

THREE ESSAYS IN HEALTH ECONOMICS

THREE ESSAYS IN HEALTH ECONOMICS

By Zichun Zhao, B.A., M.A.

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

McMaster University © Copyright by Zichun Zhao, November 4, 2025

Doctor of Philosophy (2025)

Economics

McMaster University

Hamilton, Ontario, Canada

TITLE: Three Essays in Health Economics

AUTHOR:

Zichun Zhao,

B.A. (Economics) (HeFei University of Technology)

M.A. (Economics) (University of Windsor)

SUPERVISOR:

Michel Grignon

Professor, Economics,

McMaster University, ON, Canada

SUPERVISORY COMMITTEE MEMBERS:

Katherine Cuff,

Professor, Economics,

McMaster University, ON, Canada

Jonathan Zhang,

Assistant Professor, Economics,

Duke University, NC, United States of America

NUMBER OF PAGES: xiii, 108

Lay Abstract

This thesis examines the effects of Canadian public policies on prescription drug access and healthcare utilization, as well as how health shocks influence household spending decisions.

The first chapter asks how raising the minimum wage influences workers' access to drug benefits from their employers. It shows that when the minimum wage rises by a certain amount, some workers—especially women, young people, immigrants, and racial minorities—are less likely to have drug coverage through their jobs.

The second chapter examines whether Ontario's OHIP+ program, launched in 2018 to provide free coverage for prescription drugs to everyone under the age of 25, had any effect on visits to the emergency department. While the program did not change overall emergency department visits among young people, it did reduce visits for those from low-income families. This suggests that before OHIP+, some youth may have gone to the emergency department to get medicines they could not otherwise afford.

The third chapter looks at how a cancer diagnosis changes family budgetary decisions. It finds that affected households cut their total spending and shift money around—for example, reducing food spending and increasing spending on housing and healthcare.

Abstract

This thesis comprises three essays in health economics. Chapter 1, co-authored with Dr. Michel Grignon, examines how minimum wage increases affect access to employer-sponsored prescription drug insurance. Using cross-sectional data linked with provincial minimum wages changes from 2008 to 2019, the study identifies threshold effects: increases of 20–30 cents reduce coverage by about three percent, with the strongest impacts among women, young workers, immigrants, and racial minorities.

Chapter 2 evaluates the impact of the Ontario Health Insurance Plan Plus (OHIP+), introduced in 2018 to provide free prescription drug coverage to residents under 25. Applying event study and Difference-in-differences methods with administrative emergency department data, the analysis finds no overall effect on utilization but reveals significant declines among low-income households. This suggests that improved drug access reduced reliance on emergency departments as a substitute source of medication.

Chapter 3 investigates how a cancer diagnosis influences household spending patterns by linking the Canadian Cancer Registry with household expenditure survey data. The results show an average decline in total spending of about seven percent following a diagnosis, with the largest reductions in food and income tax expenditures. Although budget shares remain broadly stable, heterogeneity analysis reveals meaningful reallocations across families with and without children, single parents, and younger households. In contrast, subsequent diagnoses generate smaller adjustments.

Acknowledgements

Completing my Ph.D. has been an incredible journey, filled with unexpected challenges and surprises. I am deeply grateful to everyone who supported and encouraged me throughout this process.

First and foremost, I am especially indebted to my supervisor, Dr. Michel Grignon, for his exceptional mentorship and encouragement. His guidance has been a constant source of inspiration, challenging me to think critically, sharpen my research skills, and approach problems with curiosity and persistence. I am truly grateful for his patience, generosity, and unwavering belief in my potential.

I would also like to offer my heartfelt thanks to Dr. Katherine Cuff and Dr. Jonathan Zhang for their thoughtful advice and encouragement. Their guidance and support during challenging times were especially meaningful, and I feel fortunate to have had them as members of my committee.

Beyond my committee, I wish to acknowledge Dr. Marc-André Letendre, Dr. Alok Johri, Dr. Arthur Sweetman and other Professors in the department, each of whom provided significant guidance and support at different stages of my doctoral experience. I would also like to thank Cynthia Zhao, Emma Beamson, and Lihua Qian, for their invaluable help with administrative tasks, as well as Peter Kitchen and Li Wang for their guidance and support in navigating the Research Data Centre.

Finally, I would like to thank my parents for their countless sacrifices, which gave me the opportunities that made this journey possible. I am also grateful to my partner, Xiao Luo, whose unwavering support and encouragement carried me through the most challenging moments of my Ph.D. I would also thank my classmates, Akwugo Balogun, Oliver Loertscher, Ryan Bacic, Segei Filiasov, and Yihong Bai, for their support and

encouragement. Lastly, I must thank my cats, Taco and Roro, for reminding me to take breaks, usually by sitting on my keyboard.

Declaration of Academic Achievement

Chapter 1 is co-authored with Dr. Michel Grignon. The material in this dissertation includes collaborative research with the co-author, and I finished all empirical analysis and contributed to the writing of the manuscript. Chapters 2 and 3 are solely authored by me. The first paper has been accepted for publication in the Canadian Journal of Economics and is available online at: <https://www.economics.ca/cje-journal-content>.

Contents

Lay Abstract	iii
Abstract	iv
Acknowledgements	v
Declaration of Academic Achievement	vii
Introduction	1
Chapter 1: Minimum Wage and Employer-Sponsored Supplementary Health Insurance: Evidence from Canada	3
1.1 INTRODUCTION	1
1.2 DATA AND VARIABLES	6
1.2.1 Sample	6
1.2.2 Drug Insurance	7
1.2.3 Minimum Wage	8
1.2.4 Education	9
1.2.5 Control Variables	9
1.3 EMPIRICAL STRATEGY	10
1.3.1 Baseline Models: Linear Effects	10
1.3.2 Non-Linear Effects: Models on Change in the Value of the Mini- mum Wage at Various Thresholds	13

1.4	RESULTS	14
1.4.1	Baseline Models: Estimates of the Effect of Higher Levels of Minimum Wages in a Given Province	14
1.4.2	Non-linear Model Estimating the Effect of Yearly Changes in the Minimum Wage at Various Thresholds	15
1.4.3	Underlying Mechanism	16
1.5	HETEROGENEOUS TREATMENT EFFECTS	18
1.6	DISCUSSION AND CONCLUSION	19
1.7	REFERENCES	22
1.8	FIGURES AND TABLES	26
1.9	APPENDIX	33
 Chapter 2: The Effects of Public Prescription Drug Insurance Expansion on Emergency Department: Evidence from Canada		
		37
2.1	INTRODUCTION	39
2.2	INSTITUTIONAL BACKGROUND	41
2.2.1	Ontario Public Drug Insurance System	42
2.3	LITERATURE REVIEW	44
2.4	DATA AND METHODOLOGY	45
2.4.1	Emergency Department Admissions	46
2.4.2	Income and Low-income Family	47
2.4.3	Control Variables	48
2.4.4	Sample Selection	49
2.4.5	Empirical Study Framework	49
2.5	RESULTS	51
2.5.1	Beneficiaries	51
2.5.2	Ambulatory Care Sensitive Conditions	53
2.6	CONCLUSION AND DISCUSSION	54

2.7	REFERENCES	56
2.8	FIGURES AND TABLES	60
2.9	APPENDIX	64
Chapter 3: The Role of Cancer Diagnosis in Household Spending Pat-		
	terns: Evidence from Canada	65
3.1	INTRODUCTION	67
3.2	DATA AND VARIABLES	69
3.2.1	Data	69
3.2.2	Dependent Variables	72
3.2.3	Main Independent Variable	73
3.2.4	Control Variables	74
3.3	EMPIRICAL STRATEGY	75
3.3.1	The Value of Expenditures	75
3.3.2	Household Expenditure Pattern	76
3.4	RESULTS	77
3.4.1	The Effects of Cancer on the Value of Household Expenditure . . .	77
3.4.2	The Effects of Cancer on Household Expenditure Pattern	78
3.4.3	Seemingly Unrelated Regression	78
3.5	HETEROGENEITY ANALYSES	79
3.5.1	Households with Children	79
3.5.2	Single, Couple and Children	80
3.5.3	Cancer Patient Younger Than 55	81
3.5.4	Previous Cancer Diagnosis History	82
3.6	CONCLUSION AND DISCUSSION	82
3.7	REFERENCES	85
3.8	TABLES	88
3.9	APPENDIX	94

List of Figures

1.1	Provincial Minimum Wage from 2013 - 2019	26
2.1	Expansion of OHIP and Emergency Department Visits, Aged 18-24	60
2.2	Expansion of OHIP+ and Emergency Department Visits, 18-24 from Low-income Families.	61
2.3	Expansion of OHIP and Emergency Department Visits, 18-24 from Low-income Families, ACSC and Non-ACSC	61

List of Tables

1.1	Questions Selected by Provinces and Years in CCHS	27
1.2	Nominal Provincial Minimum Wage 2008-2019	27
1.3	Summary Statistics	28
1.4	Linear DD Model with Nominal Minimum Wage for Low-educated Individuals	29
1.5	Linear Triple Differences Model with Nominal Minimum Wage	29
1.6	Non-linear Model with Nominal Minimum Wage Change for Low-educated Individuals	30

1.7	Non-linear Model with Nominal Minimum Wage Change for Low-educated, Single and Employed Individuals	30
1.8	Non-linear Model with Nominal Minimum Wage Change for Low-educated, Unemployed Individuals Living in Couple	31
1.9	Non-linear Two-year Lag Model with Nominal Minimum Wage Change for Low-educated Individuals	32
A1.1	The Nominal Income Distribution by Education Groups	33
A1.2	Linear DD Model with Real Minimum Wage for Low-educated Individuals	33
A1.3	Linear Triple Differences Model with Real Minimum Wage	34
A1.4	Non-linear Two-year Lag Model with Nominal Minimum Wage Change for Low-educated Individuals, Province Effects	34
A1.5	Non-linear Model with Real Minimum Wage Change for Low-educated Individuals	35
A1.6	Effect of Minimum Wage on Employment, Non-linear Model with Nom- inal Minimum Wage Change for Low-educated Individuals	35
A1.7	Two-year Lag Non-linear Model with Real Minimum Wage Change for Low-educated Individuals	36
A1.8	Reverse Causality	36
2.1	Summary Statistics - Emergency Department Visits Aged 18 - 24	62
2.2	Difference-in-differences model: Emergency Department Visits, Age 18-24	62
2.3	Difference-in-differences Model: Emergency Department Visits, 18-24 From Low-income Families	63
A2.1	Elements of ACSC Defined by CIHI, with ICD-10 Codes	64
3.1	Summary Statistics	88
3.2	The Effects on the Value of Household Spending	89
3.3	The Effects on Household Spending Pattern	89

3.4	The Effects on Household Spending Pattern – Seemingly Unrelated Regression	89
3.5	The Effects on Household Spending Pattern – Household with Children	90
3.6	The Effects on Household Spending Pattern – Single Parent with Children	90
3.7	The Effects on Household Spending Pattern – Single Adult Without Children	90
3.8	The Effects on Household Spending Pattern – Coupled Adults with Children	91
3.9	The Effects on Household Spending Pattern – Coupled Adults without Children	91
3.10	The Effects on Household Spending Pattern – Cancer Patients Younger than 55	92
3.11	The Effects on Household Spending Pattern – Households with Previous Cancer Diagnosis History	92
3.12	The Effects on Household Spending Pattern – Single Parent with Children	93
A3.1	Household Expenditure Categories and Items	94
A3.2	The Distribution of Cancer Type	104
A3.3	The Effects on Household Income	105

Introduction

Healthcare coverage plays a central role in determining both health outcomes and household economic security. In Canada, physician and hospital services are universally covered, but prescription drugs and other health-related costs are often excluded from public plans. These gaps in coverage can create disparities in both healthcare access and financial well-being, particularly for vulnerable populations. At the same time, labour market policies and health shocks influence how households interact with the healthcare system and make financial decisions.

In this thesis, I study the interaction of health policy, labour market conditions, and household financial responses in three separate but related essays. The first chapter examines how increases in the minimum wage affect access to employer-sponsored prescription drug insurance. The second chapter evaluates the impact of the Ontario Health Insurance Plan Plus (OHIP+), introduced in 2018, on the use of emergency departments by young adults. The third chapter investigates how a cancer diagnosis alters household spending patterns. Together, these essays contribute to our understanding of how Canadian families navigate gaps in prescription drug coverage and how public policies and health shocks shape their economic decisions.

In Chapter 1, I analyze the relationship between minimum wage increases and employer-sponsored prescription drug insurance. Employer-provided health benefits play an important role in supplementing public coverage, yet they may be affected by changes in wage-setting policies. Using provincial variation in minimum wages between 2008 and 2019, I find that incremental increases in the minimum wages reduce the likelihood that workers—especially women, young workers, immigrants, and racial minorities—retain prescription drug benefits. These results suggest that while minimum wage increases are designed to support low-wage workers, they may also have unintended consequences for

access to supplementary health coverage.

Chapter 2 examines the introduction of OHIP+ in 2018, which extended free prescription drug coverage to people under the age of 25 in Ontario. Using healthcare administrative data on emergency department visits and applying Event-study and Difference-in-differences methods, I assess whether the expansion of drug coverage reduced avoidable hospital use. The results indicate that OHIP+ had no overall effect on emergency visits among all young people, but visits declined significantly for those from low-income households. This suggests that prior to OHIP+, some young adults may have relied on emergency departments as a substitute for accessing needed medications.

In Chapter 3, I study how Canadian households adjust their spending following a cancer diagnosis. By linking the Canadian Cancer Registry with the Survey of Household Spending, I show that affected families reduce overall expenditures by about seven percent and reallocate their budgets cutting back on food and income taxes while modestly increasing spending on housing and healthcare. These findings highlight the economic burden of serious illness, even in the context of a universal healthcare system.

Taken together, these three chapters show that both public policies and health shocks play a critical role in shaping healthcare access and household financial security. The findings underscore that, despite universal coverage for hospital and physician services, significant gaps in prescription drug coverage remain, with important consequences for vulnerable populations.

Chapter 1

Minimum Wage and Employer-Sponsored Supplementary Health Insurance: Evidence from Canada

Abstract

This study explores the effect of increases in the minimum wage on the probability of receiving employer-sponsored supplementary prescription drug insurance through the workplace in Canada: Do Canadian employers respond to higher minimum wage by cutting insurance coverage? We use self-reports on supplementary health insurance through the workplace from seven waves (2013 to 2019) of the Canadian Community Health Survey. We also use the fact that the minimum wage is a provincial jurisdiction in Canada to study the effects of the level of and changes in the minimum wage across provinces and over time in a difference-in-difference and triple-difference framework. We

find that yearly changes between 20 and 30 cents in the value of the minimum wage have a persistent effect and about three percent of Canadians lose their prescription drug insurance (from an initial coverage rate of 47.4%) in such cases, the effect being concentrated on women, immigrants, non-whites and younger adults. However, changes smaller than 20 cents, by far the most frequent in Canada, do not have any discernible effect on health insurance coverage.

1.1 INTRODUCTION

The majority of OECD countries enforce a legislated minimum hourly wage, establishing a baseline remuneration that employers are obliged to pay their employees (Sturn, 2018). The most common justification for such a publicly imposed constraint on the negotiation between employers and employees is guaranteeing living standards for low-skilled workers (Cengiz et al., 2019; Dustmann et al., 2022). It is therefore important to know whether low-skilled workers actually benefit from the constraint, in other words, if their standards of living are higher in situations with a higher minimum wage than in situations without. One way to answer that question is to study the effects of decisions to increase the minimum wage in a given jurisdiction.

Most of the literature has focused on the effect of such increases on the level of unemployment of low-productivity workers (Baker et al., 1999; Brouillette et al., 2017) but no clear empirical conclusion has been reached so far. One of the reasons why studies on the effect of the level of the minimum wage on unemployment are contradictory is that, depending on context, employers can mitigate increases in the minimum wage by cutting some fringe benefits and, as a result, the overall cost of labour. They can do it for all employees or exploit the fact that most minimum wage workers are recent hires (Employment and Social Development Canada, 2019)¹ and add probationary periods in their benefits schedules to exclude some of their employees (likely close to minimum wage) from benefits. In the United States (U.S.), health insurance is a major part of these fringe benefits (Marks, 2011). In Canada, supplementary health insurance (SHI) is a less substantial but still non negligible portion of total compensation.

If employers respond to increases in the minimum wage by cutting fringe benefits such as health insurance, increases in the minimum wage could decrease the living standards of low-skilled workers, for two reasons: first, in Canada and the U.S., contributions to

¹In Canada 44% have been hired for less than a year, and 84% less than 5 years.

health insurance plans are tax free whereas wages are not, meaning that, if the value of the health insurance package offered by the employer is comparable to the minimum wage increase before tax, the after tax value of the former is higher than that of the latter. Second, group insurance (provided by employers) is usually of better value than individual health insurance because individual supplementary health insurance is much more expensive ². In this study, we explore changes in the provision of supplementary prescription drug insurance by Canadian employers to their employees in response to a raise in the minimum wage.

We identified six studies examining the impact of changes in the minimum wage on the provision of basic health insurance by employers in the U.S. for employees and their dependents who are susceptible of being affected, who are usually defined as low-income families or individuals with low education. Dube et al. (2007) use a local experiment (minimum wage hike in San Francisco) to study the impact of increases in the minimum wage in the restaurant industry and find no effect on the provision of health insurance. The other five studies use some variant of difference-in-difference, exploiting differences across states and years in the level of the minimum wage; four of these five studies use the proportion of employees who are covered as their outcome of interest and the fifth Meiselbach and Abraham (2023) uses the proportion of employers offering health insurance. Of the studies using the proportion of employees covered, two (Simon and Kaestner (2004) and Dworsky et al. (2022)), utilize difference-in-difference among the low-income or low-education portion of the population and find minimal or limited effects, with elasticities, estimated by us, based on their published estimates, at between 0 and -0.16. The other two studies (Clemens et al. (2018), Royalty et al. (2000)) use a triple difference strategy, taking workers in occupations that are highly paid (Clemens et al. (2018)) or highly educated (Royalty et al. (2000)) as a control and other workers

²In Canada, 90% of SHI contracts are group contracts, via the workplace (Canadian Life & Health Insurance Association, 2021).

(close to the minimum wage for the former or with low level of education for the latter) as the treatment and find stronger effects than the difference-in-difference studies, with elasticities (again, calculated by us based on their published results) of -0.32 for Clemens et al. (2018) and -0.61 for Royalty et al. (2000). Last, Meiselbach and Abraham (2023) find a very modest effect of -0.91 percentage points on the proportion of employers offering insurance when the minimum wage increases by \$1; theirs is also the only study of changes at the intensive margin, showing that an increase in the minimum wage by \$1 increases the proportion of employers introducing deductibles in their plans by 1.89 percentage points. Last, they show that employers do not discriminate between part-time and full-time employees when they respond to increases in the state minimum wage. Overall, the small empirical literature conducted in the United States suggests modest yet non-negligible linear impacts of minimum wage increases on the availability of employer-sponsored health insurance coverage: an elasticity of -0.32 (Clemens et al. (2018)) means that an increase in the nominal minimum wage of 70 cents in Texas (from 7.25 to 7.95) would translate into a decrease in basic health insurance coverage of 3.2 percentage points in that state, but it would take an increase of \$1.50 in California to get the same reduction in coverage.

Beside these results on the linear effect of levels of minimum wage (identified through variations in time within the state to detect the effect of an unusually high level of minimum wage relative to the state average), two studies explore the possibility that small and large yearly increases in the minimum wage do not have the same effect on eligibility to health insurance provided by employers (non-linear effects). Royalty et al. (2000) used a quadratic specification and found that it takes very large increases to detect an effect on eligibility (when the minimum wage is low, around \$3.35, it takes an increase of 30% to get a decrease in eligibility of 3.8 percentage points; when the minimum wage is higher, at \$5.15, an increase of 10%, or \$0.51, which is still considerable in absolute terms, has the same effect). Meiselbach and Abraham (2023) confirm that

the linear effects they observe are driven by the effect of very large increases: in their study of employers, an increase of \$0.50 per year over the next five years in the nominal minimum wage (which is a very large relative increase) is associated with a decrease of 2.46 percentage points in the likelihood of employers offering health insurance, but increases smaller than that threshold have no effect at all.

Canada provides an interesting contrast to the U.S. situation as it is a country with comparable labour market institutions but no federal minimum wage and provincial minimum wages that are significantly higher than state minimum wages in the U.S. In the U.S., there is a federal minimum wage and states (or municipalities) are free to set higher local levels. However, there is no equivalent federal minimum wage in Canada: the federal minimum wage in Canada applies to employees in federally regulated industries only, and, moreover, for the years under study, this federal minimum wage was set at the level of the provincial minimum wage in each province and could therefore not have any effect different from that of the provincial minimum wage. In Canada the average provincial minimum wage was about 9.50 USD in PPP, versus 7.8 in the U.S and represented 40% of the average wage of a full time worker in Canada versus only 27% in the U.S. (OECD, 2024b). We should therefore expect Canadian employers to be more responsive to increases in the provincial minimum wage and more likely to cut prescription drug coverage to (at least some of) their employees or their dependents.

In this study, we exploit the fact that Canadian provinces make independent decisions on the level of the minimum wage that applies in their jurisdiction and provinces happen to make different decisions regarding the extent of minimum wage changes each year (see TABLE 1.2 below). In addition, provinces that are more generous in a given year are not necessarily more generous in other years, making identification possible. We use a survey with self-reported information on one specific element of SHI, namely prescription

drugs coverage³, to study the impact of increases in the minimum wage on its provision by employers. We also contribute to the literature by running first a linear model on the effect of an unusual level (relative to the provincial average) of the minimum wage and then a model, adapted from Meiselbach and Abraham (2023), testing the non-linear effects of unusual changes in the minimum wage in a given province in a given year. The rationale for running the second model (on yearly changes at various thresholds) is that most changes in the minimum wage in Canadian provinces are relatively small (compared to what occurs in U.S. states at least ⁴) and, if the true effect is non-linear with smaller increases having no effect on the provision of health insurance and larger increases having disproportionately large effects, the linear model on levels will miss the effects of large increases. Last, our study is the first one to try to address the likely mechanisms underlying the effect and to measure heterogeneous effects, distinguishing the effects by sex, race, immigration status and age.

The linear model on levels suggests no statistically significant effects on the likelihood of reporting employer-sponsored drug insurance in Canada, whereas our review of the literature indicates some statistically significant albeit modest linear effects in the U.S. This is not what we predicted, based on the high level of minimum wage in Canadian provinces relative to U.S. states. However, this is due to most increases in provincial minimum wages being really small as we described above and the non-linear model indeed shows that Canadian employers are more sensitive to levels of increase in the minimum wage (\$0.20 to \$0.30) that have almost no effects in the U.S. on the provision of health insurance. Since the level of the minimum wage is already higher in Canada, Canadian employers react to what would be considered small increases by American employers

³The survey has questions on other types of SHI, such as dental coverage and vision coverage, but questions on these items are asked sporadically and in a small number of provinces only, rendering identification impossible.

⁴The minimum wage can increase substantially in the U.S (more than \$0.50 per year over five years) but such increases are quite unusual in Canada: Alberta is the only province with such repeated substantial increases in our period of observation, with four successive increases of \$1.00 or more between 2014 and 2018; increases by more than \$0.50 happen 16 times out of 60 changes in our study period and increases by more than \$1.00 only seven times.

and are willing to cut benefits to approximately 2.5 percentage points of low educated Canadians of working age, which is about 5% of the initial level of coverage among that population and therefore amounts to an elasticity of -2.5. The cuts are persistent over time and the effects seem to be driven by the coverage of women (3.2 percentage points), immigrants (6.4 percentage points), and non-White residents (10.3 percentage points), those who are more likely to be at the margins of the labour market.

The remainder of this paper is structured as follows. Section two describes the data used to analyse the effect of the minimum wage on prescription drugs insurance in Canada. Subsequently, Section three presents the empirical strategy, Section four presents the results and Section five shows the heterogeneous treatment effects across different demographic groups, and section six discusses and concludes.

1.2 DATA AND VARIABLES

1.2.1 Sample

The data come from the Canadian Community Health Survey (CCHS) from 2013 to 2019. The CCHS is an annual cross-sectional survey of a sample of individuals representative of the Canadian population residing in the community (institutionalized individuals are excluded as well as residents of the territories and remote areas). This survey is designed to gather comprehensive data on various aspects related to health status, healthcare utilization, and factors that influence these outcomes such as health insurance.

We included respondents who responded to the health insurance questions. Those who refused to answer these questions are therefore excluded from the sample.

1.2.2 Drug Insurance

We use self-reported coverage for prescription drugs as well as the self-reported origin of such coverage (an employer, public or union)⁵. Note that coverage can be from an employer who is not the respondent's employer (typically, spouse or relative, the respondent is a dependent in that case). The wording of the questions is as follows: "Do you have insurance that covers all or part of the cost of your prescription medications?" and, conditional on answering yes to the first question: "Is it an employer-sponsored benefit plan?" Respondents who answered "Yes" to both questions are considered as holding an employer-sponsored prescription drug insurance and the dependent variable was coded as 1; in any other case, the dependent variable was coded as 0. As a result, the dependent variable has two potential outcomes only and is observed for each individual. The wording of the questions remained consistent for the whole period but one issue is that the question was not made mandatory by Statistics Canada: provinces had to pay to get the question on the survey for their constituents and not all provinces bought in the questions all the years. Data availability is listed in Table 1.1.

We find that 55% of individuals of working age in the survey report having prescription drug insurance from an employer (not necessarily their employer) in the period of observation. Estimates of the proportion of workers covered published in the literature vary widely, from a low estimate of 51% for prescription drugs in 2005 (Statistics Canada, 2008) to a high of 77% for all types of SHI (prescription drugs, dental care and hospital) in 2021 (Conference Board of Canada, 2021), with a report from Health Canada suggesting 65% of individuals of working age (19 to 64) are covered by some form of SHI (Health Canada, 2016)⁶. These variations arise from different definitions (Statistics Canada and

⁵The question on coverage for vision and dental insurance was asked too infrequently and in too small a number of provinces to be analyzed.

⁶The CLHIA claims 26 million SHI contracts, which would represent 70% of the Canadian population, or more than the population of active age; of course these contracts cover some children or retired persons who want coverage for some services not covered by their province, and one individual can be covered by more than one contract. Therefore, we cannot use this to infer the proportion covered.

the Conference Board of Canada consider only employees, while Health Canada includes all working-age individuals, whether employed or not), collection methods (self-reported by Health Canada and the Conference Board of Canada, versus employer-collected data by Statistics Canada), and the year of data collection. Our own estimate, which is based on self-reported data, falls on the lower end but remains within the range of previously published estimates.

1.2.3 Minimum Wage

The independent variable of interest is the provincial level of the minimum wage. Nominal minimum wage data were obtained from Statistics Canada. We use the value at the end of each calendar year. Real values are obtained by deflating nominal values by the provincial Consumer Price Index (CPI) from Statistics Canada with 2019 as the base year. TABLE 1.2 shows values of the nominal minimum wage for each province and year⁷.

Alberta had the highest minimum wage between 2016 and 2019, followed by Ontario and BC for the period 2017-19. Ontario had the highest minimum wage in 2014 and 2015, and Manitoba in 2013. In contrast, New Brunswick, Newfoundland and Labrador, Nova Scotia, and Saskatchewan exhibited the lowest minimum wages at various times throughout the period. The range grew from \$0.50 in 2013 to \$4.00 in 2018 before declining slightly in 2019 at \$3.68. Crucially for our purpose, not all provinces increased the minimum wage by the same amount in the same years. For instance, in 2011, British Columbia increased its minimum wage by 18.75% whereas Ontario did not increase it at all; in 2014, Ontario increased it by 7.32%, a year when British Columbia's level stayed constant.

⁷Since we employed 1-year, 2-year, 3-year, and 4-year lag models to test the effects of increasing minimum wage, we also included data on minimum wages from 2008 even though the dependent variable is observed between 2013 and 2019 only.

FIGURE 1.1 illustrates the evolution of both nominal and real average minimum wage levels across all provinces throughout the period of investigation. The dashed lines (red) represent the average values of nominal and real minimum wages, and the solid lines (blue) represent the minimum and maximum range in different provinces. The data reveal a notable surge in nominal and real minimum wages, with an average increment of roughly 75% and 35%, respectively. Moreover, post-2015, a growing divergence is observable between the highest and lowest minimum wage rates, indicating a trend of widening disparity.

1.2.4 Education

We use education of the respondent as our main identification stratification variable: we conduct the difference-in-difference analysis on the sub-sample of individuals with low education and the triple difference analysis adds the sub-sample with higher education as the control group.

Low-educated individuals are those whose education level is high school diploma or less. High-educated individuals are all the others.

Here we use low education as a proxy⁸ for “close to the minimum wage” rather than income *per se* to select individuals who are likely to be affected, due to the potential endogeneity of the income variable to the assignment.

1.2.5 Control Variables

We control for typical factors that influence employer-sponsored insurance coverage, including sex, age, race, health status, marital status, immigration status, and local economic conditions. Sex is coded as 1 for female. We assign a value of 1 to race if

⁸TABLE A1.1 presents the income distribution for high-educated and low-educated groups. On average, the income of the high-educated group is 58.6% higher than that of the low-educated group.

the individual is white, and 0 for all others. Health status is self-assessed, and we re-coded as 1 if the respondent selects excellent or very good, and 0 if good, fair or poor. Marital status is 1 if the respondent is in couple and 0 if not. For immigrants, we distinguish foreign born (coded 1) from Canadian born. The provincial annual unemployment rates (average for each year) provided by Statistics Canada are used to represent local economic conditions.

TABLE 1.3 displays summary statistics for all variables used in the model, stratified by education level, and shows that the low-educated sample is slightly younger, more comprised of Canadian-born rather than immigrants, much less likely to live with a partner and to be in excellent or very good health than the overall sample.

1.3 EMPIRICAL STRATEGY

1.3.1 Baseline Models: Linear Effects

As a baseline model, following previous literature (Horn et al., 2017; Huang et al., 2021), we estimate a two-way fixed effect Difference-in-difference (DD) model on the population with low education to find the average effect of a change in the minimum wage on the probability to report employer-sponsored drug insurance. Identification relies on the fact that not all provinces have the same level in a given year.

One decision to make is the lag in time that should be allowed for the change in the minimum wage to have an effect on drug coverage. That question has not been discussed in detail in previous papers (which have mostly adopted a one year lag). Firstly, we rejected the idea of simultaneous effect because changes in the minimum wage are not planned more than one year in advance by governments and, as a result, not easily anticipated by employers: in all provinces, decisions on the minimum wage

are taken annually⁹, usually at the beginning of the calendar year (around February) with effect a few months later (usually early May, sometimes staggered over several months). An independent commission is tasked with determining the appropriate level of the provincial minimum wage based on considerations of price inflation and the health of the economy but the final decision remains with the provincial government (this was determined by the authors, after consultation of media accounts of changes in the minimum wage in each of the ten provinces of Canada for the period under study). According to Jalette et al. (2020), the duration of contracts in collective bargaining agreements (CBA) in Canada is about four years; however, most (90%) low-income workers are not covered by such a CBA contract (Employment and Social Development Canada, 2019) and only 30% of total labour force (Statistic Canada, 2022) are covered by a CBA. Therefore, if employers can adjust health insurance policies for non-CBA workers in the next policy year, Canadian workers' average contract or pseudo-contract length is 1.9 ($0.3 \times 4 + 0.7 \times 1$), and a one-year lag model is appropriate because changes in the minimum wage will occur on average halfway through the contract, or 0.95 years. Nevertheless, we re-ran the model with lags from two and three years for the minimum wage variable, to test the longer-term effects of any change in the minimum wage: do these effects remain permanently or do they fade away?

The model specification is as follows:

$$Insurance_{i,p,t} = \beta MW_{p,t-n} + \gamma_1 X_{i,p,t} + \gamma_2 Z_{p,t} + \sigma_p + \theta_t + \epsilon_{i,p,t} \quad (1.1)$$

where $Insurance_{i,p,t}$ indicates the probability of reporting employer-sponsored prescription drug insurance for individual i in province p in year t . $MW_{p,t-n}$ represents the nominal minimum wage in province p in year $t - n$ where n represent the n -year lagged

⁹It may happen in some provinces and some years that the minimum wage is increased twice during the year, but the decision is still taken once.

effects. We add the individual-level independent variables $X_{i,p,t}$ listed above, as well as the provincial unemployment rate $Z_{p,t}$ to control for economic activity. The model also includes province fixed effect (σ_p) to capture time invariant province-level factors that could affect the provision of prescription drug insurance and time fixed effects (θ_t) to control for changes in coverage rate over time that have affected all provinces simultaneously. The β coefficient represents the effect of the level of the minimum wage on the likelihood of reporting drug insurance coverage from an employer (one's own or one spouse's) relative to people who live in provinces with a different level of the minimum wage. If this coefficient is estimated to be different from 0 (and negative), we interpret this as evidence that raising the minimum wage negatively affects the probability that a worker will receive prescription drug insurance. To account for the complex sampling process and non-responses to the survey, standard errors are bootstrapped using 500 replications with initial bootstrap weights provided by Statistics Canada.

We then run a triple difference model, in which we re-include the highly-educated population and use it as the control (still assuming they should not be affected), while the low-educated people are the treatment group (assuming they should be affected).

The triple difference model specification is as follows:

$$\begin{aligned}
 Insurance_{i,p,t} = & \beta_1 MW_{p,t-n} + \beta_2 Low_{i,p,t} + \gamma_1 X_{i,p,t} + \gamma_2 Z_{p,t} \\
 & + (\beta_3 MW_{p,t-n} + \gamma_3 X_{i,p,t} + \gamma_4 Z_{p,t} + \sigma_p + \theta_t) \times Low_{i,p,t} \quad (1.2) \\
 & + \sigma_p + \theta_t + \epsilon_{i,p,t}
 \end{aligned}$$

where $Low_{i,p,t}$ denote low-educated individuals and n is the lag in the measurement of the value of minimum wage. The β_3 represents the effect of the level of the minimum wage on the likelihood of receiving employer-sponsored drug insurance for low-educated

individuals compared to high-educated individuals (who are expected to be unaffected by changes in the minimum wage).

1.3.2 Non-Linear Effects: Models on Change in the Value of the Minimum Wage at Various Thresholds

Clemens and Strain (2021) note that minor increases in the minimum wage generally do not significantly affect employment, whereas more substantial increases are associated with adverse employment outcomes. Previous studies have extensively examined the impact of minimum wage changes on the probability of acquiring health insurance, but there has been limited research focused on identifying a specific threshold at which employers begin to cut benefits. Recall that Royalty et al. (2000) showed a quadratic relationship between the level of the minimum wage and the provision of fringe benefits and Meiselbach and Abraham (2023) observed that larger increases (\$2.50 or greater over the last five years) in minimum wage are associated with significant negative impacts on the availability of employer-provided health insurance. To further investigate this phenomenon, our study utilizes similar non-linear models. We aim to determine whether significant changes in minimum wage result in more pronounced negative effects on employees reporting access to employer-sponsored drug insurance, particularly in cases where the wage increases surpass specific predefined thresholds.

In our sample, over 50% of province-year observations reported increases in their nominal minimum wage of less than 25 cents. Consequently, we categorized observations into four distinct groups: 1) no increases, 2) small increases (less than 20 cents), 3) medium increases (between 20 and 30 cents), and 4) large increases (more than 30 cents). The threshold effects model is specified as follows:

$$\begin{aligned}
Insurance_{i,p,t} = & \beta_S Small_Increase_{p,t-n,t-n-1} \\
& + \beta_M Medium_Increase_{p,t-n,t-n-1} \\
& + \beta_L Large_Increase_{p,t-n,t-n-1} \\
& + \gamma_1 X_{i,p,t} + \gamma_2 Z_{p,t} + \sigma_p + \theta_t + \epsilon_{i,p,t}
\end{aligned} \tag{1.3}$$

where the indicator variable $Small_Increase_{p,t-n,t-n-1}$ takes a value of 1 if the change in the nominal minimum wage in province p between year $t - n$ and $t - n - 1$ is small and similarly for the other two indicator variables.

1.4 RESULTS

1.4.1 Baseline Models: Estimates of the Effect of Higher Levels of Minimum Wages in a Given Province

TABLE 1.4 shows the results of the effect of higher levels of the provincial nominal minimum wage on the likelihood of reporting employer-sponsored drug insurance at various lags, estimated by applying Equation (1.1) on low-educated individuals only as they are the ones most likely to be affected. The effect at lag one is negative but very small (-0.6 percentage point) and non statistically significant at any reasonable level. Effects at higher lags are positive but essentially zero (less than one percentage point of coverage).

Contrary to the U.S., where triple difference models found that the insurance coverage of low-education or low-income individuals was affected by increases in the minimum wage, the triple difference model for Canada does not show difference between the effect on low-educated individuals and the rest of the population. The only exception is a positive effect found in the 2-year lag model. However, given that this is the only positive effect found across multiple specifications in the research, we interpret this result with

caution and consider the possibility that it may be a chance finding rather than indicative of a systematic relationship. Therefore, TABLE 1.5 confirms the results of TABLE 1.4: there is no detectable linear effect of higher levels of the provincial minimum wage on the provision of prescription drug insurance by employers in Canada¹⁰.

1.4.2 Non-linear Model Estimating the Effect of Yearly Changes in the Minimum Wage at Various Thresholds

TABLE 1.6 presents the effects of nominal yearly increases in the minimum wage on employer sponsored drug insurance. Whereas changes smaller than \$0.20 (which are the most common in Canadian provinces in the period of observation) have no effect at all on the provision of prescription drug insurance by employers, medium changes (between \$0.20 and \$0.30) have a substantial effect of about 2.5 percentage points in the 2-year lag model (about 5.5% of the initial level) and it is persistent up to 4 years after the implementation of the new minimum wage level. Large increases (larger than \$0.30 in a given year) have a small effect, peaking at almost 2 percentage points at three years, but not statistically significant, likely due to the small number of observations in that situation. The fact that the effect of large increases is smaller than that of medium changes could be due to the fact that provinces typically implement large increases when the economy is doing well, which might help employers absorb the cost of the increased minimum wage through price adjustments, automation, or extensive restructuring, rather than through cuts to employee benefits (Schmitt et al., 2013). Therefore, we found evidence that the threshold for minimum wage increases that could lead to a loss of employer-sponsored drug insurance is approximately \$0.20 - 0.30. This range appears to be the critical point

¹⁰We also analyzed the results using the real minimum wage. The results, presented in TABLE A1.2 and TABLE A1.3, show the same conclusions as with the nominal values.

at which some employers cut health benefits¹¹¹².

Our results from the 1-year lag model reveal a uniform positive effect across all categories of wage increases, suggesting an initial positive response from employers regardless of the increment size. Specifically, the coefficients for small, medium, and large increases all show statistically significant positive values, indicating that an initial increase in minimum wages tends to correspond with a higher likelihood of employers providing drug insurance benefits. However, it is critical to note that while the immediate response is positive, this effect does not persist into the 2-year, 3-year, and 4-year lags, where the impact of wage increases becomes negative or statistically non-significant positive.

1.4.3 Underlying Mechanism

In our analysis thus far, we have focused on employer-sponsored drug insurance for the entire population, including those covered by their own employers and those, employed or not, who are covered as dependents of someone with employer-sponsored coverage (e.g., a non-working person being covered by their working spouse). To delineate these two mechanisms, we re-run the analysis on two sub-groups: (1) single and employed individuals, and (2) unemployed or out of the labour force individuals who live with a partner. The first group can be covered through their own employer only (with some rare exceptions of individuals being covered by a parent) and the second group can be covered as dependent only.

TABLE 1.7 shows that increasing the minimum wage has no effect at any threshold on the probability of having employer-sponsored drug insurance for the first group, who

¹¹To test if there is a true effect across all provinces and that the results are not driven by one province only, we re-ran the model for the two year lag dropping one province at a time (see TABLE A1.4); the effect is clearly smaller, but does not disappear, when Quebec, Manitoba or Newfoundland-Labrador are dropped, suggesting that a lot of the overall effect is due to changes in these three provinces.

¹²We also test the results using changes in the real minimum wage, defining changes between 1 and 20 cents as small changes and those greater than 20 cents as large changes. Compared with provinces experiencing negative changes, we found similar results to those using nominal values. The results are shown in TABLE A1.5.

can only obtain this benefit from their own employers. Conversely, TABLE 1.8 reveals that one year after the implementation of new minimum wages, the second group, who rely on their spouses' employers for this benefit, are less likely to have it when the increase is greater than \$0.20; the effect of a medium increase in the minimum wage lasts at two and four years, but is not significantly different from 0 (possibly due to the smaller sample size, at 22,133) and the absolute value of the effect is lower than that observed for the population as a whole. There is some effect as well with a lag of two and three years. These two tables suggest that employers might cut dependent coverage first when they reduce benefits, but we cannot really prove it with the data at hand.

Another plausible mechanism is that employers actually do not cut any fringe benefit but increases in the minimum wage destroy good jobs (with fringe benefits) and the jobs created come with no fringe benefits. The effects we have found so far would simply reflect the fact that individuals who had drug insurance lost their job when the minimum wage was increased and, as a result, lost their coverage. To test this mechanism, we re-ran our non-linear model but using "employment"¹³ as the dependent variable (instead of drug coverage). If we observe effects of medium or large changes in the minimum wage that are of the same magnitude (or greater) than the ones observed on coverage, we might conclude that the main mechanism is through individuals losing jobs with coverage rather than employers cutting coverage for their employees¹⁴ Our results, shown in TABLE A1.6 of the Appendix, show that medium or large increases in the minimum wages have no statistically significant effect on employment (coefficients are non significant and values are positive and close to 0), except at lag 3 and 4 years, when large increases in the minimum wage reduce the probability to be employed by 2.8 percentage points (lag 3) and medium increases reduce the probability to be employed by 2.4 percentage points. The latter represents three quarters of the effect of medium increases in the minimum

¹³A binary variable taking a value of 1 if the individual is employed and 0 otherwise.

¹⁴Note that this is an overestimate, since not all jobs lost are necessarily jobs with coverage and we have good reasons to believe that jobs lost due to increase in the minimum wage are often precarious jobs, which do not usually come with good fringe benefits.

wage on the loss of coverage (3.2 percentage points). We can therefore say that our results that medium increases in the minimum wage have an effect on drug coverage after 2 and 3 years are not driven by job losses but rather by employers cutting coverage (likely to dependents as seen above); it is possible, however, that a portion of the effect at lag 4 is due to job losses.

1.5 HETEROGENEOUS TREATMENT EFFECTS

A 2019 report (Statistics Canada, 2019) shows that women, people younger than 25 and, to a lesser extent, immigrants, are more likely to earn the minimum wage. Therefore, we investigated whether the lack of a strong average effect might mask stronger impacts within specific sub-populations across Canada. We applied the model that firstly showed significant negative effects—a 2-year lag model—and re-ran it for distinct demographic groups: men and women, whites and non-whites, immigrants and Canadian-born individuals, across three age categories (25-35, 36-45, and 46-65). As detailed in TABLE 1.9, we found that women, new immigrants, non-whites, and younger individuals are more vulnerable to losing their employer-sponsored drug insurance following minimum wage increases. Additionally, the majority of these negative effects were observed when the minimum wage increase exceeded 20 cents, corresponding to medium and large increases. Specifically, large increases in minimum wage are associated with a decreased likelihood of retaining drug insurance among women, new immigrants, and non-white individuals. This aligns with prior research indicating negative employment impacts on these groups (e.g., Zavodny (2000); Paun et al. (2021)). Moreover, to test whether the coefficient for females (non-white, young) is significantly larger than the one for males (white, older), we ran a fully interacted model, interacted $MW_{p,t-n}$ with an indicator variable to show if individuals belong to a specific demographic group, such as female. We found that, in TABLE A1.7, compared to male and Canadian groups, increasing minimum wage do not have significantly larger effects for female and new immigrant

individuals. However, the difference is significant between white and non-white people. For each minimum wage threshold, compared to white individuals, non-white individuals are 10 percentage points less likely to have this benefit. A statistically significant difference was also observed across age groups. Compared to older individuals, younger individuals are more likely to lose these benefits when there is a medium increase in minimum wage.

1.6 DISCUSSION AND CONCLUSION

The present study investigates the relationship between the level of the minimum wage and the provision of employer-sponsored drug insurance in Canada. While previous research has predominantly focused on employment effects of the minimum wage, primarily in the United States, the effects of minimum wage policy on employer-sponsored health insurance coverage in Canada have yet to receive adequate attention and exploration. Our study provides a valuable contribution to this topic by being the first to analyze the impact of minimum wage increases on the provision of prescription drug insurance by Canadian perspective.

We utilized linear and non-linear DD and triple difference models, analyzing repeated cross-sectional survey data from the Canadian Community Health Survey spanning from 2013 to 2019. While the linear model revealed non-statistically significant negative effects, the non-linear model identified threshold effects in the 20-30 cents range, which is much lower than the thresholds identified in the U.S. Statistically significant negative effects emerged when a provincial government increased the minimum wage by 20-30 cents, with an effect of 2.5 percentage point decrease in the likelihood of individuals reporting employer-sponsored drug insurance. Furthermore, these negative effects did not vanish over a period of four years and they seem to be driven by more vulnerable groups (females, non-Whites, immigrants, young).

The literature based on the American case finds some modest linear effects which seem to be driven by some very large increases (more than \$0.50 per year over five years or more than \$1.00 in any given year) in some states. In Canada, we don't observe any linear effects, most likely because very few Canadian provinces ever increased their minimum wage so drastically. We also find that much lower increases than in the U.S (in the range of 20 to 30 cents versus \$0.50 in the U.S) have implications on health insurance coverage in Canada, suggesting that Canadian employers are more likely to respond to increases in the minimum wage than their American counterparts. This makes sense since the minimum wage is already higher in Canada than in the U.S. and drug insurance is easier to cut entirely than general (hospital, physician and drugs) health insurance as U.S. employers have to do in response to increases in the minimum wage in their jurisdiction.

The results of this paper have implications for public policy and suggest potential areas for future research.

Future research could investigate the impact of changes on other components of fringe benefits, such as job training and paid vacations. It could also investigate employers' reactions at the intensive margin (we do not have information on this in the survey). Instead of stopping providing some elements of health insurance, for example, employers could try to decrease premiums by increasing co-insurance rates or deductibles in the plan they offer. However, such changes might be more difficult to target to recent hires and would have to affect all employees, including high-skill workers, which would be more difficult to implement (and, possibly, counter-productive for the employer).

Another area for further research is that the effect found in the present study could reflect some reverse causality: governments might raise the minimum wage to mitigate the growth of precarious employment. We would see some contemporaneity between the loss of SHI (precarious employment) and increases in the minimum wage, but the

effect would go from the former to the latter. House of Commons (2019) and (OECD, 2024a) show that total employment has remained stable in Canada, but the number of workers working in precarious¹⁵ environments is growing. To examine the potential reverse causality, we define precarious job workers as part-time job workers, self-employed workers with hourly earnings lower than \$20 or workers without any SHI. TABLE A1.8 shows the effects of changes in the number of precarious job workers on contemporaneous and one-year lead minimum wage. All columns indicate that the number of precarious job workers has no positive effects on the one-year lead or contemporaneous minimum wage. Although these preliminary results alleviate the concern on causality to a certain extent, Lewchuk (2021) suggests that the official labour market data do not fully capture the information on precarious jobs including gig work, agency work and false self-employment. Therefore, our results may still be affected by reverse causality.

¹⁵Precarious job workers are defined as solo self-employed, Involuntary Part-Time and Temporary workers.

1.7 REFERENCES

- Baker, M., Benjamin, D. and Stanger, S. (1999). The highs and lows of the minimum wage effect: A time-series cross-section study of the Canadian law, *Journal of labor Economics* **17**(2): 318–350.
- Brouillette, D., Cheung, C., Gao, D., Gervais, O. et al. (2017). The impacts of minimum wage increases on the Canadian economy, *Technical report*, Bank of Canada Ottawa, ON, Canada.
- Canadian Life & Health Insurance Association (2021). Canadian life health insurance facts, 2021 edition.
- Cengiz, D., Dube, A., Lindner, A. and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs, *The Quarterly Journal of Economics* **134**(3): 1405–1454.
- Clemens, J., Kahn, L. B. and Meer, J. (2018). The minimum wage, fringe benefits, and worker welfare, *Technical report*, National Bureau of Economic Research.
- Clemens, J. and Strain, M. R. (2021). The heterogeneous effects of large and small minimum wage changes: Evidence over the short and medium run using a pre-analysis plan, *Technical report*, National Bureau of Economic Research.
- Conference Board of Canada (2021). Seeking support the future of employee health, <https://www.conferenceboard.ca/e-library/abstract.aspx?did=113603>.
- Dube, A., Naidu, S. and Reich, M. (2007). The economic effects of a citywide minimum wage, *ILR Review* **60**(4): 522–543.
- Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M. and Vom Berge, P. (2022). Reallocation effects of the minimum wage, *The Quarterly Journal of Economics* **137**(1): 267–328.

- Dworsky, M. S., Eibner, C., Nie, X. and Wenger, J. B. (2022). The effect of the minimum wage on employer-sponsored insurance for low-income workers and dependents, *American Journal of Health Economics* **8**(1): 99–126.
- Employment and Social Development Canada (2019). Federal minimum wage: Issue paper, <https://www.gc.ca/en/employment-social-development/corporate/portfolio/labour/programs/labour-standards/reports/issue-paper-federal-minimum-wage.html#h2.4>.
- Health Canada (2016). A prescription for Canada: Achieving pharmacare for all, <https://www.gc.ca/en/health-gc/corporate/about-health-gc/public-engagement/external-advisory-bodies/implementation-national-pharmacare/final-report.html>.
- Horn, B. P., Maclean, J. C. and Strain, M. R. (2017). Do minimum wage increases influence worker health?, *Economic Inquiry* **55**(4): 1986–2007.
- House of Commons (2019). Precarious work: Understanding the changing nature of work in Canada, <https://www.ourcommons.ca/Content/Committee/421/HUMA/Reports/RP10553151/humarp19/humarp19-e.pdf>.
- Huang, C., Liu, F. and You, S. (2021). The impact of minimum wage increases on cigarette smoking, *Health Economics* **30**(9): 2063–2091.
- Jalette, P., Duguay, F. L. and Laroche, M. (2020). Time is on whose side? Determining the duration of collective agreements in a decentralized collective bargaining system, *Journal of Industrial Relations* **62**(5): 758–783.
- Lewchuk, W. (2021). Collective bargaining in Canada in the age of precarious employment, *Labour & Industry: A Journal of the Social and Economic Relations of Work* **31**(3): 189–203.

- Marks, M. S. (2011). Minimum wages, employer-provided health insurance, and the non-discrimination law, *Industrial Relations: A Journal of Economy and Society* **50**(2): 241–262.
- Meiselbach, M. K. and Abraham, J. M. (2023). Do minimum wage laws affect employer-sponsored insurance provision?, *Journal of Health Economics* **92**: 102825.
- OECD (2024a). Incidence of involuntary part time employment, [https://data-explorer.oecd.org/vis?df\[ds\]=DisseminateFinalDMZ&df\[id\]=DSD_INVPT_EMP%40DF_INVPT_I&df\[ag\]=OECD.ELS.SAE&dq=...T._T._T.A&pd=2010%2C&to\[TIME_PERIOD\]=false](https://data-explorer.oecd.org/vis?df[ds]=DisseminateFinalDMZ&df[id]=DSD_INVPT_EMP%40DF_INVPT_I&df[ag]=OECD.ELS.SAE&dq=...T._T._T.A&pd=2010%2C&to[TIME_PERIOD]=false).
- OECD (2024b). Real minimum wages at constant prices, [https://data-explorer.oecd.org/vis?df\[ds\]=DisseminateFinalDMZ&df\[id\]=DSD_EARNINGS%40RMW&df\[ag\]=OECD.ELS.SAE&dq=...A...&pd=2001%2C&to\[TIME_PERIOD\]=false](https://data-explorer.oecd.org/vis?df[ds]=DisseminateFinalDMZ&df[id]=DSD_EARNINGS%40RMW&df[ag]=OECD.ELS.SAE&dq=...A...&pd=2001%2C&to[TIME_PERIOD]=false).
- Paun, C. V., Nechita, R., Patruti, A. and Topan, M. V. (2021). The impact of the minimum wage on employment: An EU panel data analysis, *Sustainability* **13**(16): 9359.
- Royalty, A. et al. (2000). Do minimum wage increases lower the probability that low-skilled workers will receive fringe benefits?, *Joint Center for Poverty Research Working Paper* **222**.
- Schmitt, J. et al. (2013). *Why does the minimum wage have no discernible effect on employment?*, Vol. 4, Center for Economic and Policy Research Washington, DC.
- Simon, K. I. and Kaestner, R. (2004). Do minimum wages affect non-wage job attributes? Evidence on fringe benefits, *ILR Review* **58**(1): 52–70.
- Statistic Canada (2022). Collective bargaining coverage rate, 1997 to 2021, <https://www150.statcan.gc.ca/n1/pub/14-28-0001/2020001/article/00015-eng.htm>.
- Statistics Canada (2008). Workplace and employee survey compendium 2005, <https://www150.statcan.gc.ca/n1/pub/71-585-x/71-585-x2008001-eng.pdf>.

Statistics Canada (2019). Maximum insights on minimum wage workers: 20 years of data,

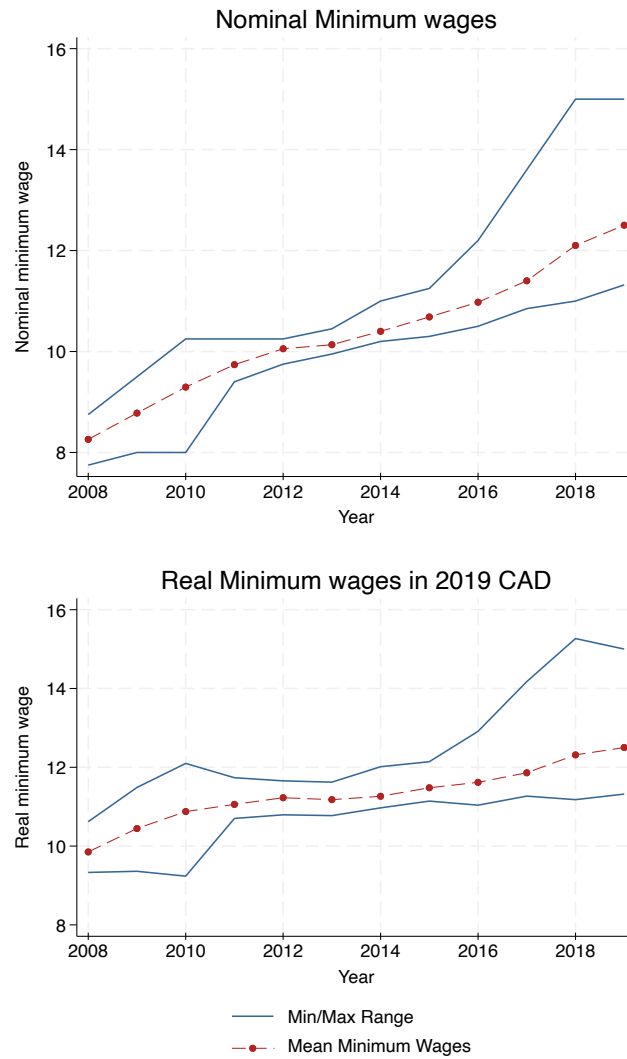
<https://www150.statcan.gc.ca/n1/pub/75-004-m/75-004-m2019003-eng.htm>.

Sturn, S. (2018). Do minimum wages lead to job losses? Evidence from OECD countries on low-skilled and youth employment, *ILR Review* **71**(3): 647–675.

Zavodny, M. (2000). The effect of the minimum wage on employment and hours, *Labour Economics* **7**(6): 729–750.

1.8 FIGURES AND TABLES

FIGURE 1.1: Provincial Minimum Wage from 2013 - 2019



Notes: This figure shows the trend of the minimum wage since 2008 to 2019.
Source: Statistics Canada and Government of Canada.

TABLE 1.1: Questions Selected by Provinces and Years in CCHS

	AB	BC	MB	NB	NL	NS	ON	PE	QC	SK
2013				X		X				
2014				X		X				
2015	X	X	X	X	X	X	X	X	X	X
2016	X	X	X	X	X	X	X	X	X	X
2017			X	X						
2018			X							
2019	X	X	X	X	X	X	X	X	X	X

Notes: This table reports the employer-sponsored prescription drug insurance question availability in 10 provinces in Canada. Data obtained from CCHS from 2013 to 2019. Provinces: AB–Alberta, BC–British Columbia, MB–Manitoba, NB–New Brunswick, NL–Newfoundland and Labrador, NS–Nova Scotia, ON–Ontario, PE–Prince Edward Island, QC–Québec, SK–Saskatchewan.

TABLE 1.2: Nominal Provincial Minimum Wage 2008-2019

	AB	BC	MB	NB	NL	NS	ON	PE	QC	SK
2008	8.4	8	8.5	7.75	8	8.1	8.75	8	8.5	8.6
2009	8.8	8	9	8.25	9	8.6	9.5	8.4	9	9.25
2010	8.8	8	9.5	9	10	9.65	10.25	9	9.5	9.25
2011	9.4	9.5	10	9.5	10	10	10.25	9.6	9.65	9.5
2012	9.75	10.25	10.25	10	10	10.15	10.25	10	9.9	10
2013	9.95	10.25	10.45	10	10	10.3	10.25	10	10.15	10
2014	10.2	10.25	10.7	10.3	10.25	10.4	11	10.35	10.35	10.2
2015	11.2	10.45	11	10.3	10.5	10.6	11.25	10.5	10.55	10.5
2016	12.2	10.85	11	10.65	10.5	10.7	11.4	11	10.75	10.72
2017	13.6	11.35	11.15	11	11	10.85	11.6	11.25	11.25	10.96
2018	15	12.65	11.35	11.25	11.15	11	14	11.55	12	11.06
2019	15	13.85	11.65	11.5	11.4	11.55	14	12.25	12.5	11.32

Notes: Data from the Government of Canada, "Hourly Minimum Wage in CANADA for Adult Workers". Provinces: AB–Alberta, BC–British Columbia, MB–Manitoba, NB–New Brunswick, NL–Newfoundland and Labrador, NS–Nova Scotia, ON–Ontario, PE–Prince Edward Island, QC–Québec, SK–Saskatchewan.

TABLE 1.3: Summary Statistics

	(1)	(2)
	All	Low-educated
Male	0.508 (0.500)	0.499 (0.500)
Age	45.288 (19.229)	43.388 (22.863)
In couple	0.582 (0.493)	0.453 (0.498)
Immigrant	0.272 (0.445)	0.228 (0.420)
White	0.746 (0.435)	0.755 (0.430)
Excellent or very good Health	0.612 (0.487)	0.552 (0.497)
Unemployment rate	6.873 (1.266)	6.897 (1.301)
Unweighted Obs	215,533	94,152

Notes: Weighted means are shown with standard deviation in parentheses. Individual variables are from CCHS 2013 - 2019. Unemployment rate is from the Statistics Canada.

TABLE 1.4: Linear DD Model with Nominal Minimum Wage for Low-educated Individuals

	(1)	(2)	(3)	(4)
	1-year lag	2-year lag	3-year lag	4-year lag
Minimum wage	-0.006 (0.005)	0.004 (0.007)	0.005 (0.011)	0.012 (0.015)
Obs	94,152	94,152	94,152	94,152
Mean dependent variables	0.474	0.474	0.474	0.474
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE 1.5: Linear Triple Differences Model with Nominal Minimum Wage

	(1)	(2)	(3)	(4)
	1-year lag	2-year lag	3-year lag	4-year lag
Minimum wage * Low	-0.006 (0.007)	0.016* (0.009)	0.010 (0.015)	-0.000 (0.020)
Obs	215,533	215,533	215,533	215,533
Mean dependent variables	0.547	0.547	0.547	0.547
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE 1.6: Non-linear Model with Nominal Minimum Wage
Change for Low-educated Individuals

	(1) 1-year lag	(2) 2-year lag	(3) 3-year lag	(4) 4-year lag
Small increase	-0.017 (0.013)	-0.016 (0.016)	-0.012 (0.010)	-0.028* (0.016)
Medium increase	-0.012 (0.012)	-0.025** (0.011)	-0.026* (0.013)	-0.032*** (0.012)
Large increase	-0.009 (0.012)	-0.012 (0.011)	-0.019 (0.013)	0.001 (0.015)
Obs	94,152	94,152	94,152	94,152
Mean dependent variables	0.474	0.474	0.474	0.474
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE 1.7: Non-linear Model with Nominal Minimum Wage
Change for Low-educated, Single and Employed Individuals

	(1) 1-year lag	(2) 2-year lag	(3) 3-year lag	(3) 4-year lag
Small increase	0.011 (0.035)	-0.010 (0.039)	0.023 (0.026)	0.009 (0.040)
Medium increase	0.031 (0.034)	-0.001 (0.030)	-0.005 (0.036)	-0.004 (0.031)
Large increase	0.048 (0.033)	-0.011 (0.028)	0.029 (0.032)	-0.021 (0.037)
Obs	14,992	14,992	14,992	14,992
Mean dependent variables	0.583	0.583	0.583	0.583
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE 1.8: Non-linear Model with Nominal Minimum Wage
Change for Low-educated, Unemployed Individuals Living in
Couple

	(1) 1-year lag	(2) 2-year lag	(3) 3-year lag	(3) 4-year lag
Small increase	-0.044 (0.027)	0.028 (0.030)	-0.017 (0.021)	-0.039 (0.031)
Medium increase	-0.048* (0.025)	-0.017 (0.022)	-0.005 (0.028)	-0.015 (0.023)
Large increase	-0.057** (0.024)	-0.009 (0.020)	0.016 (0.026)	0.007 (0.027)
Obs	22,133	22,133	22,133	22,133
Mean dependent variables	0.310	0.310	0.310	0.310
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE 1.9: Non-linear Two-year Lag Model with Nominal Minimum Wage Change for Low-educated Individuals

	(1) Male	(2) Female	(3) Canadian born	(4) Immigrant
Small increase	-0.006 (0.022)	-0.024 (0.021)	-0.002 (0.016)	-0.058 (0.043)
Medium increase	-0.017 (0.017)	-0.032** (0.016)	-0.013 (0.012)	-0.064* (0.033)
Large increase	0.003 (0.016)	-0.028** (0.014)	-0.000 (0.011)	-0.053* (0.030)
Obs	43,783	50,369	81,141	13,011
Mean dependent variables	0.492	0.456	0.502	0.378
	White	Non-white	Age <= 35	35 < Age <= 45
Small increase	0.010 (0.017)	-0.096*** (0.035)	-0.031 (0.024)	-0.019 (0.049)
Medium increase	-0.002 (0.012)	-0.103*** (0.030)	-0.046** (0.020)	0.018 (0.038)
Large increase	0.012 (0.011)	-0.092*** (0.027)	-0.022 (0.018)	0.012 (0.038)
Obs	79,937	14,215	30,898	6,300
Mean dependent variables	0.494	0.414	0.548	0.550
	Age > 45			
Small increase	0.001 (0.021)			
Medium increase	-0.009 (0.015)			
Large increase	-0.012 (0.014)			
Obs	56,954			
Mean dependent variables	0.395			
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

1.9 APPENDIX

TABLE A1.1: The Nominal Income Distribution by Education Groups

	(1) Mean	(2) SD	(3) p25	(4) p50	(5) p75
High-educated	53975.8	42466.5	24969	43060	72444
Low-educated	34031.9	30569.6	14163	25200	44828

Notes : SD, standard deviation.

TABLE A1.2: Linear DD Model with Real Minimum Wage for Low-educated Individuals

	(1) 1-year lag	(2) 2-year lag	(3) 3-year lag	(4) 4-year lag
Minimum wage	-0.004 (0.005)	0.006 (0.006)	0.006 (0.011)	0.007 (0.014)
Obs	94,152	94,152	94,152	94,152
Mean dependent variables	0.474	0.474	0.474	0.474
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE A1.3: Linear Triple Differences Model with Real Minimum Wage

	(1) 1-year lag	(2) 2-year lag	(3) 3-year lag	(4) 4-year lag
Minimum wage * Low	-0.004 (0.007)	0.016* (0.009)	0.011 (0.014)	0.013 (0.227)
Obs	215,533	215,533	215,533	215,533
Mean dependent variables	0.547	0.547	0.547	0.547
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE A1.4: Non-linear Two-year Lag Model with Nominal Minimum Wage Change for Low-educated Individuals, Province Effects

	(1) No NL	(2) No PE	(3) No NS	(4) No NB	(5) No QC
Small Increases	-0.016 (0.013)	-0.016 (0.016)	-0.015 (0.016)	-0.020 (0.016)	-0.000 (0.018)
Medium Increases	-0.011 (0.012)	-0.026** (0.011)	-0.026** (0.011)	-0.030** (0.013)	-0.013 (0.013)
Large Increases	-0.008 (0.012)	-0.013 (0.011)	-0.013 (0.011)	-0.015 (0.013)	-0.009 (0.012)
Obs	0.475	0.474	0.474	0.475	0.487
Mean dependent Variables	91,234	92,381	90,714	87,754	79,792
	No ON	No MB	No SK	No AB	No BC
Small Increases	-0.017 (0.017)	-0.031* (0.018)	-0.019 (0.020)	-0.004 (0.021)	-0.010 (0.016)
Medium Increases	-0.023 (0.016)	-0.015 (0.013)	-0.027** (0.011)	-0.022 (0.014)	-0.022* (0.012)
Large Increases	-0.029** (0.014)	-0.003 (0.012)	-0.014 (0.011)	-0.010 (0.011)	-0.007 (0.012)
Obs	56,264	87,176	90,180	86,046	85,827
Mean dependent Variables	0.464	0.472	0.474	0.469	0.474

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Provinces: AB-Alberta, BC-British Columbia, MB-Manitoba, NB-New Brunswick, NL-Newfoundland and Labrador, NS-Nova Scotia, ON-Ontario, PE-Prince Edward Island, QC-Québec, SK-Saskatchewan.

TABLE A1.5: Non-linear Model with Real Minimum Wage
Change for Low-educated Individuals

	(1) 1-year lag	(2) 2-year lag	(3) 3-year lag	(4) 4-year lag
Small increase	-0.008 (0.010)	-0.014* (0.008)	0.013 (0.012)	-0.017 (0.011)
Large increase	0.002 (0.010)	-0.003 (0.009)	-0.006 (0.015)	0.000 (0.012)
Obs	94,152	94,152	94,152	94,152
Mean dependent variables	0.474	0.474	0.474	0.474
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE A1.6: Effect of Minimum Wage on Employment,
Non-linear Model with Nominal Minimum Wage Change for
Low-educated Individuals

	(1) 1-year lag	(2) 2-year lag	(3) 3-year lag	(3) 4-year lag
Small increase	0.001 (0.014)	-0.009 (0.014)	-0.016 (0.011)	-0.017 (0.017)
Medium increase	0.008 (0.013)	-0.008 (0.011)	-0.013 (0.013)	-0.024** (0.012)
Large increase	0.006 (0.012)	0.003 (0.010)	-0.028** (0.013)	-0.020 (0.014)
Obs	94,152	94,152	94,152	94,152
Mean dependent variables	0.443	0.443	0.443	0.443
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1.

TABLE A1.7: Two-year Lag Non-linear Model with Real Minimum Wage Change for Low-educated Individuals

Groups:	(1) Female	(2) Immigrant	(3) Non-white	(4) Young
Small increase* Group	-0.020 (0.030)	-0.050 (0.044)	-0.097*** (0.037)	-0.025 (0.031)
Medium increase* Group	-0.015 (0.023)	-0.052 (0.035)	-0.099*** (0.033)	-0.042* (0.025)
Large increase* Group	-0.031 (0.021)	-0.050 (0.031)	-0.100*** (0.029)	-0.011 (0.022)
Obs	94,152	94,152	94,152	94,152
Mean dependent variables	0.474	0.474	0.474	0.474
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes : Regressions are controlled by sex, age, race, health status, marital status, immigration status and provincial unemployment rate. Standard errors are reported in parentheses and bootstrapped using 500 replications with bootstrap weights. Statistical significance level indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE A1.8: Reverse Causality

Dependent Variable	(1) 1-year lead real MW	(2) 1-year lead nominal MW	(3) Current real MW	(4) Current nominal MW
Precarious (Per thousand)	-0.044 (0.049)	-0.062 (0.053)	-0.011 (0.043)	-0.020 (0.0493)
Province FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Other controls	YES	YES	YES	YES

Notes : *,** and *** indicate statistical significance at the 0.10, 0.05 and 0.01 level respectively. Standard errors are clustered at the province level.

Chapter 2

The Effects of Public Prescription Drug Insurance Expansion on Emergency Department: Evidence from Canada

Abstract

This study examines the impact of public prescription drug coverage on emergency department utilization. I use the implementation of the Ontario Health Insurance Plan Plus (OHIP+) in Ontario, Canada, in 2018, as a quasi-experiment and compare the use of emergency department by the 18-24 population (affected by OHIP+) before and after 2018 in Ontario and other provinces (difference-in-difference framework). It is hypothesized that prior to OHIP+, individuals without coverage for prescription drugs were less likely to visit a family physician, potentially leading to increased emergency department

visits, either directly, because prescription drugs can be obtained for free at the hospital's pharmacy (substitution effect) or indirectly, as an offset effect of primary care (a neglect of ambulatory care, leading to more uncontrolled conditions and, therefore, emergency department visits due to deteriorating health). The first difference-in-difference analysis on the whole population aged 18 to 24 does not reveal any significant effect but a difference-in-difference analysis focusing on low-income individuals aged 18 to 24, those most likely not to be covered by private insurance, shows a significant decline in emergency department utilization in Ontario after OHIP+ was implemented. The statistically significant decline is found in emergency visits for conditions that are not usually preventable with good primary care, which suggests that young people may be using the emergency department as a substitute for other ways of getting prescriptions.

2.1 INTRODUCTION

Within the context of healthcare economics, the increase in the consumption of healthcare goods or services upon gaining insurance coverage is a well-documented phenomenon termed “moral hazard”. This term traditionally carries a negative connotation, as it suggests a welfare loss due to the consumption of care that may exceed what individuals would opt for if they bore the full cost (Pauly, 1968). However, this increased utilization may also be construed positively if it translates into significant long-term health benefits that individuals cannot fully anticipate or value at the point of decision-making, given their limited information about future health outcomes. In scenarios where an insurer, whether public or private, provides comprehensive risk coverage without relying solely on experience-based rating, a deliberate strategy may be adopted. This strategy involves promoting the use of preventative measures such as ambulatory care or prescription medications with the expectation that such an investment will result in lower future hospitalization costs. This concept, known as the offset effect, posits that immediate higher expenditures on preventative care are counterbalanced by subsequent savings on more costly acute care, especially hospital and emergency department care. The offset effect serves as a foundational principle for Value-Based Health Insurance (VBHI), which aims to optimize healthcare spending by incentivizing interventions that promise greater health returns for the investment (Pauly and Held, 1990). Empirically, the VBHI model is contingent upon the presence and extent of what are referred to as ‘spillover effects’ which denote the impact of the provision of a particular category of health care goods or services on the utilization of different categories within the health care system.

In the case of prescription drug insurance, the rationale for VBHI is as follows: individuals who lack prescription drug insurance and have low ability to pay do not fill prescriptions when they visit a primary care doctor, which is detrimental to their health

in the long run, thus may increase their risk of emergency department visits or hospitalization; even more problematic for their health, they don't even visit their primary care provider because they know they will not be able to fill the prescription.

Besides the offset effect, another rationale for "benign" moral hazard is a substitution effect: because prescription drugs can be distributed for free at the hospital pharmacy, some low-income individuals without coverage for prescription drugs might choose to use the emergency department as a substitute for family medicine visits. Covering prescription drugs for these individuals would help the health care system better manage the emergency department and help the emergency department to fulfill its true mission (emergency care).

In this study, I exploit the implementation of the Ontario Health Insurance Plan Plus (OHIP+) to examine potential offset and substitution effects in emergency department utilization. The analysis focuses on a subset of the program's beneficiary group, Ontario residents aged 18–24, by comparing their emergency department visits before and after the policy's introduction in 2018 and the 2019 revision, which restricted eligibility to those without private drug insurance. I study those aged 18 to 24 instead of the whole population younger than 25 (who is eligible for OHIP+) because I want to link data on utilization to data on income through tax returns (more on this below). To identify the causal impact, I begin with an inter-provincial difference-in-differences event-study design, contrasting Ontario's outcomes (quarterly emergency department visits) with those of the same age group in other provinces. This approach evaluates both quarterly dynamics and overall post-policy effects. The results indicate no statistically significant impact of OHIP+ on emergency department visits among Ontario youth, whether measured quarter by quarter or in aggregate after the policy change.

However, it is reasonable to think that youth already covered for prescription drugs through their parents did not really benefit from OHIP+. Because the likelihood of not

being covered by one's parents is much higher among individuals from low-income background (Bolatova and Law, 2019), I re-run the difference-in-differences analysis stratified by the low-income threshold (using a Statistics Canada threshold for low income), meaning one analysis for the 18-24 below and one for the 18-24 above the threshold. I find that emergency department visits in Ontario declined following the implementation of OHIP+ in 2018 for those below the threshold, and this negative effect became even stronger after the 2019 policy revision.

The remainder of the paper is organized as follows. Section 2 provides background on Canada's and Ontario's healthcare systems, with particular attention to the design and policy details of OHIP+. Section 3 describes the data sources, variables, and empirical study design. Section 4 presents the main results, and Section 5 concludes with a discussion of the limitations.

2.2 INSTITUTIONAL BACKGROUND

In Canada, the provision of physician visits and hospital care, encompassing emergency department visits, inpatient hospitalizations, and day surgery, is ensured through a public, universal, and mandatory health insurance system. The *Canada Health Act* (CHA) of 1984 underpins the allocation of federal funds to provinces, contingent on adherence to five principles, with universal coverage being one of them-with certain minor exceptions notably associated with recent immigration (Martin et al., 2018; Marchildon et al., 2021). The coverage provided under this system is not only universal but also comprehensive, prohibiting user fees such as co-payments, co-insurance, and extra-billing.

Despite the broad coverage for these specified services, the scope in terms of the types of services and goods covered is limited by the framework of the CHA. The extent to which services or goods outside this framework are publicly funded is subject to the discretion of each provincial government. Notably, Canada stands alone among OECD

countries in not offering universal pharmaceutical coverage (Morgan et al., 2013). Public coverage for outpatient prescription drugs is typically reserved for particular segments of the population, like seniors and individuals receiving social assistance. This public coverage varies across provinces and territories in terms of co-payments, deductibles, and the range of medications that are included (Gagnon, 2021).

For those not included in these select categories, the employed demographic and their dependents, prescription drug coverage must be sourced from employer-sponsored plans or, less commonly, individual insurance plans. An estimated one in ten Canadians does not follow through with prescribed medications due to financial barriers, and a primary factor contributing to this non-adherence is the lack of prescription drug insurance (Law et al., 2012).

2.2.1 Ontario Public Drug Insurance System

In Ontario, public drug insurance coverage is principally offered through the Ontario Drug Benefit (ODB) program, which operates in conjunction with the Ontario Health Insurance Plan (OHIP). The ODB covers all individuals aged 65 and over, representing around 18%¹ of the province's population, as well as those on welfare-groups, representing 5.8% of the province's population^{2 3}. Moreover, some limited initiatives aimed at specific diseases offer public coverage for therapeutic treatments, for example prescription drugs for diabetes and hypertension. Last, for residents not covered by the ODB or specialized disease-targeted initiatives, the Trillium Drug Program offers a safety mechanism to protect against catastrophic drug expenditures. Under this program, once an

¹The proportion of seniors aged 65+ went from 8.3 per cent in 1971 to 18.3 per cent in 2023 and is projected to reach 20.3 per cent by 2046. <https://www.ontario.ca/document/ontarios-long-term-report-economy-2024/chapter-1-demographic-trends-and-projections-2024c18>.

²In 2023, about 910,000 Ontario residents received social assistance, including beneficiaries of Ontario Works and the Ontario Disability Support Program. https://maytree.com/changing-systems/data-measuring/social-assistance-summaries/ontario/?utm_source=chatgpt.com.

³The Ontario population is 15.6 million in 2023. <https://www.ontario.ca/document/ontarios-long-term-report-economy-2024/chapter-1-demographic-trends-and-projections-2024c18>.

individual has spent 4% of their after-tax household income on prescription drugs, they benefit from full coverage except for a co-payment of \$2 per prescription.

Despite the coverage provided by OHIP, ODB, and the Trillium Drug Program, numerous individuals in Ontario continue to experience insufficient drug coverage (Canadian Life & Health Insurance Association, 2021). These programs sometimes do not extend to the full cost of certain medications or may impose limitations on the accessibility of specific treatments. The consequent financial burden can be particularly onerous for younger populations, such as children and young workers contending with chronic illnesses or severe medical conditions. Young workers, who are often at an early stage in their financial lives, and families with children requiring continuous medication, face challenges due to the cumulative costs of drugs. Moreover, for those with lower incomes, incomplete coverage or the requirement for co-insurance could be significant obstacles to obtaining prescribed medications, even though they are nominally covered by an employer-sponsored plan.

On January 1st, 2018, the Ontario government introduced OHIP+, a program extending comprehensive drug coverage to individuals under the age of 25. This initiative, under the umbrella of OHIP, initially provided access to over 4,400 prescription medications⁴, providing coverage without any deductible, co-insurance or co-payment. In April 2019, OHIP+ was modified and coverage was made available exclusively to those without private drug plans, thus generally excluding individuals who have parental coverage through private insurance. This change narrowed the scope of the program, impacting the extent of its reach among the youth and young adult population in Ontario and likely targeting the low-income population⁵.

⁴The number of drug products covered by OHIP+ had expanded to over 5,000 by 2022.

⁵For some low-income households with poor quality coverage through an employer, the dilemma was either to renounce high quality coverage for a young dependent through OHIP+ by keeping their employer-sponsored plan or renouncing the plan for the whole family, thus putting adults at risk.

2.3 LITERATURE REVIEW

In Canada, the scope of research exploring the impact of public drug insurance on healthcare utilization is somewhat limited. Several papers provide evidence consistent with substitution effects, showing that expanded drug or health coverage encourages individuals to use more primary and preventive care, thereby reducing reliance on high-cost emergency or inpatient services. Allin and Hurley (2009) report that individuals with prescription drug coverage have a higher frequency of physician visits compared to those without such coverage. A cross-sectional study has drawn associations between prescription drug coverage and the incidence of general practitioner and specialist consultations. Antonipillai et al. (2021) found that compared with uninsured adults, those covered by private insurance had a greater likelihood of visiting a general practitioner. Wang et al. (2015) found that Québec's 1997 mandatory drug insurance policy increased drug consumption and primary care visits without affecting specialist or inpatient use. Additionally, this policy change was linked to health status improvements among those with initially poor health. Tamblyn et al. (2001) reported that the implementation of a prescription coinsurance and deductible cost-sharing policy in Québec in 1996 for seniors and welfare recipients led to reduced use of essential medications and, consequently, to higher rates of serious adverse events and emergency department visits.

In the United States, extensive research has focused on the ramifications of public health insurance expansion on healthcare utilization, including medications, emergency department services and hospitalizations. The results have been mixed. Some studies suggest that the availability of health insurance leads to greater substitution effects or utilization of primary and preventive care (Finkelstein et al., 2012), including routine checkups and various screenings (Courtemanche et al., 2019). Also, Baicker et al. (2013) observed that Medicaid coverage increased the likelihood of diabetes diagnosis and medication usage. The extension of public drug insurance has also demonstrated impacts

on healthcare utilization. The introduction of Medicare Part D, for example, was correlated with a decline in total hospital admissions (Afendulis et al., 2011; Kaestner et al., 2019), although such an effect on hospitalization was not confirmed in all studies (Liu et al., 2011). On the other hand, other studies highlight patterns that align with offset effects, suggesting that insurance expansions can sometimes reduce access to primary care or increase demand for costly services: Medicaid expansion, for instance, has been associated with an increase in emergency department visitation rates (Anderson et al., 2014; Taubman et al., 2014; Nikpay et al., 2017), as well as inpatient hospitalizations (Dafny and Gruber, 2005) and outpatient hospital services (Dunn et al., 2021) in the population as a whole. Utilizing machine learning techniques to investigate the relationship between access to primary care and emergency department usage, Ellis and Esson (2021) found that the increase in emergency department services might be due to a reduction in primary care access for those who had insurance before the public health insurance expansion, leading to a 'crowding out' effect. Last, Miller and Wherry (2017) reported no significant link between Medicaid expansion and the frequency of doctor visits or overnight hospital stays, though they noted longer wait times and more difficulty in securing appointments for low-income adults after the expansion.

This study makes several contributions. First, I provide evidence on the offset and substitution effects of public drug insurance for young patients, who are usually healthier than other groups of patients, on emergency department services. Second, this paper is the first using administrative data to test the effect of public drug insurance on healthcare utilization in Canada.

2.4 DATA AND METHODOLOGY

The dataset in question comprises administrative records detailing the utilization of emergency department within Ontario, along with comparable data from other Canadian

provinces serving as controls. This information spans from January 2017 to December 2019, thereby encompassing periods both prior to and subsequent to the implementation of OHIP+. Such longitudinal data are instrumental for assessing the impact of OHIP+ on healthcare service usage, facilitating a before-and-after comparative analysis. This time frame allows for the evaluation of trends and shifts in health service utilization attributable to the policy changes introduced by OHIP+.

The analysis is at the aggregate level, using quarterly emergency department admissions per population in various populations (by age, income and province) as its main dependent variable.

2.4.1 Emergency Department Admissions

Emergency department admission data are drawn from the National Ambulatory Care Reporting System (NACRS), which records detailed information on ambulatory care visits, including patient demographics, reasons for visits, and diagnostic codes. NACRS covers multiple healthcare settings, such as emergency department, specialized clinics, and outpatient departments, but for this study, only emergency department visit records are analyzed.⁶

The main dependent variable is the total number of emergency department visits per quarter and per province, obtained by aggregating NACRS records. One limitation of the NACRS dataset is incomplete provincial coverage. For example, in Prince Edward Island (PEI), only about 26% of emergency department visits are reported. To address this problem, the analysis adjusts the reported counts using coverage rate estimates from the Canadian Institute for Health Information (CIHI) to approximate total visits.

⁶Québec is not included in the NACRS, as the province maintains its own administrative data systems and has historically not participated in national emergency department reporting to CIHI.

With the exception of British Columbia and Manitoba, Canadian provinces record each emergency department visit in NACRS using the International Classification of Diseases, Tenth Revision (ICD-10). This detailed diagnostic coding enables a nuanced assessment of OHIP+'s impact across different types of conditions, particularly Ambulatory Care Sensitive Conditions (ACSC) and non-ACSC. Effects on ACSC visits would suggest an offset effect, while effects on non-ACSC visits would indicate a substitution effect. In this study, emergency department visits are classified into these two categories⁷. ACSC are health conditions for which timely and effective primary care can often prevent the need for hospital treatment; thus, high-quality, accessible primary care should reduce emergency department use for ACSC. Here, this classification is used to distinguish between necessary and potentially avoidable emergency department visits. TABLE A2.1 in the appendix shows the list of ACSC followed by CIHI instruction.

2.4.2 Income and Low-income Family

The T1 Family File (T1FF), which consolidates tax-based data from individual income tax returns, offering a wealth of information including demographic profiles, income levels and a range of tax-related attributes, is linked to NACRS to obtain patients' demographic, such as household income, into the evaluation of healthcare utilization trends and their association with the OHIP+ policy. This integrated approach allows for a more nuanced understanding of how socioeconomic factors intersect with health service use in the context of the OHIP+ program's implementation.

A key component used in this research is the Low-Income Measure (LIM) provided in the T1FF. LIM is a relative measure of low income, set at 50 percent of adjusted median household income. This measure is crucial for identifying families with lower

⁷British Columbia and Manitoba were excluded from all ASCS analyses due to the absence of diagnosis codes.

incomes who may not have adequate access to employer-provided or private health insurance coverage (Bolatova and Law, 2019). Based on the LIM, the low-income rate was 12.3% in Canada in 2018⁸, while in Ontario, the rate was higher, at 14.4% according to the 2016 Census⁹. Furthermore, Miregwa et al. (2022) reported that more than 60% of ODB recipients in the pre-OHIP+ period came from low or low-middle socioeconomic households¹⁰, highlighting the program's disproportionate relevance for economically disadvantaged groups. The 2019 policy revision, which removed eligibility for individuals with private prescription drug coverage, further concentrated the program's target population among lower-income households. Given this shift in coverage and its potential implications for access to medications and household budgets, this study undertakes a comparative analysis of low-income households in Ontario and their counterparts in other provinces to better isolate the distributional effects of OHIP+.

2.4.3 Control Variables

The set of control variables includes both individual patient demographics and broader province-level characteristics to ensure a comprehensive analysis. From the NACRS dataset, I obtain information about patients' age and sex of those who visited the emergency department. These demographic variables are crucial as they often influence healthcare utilization patterns and can help isolate the effect of the OHIP+ program from other factors.

Moreover, to account for the broader economic environment which could impact health service use, I incorporate provincial unemployment rates on a quarterly basis, as provided by Statistics Canada. Unemployment rates serve as a proxy for economic

⁸Canadian Income Survey, 2018: <https://www150.statcan.gc.ca/n1/daily-quotidien/200224/dq200224a-eng.htm>

⁹Income Security Advocacy Centre\Centre d'action pour la sécurité du revenu: <https://incomesecurity.org/wp-content/uploads/2020/04/Fast-Facts-Poverty-and-Social-Assistance.pdf>

¹⁰The authors reported that 63.8% of the study sample were in the lowest two income quintiles, representing 33,964 and 18,119 individuals respectively.

conditions, as they may affect individuals' ability to afford healthcare services or their health insurance status, which in turn can impact their use of health services.

2.4.4 Sample Selection

A limitation of linking NACRS and T1FF data concerns individuals under the age of 18 who cannot be linked from NACRS to T1FF. Because of this, it is not possible to verify whether these younger beneficiaries fall within the low-income families. To maintain consistency in identifying low- and non-low-income populations, individuals under 18 are therefore excluded from the analysis. Therefore, individuals aged 18-24 are defined as beneficiaries, being covered by the program's prescription drug insurance. Furthermore, I excluded emergency department visits from Ontarians in other provinces, to avoid spillover effects of OHIP+ in other provinces (a very small issue numerically). TABLE 2.1 presents descriptive statistics for the full sample, Ontario patients, and other province emergency department patients aged 18-24. The mean age is similar in these groups around 21. The share of male patients is about 40%, indicating a slight female majority. The proportion of low-income families in Ontario is 29% and 31% in other provinces.

2.4.5 Empirical Study Framework

To estimate the effect of OHIP+ on healthcare utilization, I use a Difference-in-differences event-study model with aggregate quarterly data. Causality relies on parallel trends in Ontario and other provinces before OHIP+ implementation. The event-study model allows me to examine the common trend assumption, but also shows the dynamic effects. The coefficients denote the difference between total emergency department visits in Ontario and in other provinces. The main specification is given by:

$$\ln(Y_{p,t}) = \sum_{i=-4, i \neq -1}^7 \beta_i ON_p \mathbf{1}\{t - Q1, 2018 = i\} + Prov_p + Year_Quarter_t + X_{p,t} + e_{p,t} \quad (2.1)$$

$\ln(Y_{p,t})$ is the natural logarithm of the number of emergency department visits in the province p in time t , ON_p is 1 for Ontario and 0 for other provinces. $\mathbf{1}\{t - Q1, 2018 = i\}$ is an indicator variable equal to 1 if the observation time is $-i$ quarters from the first quarter in 2018¹¹. I use the fourth quarter in 2017 as the reference period for the analysis. $Prov_p$ and $Year_Quarter_t$ represent province fixed effects and time fixed effects. $X_{p,t}$ includes patients' average age and the proportion of males of the population who visited the emergency department, calculated from the NACRS dataset. Additionally, I added provincial unemployment rates to control the macroeconomics situation. Standard errors are clustered at the province-level to allow for autocorrelation within provinces (Bertrand et al., 2004). All regressions are weighted by province-level population using the relevant age group¹².

The coefficient of interest, denoted as β_i , represents the estimated effect of the implementation of OHIP+ on healthcare utilization for each term between winter 2017 and fall 2019; having one coefficient per quarter generates an event-study model. It captures the relationship between OHIP+ and changes in healthcare utilization patterns over time, both the pre- and post-expansion periods of OHIP, by comparing patients in Ontario with those in other provinces. Recall that the parallel trends assumption is the important assumption of the model, which assumes the trends of outcomes are common before the OHIP+. One advantage of the event-study model is that the test of the assumption is embedded. If the coefficients β_i before OHIP+ implementation are

¹¹Notes: $i = -4$ represents Q1 2017, $i = 0$ represents Q1 2018, $i = 4$ represents Q1 2019, and $i = 7$ represents Q4 2019.

¹²Population data is available in Statistics Canada: <https://open.canada.ca/data/en/dataset/ecdee020-5919-4996-8d3d-c3df75f50ca0>.

statistically insignificant and close to zero, the model would support the parallel trends assumption.

Additionally, following Antwi et al. (2015), I use a two-way fixed effect Difference-in-differences (DD) model to summarize the post-treatment event-study estimates:

$$\begin{aligned} \ln(Y_{p,t}) = & \alpha + \beta_1 \text{Implement}_t \times ON_p + \beta_2 \text{Modification}_t \times ON_p \\ & + X_{p,t} + Prov_p + Year_Quarter_t + e_{p,t} \end{aligned} \quad (2.2)$$

where Implement_t denotes a dummy variable for the period between the first quarter of 2018 and first quarter of 2019, and Modification_t denotes a dummy variable for the period after the law was modified in the second quarter of 2019. These two variables are interacted with treatment group ON_p and captures the average treatment effects after the OHIP+ is implemented after the January 2018 and modified after the April 2019 by comparing the healthcare utilization to the period before the enactment of the law among the Ontario patients relative to other provinces.

2.5 RESULTS

2.5.1 Beneficiaries

FIGURE 2.1 presents the results of the event-study model derived from equation (2.1), providing insights into the pre- and post-treatment effects of OHIP+ on total emergency department visitors among aged 18-24 between patients from Ontario and those from other provinces. The analysis indicates that the effects of OHIP+ on young patients' emergency department utilization are close to zero and statistically insignificant, both after the introduction in 2018 and modification in 2019. This would suggest that access to publicly covered prescription drugs has no effect on the frequency with which young patients (younger than 25) use the emergency department, either because they don't

substitute family medicine visits for emergency department visits or because two years is not enough for them to get healthier thanks to a better access to prescription drugs.

It could also be that the introduction of OHIP+ did not change anything for those who were already covered by their parents' employer-sponsored plan, thus swamping the effect on some specific populations. To test for this, I examined heterogeneity within this no effect result, under the assumption that individuals from low-income families are both more sensitive to the cost of prescription drugs when not covered and less likely to be covered prior to the introduction of OHIP+; I then test whether the effect is more sensitive on ACSC or non-ACSC visits.

FIGURE 2.2 illustrates the outcomes of the event-study model by equation (2.1), specifically for beneficiaries residing in low-income households. The figure confirms that prior to the enactment of OHIP+ in Ontario, there was no discernible difference between Ontario and other provinces in terms of total emergency department visits, thus supporting the hypothesis of equivalent pre-trend conditions. Following the implementation of OHIP+, the model reveals statistically significant negative effects, suggesting a reduced propensity for emergency department visits among this demographic. Furthermore, these negative impacts persist after the policy change.

TABLE 2.2 shows the post-treatment effects for beneficiaries following the implementation of the OHIP+ policy, using Equation (2.2), summarizing effects illuminated by the event-study analysis. In the first column, the data illustrates that subsequent to the introduction and subsequent refinement of OHIP+, there is an indication of negative effects; nonetheless, these effects are not statistically significant. Statistically significant negative effects are found in column (2), for beneficiaries from low-income families, a demographic less inclined to hold private health insurance. Post-OHIP+ implementation, the emergent patterns disclose statistically significant negative effects, which become more pronounced upon the exclusion of individuals with pre-existing private insurance

coverage. Specifically, the likelihood of emergency department utilization decreases by 5.5% ($p < .01$) following the policy's initiation and exhibits a further decrement of 6.6% ($p < .05$) subsequent to the policy's modification.

Therefore, TABLE 2.2 provides evidence of OHIP+'s effect in fostering a decline in emergency department utilization among the more economically vulnerable cohorts, suggesting that public health policy can play a critical role in equilibrating healthcare access disparities.

2.5.2 Ambulatory Care Sensitive Conditions

This section examines the impact of the OHIP+ on emergency department visits distinguished by ACSC and non-ACSC instances. Since British Columbia and Manitoba do not provide information on the reasons for emergency department visits, these two provinces were excluded from the analysis. The study specifically focuses on beneficiaries within low-income brackets, using Equation (2.1).

FIGURE 2.3 illustrates that the trends among low-income beneficiaries with respect to emergency department visits for ACSC cases, revealing an absence of significant post-OHIP+ effects. Conversely, for non-ACSC visits, a small decrement is observed following the policy's implementation, reaching statistical significance approximately 7 quarters subsequent to OHIP+'s introduction (or 2 quarters after its subsequent modification). This particular outcome suggests a potential reduction in non-urgent emergency department usage among this demographic, potentially indicating improved access to necessary medications under OHIP+ that precludes the need for such emergency department visits.

TABLE 2.3 shows the results using Equation (2.2) to summarize the post-treatment effects found before. Column (2) shows that low-income patients are less likely to visit the emergency department due to non-ACSC cases. Specifically, the probability reduces by 4% ($p < .1$) and 5.6% ($p < .05$) after the introduction and modification, respectively. For

people from non-low-income families, statistically significant positive effects were found for ACSC cases. However, for individuals from non-low-income brackets, a contrasting pattern emerges. The analysis delineates discernible statistically significant increases in emergency department visits for ACSC cases.

2.6 CONCLUSION AND DISCUSSION

This study contributes to the existing literature on the relationship between public prescription drug insurance and healthcare utilization, and it also contributes to the debate on the introduction of a national pharmacare programme in Canada. The paper examines the impact of the OHIP+ program in Ontario, Canada, which provides prescription drug insurance to young individuals, on the utilization of emergency department services by both beneficiaries and non-beneficiaries.

Using a Difference-in-differences event-study model, the findings reveal that beneficiaries between the ages of 18 and 24 from low-income families were less likely to visit the emergency department following the implementation of OHIP+. This effect is further magnified after the program's modification (which I attribute to the effect of duration since the creation of OHIP+ rather than to the modification per se), and the observed negative effect primarily stems from non-ACSC cases. The findings provide useful information for the implementation of a public prescription drug insurance program. Providing free prescription drugs for individuals who do not have private drug insurance can enhance access to essential primary care services.

However, it is important to note that this research has certain limitations. The analysis is restricted to a two-year period following the introduction of OHIP+, which may not capture the long-term effects of the program on healthcare utilization patterns. Data availability beyond this period was limited due to several factors, including the potential impact of the COVID-19 pandemic, which could have influenced healthcare

utilization patterns. Also, since the income data is not available to locate children's family status, it is hard to determine the effect on children (0 - 18), especially for children from low-income families. Future studies with extended follow-up periods and more comprehensive data may provide a clearer understanding of the program's impact on healthcare utilization, such as hospitalization, which may have a longer lag effect than emergency department use.

2.7 REFERENCES

- Afendulis, C. C., He, Y., Zaslavsky, A. M. and Chernew, M. E. (2011). The impact of medicare part d on hospitalization rates, *Health Services Research* **46**(4): 1022–1038.
- Allin, S. and Hurley, J. (2009). Inequity in publicly funded physician care: what is the role of private prescription drug insurance?, *Health Economics* **18**(10): 1218–1232.
- Anderson, M. L., Dobkin, C. and Gross, T. (2014). The effect of health insurance on emergency department visits: Evidence from an age-based eligibility threshold, *Review of Economics and Statistics* **96**(1): 189–195.
- Antonipillai, V., Guindon, G. E., Sweetman, A., Baumann, A., Wahoush, O. and Schwartz, L. (2021). Associations of health services utilization by prescription drug coverage and immigration category in ontario, canada, *Health Policy* **125**(10): 1311–1321.
- Antwi, Y. A., Moriya, A. S. and Simon, K. I. (2015). Access to health insurance and the use of inpatient medical care: Evidence from the affordable care act young adult mandate, *Journal of Health Economics* **39**: 171–187.
- Baicker, K., Taubman, S. L., Allen, H. L., Bernstein, M., Gruber, J. H., Newhouse, J. P., Schneider, E. C., Wright, B. J., Zaslavsky, A. M. and Finkelstein, A. N. (2013). The oregon experiment - effects of medicaid on clinical outcomes, *New England Journal of Medicine* **368**(18): 1713–1722.
- Bertrand, M., Duflo, E. and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates?, *The Quarterly Journal of Economics* **119**(1): 249–275.

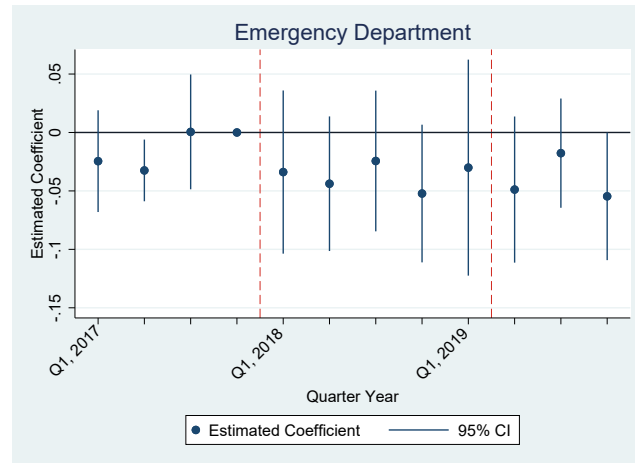
- Bolatova, T. and Law, M. R. (2019). Income-related disparities in private prescription drug coverage in canada, *Canadian Medical Association Open Access Journal* **7**(4): E618–E623.
- Canadian Life & Health Insurance Association (2021). Canadian life health insurance facts, 2021 edition.
- Courtemanche, C., Marton, J., Ukert, B., Yelowitz, A. and Zapata, D. (2019). Effects of the affordable care act on health behaviors after 3 years, *Eastern Economic Journal* **45**: 7–33.
- Dafny, L. and Gruber, J. (2005). Public insurance and child hospitalizations: access and efficiency effects, *Journal of Public Economics* **89**(1): 109–129.
- Dunn, A., Knepper, M. and Dauda, S. (2021). Insurance expansions and hospital utilization: Relabeling and reabling?, *Journal of Health Economics* **78**: 102482.
- Ellis, C. M. and Esson, M. I. (2021). Crowd-out and emergency department utilization, *Journal of Health Economics* **80**: 102542.
- Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J. P., Allen, H., Baicker, K. and Group, O. H. S. (2012). The oregon health insurance experiment: evidence from the first year, *The Quarterly Journal of Economics* **127**(3): 1057–1106.
- Gagnon, M.-A. (2021). Understanding the battle for universal pharmacare in canada comment on " universal pharmacare in canada", *International Journal of Health Policy and Management* **10**(3): 168.
- Kaestner, R., Schiman, C. and Alexander, G. C. (2019). Effects of prescription drug insurance on hospitalization and mortality: evidence from medicare part d, *Journal of Risk and Insurance* **86**(3): 595–628.

- Law, M. R., Cheng, L., Dhalla, I. A., Heard, D. and Morgan, S. G. (2012). The effect of cost on adherence to prescription medications in canada, *Canadian Medical Association Journal* **184**(3): 297–302.
- Liu, F. X., Alexander, G. C., Crawford, S. Y., Pickard, A. S., Hedeker, D. and Walton, S. M. (2011). The impact of medicare part d on out-of-pocket costs for prescription drugs, medication utilization, health resource utilization, and preference-based health utility, *Health Services Research* **46**(4): 1104–1123.
- Marchildon, G. P., Allin, S. and Merkur, S. (2021). *Health Systems in Transition Third Edition*, University of Toronto Press.
- Martin, D., Miller, A. P., Quesnel-Vallée, A., Caron, N. R., Vissandjée, B. and Marchildon, G. P. (2018). Canada’s universal health-care system: achieving its potential, *The Lancet* **391**(10131): 1718–1735.
- Miller, S. and Wherry, L. R. (2017). Health and access to care during the first 2 years of the aca medicaid expansions, *New England Journal of Medicine* **376**(10): 947–956.
- Miregwa, B. N., Holbrook, A., Law, M. R., Lavis, J. N., Thabane, L., Dolovich, L. and Wilson, M. G. (2022). The impact of ohip+ pharmacare on use and costs of public drug plans among children and youth in ontario: a time-series analysis, *Canadian Medical Association Open Access Journal* **10**(3): E848–E855.
- Morgan, S., Daw, J. and Law, M. R. (2013). Rethinking pharmacare in Canada, *CD Howe Institute Commentary* **384**.
- Nikpay, S., Freedman, S., Levy, H. and Buchmueller, T. (2017). Effect of the affordable care act medicaid expansion on emergency department visits: evidence from state-level emergency department databases, *Annals of Emergency Medicine* **70**(2): 215–225.
- Pauly, M. V. (1968). The economics of moral hazard: comment, *The American Economic Review* **58**(3): 531–537.

- Pauly, M. V. and Held, P. J. (1990). Benign moral hazard and the cost-effectiveness analysis of insurance coverage, *Journal of Health Economics* **9**(4): 447–461.
- Tamblyn, R., Laprise, R., Hanley, J. A., Abrahamowicz, M., Scott, S., Mayo, N., Hurley, J., Grad, R., Latimer, E., Perreault, R. et al. (2001). Adverse events associated with prescription drug cost-sharing among poor and elderly persons, *Jama* **285**(4): 421–429.
- Taubman, S. L., Allen, H. L., Wright, B. J., Baicker, K. and Finkelstein, A. N. (2014). Medicaid increases emergency-department use: evidence from oregon’s health insurance experiment, *Science* **343**(6168): 263–268.
- Wang, C., Li, Q., Sweetman, A. and Hurley, J. (2015). Mandatory universal drug plan, access to health care and health: evidence from canada, *Journal of Health Economics* **44**: 80–96.

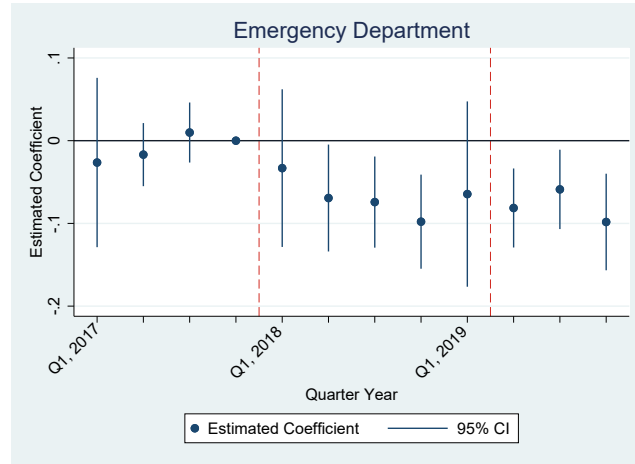
2.8 FIGURES AND TABLES

FIGURE 2.1: Expansion of OHIP and Emergency Department Visits, Aged 18-24



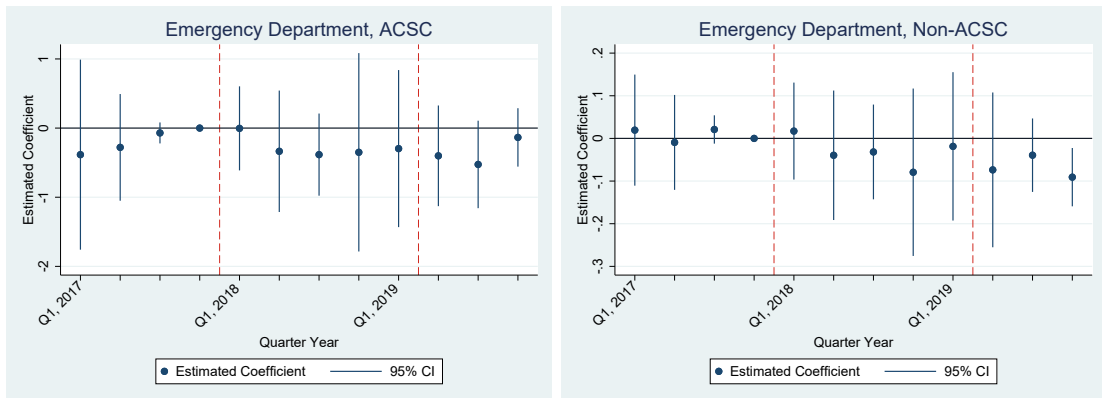
Notes: Each point represents the estimated quarterly coefficient from the difference-in-differences event study model for emergency department visits among patients aged 18–24 between emergency department visitors from Ontario and those from other provinces, with vertical lines indicating 95% confidence intervals. The red dashed lines denote OHIP+ implementation (January 2018) and subsequent policy modification (April 2019). Standard errors clustered at the provincial level.

FIGURE 2.2: Expansion of OHIP+ and Emergency Department Visits, 18-24 from Low-income Families.



Notes: Each point represents the estimated quarterly coefficient from the difference-in-differences event study model for emergency department visits among patients aged 18–24 from low-income families, with vertical lines indicating 95% confidence intervals. The red dashed lines denote OHIP+ implementation (January 2018) and subsequent policy modification (April 2019). Standard errors clustered at the provincial level.

FIGURE 2.3: Expansion of OHIP and Emergency Department Visits, 18-24 from Low-income Families, ACSC and Non-ACSC



Notes: Each point represents the estimated quarterly coefficient from the difference-in-differences event study model for emergency department ACSC and non-ACSC visits among patients aged 18–24 from low-income families, with vertical lines indicating 95% confidence intervals. The red dashed lines denote OHIP+ implementation (January 2018) and subsequent policy modification (April 2019). Standard errors clustered at the provincial level.

TABLE 2.1: Summary Statistics - Emergency Department Visits
Aged 18 - 24

	(1) Overall	(2) Ontario	(3) Other Province
Age	21.12 (1.97)	21.11 (1.97)	21.14 (1.97)
Male	0.42 (0.50)	0.42 (0.50)	0.41 (0.49)
Unemployment rate	11.51 (1.60)	11.73 (0.80)	11.20 (2.24)
Low income family rate	0.30 (0.46)	0.29 (0.29)	0.31 (0.46)
Obs	2,328,155	1,346,095	982,060

Notes: Mean values of each variable are showed with standard deviation in parentheses. Age and gender variables obtained from NACRS database. Income and low-income family variables are linked from T1FF data. Provincial unemployment rates obtained from Statistic Canada.

TABLE 2.2: Difference-in-differences model: Emergency
Department Visits, Age 18-24

	(1) All Patients	(2) Patients from low- income families
Introduction	-0.023 (0.021)	-0.055*** (0.009)
Modification	-0.024 (0.026)	-0.066** (0.020)
Obs	84	84
Time FE	Yes	Yes
Province FE	Yes	Yes

Notes: This table represents the estimated effects of OHIP+ introduction and modification on emergency department admissions. Using equation (2), column (1) shows the results on total emergency department visits for all patients, column (2) shows the effects for patients from low-income families. Standard errors at province level are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

TABLE 2.3: Difference-in-differences Model: Emergency Department Visits, 18-24 From Low-income Families

	(1) ACSC	(2) Non-ACSC
Introduction	0.010 (0.037)	-0.040*** (0.015)
Modification	-0.057 (0.124)	-0.056** (0.015)
Obs	60	60
Time FE	Yes	Yes
Province FE	Yes	Yes

Notes: This table represents the estimated effects of OHIP+ introduction and modification on emergency department admissions because of ACSC cases and Non-ACSC cases. Using equation (2), column (1) and (2) show the results on patients from low-income families. Standard errors at province level are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

2.9 APPENDIX

TABLE A2.1: Elements of ACSC Defined by CIHI, with ICD-10 Codes

a. Grand mal status and other epileptic convulsions
ICD-9/9-CM: 345
ICD-10-CA: G40, G41
b. Chronic lower respiratory diseases (except asthma)
Any most responsible diagnosis (MRDx) code of
ICD-9/9-CM: 491, 492, 494, 496
ICD-10-CA: J41, J42, J43, J44, J47
c. MRDx of acute lower respiratory infection, only when a secondary diagnosis of J44 in
ICD-10-CA or 496 in ICD-9/9-CM is also present
ICD-9/9-CM: 466, 480–486, 487.0
ICD-10-CA: J10.0, J11.0, J12–J16, J18, J20, J21, J22
d. Asthma
ICD-9/9-CM: 493
ICD-10-CA: J45
e. Diabetes
ICD-9: 250.0, 250.1, 250.2, 250.7
ICD-9-CM: 250.0, 250.1, 250.2, 250.8
ICD-10-CA: E10.0, E10.1, E10.63, E10.64, E10.9, E11.0, E11.1, E11.63,
E11.64, E11.9, E13.0, E13.1, E13.63, E13.64, E13.9, E14.0, E14.1, E14.63, E14.64, E14.9
f. Heart failure and pulmonary edema*
ICD-9/9-CM: 428, 518.4
ICD-10-CA: J81 (MRDx), I50 (MRDx), I50 as diagnosis type (1) when I11 is MRDx
g. Hypertension*
ICD-9/9-CM: 401.0, 401.9, 402.0, 402.1, 402.9
ICD-10-CA: I10 (MRDx), I11 as MRDx when I50 as diagnosis type (1) is not present
h. Angina*
ICD-9: 411, 413
ICD-9-CM: 411.1, 411.8, 413
ICD-10-CA: I20, I23.82, I24.0, I24.8, I24.9

Notes : *Excluding cases with cardiac procedures.

Chapter 3

The Role of Cancer Diagnosis in Household Spending Patterns: Evidence from Canada

Abstract

Linking the 2016–2017 Survey of Household Spending to the Canadian Cancer Registry, this study quantifies how a recent cancer diagnosis reshapes Canadian family budgets. Ordinary Least Squares and Seemingly Unrelated Regression models are used to compare spending patterns of households with and without a diagnosis in the past five years. On average, affected families cut total outlays by 7.1 percent, driven mainly by reductions in food and income taxes. Despite this contraction, most budget shares move by less than one percentage point. Families with children shift roughly five percentage points of their budget toward housing; single parents simultaneously boost housing and personal-insurance spending while trimming food; working-age households redirect resources from transportation and taxes to housing and health care, reflecting labour-market disruption and medical needs; and families experiencing a repeat diagnosis show only a modest rise

in recreation. The results provide insights into how an income shock prompted by a cancer diagnosis tends to reshape households' expenditure.

3.1 INTRODUCTION

The relationship between household expenditure and income has been an important theme in applied microeconomics since at least the seminal work of Deaton and Muellbauer (1980). Most of the attention has been devoted to the dynamics of total consumption (versus savings) in response to income shocks (e.g., Agarwal and Qian (2014); Cho et al. (2019); Agarwal et al. (2024)). However, it is also of interest to economists and policy makers to understand changes in consumption patterns in response to income shocks. This is a much smaller literature but it shows that a positive income shock increases spending on non-durable goods (Shapiro and Slemrod, 2003; Krueger and Perri, 2011; Cloyne and Surico, 2017). In Canada, a permanent positive income shock for households with children led to an increase in the share of child care spending in total expenditure (Adams et al., 2020). Exploring the impact of negative income shocks on various types of expenditures within the total budget remains crucial for studies into poverty and well-being, such as the well-known Engel's curve that links income levels to the budget share of food expenditures.

Cross-sectional analyses often struggle to differentiate between differences in preferences across income levels and the causal effect of differences in budget constraints. For instance, the question arises: do lower-income families allocate a larger portion of their budget to basic necessities like food because they prefer to, or is it a strategy to maximize their well-being given their financial constraints? This distinction is critical for accurately assessing well-being; if spending patterns are driven more by preference (behaviour remains stable with income shocks) than constraints (behaviour changes with income shocks), changes in budget allocation might not truly reflect changes in well-being. A cancer diagnosis can therefore be viewed not only as an exogenous shock to income, but also as a potential shock to preferences. The key assumption is that the shock does not differ according to households' pre-diagnosis preferences.

Exogenous shocks such as a cancer diagnosis can be used to mimic a natural experiment and approximate causal inference within cross-sectional data. A cancer diagnosis constitutes a sudden and largely unanticipated health shock that often leads to reductions in household income and increases in out-of-pocket (OOP) medical expenditures (Pak et al., 2020). Biological evidence strongly suggests cancer is indeed unpredictable and exogenous: Tomasetti and Vogelstein (2015) argue that stochastic mutations arising during DNA replication are the primary drivers of cancer in humans, rather than lifestyle factors such as poor diet, environmental exposures, or inherited genetic predispositions¹.

Economic evidence shows that, even in a country with public health insurance covering hospitalization and physician services, such as Canada, a cancer diagnosis represents on average an increase in constrained expenditures (out-of-pocket expenditures linked to treatment) and a decrease in income. Increase in treatment-related out-of-pocket spending is documented by Longo et al. (2021) who show that the average monthly out-of-pocket cost for Canadian cancer patient is \$518 with \$179 for treatment-related travel and \$84 for parking, and by Essue et al. (2022) who find \$1,600 per year or about 3% of the household income in Canada. The decrease in income following breast cancer for Canadian women is documented by Lauzier et al. (2008). Similar results are found by Jeon (2017) that Canadian cancer patients are less likely to work for the first three years after diagnosis. Additionally, Jung et al. (2022) found that among cancer survivors in Canada, earnings were \$11,244 (27.7%) lower than for people without cancer diagnosis one year after diagnosis. A recovery began around year two, yet by year five survivors still earned \$6,591 (15.1%) less than controls.

¹This interpretation is drawn from the authors' interview about the study, as reported in NBC News, "It's Not Your Fault: Researchers Confirm Cancer Is Often Random." Available at: <https://www.nbcnews.com/health/cancer/it-s-not-your-fault-researchers-confirm-cancer-often-random-n737776>.

Therefore, by comparing the budget shares of various expenditure items for households with and without a recent cancer diagnosis, while controlling for observable characteristics (e.g., age, household size), we can assess how household spending adjusts in response to an income shock. If households with a cancer diagnosis spend more of their budget on necessities and less on discretionary spending than similar households without a diagnosis, this provides suggestive evidence that financial constraints - rather than preferences - drive spending behaviour.

This study analyzes how a cancer diagnosis affects the share of the total budget a household spends on food, housing, transportation, healthcare, recreation, education, income tax, personal insurance, and other expenditure items by linking the 2016–2017 SHS with administrative cancer records from the CCR. It reveals that affected households reduce their overall expenditures but that the shares devoted to each category remain relatively stable. The impact is not uniform, however, spending responses differ markedly by household composition, with single versus partnered adults and families with versus without children adjusting their budgets in distinct ways. This study contributes to a deeper understanding of how a cancer diagnosis influences household financial decisions beyond just out-of-pocket expenses (OOPE).

The remainder of this paper is organized as follows: Section 2 describes the data, Section 3 outlines the empirical strategy, Section 4 presents the results, Section 5 covers the heterogeneity effects, and Section 6 discusses the findings and concludes.

3.2 DATA AND VARIABLES

3.2.1 Data

The analysis is based on two waves of repeated cross-sectional data from the Canadian Survey of Household Spending (SHS) for the period 2016 to 2017, with each cross-section

linked to the Canadian Cancer Registry (CCR) from 2011 to 2017.

The SHS, a national survey conducted across Canada's ten provinces and three territorial capitals, gathers comprehensive data on household expenditures on various types of goods and services. It also captures details on demographic and dwelling characteristics, as well as household equipment for approximately 48,000 households across Canada annually (Statistic Canada, 2017). The SHS employs two primary data collection tools: a questionnaire and an expenditure diary. The questionnaire gathers information on large and infrequent expenses. The expenditure diary, distributed to a subset of SHS households, records frequent or minor expenses that might be challenging to remember in a retrospective interview. Because completion of the diary was optional (volunteers) and less than 50% of respondents chose to do so, this study focuses solely on data obtained from the questionnaire². The recall period ranges from two weeks to twelve months depending on the item of expenditure. Thus, I used the modified dataset provided by Statistics Canada, which converts all dollar values to annual figures.

The SHS and Statistics Canada defined Total Expenditure as the sum of Total consumption, Income taxes, Personal insurance and pension contributions, and Gifts of money, support payments and charitable contributions Statistics Canada (2017), where Total consumption is further decomposed into fourteen categories:

- Food: Food purchased from stores
- Shelter: Rent, water, fuel and electricity fees, etc.
- Household operations: Cell phone, internet services, household cleaning and supplies, etc.
- Household furnishings and equipment: Furniture, air conditioners, heating equipment, etc.

²In 2016 and 2017, the response rates in questionnaire are 65% and 67%.

- Clothing and accessories: Foot wear, clothing, jewellery, laundry services, etc.
- Transportation: Automobiles, fees for lease, parking, public transportation, etc.
- Healthcare: Medicines, eye-care services, dental services, etc.
- Personal care: Hair grooming, and other personal care services.
- Recreation: Computer, E-book readers, entertainment, trip, children's camps, etc.
- Education: Tuition fees, textbooks, etc.
- Reading materials and other printed matter: Books and E-books.
- Tobacco products, alcoholic beverages and cannabis for non-medical use: Cigarettes, alcoholic beverages purchased from stores, etc.
- Games of chance: Government-run lotteries, casinos, etc.
- Miscellaneous expenditures: Financial services, fines, etc.

Because Tobacco products, alcoholic beverages and cannabis for non-medical use as well as Games of chance expenditure are only available in the diary, Total Expenditure is defined as the sum of spending on the remaining twelve items of Total consumption plus the other components of Total expenditures (taxes, contributions, donations etc.).

The CCR, a national population-based cancer registry, compiles data on new primary cancer diagnoses in people residing in Canada, reported by each provincial/territorial cancer registry to Statistics Canada. Data from Quebec have been absent from the CCR since 2011; therefore, households from Quebec were excluded from this study. The registry is exhaustive: any time a patient is diagnosed with a new cancer, they enter the registry with a common identifier that allows to link their cancer information to the SHS, including the date of diagnosis (which is used in this study to determine households with

a member with a recent diagnosis of cancer). In addition, the CCR provides longitudinal records of cancer diagnoses over multiple years, allowing the identification of patients' documented cancer histories. For instance, it is possible to observe cases where an individual was diagnosed with lung cancer in 2010 and subsequently with liver cancer in 2017. In the linked data in the Research Data Centre (RDC), CCR records are available from 2010 to 2017. Consequently, cancer diagnoses are observable only from 2010 onward, and events prior to 2010 are not captured. I use cancer diagnoses from 2011 to 2016 to determine households with a cancer diagnosis in the past five years in SHS 2016 and cancer diagnoses from 2012 to 2017 for SHS 2017.

3.2.2 Dependent Variables

The SHS Interview reported the annual value of total expenditure, and expenditures for all its components including a) Food, b) Shelter, c) Household operations, d) Household furnishings and equipment, e) Clothing and accessories, f) Transportation, g) Healthcare, h) Personal care, i) Recreation, j) Education, k) Reading materials and other printed matter, l) Miscellaneous expenditures, m) Personal taxes, n) Total personal insurance payments and pension contributions, o) Total gifts of money and contributions. A detailed list of each expenditure group is shown in TABLE A3.1 in the appendix.

To simplify the presentation of the results, I grouped Shelter, Household operations, Household furnishings and equipment as Housing. Additionally, I grouped Clothing and accessories, Personal care, Reading materials and other printed matter, Miscellaneous expenditures and Gifts of money, support payments and charitable contributions as Others because of low budget shares for each of them. Therefore, we have nine components left, a) Food, b) Housing, c) Transportation, d) Healthcare, e) Recreation, f) Education, g) Personal taxes, h) Total personal insurance payments and pension contributions, i) Others.

To examine the extent to which a cancer diagnosis influences household expenditure patterns, I first transformed annual total expenditure and each of the nine components into their natural logarithmic form. These ten dependent variables are using in the Model (1) below to estimate the effects of cancer diagnosis on household expenditure. Subsequently, for each of the nine components of the total expenditure, the budget share is calculated by dividing the expenditure on that category by the total expenditure. These budget shares are then employed as dependent variables in separate regression models using Model (2) below to estimate the association between cancer diagnosis and the composition of household spending. Therefore, these dependent variables allow for the assessment of both overall changes in expenditure levels and shifts in the allocation of resources across categories, providing a comprehensive view of the household's response of a cancer diagnosis.

3.2.3 Main Independent Variable

To investigate the differences in consumption patterns between households with and without a cancer patient, this study focuses on the presence of incident cancer in the past 5 years in CCR. This variable is captured through a dummy indicator signifying the existence or absence of a cancer patient diagnosed within the previous five years (Jeon, 2017). The reason we choose five-year as the threshold is because Parkin et al. (2001); Canadian Cancer Society (2023); Statistics Canada (2023) show individuals who have survived cancer for five years or more are expected to survive longer as the mortality rate past five years declines substantially for most cancer types. Therefore, the baseline model seeks to examine the extent of impacts on household consumption patterns, tracking these effects over a five-year period post-diagnosis. TABLE A3.2 in the Appendix reports the distribution of cancer types classified according to ICD-10 diagnosis codes for the study sample.

3.2.4 Control Variables

Because I use a cross section and the difference between households with and without a member diagnosed with cancer, the effect of a cancer diagnosis on expenditure patterns must be controlled for potential confounding factors, which are the usual individual determinants of budget shares, as well as the provincial ones (macro-economic environment). At the individual (household) level, these determinants include: the square root of household size³; the urban nature of the place of residence, classified as a binary variable, where rural areas⁴ were assigned a value of 0 and urban areas a value of 1; household after-tax income because it is an obvious determinant of consumption patterns Kronmal (1993); age is measured as follows: when only the interviewer's age is available, that value is used; when both the interviewer's and spouse's ages are reported, their average age is used instead. For education, I created an indicator to show if the highest education level in the household is higher than high school or not.⁵ To control for broader macroeconomic conditions that might influence spending patterns, I included the unemployment rate for each province and year, as well as the GDP per capita for each province and year.

TABLE 3.1 shows the summary statistics for all variables used in the analysis, separately for the full sample and for households with a cancer diagnosis in the past five years. Over the study period, 4.2 percent of households (989 of 23,340) reported a recent cancer diagnosis. Average total expenditure is similar in the two groups, yet households affected by cancer spend less on housing, transportation, education, and personal insurance. Households affected by cancer are, on average, older and have higher after-tax

³Previous literature found non-linear relationship between the household size and household expenditure (Cutright, 1971; Kiran et al., 2015)

⁴In the SHS dataset, the variable 'UrbanSize' is used to distinguish between urban and rural households. Values 1 through 6 correspond to different categories of urban population size, while a value of 7 indicates a rural area. Accordingly, households with an 'UrbanSize' value not equal to 7 are classified as residing in urban areas.

⁵Education is coded from 1 to 7, from 'Less than high school' to 'University degree above a Bachelor'.

income. Roughly 90 percent of households in both groups reside in urban areas, and 65 percent have obtained education beyond high school.

Based on the data privacy policy of the SHS-CCR linkage, all observation counts presented in the summary statistics and regression tables are subject to mandatory rounding to the nearest multiple of 5 or 10. For instance, an observed count of 104 is reported as 105.

3.3 EMPIRICAL STRATEGY

To examine the impact of cancer on household expenditure (both total and for each component), I employed a log-linear regression model. Furthermore, to assess how cancer influences household expenditure patterns, I utilized an Ordinary Least Squares (OLS) regression model in which the dependent variable is the share of each expenditure category, for instance, the ratio of housing expenditure to total household expenditure. It is important to note that not all households have expenses in every category, and the presence of cancer may prompt some households to begin allocating resources to new categories, such as healthcare. Therefore, a Probit model was used to examine the likelihood that a household incurs expenditure in each category.

3.3.1 The Value of Expenditures

To estimate the effects of cancer on household spending and its various components, a log-linear model was applied by converting expenditure values (dependent variable) to their natural logarithms. This transformation helps to satisfy the assumption of normal distribution. The model is specified as follows:

$$\log(Y_i^j) = \beta^j Cancer_i + X_i + Z_{p,t} + \eta_p + \phi_t + \epsilon_i \quad (3.1)$$

where Y_i^j denotes household expenditure⁶, either total or a component for household i and the component j . The vector X_i includes the individual and household attributes listed above that are known to affect the expenditure ratio. $Z_{p,t}$ are macroeconomic variables. To control for unobserved heterogeneity across provinces and over time, the model employs fixed effects for provinces (η_p) and years (ϕ_t). Standard errors are estimated using a bootstrap procedure with 500 replications, employing the SHS bootstrap weights to account for sampling variability. β^j represents the estimated effect of a cancer diagnosis on household expenditure, a positive value meaning that households affected by cancer spend more than unaffected households.

3.3.2 Household Expenditure Pattern

The presence of a cancer patient in the household not only influences overall household expenditure, but may also alter the allocation of spending across different categories. For instance, families may increase their spending on healthcare services while reducing expenditures on other areas such as travel. To examine the impact of a cancer diagnosis on household consumption patterns, I employed an OLS regression model in which the dependent variable is the ratio of each expenditure component to total household expenditure. This approach allows for the analysis of changes in spending shares across categories. The model specification is as follows:

$$\frac{Y_i^j}{Total\ Expenditure} = \beta^j Cancer_i + X_i + Z_{p,t} + \eta_p + \phi_t + \epsilon_i \quad (3.2)$$

where Y_i^j denotes the ratio of the level of expenditure on each of the nine items j for the household i . This dependent variable captures the household's budgetary allocation, offering insight into its priorities given available resources. $Cancer_i$ indicates whether the household has (a) cancer patient(s)/patient(s) diagnosed within the five years prior to

⁶I also test the results on household income, both before and after tax.

the survey year. Other variables are defined as above and standard errors bootstrapped 500 times.⁷

Additionally, given that household expenditures across categories (e.g., housing, health, recreation) may be jointly determined and influenced by common unobserved factors, I employ a Seemingly Unrelated Regression (SUR) model to estimate the system of equations, which allows for contemporaneous correlation in the error terms across different expenditure equations, improving estimation efficiency compared to running separate OLS regressions.

3.4 RESULTS

3.4.1 The Effects of Cancer on the Value of Household Expenditure

TABLE 3.2 presents the estimated effects of a cancer diagnosis on total household expenditure and its major components, using equation (3.1). Each column displays results from a separate regression, where the dependent variable is the natural logarithm of a specific expenditure category. Column (1) indicates that households with a cancer diagnosis spend 7.1% less in total than those without cancer ($p < 0.01$), controlling for all other determinants of total expenditures. Similarly, significant negative associations are found for food expenditure (Column (2) - 4.6% lower, $p < 0.1$) and income tax (Column (8) - 13.9% lower, $p < 0.05$). The reduction in income tax expenditure may reflect households' eligibility for caregiver tax credits and medical expense deductions when providing care for a cancer patient. Although only decreases in food and income tax expenditures are statistically significant, most other categories also show a downward trend, with the exception of healthcare services, which exhibit an increase. Overall, these findings suggest that the presence of a cancer patient in the household is

⁷To accommodate the skewed distribution in Education expenditure, since about 20% of households reported zero expenditure in Education, I used a Tobit model as a sensitivity analysis. The result is similar to the OLS model.

associated with a notable reduction in total and component expenditures. TABLE A3.3 in the Appendix reports the results for household income before and after tax. In both cases, the estimates indicate that a cancer diagnosis is associated with a lower household income, although the effects are not statistically significant.

3.4.2 The Effects of Cancer on Household Expenditure Pattern

TABLE 3.3 presents the estimated effects of a cancer diagnosis on the household expenditure patterns, using equation (3.2). Each column corresponds to a separate regression, and the dependent variable is the proportion of household spending devoted to a specific category. A recent cancer diagnosis increases the budget shares of food, housing, transportation, healthcare services, recreation and other spending, although the effects are small and not statistically significant. For instance, having a recent cancer patient in the family will increase the share of expenditure on healthcare by 0.2 percentage points compared with households without a recent cancer patient, which is equivalent to an increase of 5.8 % of the initial budget share. Negative effects are observed for education, income tax, and personal insurance expenditures, with the respective shares of household spending decreasing by 0.2 percentage points, 0.7 percentage points, and 0.2 percentage points. Overall, the results indicate that while there are some shifts in the composition of household spending associated with a cancer diagnosis, the magnitude of these changes is limited and none of the effects are statistically significant. This suggests that the presence of a cancer patient does not lead to substantial reallocation of household expenditure shares across major spending categories.

3.4.3 Seemingly Unrelated Regression

The results from the SUR, shown in TABLE 3.4, are similar to those from the OLS models suggest that the error terms across the different expenditure categories (Food,

housing, transportation, health, recreation, education, income tax and personal insurance, excluded other expenditure) are not significantly correlated. This lack of correlation implies that the determinants of each expenditure category operate relatively independently, resulting in minimal efficiency gains from using SUR over OLS. Thus, the OLS models are sufficient for estimating the effects of cancer on household spending, as they provide reliable and robust estimates without the need for the more complex SUR approach. This finding simplifies the analysis process and supports the use of OLS in similar future studies.

3.5 HETEROGENEITY ANALYSES

The average effects may mask important differences across households. Since family structure (single, couple, with and without children), patient's type and prior cancer history may have different financial responses to a cancer diagnosis, analyzing heterogeneous groups helps reveal how the burden is distributed and through which channels spending patterns are affected. Therefore, below I present the results for 1) households with children, 2) single and couple, with and without children, 3) cancer patients younger than 55, and 4) patients with and without a previous cancer diagnosis.

3.5.1 Households with Children

The analysis so far has analyzed household expenditures without distinguishing between those with and without children⁸, potentially introducing a negative bias in the expenditure results related to children. To uncover more specific effects on households with children, TABLE 3.5 presents results exclusively for these households. Column (2) shows that, for households with children, having a recent cancer patient is associated with a 5 percentage point increase in housing expenditure share, equivalent to a 14.7% rise. This finding may reflect the heightened importance of maintaining stability in schooling and

⁸Households with children are defined as those with at least one youngest child under 18.

social environments during periods of health-related stress. In such circumstances, families may allocate additional resources toward securing stable and higher-quality housing to minimize disruptions to their children's education and social networks. Furthermore, in an effort to reduce the impact on children's activities and life, households may choose to reside closer to specialized healthcare facilities or support services, which are often located in areas with higher housing costs. Other non-statistically significant positive effects are found in food and healthcare expenditures. Negative effects are found in transportation, recreation goods, education spending, income tax, insurance and others, but none of them are statistically significant.

3.5.2 Single, Couple and Children

To further investigate heterogeneity in the effect of a recent cancer diagnosis by household composition, I extend the analysis to examine single and coupled households both with and without children. As shown in TABLE 3.6, for single-parent households, cancer is associated with increased shares on housing and personal insurance, and decreased shares on food. More specifically, the share of expenditure allocated to housing rises by 10.9 percentage points, while personal insurance increases by 4.9 percentage points. These changes may reflect the heightened need for housing stability and financial security in response to health-related uncertainty, as well as a greater emphasis on safeguarding the well-being of both the patient and dependents. At the same time, the reduction in food expenditure could indicate the need to reallocate limited resources toward essential fixed costs or reflect changes in household consumption patterns following a cancer diagnosis. In contrast, as shown in TABLE 3.7, the decrease in food expenditure is not observed among households consisting of a single adult without children. While the positive association between cancer and housing expenditure persists in these households, the magnitude declines to 6.4 percentage points. Additionally, there is a notable reduction in education spending, which decreases by 1.9 percentage points. These findings

suggest that the effects of cancer on household spending patterns may vary according to household composition and the presence of children. Moreover, since no negative effects are observed among households with children, it appears that, while cancer affects various household expenditure categories, these families prioritize and safeguard investments in their children's development.

For couple-with-children households, consumption patterns remain relatively stable following a cancer diagnosis. As indicated in TABLE 3.8, a small rise in the share of housing expenditure is partially offset by a decline in personal-insurance spending, suggesting that these households prioritize residential stability while reducing outlays on discretionary insurance products deemed less immediately essential. Such reallocation leaves overall spending patterns largely unchanged, consistent with the larger income base and intra-household risk-sharing capacity typical of two-adult families with children. By contrast, among couple households without children, TABLE 3.9 shows only one statistically significant effect: the share of expenditure devoted to healthcare services increases by 0.8 percentage points, implying that in the absence of child-related needs, additional resources are directed primarily toward medical care.

3.5.3 Cancer Patient Younger Than 55

I introduce that heterogeneity study because individuals younger than 55 are more likely to be employed and to face binding mortgage and childcare costs. When cancer occurs in this group, it can reduce work hours and earnings, and change commuting and housing choices - effects that are smaller for retirees. Also, many public pensions and health programs do not start until about age 55–65. By focusing on those under 55, we avoid mixing in the impact of these benefits and get a clearer picture of behaviour. TABLE 3.10 reports how a cancer diagnosis is associated with budget shares for households with recently diagnosed patients younger than 55. Relative to households in which the interviewer is under 55 and no recent cancer diagnosis patient, a cancer diagnosis in

households with a patient under 55 is associated with shifting the budget toward housing and health and away from transportation and income tax. These patterns are consistent with prioritizing residential stability and medical needs.

3.5.4 Previous Cancer Diagnosis History

If families have already shifted resources toward medical needs and related fixed costs, later shocks may show a smooth response to a subsequent cancer diagnosis, resulting in smaller and potentially statistically insignificant changes in expenditure. TABLE 3.11 therefore compares households with a documented cancer history with households without a cancer history. Most coefficients are small and not statistically different from zero. Transportation rises by 1.6 percentage points, but is not significant. The only statistically significant reallocation is in recreation: the share increases by 1.0 percentage points ($p < 0.10$).

Moreover, in order to examine the effects of multiple cancer diagnoses among households with a cancer patient, I re-estimated the model (2) on two subsamples - households with a single cancer diagnosis and those with two or more diagnoses in the research period - to show that multiple cancer episodes tighten budgets: as TABLE 3.12 indicates, such households allocate 0.9 percentage points less of total spending to food (Column 1) and 0.7 points less to personal insurance (Column 8) than single cancer diagnosis families.

3.6 CONCLUSION AND DISCUSSION

This analysis linking the 2016–2017 SHS with the CCR reveals that a recent cancer diagnosis reshapes household budgets modestly on average but more strongly for some specific categories of households. On average, diagnosed households register lower total expenditure than households without a cancer diagnosis records in the past five years,

with the largest absolute reductions occurring in food purchases and income-tax payments; because budget shares remain broadly stable, the primary adjustment appears to occur through a contraction in overall spending equally distributed across consumption items rather than a shift across categories.

However, the aggregate picture conceals important heterogeneity. Families with children channel a greater share of resources toward housing after a recent diagnosis of cancer. This result is consistent with efforts to preserve residential stability and school continuity, while single-parent families simultaneously increase personal insurance spending and trim food outlays. Among child-free couples, additional resources flow to healthcare, whereas single adults without children redirect expenditure from education to housing. Working-age households in which the patient is younger than fifty-five show the most pronounced compositional movement: housing and healthcare shares rise, offset by declines in transportation and income-tax shares, patterns that reflect both labour-market disruptions and heightened medical needs. Moreover, spending responses are considerably smaller when the cancer episode is not the household's first; apart from a modest rise in recreation outlays, subsequent diagnoses produce few significant reallocations, suggesting that earlier episodes may already have induced the principal financial adjustments.

While a cancer diagnosis is unanticipated, the inability to observe pre-diagnosis spending means that part of the expenditure response may be delayed due to commitments made before the health shock. For example, some expenditures like vacations, renovations and tuition may have been committed to before the diagnosis. Households cannot immediately cut those expenses, so observed spending may not fully reflect the true behavioural change. This could bias the estimated effects downward. Another limitation of this project is that the SHS is cross-sectional, meaning that it provides household spending at a single point in time. As a result, I lack the longitudinal data

needed to analyze the trends in household spending before and after health shock within the same household. This limitation prevents this paper from capturing the dynamic changes and long-term financial adjustments that households may undergo in response to a cancer diagnosis. There is potential for reverse causality, as past household spending patterns may influence the likelihood of a cancer diagnosis. For example, high spending on unhealthy goods may increase cancer risk. Moreover, to interpret the cross-sectional estimates as uncovering causal impacts, several assumptions are required. First, cancer diagnoses must be treated as effectively exogenous shocks, unrelated to unobserved determinants of household spending. Even though we argue for the exogeneity of cancer in the introduction, this assumption may still be challenged. For example, if households with riskier lifestyles are both more likely to develop cancer and to spend differently on consumption goods, then the exogeneity assumption would be violated. Second, the timing of expenditures relative to diagnosis is unobserved, meaning that some reported spending may have been committed prior to the health shock (e.g., tuition or vacations), which could attenuate the measured effect. These assumptions may not fully hold, and violations, such as unobserved heterogeneity or sample selection, could bias the results. These limitations underscore the need for longitudinal data to establish stronger causal inference. Future research could benefit from panel data to track spending patterns over time, providing a more comprehensive understanding of how a cancer diagnosis affects household consumption behaviour.

3.7 REFERENCES

- Adams, J., Amedah, S. A. and Fougere, M. (2020). Measuring the effect of child benefit on household expenditures: evidence from canadian households' survey data, *Open Journal of Social Sciences* **8**(6): 44–58.
- Agarwal, S., Ghosh, P. and Zheng, H. (2024). Consumption response to a natural disaster: evidence of price and income shocks from chennai flood, *Energy Economics* **131**: 107323.
- Agarwal, S. and Qian, W. (2014). Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in singapore, *American Economic Review* **104**(12): 4205–4230.
- Canadian Cancer Society (2023). Canadian cancer statistics, https://cdn.cancer.ca/-/media/files/research/cancer-statistics/2023-statistics/2023_pdf_en.pdf?rev=7e0c86ef787d425081008ed22377754d&hash=DBD6818195657364D831AF0641C4B45C&gl=1*14w6wrw*_gcl_au*MTc4NDU4NzgWmi4xNzEzODk3MTM5.
- Cho, Y., Morley, J. and Singh, A. (2019). Household balance sheets and consumption responses to income shocks, *Unpublished manuscript* **13**.
- Cloyne, J. S. and Surico, P. (2017). Household debt and the dynamic effects of income tax changes, *The Review of Economic Studies* **84**(1): 45–81.
- Cutright, P. (1971). Income and family events: family income, family size, and consumption, *Journal of Marriage and the Family* pp. 161–173.
- Deaton, A. and Muellbauer, J. (1980). *Economics and Consumer Behavior*, Cambridge university press.

- Essue, B. M., Oliveira, C. d., Bushnik, T., Fung, S., Hwee, J., Sun, Z., Navas, E. G., Yong, J. H. E. and Garner, R. (2022). The burden of health-related out-of-pocket cancer costs in canada: A case-control study using linked data, *Current Oncology* **29**(7): 4541–4557.
- Jeon, S.-H. (2017). The long-term effects of cancer on employment and earnings, *Health Economics* **26**(5): 671–684.
- Jung, Y., Longo, C. and Tompa, E. (2022). Longitudinal assessment of labor market earnings among patients diagnosed with cancer in canada, *JAMA Network Open* **5**(12): e2245717–e2245717.
- Kiran, T., Dhawan, S. et al. (2015). The impact of family size on savings and consumption expenditure of industrial workers: a cross-sectional study, *American Journal of Economics and Business Administration* **7**(4): 177–184.
- Kronmal, R. A. (1993). Spurious correlation and the fallacy of the ratio standard revisited, *Journal of the Royal Statistical Society Series A: Statistics in Society* **156**(3): 379–392.
- Krueger, D. and Perri, F. (2011). How does household consumption respond to income shocks?, *Technical report*, mimeo, July.
- Lauzier, S., Maunsell, E., Drolet, M., Coyle, D., Hébert-Croteau, N., Brisson, J., Mâsse, B., Abdous, B., Robidoux, A. and Robert, J. (2008). Wage losses in the year after breast cancer: extent and determinants among canadian women, *Journal of the National Cancer Institute* **100**(5): 321–332.
- Longo, C. J., Fitch, M. I., Loree, J. M., Carlson, L. E., Turner, D., Cheung, W. Y., Gopaul, D., Ellis, J., Ringash, J., Mathews, M. et al. (2021). Patient and family financial burden associated with cancer treatment in canada: a national study, *Supportive Care in Cancer* **29**(6): 3377–3386.

- Pak, T.-Y., Kim, H. and Kim, K. T. (2020). The long-term effects of cancer survivorship on household assets, *Health Economics Review* **10**(1): 2.
- Parkin, D. M., Bray, F. and Devesa, S. (2001). Cancer burden in the year 2000. the global picture, *European Journal of Cancer* **37**: 4-66.
- Shapiro, M. D. and Slemrod, J. (2003). Consumer response to tax rebates, *American Economic Review* **93**(1): 381-396.
- Statistic Canada (2017). Survey of household spending (shs), <https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&Id=314214>.
- Statistics Canada (2017). Five-year cancer survival by stage at diagnosis in canada, <https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&Id=314214>.
- Statistics Canada (2023). Five-year cancer survival by stage at diagnosis in canada, <https://www150.statcan.gc.ca/n1/pub/82-003-x/2023001/article/00001-eng.htm>.
- Tomasetti, C. and Vogelstein, B. (2015). Variation in cancer risk among tissues can be explained by the number of stem cell divisions, *Science* **347**(6217): 78-81.

3.8 TABLES

TABLE 3.1: Summary Statistics

	(1)	(2)
	All Households	Households with Cancer Patient
Total Expenditure	75548.41 (66140.90)	77505.24 (80844.17)
Food	7146.70 (4659.645)	7218.50 (6082.686)
Housing	23119.36 (18035.67)	22574.49 (17520.31)
Transportation	10203.93 (15080.65)	10069.75 (14603.63)
Healthcare	2163.49 (2971.404)	2357.32 (2531.284)
Recreation	2948.02 (5351.483)	3012.83 (4965.016)
Education	1705.00 (5378.714)	1205.67 (3930.361)
Personal Tax	15226.69 (34471.28)	17670.55 (47256.07)
Personal Insurance	5125.43 (5929.732)	4695.78 (6703.96)
Others	4553.02 (10344.24)	5681.61 (9829.629)
After-Tax Income	74121.56 (52650.51)	86041.78 (63029.27)
Education Higher Than High School	0.65 (0.48)	0.63 (0.48)
Average Age	51.92 (16.72)	63.16 (13.99)
Sqrt of Household Size	1.51 (0.44)	1.54 (0.42)
Urban	0.90 (0.30)	0.87 (0.34)
Provincial Unemployment Rate	5.86 (1.39)	5.89 (1.59)
GDP Per Capita	45.41 (2.60)	46.70 (1.67)
Unweighted Number of Observations	23,340	990

Notes : Weighted s are shown with standard deviation in parentheses with SHS sampling weights. Household variables are from SHS 2016 - 2017. Household size is reported by square root of household size. Unemployment rate and GDP per Capita are from the Statistics Canada. Personal Insurance represents the Total personal insurance payments and pension contributions.

TABLE 3.2: The Effects on the Value of Household Spending

	(1) Total Exp.	(2) Food	(3) House	(4) Transp.	(5) Health	(6) Rec.	(7) Edu.	(8) Pers. Tax	(9) Pers. Ins.	(10) Others
Cancer	-0.071*** (0.023)	-0.046* (0.026)	-0.044 (0.027)	-0.043 (0.064)	0.070 (0.058)	-0.071 (0.063)	-0.287 (0.181)	-0.139** (0.060)	-0.110 (0.071)	-0.003 (0.059)
Mean	10.968	8.683	9.828	8.483	7.182	7.393	7.125	8.980	8.192	7.665
Obs	23,340	23,255	23,335	22,650	21,635	21,975	8,210	19,340	18,815	23,025
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.3: The Effects on Household Spending Pattern

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	0.002 (0.004)	0.004 (0.006)	0.005 (0.006)	0.002 (0.002)	0.001 (0.003)	-0.002 (0.002)	-0.007 (0.005)	-0.002 (0.003)	0.001 (0.004)
Mean	0.123	0.353	0.120	0.034	0.039	0.019	0.150	0.061	0.058
Obs	23,340	23,340	23,340	23,340	23,340	23,340	23,340	23,340	23,340
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.4: The Effects on Household Spending Pattern –
Seemingly Unrelated Regression

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.
Cancer	0.002 (0.004)	0.004 (0.006)	0.005 (0.006)	0.002 (0.002)	0.001 (0.003)	0.002 (0.002)	0.007 (0.005)	0.002 (0.003)
Mean	0.124	0.353	0.123	0.038	0.042	0.047	0.179	0.075
Obs	23,255	23,335	22,650	21,635	21,975	8,210	19,340	18,815
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.5: The Effects on Household Spending Pattern –
Household with Children

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	0.007 (0.010)	0.050*** (0.017)	-0.023 (0.017)	0.001 (0.004)	-0.006 (0.004)	-0.003 (0.006)	-0.016 (0.017)	-0.006 (0.009)	-0.002 (0.006)
Mean	0.121	0.341	0.125	0.025	0.037	0.024	0.153	0.075	0.043
Obs	5,560	5,560	5,560	5,560	5,560	5,560	5,560	5,560	5,560
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.6: The Effects on Household Spending Pattern – Single
Parent with Children

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	-0.075*** (0.026)	0.109** (0.053)	-0.057 (0.049)	-0.006 (0.013)	0.002 (0.014)	-0.014 (0.024)	0.014 (0.034)	0.049* (0.027)	0.014 (0.031)
Mean	0.151	0.404	0.107	0.026	0.035	0.032	0.074	0.054	0.049
Obs	1,090	1,090	1,090	1,090	1,090	1,090	1,090	1,090	1,090
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.7: The Effects on Household Spending Pattern – Single
Adult Without Children

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	0.009 (0.019)	0.064** (0.030)	-0.032 (0.026)	0.004 (0.006)	-0.001 (0.005)	-0.019** (0.008)	-0.047 (0.036)	0.020 (0.017)	-0.002 (0.018)
Mean	0.132	0.403	0.102	0.035	0.036	0.019	0.122	0.048	0.064
Obs	8,125	8,125	8,125	8,125	8,125	8,125	8,125	8,125	8,125
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.8: The Effects on Household Spending Pattern –
Coupled Adults with Children

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	0.009 (0.011)	0.052** (0.025)	-0.013 (0.027)	0.004 (0.006)	-0.004 (0.006)	-0.010 (0.016)	-0.012 (0.010)	-0.017** (0.008)	-0.009 (0.007)
Mean	0.117	0.331	0.128	0.025	0.037	0.022	0.165	0.078	0.042
Obs	4,465	4,465	4,465	4,465	4,465	4,465	4,465	4,465	4,465
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.9: The Effects on Household Spending Pattern –
Coupled Adults without Children

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	0.008 (0.009)	0.019 (0.012)	-0.019 (0.012)	0.008** (0.003)	-0.003 (0.006)	-0.002 (0.007)	-0.018 (0.014)	0.003 (0.011)	0.006 (0.007)
Mean	0.115	0.311	0.113	0.038	0.042	0.016	0.176	0.067	0.059
Obs	8,900	8,900	8,900	8,900	8,900	8,900	8,900	8,900	8,900
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.10: The Effects on Household Spending Pattern –
Cancer Patients Younger than 55

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	0.004 (0.007)	0.036*** (0.011)	-0.017* (0.010)	0.004* (0.003)	-0.004 (0.004)	-0.005 (0.005)	-0.023** (0.010)	0.004 (0.007)	0.001 (0.005)
Mean	0.123	0.353	0.119	0.034	0.038	0.019	0.150	0.062	0.057
Obs	22,565	22,565	22,565	22,565	22,565	22,565	22,565	22,565	22,565
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.11: The Effects on Household Spending Pattern –
Households with Previous Cancer Diagnosis History

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Cancer	-0.005 (0.008)	-0.005 (0.016)	0.016 (0.016)	-0.001 (0.004)	0.010* (0.006)	-0.005 (0.003)	-0.011 (0.010)	-0.004 (0.005)	0.012 (0.011)
Mean	0.123	0.353	0.120	0.034	0.039	0.019	0.149	0.061	0.058
Obs	22,530	22,530	22,530	22,530	22,530	22,530	22,530	22,530	22,530
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** p<0.01, ** p<0.05, * p<0.1. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

TABLE 3.12: The Effects on Household Spending Pattern – Single Parent with Children

	(1) Food	(2) House	(3) Transp.	(4) Health	(5) Rec.	(6) Edu.	(7) Pers. Tax	(8) Pers. Ins.	(9) Others
Multiple Diagnoses	-0.009* (0.006)	0.001 (0.013)	0.012 (0.011)	-0.004 (0.003)	0.006 (0.004)	0.002 (0.003)	-0.010 (0.008)	-0.007* (0.003)	0.010 (0.008)
Mean	0.124	0.348	0.124	0.040	0.042	0.010	0.155	0.050	0.072
Obs	990	990	990	990	990	990	990	990	990
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, after-tax income, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Total Exp. represents total expenditure; House represents housing; Transp. represents transportation; Health represents healthcare; Rec. represents recreation; Edu. represents education; Pers. Tax represents personal tax; Pers. Ins. represents the total personal insurance payments and pension contributions.

3.9 APPENDIX

TABLE A3.1: Household Expenditure Categories and Items

1 - Total current consumption

1.1 - Food expenditures

1.1.1 - Food purchased from stores

1.2 - Shelter

1.2.1 - Principal accommodation

1.2.1.1 - Rented living quarters

1.2.1.1.1 - Rent

1.2.1.1.2 - Tenants' repairs and improvements

1.2.1.1.3 - Tenants' insurance premiums

1.2.1.1.4 - Parking at rented living quarters (excluding amounts reported with rent)

1.2.1.2 - Owned living quarters

1.2.1.2.1 - Mortgage paid for owned living quarters

1.2.1.2.2 - Repairs and maintenance for owned living quarters

1.2.1.2.3 - Condominium fees for owned living quarters

1.2.1.2.4 - Property and school taxes for owned living quarters

1.2.1.2.5 - Homeowners' insurance premiums for owned living quarters

1.2.1.2.6 - Other expenditures for owned living quarters

1.2.1.2.6.1 - Commissions for sale of real estate owned by the household

1.2.1.2.6.2 - Legal fees related to owned living quarters

1.2.1.2.6.3 - Mortgage insurance premiums for owned living quarters

1.2.1.2.6.4 - Registration fees, renewal fees and early renewal or closing penalties for owned living quarters

1.2.1.2.6.5 - Transfer taxes and land registration fees for owned living quarters

Continued on next page

TABLE A3.1 continued from previous page

Category
1.2.1.2.6.6 - All other expenses related to owned living quarters (excluding repairs and maintenance)
1.2.1.3 - Water, fuel and electricity for principal accommodation
1.2.1.3.1 - Water and sewage for principal accommodation
1.2.1.3.2 - Electricity for principal accommodation
1.2.1.3.3 - Natural gas for principal accommodation
1.2.1.3.4 - Other fuel for principal accommodation
1.2.1.3.5 - Heating oil
1.2.1.3.6 - Propane for heating and cooking
1.2.1.3.7 - Wood and other fuel for heating and cooking
1.2.2 - Other accommodation
1.2.2.1 - Owned secondary residences
1.2.2.1.1 - Mortgage paid for owned secondary residences
1.2.2.1.2 - Property and school taxes, water and sewage charges for owned secondary residences
1.2.2.1.3 - Insurance premiums for owned secondary residences
1.2.2.1.4 - Electricity and fuel (e.g. natural gas and wood) for owned secondary residences
1.2.2.1.5 - Communication and home security services (e.g. landline telephone, television, satellite radio and Internet) for owned secondary residences
1.2.2.1.6 - Other expenses for owned secondary residences
1.2.2.2 - Other owned properties
1.2.2.3 - Accommodation away from home
1.2.2.3.1 - Hotels and motels
1.2.2.3.2 - Other accommodation away from home

Continued on next page

TABLE A3.1 continued from previous page

Category
1.3 - Household operations
1.3.1 - Communications
1.3.1.1 - Telephone
1.3.1.1.1 - Landline telephone services
1.3.1.1.2 - Cell phone, pager and handheld text messaging services
1.3.1.1.3 - Purchase of telephones and equipment
1.3.1.2 - Internet access services
1.3.1.3 - On-line services
1.3.2 - Pet expenses
1.3.2.1 - Veterinarian and other services
1.3.3 - Household cleaning supplies and equipment
1.3.4 - Garden supplies and services
1.3.4.1 - Groundskeeping services, snow and garbage removal
1.3.5 - Child care
1.3.5.1 - Child care outside the home
1.3.5.1.1 - Day care centres
1.3.5.1.2 - Other child care outside the home
1.3.5.1.2.1 - Child care offered in school
1.3.5.1.2.2 - Child care offered in private households
1.3.5.2 - Child care in the home
1.4 - Household furnishings and equipment
1.4.1 - Household furnishings
1.4.1.1 - Furniture
1.4.1.2 - Rugs, mats and underpadding

Continued on next page

TABLE A3.1 continued from previous page

Category
1.4.1.3 - Art, antiques and decorative ware
1.4.2 - Household equipment
1.4.2.1 - Household appliances
1.4.2.1.1 - Refrigerators and freezers
1.4.2.1.2 - Microwave ovens
1.4.2.1.3 - Cooking appliances
1.4.2.1.4 - Washers and dryers
1.4.2.1.5 - Dishwashers
1.4.2.1.6 - Room air conditioners, portable humidifiers and dehumidifiers
1.4.2.2 - Other household equipment
1.4.2.2.1 - Home and workshop tools and equipment
1.4.2.2.2 - Lawn, garden and snow-removal equipment and tools
1.4.3 - Services related to household furnishings and equipment
1.4.3.1 - Rental of heating equipment
1.4.3.2 - Rental of heating equipment for rented living quarters
1.4.3.3 - Home security services
1.5 - Clothing and accessories
1.5.1 - Women's and girls' wear (4 years and over)
1.5.1.1 - Footwear, women and girls aged 4 years and over
1.5.1.2 - Jewellery and watches, women and girls aged 4 years and over
1.5.2 - Men's and boys' wear (4 years and over)
1.5.2.1 - Footwear, men and boys aged 4 years and over
1.5.2.2 - Jewellery and watches, men and boys aged 4 years and over
1.5.3 - Children's wear (under 4 years)

Continued on next page

TABLE A3.1 continued from previous page

Category
1.5.3.1 - Clothing and cloth diapers, children under 4 years
1.5.3.2 - Footwear, children under 4 years
1.5.4 - Clothing services
1.5.4.1 - Laundromats, dry-cleaning and laundry services
1.6 - Transportation
1.6.1 - Private transportation
1.6.1.1 - Private use automobiles, vans and trucks
1.6.1.1.1 - Purchase of automobiles, vans and trucks
1.6.1.1.1.1 - Automobiles (purchase)
1.6.1.1.1.2 - Vans (including mini-vans, purchase)
1.6.1.1.1.3 - Trucks (including sport utility vehicles, purchase)
1.6.1.1.2 - Accessories for automobiles, vans and trucks
1.6.1.1.3 - Fees for leased automobiles, vans and trucks
1.6.1.1.3.1 - Regular fees for leased automobiles, vans and trucks
1.6.1.1.3.1.1 - Regular fees for leased automobiles
1.6.1.1.3.1.2 - Regular fees for leased vans and trucks
1.6.1.1.3.2 - Other costs for leased automobiles, vans and trucks (include down payment and closing costs)
1.6.1.2 - Rented automobiles, vans and trucks
1.6.1.3 - Automobile, van and truck operations
1.6.1.3.1 - Registration fees for automobiles, vans and trucks (including insurance if part of registration)
1.6.1.3.2 - Private and public vehicle insurance premiums
1.6.1.3.3 - Tires, batteries, and other parts and supplies for vehicles

Continued on next page

TABLE A3.1 continued from previous page

Category
1.6.1.3.4 - Maintenance and repairs of vehicles
1.6.1.3.5 - Vehicle security and communication services
1.6.1.3.6 - Parking (excluding parking fees included in rent) and traffic and parking tickets
1.6.1.3.9 - Drivers' licences and tests, and driving lessons
1.6.1.3.9.1 - Drivers' licences and tests
1.6.1.3.9.2 - Driving lessons
1.6.2 - Public transportation
1.6.2.1 - City or commuter bus, subway, street car and commuter train
1.6.2.2 - Taxi (including tips)
1.6.2.3 - Other local passenger transportation
1.6.2.4 - Airplane
1.6.2.5 - Inter-city bus
1.6.2.6 - Other inter-city passenger transportation services
1.6.2.7 - Household moving, storage and delivery services
1.7 - Health care
1.7.1 - Direct health care costs to household
1.7.1.1 - Prescribed medicines and pharmaceutical products
1.7.1.2 - Non-prescribed medicines, pharmaceutical products, health care supplies and equipment
1.7.1.3 - Health care services
1.7.1.3.1 - Health care practitioners (excluding general practitioners and specialists)
1.7.1.3.2 - Health care by general practitioners and specialists
1.7.1.3.3 - Weight control programs, smoking cessation programs and other medical services
1.7.1.3.4 - Hospital care, nursing homes and other residential care facilities

Continued on next page

TABLE A3.1 continued from previous page

Category
1.7.1.4 - Eye-care goods and services
1.7.1.4.1 - Prescription eye wear
1.7.1.4.2 - Eye-care services (e.g. surgery, exams)
1.7.1.5 - Dental services
1.7.2 - Private health insurance plan premiums
1.7.2.1 - Private health care plan premiums
1.7.2.2 - Dental plan premiums
1.7.2.3 - Accident or disability insurance premiums
1.7.3 - Health care equipment
1.7.4 - Health care supplies and equipment
1.8 - Personal care
1.8.1 - Personal care services
1.8.1.1 - Hair grooming services
1.8.1.2 - Other personal care services
1.9 - Recreation
1.9.1 - Recreation equipment and related services
1.9.1.6 - Computer equipment and supplies
1.9.1.6.1 - Computer hardware
1.9.1.6.2 - Tablet computers
1.9.1.6.3 - E-Book readers
1.9.1.7 - Photographic goods and services
1.9.1.7.1 - Camcorders, cameras, parts, accessories and related equipment
1.9.1.7.2 - Photographic services
1.9.1.8 - Collectors' items (e.g. stamps, coins)

Continued on next page

TABLE A3.1 continued from previous page

Category
1.9.2 - Home entertainment equipment and services
1.9.2.1 - Home entertainment equipment
1.9.2.1.1 - Audio equipment
1.9.2.1.1.1 - Portable audio equipment
1.9.2.1.1.1 - Non-portable audio equipment
1.9.2.1.2 - Video equipment
1.9.2.1.2.1 - DVD players, Blu-Ray players and other video equipment and accessories
1.9.2.1.2.2 - Televisions and other video equipment and accessories
1.9.2.1.3 - Home theatre systems
1.9.3 - Recreation services
1.9.3.1 - Entertainment
1.9.3.1.1 - Television and satellite radio services (including installation, service and pay TV charges)
1.9.3.2 - Use of recreational facilities and fees for other recreational activities
1.9.3.2.1 - Dues and fees for sports and recreational activities and athletic and recreational facilities
1.9.3.2.2 - Children's camps
1.9.3.3 - Package trips
1.9.4 - Recreational vehicles and associated services
1.9.4.1 - Purchase of recreational vehicles
1.9.4.1.1 - Motorcycles and snowmobiles (purchase)
1.9.4.1.2 - All-terrain vehicles (purchase)
1.9.4.1.3 - Bicycles (purchase), parts and accessories
1.9.4.1.4 - Other recreational vehicles (purchase)

Continued on next page

TABLE A3.1 continued from previous page

Category
1.9.4.2 - Operation of recreational vehicles
1.9.4.2.1 - Insurance premiums for recreational vehicles
1.9.4.2.2 - Registration fees and licences for recreational vehicles
1.9.4.2.3 - Parking, hangar and airport fees, mooring and boat storage and harbour dues
1.9.4.2.4 - Other expenses for recreational vehicles
1.10 - Education
1.10.1 - Tuition fees
1.10.1.1 - Tuition fees for kindergarten, elementary and secondary schools
1.10.1.2 - Tuition fees for university
1.10.1.3 - Tuition fees for other post-secondary education (college, trade and professional courses)
1.10.1.4 - Other educational services
1.10.1.5 - Personal interest courses and lessons (excluding driving lessons)
1.10.2 - Textbooks and school supplies
1.11 - Reading materials and other printed matter
1.11.1 - Books and E-books (excluding school books)
1.12 - Miscellaneous expenditures
1.14.1 - Financial services
1.14.1.1 - Service charges for banks and other financial institutions
1.14.1.2 - Administration fees for brokers and stock and bond commissions
1.14.1.3 - Brokerage fees and other similar services
1.14.1.4 - Other financial services
1.14.2 - Other miscellaneous goods and services
1.14.2.1 - Fines

Continued on next page

TABLE A3.1 continued from previous page

Category
1.14.2.2 - Legal services not related to dwellings
1.14.2.3 - Dues to unions and professional associations
1.14.2.4 - Contributions and dues for social clubs and other organizations
1.14.2.5 - Funeral services
1.14.2.6 - Government services
1.14.2.7 - Wholesale/retail memberships
2 - Personal taxes (net of refunds)
2.1 - Provincial health insurance premiums
3 - Total personal insurance payments and pension contributions
3.1 - Life insurance premiums
3.2 - Annuity contracts and transfers to Registered Retirement Income Funds (RRIFs)
3.3 - Employment insurance premiums
3.4 - Retirement and pension fund payments
3.4.1 - Canada and Quebec Pension Plan
4 - Total gifts of money and contributions
4.1 - Money and support payments
4.1.1 - Alimony and child support
4.1.2 - Gifts of money and support payments (excluding alimony and child support) to persons living inside Canada
4.1.3 - Gifts of money and support payments (excluding alimony and child support) to persons living outside Canada
4.2 - Contributions to charity
4.2.1 - Contributions to religious organizations
4.2.2 - Contributions to non-religious charitable organizations

Continued on next page

TABLE A3.1 continued from previous page**Category**

Notes: This table outlines the various categories and specific items considered under household expenditure. The classification method is based on SHS and Statistics Canada's method.

TABLE A3.2: The Distribution of Cancer Type

ICD-10 Code	Percent	Diagnosis Description
C619	15.3%	Malignant neoplasm of prostate
C504	6.3%	Malignant neoplasm of upper-outer quadrant of breast
C421	5.8%	Malignant neoplasm of bone marrow
C541	5.4%	Malignant neoplasm of endometrium
C341	4.3%	Malignant neoplasm of upper lobe, bronchus or lung
C209	4.2%	Malignant neoplasm of rectum, unspecified
C739	4.2%	Malignant neoplasm of thyroid gland, unspecified
C508	4.0%	Malignant neoplasm of overlapping sites of breast
C679	3.8%	Malignant neoplasm of bladder, unspecified
C649	3.3%	Malignant neoplasm of kidney, unspecified
C187	3.2%	Malignant neoplasm of sigmoid colon
C509	2.7%	Malignant neoplasm of breast, unspecified
C447	1.9%	Malignant neoplasm of skin of lower limb, including hip
C502	1.9%	Malignant neoplasm of upper-inner quadrant of breast
C180	1.8%	Malignant neoplasm of cecum
C446	1.6%	Malignant neoplasm of skin of upper limb, including shoulder
C445	1.5%	Malignant neoplasm of skin of trunk
Others	28.5%	
Obs	990	

Notes: The cancer diagnosis information are obtained from SHS-CCR linkage.

TABLE A3.3: The Effects on Household Income

	(1) Income Before Tax	(2) Income After Tax
Cancer	-0.013 (0.020)	-0.001 (0.018)
Mean	11.067	10.953
Obs	23,340	23,340
Year FE	Y	Y
Province FE	Y	Y

Notes : Regressions are controlled by square root of household size, urban status, average age and household highest education indicator, provincial unemployment rate and GDP per capita. Standard errors are reported in parentheses. All regressions are bootstrapped 500 times with SHS bootstrap weights. Statistical significance level indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Pers. Tax represents personal tax.

Conclusion

This thesis has examined the relationship between health coverage and well-being in Canada through three interconnected essays. Using causal inference methods, it shows that labour market policies, public drug insurance, and serious illness each shape access to care and household economic security, and that vulnerability arises when protection is incomplete. The first essay shows how labour market interventions can unintentionally erode access to employer-sponsored benefits, thereby weakening the safety net for low-educated workers. The second demonstrates that targeted expansions of public drug coverage can reduce reliance on costly emergency services, illustrating the efficiency and equity gains from filling gaps in insurance. The third highlights how severe health shocks create substantial financial strain even in the presence of universal medical coverage, underscoring that well-being depends not only on access to healthcare but also on protection against the broader economic consequences of illness. Collectively, the results underscore that health coverage is not merely as a financing tool, but as a core determinant of household stability and social equity, highlighting the need for policies that jointly address health and economic risks.

In chapter 1, Michel Grignon and I examine threshold effects of minimum wage increases on employer-sponsored prescription drug coverage. The paper provides evidence that increases in the minimum wage can unintentionally erode access to employer-sponsored prescription drug insurance for low-educated people. The analysis shows that medium increases of \$0.20–\$0.30 are associated with a statistically significant 2.5 percentage point reduction in the likelihood of low-educated individuals receiving employer-sponsored drug insurance in the two years, and this effect persists for up to four years post-implementation. Large increases exceeding \$0.30 show only modest declines, peaking at about 2 percentage points after three years, though these estimates are not statistically significant. Moreover, this reduction appears to be concentrated among more

vulnerable groups, including women, non-white individuals, immigrants, and younger workers.

Chapter 2 shows that beneficiaries aged 18 to 24 from low-income families were less likely to use the emergency department after the implementation of OHIP+. For this group, the probability of emergency department visits declined by 5.5% following the program's introduction and by an additional 6.6% after its subsequent modification, which suggesting that targeted public programs can fill coverage gaps and improve health system efficiency. The stronger effect observed after the modification appears to reflect the cumulative impact of program duration rather than the policy change itself. Moreover, the reduction in visits is driven primarily by non-ACSC cases indicates a substitution effect.

Chapter 3 highlights the economic vulnerability of households facing a cancer diagnosis. I find that households with a recent cancer diagnosis spend less overall than those without a diagnosis in the past five years, with the largest absolute reductions in food and income tax. Total expenditure shares remain relatively stable for all individuals, these changes reflect broad contractions in total spending rather than major shifts across categories. Heterogeneity analysis finds that households with children increase housing expenditure share, single parents raise insurance spending while reducing food spending, childless couples shift resources toward healthcare, and younger cancer patients (under age 55) show the largest spending pattern changes. In contrast, households facing subsequent cancer diagnoses exhibit smaller adjustments, apart from a modest increase in recreation spending, suggesting that earlier episodes may have already prompted major financial adaptations.

Several avenues for future research could be done. First, richer longitudinal data could illuminate the longer-term effects of policies and drug coverage expansions. Second, survey instruments could be expanded to capture more detailed questions. For

instance, including survey items such as “What is the co-payment rate of your employer-sponsored drug insurance?” would enable a more precise assessment of the intensive margins through which minimum wage policies affect coverage and out-of-pocket costs. Third, administrative data linkages, such as between employment records, prescription claims, and health outcomes, would allow researchers to trace the mechanisms connecting coverage, health, and well-being with greater precision.