Occasional smoker	0.048	(0.110)	-0.047	(0.051)
Former smoker	0.021	(0.034)	0.018	(0.023)
Regular MD	0.090***	(0.029)	0.038	(0.028)
Constant	0.056	(0.243)	-0.427***	(0.116)
R^2	0.217		0.180	
N	724		3,936	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C6: Quebec

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.000	(0.011)	0.027***	(0.007)
m35-44	0.011	(0.021)	0.033*	(0.020)
m45-54	0.005	(0.023)	0.038*	(0.021)
m55-64	0.013	(0.030)	0.119***	(0.021)
m65-74	0.207***	(0.058)	0.379***	(0.027)
m75-84	0.366***	(0.088)	0.540***	(0.029)
m85plus	0.010	(0.115)	0.501***	(0.109)
f25-34	-0.017	(0.016)	0.035*	(0.018)
f35-44	0.010	(0.019)	0.043**	(0.020)
f45-54	-0.005	(0.023)	0.071***	(0.021)
f55-64	0.004	(0.029)	0.218***	(0.022)
f65-74	0.242***	(0.053)	0.441***	(0.027)
f75-84	0.349***	(0.085)	0.486***	(0.029)
f85plus	0.350**	(0.139)	0.464***	(0.056)
NACI chronic conditions	0.064**	(0.026)	0.124***	(0.014)
Non-NACI chronic conditions	0.034**	(0.015)	0.050***	(0.011)
Very good SAH	0.001	(0.016)	0.014	(0.013)
Good SAH	-0.012	(0.019)	0.010	(0.014)
Fair SAH	0.081*	(0.045)	0.030	(0.021)
Poor SAH	-0.037	(0.062)	0.080**	(0.036)
Less-than-secondary	0.018	(0.025)	-0.027*	(0.016)
Some post-secondary	0.020	(0.022)	0.004	(0.023)
Post-secondary	0.008	(0.019)	0.029**	(0.014)
Recent Immigrant	0.035	(0.061)	0.003	(0.030)
Non-recent Immigrant	0.054	(0.045)	-0.022	(0.021)
Married	0.009	(0.016)	0.032***	(0.012)
Former Married	0.001	(0.025)	-0.011	(0.016)
Rural	-0.003	(0.016)	-0.016	(0.011)
Heavy smoker	-0.046***	(0.015)	-0.056***	(0.014)
Occasional smoker	-0.077***	(0.028)	-0.020	(0.025)
Former smoker	-0.004	(0.021)	-0.004	(0.012)
Regular MD	0.044***	(0.012)	0.078***	(0.012)
Constant	-0.025	(0.109)	-0.260***	(0.073)
R^2	0.188		0.183	
N	1,870		17,453	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C7: Ontario

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.000	(0.003)	0.014**	(0.006)
m35-44	0.018**	(0.009)	0.026	(0.017)
m45-54	0.045***	(0.011)	0.101***	(0.020)
m55-64	0.141***	(0.015)	0.222***	(0.023)
m65-74	0.425***	(0.019)	0.439***	(0.022)
m75-84	0.557***	(0.027)	0.523***	(0.024)
m85plus	0.620***	(0.070)	0.549***	(0.037)
f25-34	0.003	(0.008)	0.045**	(0.018)
f35-44	0.021**	(0.008)	0.096***	(0.018)
f45-54	0.063***	(0.011)	0.142***	(0.019)
f55-64	0.190***	(0.015)	0.273***	(0.021)
f65-74	0.449***	(0.018)	0.456***	(0.021)
f75-84	0.580***	(0.021)	0.478***	(0.024)
f85plus	0.573***	(0.044)	0.579***	(0.029)
NACI chronic conditions	0.111***	(0.009)	0.110***	(0.012)
Non-NACI chronic conditions	0.033***	(0.006)	0.070***	(0.010)
Very good SAH	0.014**	(0.006)	0.018	(0.012)
Good SAH	0.032***	(0.008)	0.029**	(0.013)
Fair SAH	0.076***	(0.013)	0.068***	(0.019)
Poor SAH	0.101***	(0.022)	0.074**	(0.037)
Less-than-secondary	0.015	(0.010)	-0.001	(0.017)
Some post-secondary	0.005	(0.008)	0.003	(0.022)
Post-secondary	0.016**	(0.007)	0.032***	(0.012)
Recent Immigrant	-0.025*	(0.013)	0.008	(0.022)
Non-recent Immigrant	-0.007	(0.008)	-0.007	(0.011)
Married	-0.015*	(0.008)	-0.008	(0.013)
Former Married	-0.032***	(0.011)	-0.029*	(0.016)
Rural	-0.022***	(0.007)	-0.039***	(0.009)
Heavy smoker	-0.019***	(0.007)	-0.064***	(0.014)
Occasional smoker	0.012	(0.014)	-0.033	(0.024)
Former smoker	0.025***	(0.007)	-0.002	(0.011)
Regular MD	0.052***	(0.010)	0.092***	(0.017)
Constant	-0.028	(0.033)	-0.082	(0.070)
R^2	0.259		0.163	
N	23,371		30,471	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C8: Manitoba

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	-0.006	(0.008)	0.040***	(0.009)
m35-44	-0.038*	(0.019)	0.012	(0.038)
m45-54	-0.021	(0.024)	0.009	(0.037)
m55-64	0.064*	(0.035)	0.087**	(0.044)
m65-74	0.411***	(0.047)	0.441***	(0.046)
m75-84	0.558***	(0.048)	0.489***	(0.050)
m85plus	0.569***	(0.090)	0.541***	(0.083)
f25-34	-0.038	(0.024)	0.037	(0.031)
f35-44	0.000	(0.027)	0.039	(0.036)
f45-54	-0.012	(0.025)	0.121***	(0.042)
f55-64	0.127***	(0.037)	0.190***	(0.044)
f65-74	0.375***	(0.042)	0.402***	(0.051)
f75-84	0.358***	(0.052)	0.494***	(0.049)
f85plus	0.398***	(0.085)	0.464***	(0.071)
NACI chronic conditions	0.098***	(0.022)	0.133***	(0.029)
Non-NACI chronic conditions	0.028**	(0.013)	0.085***	(0.021)
Very good SAH	0.016	(0.016)	0.046*	(0.025)
Good SAH	0.049***	(0.018)	0.063**	(0.028)
Fair SAH	0.094***	(0.029)	0.120***	(0.041)
Poor SAH	0.242***	(0.067)	0.064	(0.066)
Less-than-secondary	-0.019	(0.021)	0.006	(0.029)
Some post-secondary	0.005	(0.021)	0.059	(0.040)
Post-secondary	-0.001	(0.019)	0.036	(0.023)
Recent Immigrant	-0.046	(0.056)	0.023	(0.041)
Non-recent Immigrant	0.013	(0.021)	0.039	(0.039)
Married	0.001	(0.021)	0.020	(0.024)
Former Married	-0.050**	(0.025)	0.000	(0.033)
Rural	-0.020	(0.013)	-0.013	(0.019)
Heavy smoker	-0.044***	(0.015)	-0.016	(0.025)
Occasional smoker	-0.040*	(0.022)	-0.053	(0.034)
Former smoker	0.014	(0.016)	0.033	(0.023)
Regular MD	0.051***	(0.012)	0.053**	(0.024)
Constant	0.055	(0.077)	-0.464***	(0.100)
R^2	0.301		0.214	
N	8,140		5,087	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C9: Saskatchewan

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.002	(0.010)	0.043***	(0.012)
m35-44	0.017	(0.035)	0.065*	(0.033)
m45-54	0.079*	(0.046)	0.027	(0.034)
m55-64	0.077*	(0.044)	0.125***	(0.039)
m65-74	0.539***	(0.092)	0.265***	(0.044)
m75-84	0.487***	(0.105)	0.555***	(0.043)
m85plus	0.647**	(0.266)	0.562***	(0.090)
f25-34	-0.011	(0.022)	0.049	(0.031)
f35-44	0.034	(0.031)	0.139***	(0.037)
f45-54	0.095*	(0.051)	0.164***	(0.038)
f55-64	0.146**	(0.057)	0.247***	(0.037)
f65-74	0.490***	(0.082)	0.476***	(0.039)
f75-84	0.703***	(0.077)	0.554***	(0.043)
f85plus	0.438***	(0.152)	0.644***	(0.048)
NACI chronic conditions	0.028	(0.047)	0.142***	(0.026)
Non-NACI chronic conditions	0.022	(0.024)	0.019	(0.018)
Very good SAH	0.021	(0.029)	0.020	(0.024)
Good SAH	0.029	(0.032)	0.027	(0.025)
Fair SAH	0.049	(0.054)	0.056*	(0.034)
Poor SAH	-0.196	(0.124)	0.121**	(0.051)
Less-than-secondary	-0.056*	(0.032)	-0.012	(0.024)
Some post-secondary	0.063*	(0.035)	0.053	(0.038)
Post-secondary	0.017	(0.030)	0.090***	(0.020)
Recent Immigrant	-0.027	(0.040)	-0.019	(0.057)
Non-recent Immigrant	-0.027	(0.071)	-0.021	(0.040)
Married	-0.037	(0.031)	-0.032	(0.028)
Former Married	-0.068	(0.044)	-0.075**	(0.034)
Rural	-0.022	(0.026)	-0.021	(0.016)
Heavy smoker	-0.030	(0.028)	-0.059**	(0.025)
Occasional smoker	0.043	(0.054)	-0.077**	(0.039)
Former smoker	0.004	(0.031)	0.000	(0.020)
Regular MD	0.006	(0.038)	0.085***	(0.020)
Constant	-0.014	(0.114)	-0.435***	(0.129)
R^2	0.328		0.202	
N	694		5,151	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C10: Alberta

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	0.015***	(0.004)	0.009	(0.010)
m35-44	0.005	(0.012)	-0.020	(0.028)
m45-54	0.017	(0.016)	0.014	(0.033)
m55-64	0.075***	(0.021)	0.023	(0.036)
m65-74	0.444***	(0.032)	0.286***	(0.045)
m75-84	0.571***	(0.043)	0.512***	(0.043)
m85plus	0.402***	(0.107)	0.535***	(0.083)
f25-34	0.001	(0.012)	0.039	(0.031)
f35-44	0.029**	(0.014)	0.031	(0.031)
f45-54	0.092***	(0.020)	0.050	(0.035)
f55-64	0.197***	(0.024)	0.162***	(0.035)
f65-74	0.480***	(0.030)	0.385***	(0.042)
f75-84	0.556***	(0.033)	0.459***	(0.044)
f85plus	0.341***	(0.071)	0.489***	(0.069)
NACI chronic conditions	0.119***	(0.015)	0.108***	(0.022)
Non-NACI chronic conditions	0.009	(0.009)	0.035**	(0.016)
Very good SAH	0.014	(0.010)	0.040*	(0.020)
Good SAH	0.026**	(0.012)	0.073***	(0.023)
Fair SAH	0.079***	(0.020)	0.054*	(0.031)
Poor SAH	0.132***	(0.035)	0.042	(0.050)
Less-than-secondary	-0.004	(0.015)	-0.020	(0.025)
Some post-secondary	0.022*	(0.013)	-0.021	(0.029)
Post-secondary	0.012	(0.011)	0.057***	(0.020)
Recent Immigrant	-0.059***	(0.017)	0.036	(0.040)
Non-recent Immigrant	0.014	(0.015)	-0.018	(0.023)
Married	-0.006	(0.011)	-0.003	(0.022)
Former Married	-0.013	(0.016)	0.009	(0.030)
Rural	-0.024**	(0.011)	-0.017	(0.020)
Heavy smoker	-0.019*	(0.010)	-0.040*	(0.022)
Occasional smoker	0.003	(0.022)	-0.040	(0.034)
Former smoker	0.011	(0.011)	0.013	(0.018)
Regular MD	0.044***	(0.010)	0.106***	(0.020)
Constant	-0.145***	(0.048)	-0.069	(0.106)
R^2	0.243		0.143	
N	8,728		7,800	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.C11: British Columbia

Dependent variable:	1996/97		2007/08	
Flu shot use [0/1]	Coef.	S.E.	Coef.	S.E.
ln(hincome)	-0.007	(0.013)	0.010	(0.007)
m35-44	0.003	(0.036)	0.031	(0.029)
m45-54	0.054	(0.051)	0.060**	(0.029)
m55-64	0.064	(0.059)	0.131***	(0.029)
m65-74	0.365***	(0.078)	0.300***	(0.034)
m75-84	0.545***	(0.091)	0.468***	(0.039)
m85plus	0.362*	(0.208)	0.567***	(0.053)
f25-34	-0.030	(0.036)	0.020	(0.026)
f35-44	0.006	(0.039)	0.048*	(0.025)
f45-54	0.135**	(0.055)	0.076***	(0.028)
f55-64	0.256***	(0.068)	0.186***	(0.028)
f65-74	0.376***	(0.072)	0.375***	(0.032)
f75-84	0.389***	(0.086)	0.520***	(0.033)
f85plus	0.469***	(0.127)	0.467***	(0.054)
NACI chronic conditions	0.152***	(0.041)	0.126***	(0.018)
Non-NACI chronic conditions	0.036	(0.026)	0.063***	(0.014)
Very good SAH	-0.010	(0.029)	-0.021	(0.019)
Good SAH	0.063*	(0.033)	-0.010	(0.020)
Fair SAH	0.057	(0.051)	0.038	(0.028)
Poor SAH	-0.127	(0.096)	0.034	(0.045)
Less-than-secondary	-0.019	(0.042)	-0.016	(0.024)
Some post-secondary	0.013	(0.036)	-0.022	(0.026)
Post-secondary	-0.012	(0.032)	0.041**	(0.020)
Recent Immigrant	-0.054	(0.035)	-0.031	(0.029)
Non-recent Immigrant	0.019	(0.034)	0.026	(0.019)
Married	-0.041	(0.033)	0.020	(0.016)
Former Married	-0.090**	(0.043)	0.003	(0.021)
Rural	-0.012	(0.031)	-0.055***	(0.020)
Heavy smoker	-0.012	(0.032)	-0.058***	(0.020)
Occasional smoker	0.042	(0.082)	-0.062**	(0.028)
Former smoker	0.037	(0.027)	-0.014	(0.016)
Regular MD	0.069**	(0.029)	0.092***	(0.018)
Constant	0.069	(0.137)	-0.044	(0.088)
R^2	0.246		0.159	
N	1,098		10,685	

Note: Regressions are estimated using OLS. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D: Data and Variable Description

Variable name	Definition
Dependent variables	
Flu shot use	An indicator variable of whether an individual received a flu shot in the last year based on the following two questions: "Have you ever had a flu shot?" Those answering in the affirmative were then asked "When did you have your last flu shot: (less than 1 year ago, 1 year to less than 2 years ago, or 2 years ago or more)?"
Independent variables	
ln(hincome)	The natural log of equalized predicted household income income from all sources in the past 12 months.
m25-34 to f85plus	Age-sex interaction indicators, where age is specified in 7 categories (25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85 plus).
NACI chronic conditions	Indicator variable taking the value of one if the respondent has either cancer, heart disease, diabetes, chronic bronchitis or emphysema, asthma, or suffers effects of stroke.
Non-NACI chronic conditions	Indicator variable taking the value of one if the respondent does not have a NACI chronic condition, but has ...
No chronic conditions	Indicator variable taking the value of one if the respondent does not have any chronic conditions.
Excellent SAH	An indicator variable taking the value of one if the respondent assessed their health as "excellent". This is based on the following question: "In general, would you say your health is: (excellent, very good, good, fair, or poor)? By health, we mean not only the absence of disease or injury but also physical, mental and social wellbeing."
Very good SAH	An indicator variable taking the value of one if the respondent assessed their health as "very good".
Good SAH	An indicator variable taking the value of one if the respondent assessed their health as "good".
Fair SAH	An indicator variable taking the value of one if the respondent assessed their health as "fair".
Poor SAH	An indicator variable taking the value of one if the respondent assessed their health as "poor".

Continued on Next Page...

Less than secondary school	An indicator variable taking the value of one if the respondent's highest level of education is less than secondary school.
Secondary	An indicator variable taking the value of one if the respondent's highest level of education is secondary school.
Some post-secondary	An indicator variable taking the value of one if the respondent's highest level of education is some post-secondary school.
Post-secondary	An indicator variable taking the value of one if the respondent's highest level of education is post-secondary and above.
Recent Immigrant	An indicator variable taking the value of one if the respondent immigrated to Canada less than 10 years ago.
Non-recent Immigrant	An indicator variable taking the value of one if the respondent immigrated to Canada more than 10 years ago.
Native	An indicator variable taking the value of one if the respondent is native born.
Married	An indicator variable taking the value of one if the respondent's current marital status is married, common-law, or partnered.
Former Married	An indicator variable taking the value of one if the respondent's current marital status is widowed, separated, or divorced.
Single	An indicator variable taking the value of one if the respondent is currently single.
Rural	An indicator variable taking the value of one if the respondent resides in a rural area.
Heavy smoker	An indicator variable taking the value of one if the respondent is a heavy smoker.
Occasional smoker	An indicator variable taking the value of one if the respondent is an occasional smoker.
Former smoker	An indicator variable taking the value of one if the respondent is a former smoker.
Never smoked	An indicator variable taking the value of one if the respondent never smoked.
Regular MD	An indicator variable taking the value of one if the respondent has a regular doctor.

Conclusion

This thesis, which consists of three self-contained essays, has empirically investigated a range of important questions in the field of health economics.

In the first essay, I attempt to measure the impact of medical innovations on non-health economic outcomes, by studying the effects of a class of anti-arthritic drugs called Cox-2 selective inhibitors on labor supply. Examining the effects of medical care use on economic outcomes is difficult, as the relationship may be confounded by unobservable, time-varying differences across individuals that may be correlated with both healthcare use and with labor supply choices. I contribute to the literature by taking advantage of the introduction of Cox-2 drugs as a natural experiment, which provides me with plausibly exogenous variation in the use of these drugs and helps overcome the identification problem.

I find that the introduction of Cox-2 drugs had a positive and economically significant impact on the probability of working among individuals with long-term arthritis. Moreover, there is substantial heterogeneity in these effects, with stronger effects seen amongst older individuals, the less-educated, and those working in physical occupations. However, I find no evidence of any impact on the number of hours worked conditional on working.

These findings demonstrate that wider economic benefits of medical innovations such as labor supply effects can be substantial. Given the potential significance of such effects as well as accelerated trends towards the development of new treatments to improve quality of life, these findings highlight the importance of accounting for these benefits when evaluating medical innovations.

In the second essay, I explore the measurement of access to healthcare, by studying the relationship between self-reported unmet needs for healthcare and healthcare utilization. Building on previous studies in this area, this essay contributes to the literature in two important ways. First, unlike previous studies that work exclusively with cross-sectional data, I exploit panel data that allows me to control for time-invariant unobserved heterogeneity. Second, I model healthcare demand using latent class panel data models, which are shown to significantly outperform traditionally applied hurdle models.

I observe different patterns of healthcare utilization among individuals with personal unmet needs, system-related unmet needs, and those with no unmet needs. People with personal unmet needs use the same or less healthcare than predicted, whereas those with system-related unmet needs use more healthcare than predicted. These results are consistent with findings from previous studies. In addition, the finding that individuals with system-related unmet needs are higher-than-expected users of healthcare appears to be driven by these individuals being on waiting lists and incurring additional visits to have their condition monitored.

The findings highlight the importance of better understanding reasons behind why people report unmet needs for healthcare. Moreover, they suggest that having a system-related unmet need represents a genuine failure of the health system, and is not driven by other factors such as individual preferences.

The third essay explores socioeconomic inequalities in the access to and uptake of new healthcare technologies, by examining long-term trends in both coverage and socioeconomic inequity in influenza vaccination uptake in Canada. While previous work has largely focused on average coverage rates, these can mask underlying socioeconomic inequalities in the uptake of vaccination. I contribute to the literature by examining coverage in conjunction with socioeconomic inequity in vaccination uptake across provinces. In addition, I explore the merits of universal versus targeted vaccination programs, by comparing a unique universal vaccination program introduced by the province of Ontario to the targeted programs maintained by all other provinces.

Despite most provinces offering near identical coverage (with the exception of Ontario) through long-standing influenza immunization programs, I observe large variations in coverage and inequity trends across provinces. Moreover, I find that increases in coverage levels among a number of provinces appear to have drawn disproportionately from those of higher socioeconomic status thereby contributing to a growing pro-rich inequity in utilization; a finding in accordance with the literature on inequalities in the uptake of new medical technologies. In addition, Ontario's performance over the long-term under a universal vaccination program was matched by Nova Scotia with a targeted program, although both fell short of national vaccination targets.

These findings have a number of implications regarding vaccine delivery and program design. In particular, they highlight the need for more targeted efforts aimed at specific groups with low socioeconomic status to help reduce inequities in vaccination and boost overall coverage rates. Such efforts may include using active recruitment strategies and issuing vaccination reminders, as well as expanding vaccine delivery to settings outside physician offices.