THREE ESSAYS IN APPLIED MICRO-ECONOMETRICS

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Lay Abstract

This thesis demonstrates how econometric methods can be used to inform policy-relevant questions relating to two international epidemics: the prescription opioid epidemic and the COVID-19 pandemic. This thesis consists of three chapters. Chapters 1 and 2 demonstrate how nonparametric estimation methods can serve as flexible and data-driven alternatives to conventional parametric estimation methods and provide insight into the determinants of prescription opioid use. Chapter 3 uses Canadian microdata to analyze the labour market effects of the COVID-19 pandemic on Canadian immigrants.

Abstract

This thesis, comprised of three chapters, demonstrates how econometric methods can be used to inform policy-relevant questions relating to two international epidemics: the prescription opioid epidemic and the COVID-19 pandemic.

Over the past two decades, Canada has experienced rapid growth in the consumption of prescription opioids. The increase in the consumption of these medications has brought pain relief to many people suffering from chronic and acute pain. Unfortunately, it has also led to a parallel increase in prescription opioid abuse, dependence, and overdose. To develop evidence-based policies that curtail prescription opioid morbidity and mortality without hindering access to necessary pain treatment, it is imperative to use statistical modelling techniques to identify the critical predictors of prescription opioid use and abuse. Chapter 1 illustrates how the existing literature on prescription opioid use consists primarily of analyses that use multivariate logistic regression to model prescription opioid use. Then we demonstrate how nonparametric kernel methods can be used to model prescription opioid use and significantly outperform the logistic regression models from the perspective of correctly classifying prescription opioid users, both in-sample and out-of-sample. Chapter 2 utilizes a natural experiment and exploits robust nonparametric estimation methods to examine the impact of mandatory universal pharmaceutical insurance on prescription opioid use. The results show that, among the general population, the policy led to a significant increase in pharmaceutical insurance coverage and a small in magnitude but statistically significant decrease in prescription opioid use. Additionally, the analysis does not find evidence that the increase in pharmaceutical insurance coverage led to a substitution effect away from over-the-counter pain medications and towards prescription opioids for pain treatment.

Moving from one crisis to another, i.e., from the Canadian prescription opioid epidemic

to the global COVID-19 pandemic, we refocus attention on the labour market impacts of the latter. As the Corona Virus (SAR-CoV2) spread across the globe in 2020, many government bodies were forced to implement restrictions to slow down the spread of the virus; this included the shutdown of non-essential businesses and services, the cancellation of in-person events and entertainment, school closures, and the start of work-from-home orders. Many sectors saw a drastic drop-in economic activity, resulting in job losses and reductions in hours worked. Chapter 3 uses Canadian microdata to analyze the labour market effects of the COVID-19 pandemic on Canadian immigrants. Trends in employment status and aggregate hours worked are examined by gender and immigrant status and we find evidence that the labour supply of immigrants, especially immigrant women, was more affected than the labour supply of their non-immigrant counterparts.

Acknowledgements

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Contents

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List of Abbreviations

- AME: Average Marginal Effect
- ARPDI: Act Respecting Prescription Drug Insurance
- ATET: Average Treatment Effect on the Treated
- AUC: Area Under the Curve
- CCR: Correct Classification Ratio
- CDF: Cumulative Distribution Function
- CERB: Canada Emergency Response Benefit
- CHA: Canada Health Act
- CIDI: Composite International Diagnostic Interview
- CNCP: Chronic Non-Cancer Pain
- CRNA: Cost-Related Non-Adherence
- DGP: Data Generating Process
- ECG: Electrocardiogram
- FN: False Negative
- FNR: False Negative Rate
- FP: False Positive
- FPR: False Positive Rate
- LFS: Canadian Labour Force Survey
- MEM: Marginal Effect at the Mean

- MLE: Maximum Likelihood Estimator
- NP: Non-Parametric
- NPHS: National Population Health Survey
- NSAIDS: Non-Steroidal Anti-Inflammatory Drugs
- OECD: Organisation for Economic Co-operation and Development
- OLS: Ordinary Least Squares
- OTC: Over-the-Counter
- PDF: Probability Density Function
- PO: Prescription Opioids
- PUMF: Public Use Micro-Data Files
- RAMQ: Regie de l'Assurance Maladie du Quebec
- ROC: Receiver Operator Characteristic
- TETII: Treatment Effect on the Treated Individual
- TN: True Negative
- TNR: True Negative Rate
- TP: True Positive
- TPR: True Positive Rate

Declaration of Academic Achievement

I am the sole author of the material presented in this thesis. The research material presented in this thesis was developed by me during the years 2016-2022.

1 Chapter 1: Predicting Rare Events: The Case of Prescription Opioid (Ab)Use

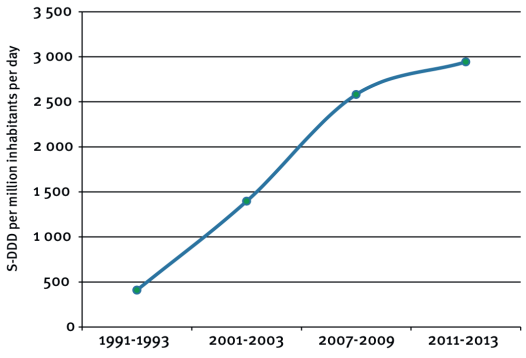
1.1 Introduction

1.1.1 The Prescription Opioid Crisis

1.1.1.1 What are Prescription Opioids Prescription opioids are a class of medications made directly from the opium poppy plant or synthetically by replicating the opium chemical structure. Unlike heroin which is an illegal opioid, prescription opioids are legally produced by pharmaceutical companies for the medical treatment of moderate to severe pain. Prescription opioids can be highly addictive, and overdoses are common (Fischer, Pang, and Jones 2020); as a result, prescription opioids are highly regulated narcotic medications. Obtaining these medications from a pharmacist requires a prescription from a physician. Popular examples of prescription opioid analgesics include hydrocodone (Vicodin®), oxycodone (Oxycontin®, Percocet®), oxymorphone (Opana®), morphine (Kadian®, Avinza®), codeine, and fentanyl. In recent years this class of medications has received a lot of policy and media attention due to concerns regarding the rapid growth in consumption in some countries and the associated rise in prescription opioid morbidity and mortality. Prescription opioids are also referred to as opioid analgesics, opioid narcotics or, informally, simply as opioids.

1.1.1.2 International Rise in Consumption of Prescription Opioids Reports by the International Narcotics Control Board illustrate the global upward trend in consumption of opioid analgesics, with average consumption increasing by a factor of six from 1991-1993 to 2011-2013 (International Narcotics Control Board 2016). As illustrated in Figure 1, the consumption of opioid analgesics increased rapidly in the

1990s and early 2000s and then subsequently continued to rise at a slower rate. When consumption of these medications is measured by geographic region (see Figure 2), it is evident that North America's consumption far exceeds that in any other part of the world (International Narcotics Control Board 2016). Similar to the global trend, the North American consumption of opioid analgesics initially experienced rapid growth and continues to grow but at a slower rate. The high consumption in North America is primarily driven by increased consumption in Canada and the U.S. since consumption in Mexico is limited (International Narcotics Control Board 2016). When prescription opioid consumption is measured in total quantities, the U.S has the highest global consumption; however, when population size is taken into account, Canada is the world's largest per-capita consumer of opioid analgesics (International Narcotics Control Board 2016), as illustrated in Figure 3. The rapid rise in prescription opioid consumption has started to extend beyond Canada and the U.S, to other OECD countries, most notably Australia, Germany, and Austria (International Narcotics Control Board 2019).

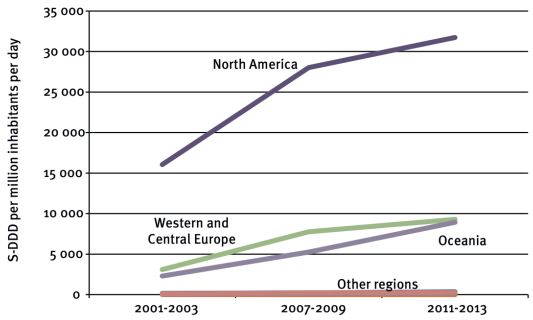


Source: International Narcotics Control Board.

Figure 1: Global Trend in the Consumption of Opioid Analgesics

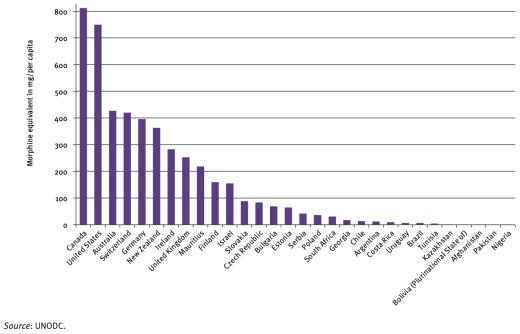
1.1.1.3 Implications of Growth in Consumption of Prescription Opioids

On the bright side, the growth in prescription opioid consumption represents a move-



Source: International Narcotics Control Board.

Figure 2: Trends in Consumption, by Region



Source: UNODC.

Figure 3: Per Capita Consumption of Opioid Analgesics, 2011

ment by Canada and the United States towards meeting previously unmet demand for chronic non-cancer pain (CNCP) treatment. Prior to the mid-1980s, the medical opinion held that prescription opioids should not be used for the treatment of CNCP (Jovey et al. 2003). Physicians held this opinion because studies from multidisciplinary pain programs suggested that the regular use of opioid analgesics had a high risk of achieving poor outcomes and might lead to increased psychological stress, impaired cognition, and an increased risk of addiction (Sees and Clark 1993). Thus, physicians were reluctant to prescribe opioid analgesics for CNCP. These opinions were later challenged by a series of clinical trials and case studies that presented evidence in favor of using prescription opioids for CNCP treatment (Jovey et al. 2003). In 2000, the College of Physician and Surgeons of Ontario published its "Evidence-based

recommendations for the treatment of chronic non-malignant pain," which concluded:

"… from our systematic literature search suggest that sustained-release opioid therapy benefits selected patients with chronic musculoskeletal and neuropathic pain ... Significant pain relief can be achieved with a low risk of psychological dependence or addiction in the absence of a history of substance abuse. Cognitive impairment can be minimized or eliminated with an individualized dose titration program" (Jovey et al. 2003).

Since 2000, subsequent controlled trials were published providing further evidence of the effectiveness of opioid therapy for non-cancer pain and made physicians more comfortable prescribing opioid analgesics for non-cancer pain (Jovey et al. 2003). Thus, some of the growth in prescription opioid consumption is attributable to the increase in the number of prescriptions written for chronic and acute non-cancer pain treatment.

However, the rapid growth in prescription opioid consumption also represents an over-consumption of these narcotics. Parallel to the increase in prescription opioid consumption there has been an increase in prescription opioid-related problems and harms (Fischer, Gittins, and Rehm 2008). These problems and harms include prescription opioid-related abuse, morbidity, and mortality that have increased across Canada and the United States over the past decade (Fischer, Keates, et al. 2013; Fischer et al. 2014). Prescription opioid abuse not only poses a concern for Canadian and American healthcare systems but for law enforcement systems as well, as the presence of prescription opioid analgesics in illicit drug markets has become more prominent. Evidence from Canada suggests that "heroin use has become an increasingly marginal form of drug use among illicit opioid users...[i]nstead, the use of prescription opioids in varying forms has become the prominent form of illicit opioid use" (Fischer et al.

2006). The rapid rise in opioid morbidity and mortality that Canada and the U.S. are facing is often referred to as the prescription opioid crisis or the prescription opioid epidemic.

1.1.2 Informing Solutions Through Model Estimation

Canada and the U.S. face a prescription opioids dilemma, where increased prescription opioid consumption provides a social benefit through the increased treatment of patient pain but imposes a social cost when it leads to misuse, abuse, or dependence on prescription opioids. The rising social costs associated with prescription opioid use are of concern to many stakeholders demanding action by policy makers to mitigate the situation. However, to develop efficient policies that are not unnecessarily restrictive, an overemphasis on the costs must not drown out the merits of prescription opioids. In order to create evidence-based policies and guidelines that curtail the prescription opioid harms without hindering access to necessary pain treatment, it is important to identify the factors that drive prescription opioid use and abuse. Also, mitigating the prescription opioid crisis will require the development of technologies to assist physicians in accurately identifying probable cases of prescription opioid abuse. Identifying the determinants of prescription opioid (ab)use and developing screening tools will require estimating models of prescription opioid (ab)use that are as precise as possible. In recent years many new methods of data-driven model estimation have been developed and shown to have superior statistical performance than some popular methodologies; thus, it is worth examining if the methods currently being used to model prescription opioid use are the most appropriate available methods.

1.2 Literature Review

Due to the prescription opioid crisis being a prominent public health concern, this topic has received a lot of attention from academic researchers across various fields of study, resulting in an extensive and multidisciplinary literature. Prescription opioid use has been explored from the perspective of health economists, epidemiologists, health policy analysts, medical researchers, demographers, and several other research communities, with researchers from each group using their expertise to identify the determinants/covariates of prescription opioid use as some combination of physiological, psychological, demographic, socioeconomic, health behavior, and healthcare utilization factors. Although there has been extensive research on identifying the determinants of prescription opioid use, there still exist many important gaps in the literature.

A thorough search for papers meeting the following criteria was conducted: peer-reviewed journal articles in which the analysis involved modeling some measure of prescription opioid use as a function of a combination of individual physiological, psychological, demographic, socioeconomic, health-related behavior, and healthcare utilization variables. Note that for a paper to meet the inclusion criteria, it must utilize a model for which predicted prescription opioid use is conditional on multiple variables. Thus, papers that conducted a descriptive analysis illustrating the mean or prevalence rate of characteristics (e.g., age, gender, etc.) from a sample of prescription opioid users were exempt from the review. Similarly, papers which only obtained bivariate correlation between prescription opioid use and characteristic variables were exempt. As well, clinical papers that analyzed the efficacy of prescription opioid use as a function of health and demographic variables were not included as the objective of such papers is to identify the determinants of effective treatment. Whereas the objective of the literature of interest is to identify the determinants of the choice to

engage in some type of prescription opioid use.

From the papers reviewed and listed in Appendix 4.1.1, it was observed that the type of prescription opioid use measured ranged from measures of appropriate use (e.g., medical prescription opioid use) to measures of harmful prescription opioid use (e.g., fatal overdoses). Although the type of prescription opioid use varied widely, how it is coded into a model is restricted to one of three mutually exclusive options: a binary variable, a categorical variable, or a continuous variable.[1] Appendix 4.1.1 presents three tables illustrating papers that model prescription opioid use as a binary, categorical, or continuous variable, respectively. For each table, the type of use (e.g., medical use, non-medical use, overdose, etc.) and the country from which the data analyzed are collected are listed along with citations to papers that match those characteristics. These tables provide a visual overview of what the literature on the determinants of prescription opioid use looks like and some common characteristics among papers. The tables make three features of the literature evident. First, most papers use a binary prescription opioid use variable. Second, "Non-Medical Prescription Opioid Use" is the most commonly analyzed type of prescription opioid use. Lastly, the vast majority of papers use data from the U.S. Therefore, it is notable that there is limited research on appropriate and general use of prescription opioids, and evidence from countries other than the U.S. is lacking. Expanding the literature in ways that are currently limited can provide valuable insight for policy development.

[1]A binary variable is a variable that can take one of two possible values. In practice, binary variables are most often coded to equal either zero or one, where the variable equals one if some condition is true and equals zero otherwise. A categorical variable is a variable that can take one of a limited number of values. A categorical variable can be ordered, in which there is an intrinsic order to the categories and the distance between the categories may not be known (e.g., a variable recording self-rated health, where 1 indicates "poor," 2 indicates "good health," and 3 indicates "excellent health"). Alternatively, an unordered categorical variable does not have an intrinsic ordering (e.g., a variable recording the province of residence of individuals). Finally, the continuous variable can take any of the infinite numbers of values within its support.

First, the peer-reviewed literature on the determinants of prescription opioid (ab)use using Canadian data is minute in comparison to the amount of research conducted using U.S. data (Fischer et al. 2008). Although the literature regarding prescription opioid use in the U.S. provides valuable information, the healthcare systems of these two countries differ substantially in ways that may influence prescription opioid use, thus the results obtained from analyses of U.S. data may not apply to the Canadian context. Given that per capita consumption of prescription opioid is higher in Canada than anywhere else in the world, and the prevalence of prescription opioid misuse in Canada is among the top ten globally (International Narcotics Control Board 2016), it is pertinent that there be more studies using Canadian data to adequately inform Canadian health policy regarding prescription opioids.

Second, in both the Canadian and U.S. literature, the large majority of papers have focused on identifying the factors associated with undesirable types of prescription opioid use (e.g., medical misuse, non-medical use, use disorder, abuse, and overdose use) and few papers have explored covariate associations with appropriate medical use or general use (e.g., the individual has indicated taking prescription opioids, but it is unclear whether it is proper use or misuse). It is important to explore the determinants of proper prescription opioid use so that these factors can be used to identify individuals who may benefit from using these medications and are not likely to misuse them. As well, by studying general prescription opioid use we can gain an understanding of all the types of prescription opioid users, which is important as any policy aimed at restricting access to these medications will affect all types of users and therefore all stakeholders should be considered.

Third, in the Canadian context, very few papers have sought to explore the nationwide use of prescription opioids. Instead, most studies look at the determinants of prescrip-

tion opioid use for small and selective sub-groups of the population such as high-school students (Fischer, Ialomiteanu, et al. 2013), Alberta cancer patients (Cuthbert et al. 2020), opioid naive post-operative patients (Clarke et al. 2014), and Ontario Adults (Shield et al. 2011). Research by Sullivan et al. (2006) utilized data from a nationally representative survey to explore regular prescription opioid use in the American adult population. Respondents were identified as a regular prescription opioid user if they reported taking prescription opioids at least several times a week for a month or more in the past 12 months. The data used by Sullivan et al. (2006) did not contain information regarding the details of why or how the individual was consuming prescription opioids (e.g., was the medication prescribed to them and if so, what was the medication prescribed for, how the individual obtained the medication, what dosage was being consumed and how frequently). Although the data limitations did not allow Sullivan et al. (2006) to distinguish regular medical use from regular non-medical use, misuse, or abuse, they were able to nonetheless extract very helpful information about prescription opioid use in the U.S. They estimated the proportion of the national population taking prescription opioids in 1998, 2001, and both periods, and they identified the most common chronic conditions among prescription opioid users and analyzed the multivariate relationship between prescription opioid use and sociodemographic, mental health, clinical physical health, problem alcohol, and drug use variables, which is essential information to consider in the development of prescription opioid policies. A study similar to the one by Sullivan et al. (2006) using Canadian nationwide data of general prescription opioid use would address the aforementioned gaps in the existing literature and provide further guidance on how the prescription opioid crisis in Canada may be tackled.

Finally, as previously noted, the large majority of papers reviewed treat prescription

opioid use as a binary variable and consequently use a multivariate logistic regression model, also known as the logit model, for the analysis. Although a logit model is the predominantly used model in the literature, it may not be the most adequate. Often in studies analyzing prescription opioid use (e.g., general use, misuse, abuse, dependence, overdose, etc.), the binary outcome variable is highly imbalanced, meaning that the proportion of cases of prescription opioid use are very few compared to cases of non-use. This is especially the case when analyzing forms of prescription opioid use in data sets representing state, province, or national population. When a logit model is fitted with imbalanced data, this can lead to biased parameter estimates and reduced classification performance (Abd Rahman, Wah, and Huat 2021; Salas-Eljatib et al. 2018). To solve these problems, machine learning binary classifiers (such as decision trees, artificial neural networks, support vector machines, and random forest algorithms) have been analyzed to explore if they can achieve better results than logistic regression. Several studies working with highly imbalanced data have found that machine learning algorithms yielded better classification performance than logistic regression (Yang et al. 2021; Brahma and Mukherjee 2020; Kirasich 2018; Jones, Johnstone, and Wilson 2015). Studies by Yang et al. (2021) and Brahma and Mukherjee (2020) illustrate the value that newer machine learning methods can have for the clinical prediction of rare events. Yang et al. (2021) propose an automatic Electrocardiogram (ECG) heartbeat classification system, based on ensemble learning and multi-kernel learning, to identify irregular heartbeats. The method proposed by Yang et al. (2021) displays higher overall accuracy and higher correct prediction of irregular heartbeats than previous studies using various methods. Brahma and Mukherjee (2020) employ multiple machine learning techniques to model and predict neonatal mortality. Brahma and Mukherjee (2020)'s results find that the machine learning methods obtain higher accuracy than the standard logit. However, a systematic review found that there

was not sufficiently strong evidence of a performance benefit of machine learning methods over logistic regression for clinical prediction models (Christodoulou et al. 2019). Although the evidence on the performance benefits of machine learning methods over logistic regression is currently mixed, the limitations of logistic regression when faced with highly imbalanced data still exist. This paper explores whether there is a performance benefit to using a nonparametric mixed-kernel approach to model prescription opioid use over the logistic regression, as the nonparametric approach has been shown to produce more robust estimates of propensity scores (Li, Racine, and Wooldridge 2009).

The research presented in this chapter aims to fill the gaps in the "determinants of prescription opioid use" literature by using a rich household survey of the Canadian population to modeling general prescription opioid use using a modern modeling approach with potentially superior classification capabilities.

1.3 Data

1.3.1 Data Source

The data used for the analysis presented in this paper come from the National Population Health Survey (NPHS) household component, a nationally representative interview survey conducted biennially by Statistics Canada. The survey was designed to collect information on content related to health status, use of health services, determinants of health, a health index, chronic conditions, activity restrictions, as well as related socio-demographic variables. The NPHS survey spanned the period from 1994 to 2011, was conducted every two years, and would take a year to collect the data from the whole sample; thus, NPHS data were collected in nine survey cycles as shown in Table 12. The NPHS has a household component for all nine cycles, a

healthcare institutions (H.I.s) component[2] for the first five cycles and a Northern territories (N.T.s) component[3] for the first three cycles. The target population of the NPHS household component includes community-based household residents in the ten provinces, excluding populations on Native Reserves, Canadian Force Bases, and some remote areas in Quebec and Ontario.

In the first cycle (1994/1995), an initial sample of approximately 20,000 households was gathered. For each household, a limited amount of information (i.e., demographics, socio-economic, and basic health information) was collected on all household members; then, one household member was randomly selected for a more in-depth interview. The longitudinal data follows up on the randomly selected individual while still collecting limited data on his/her household members.

In the second cycle (1996/1997), the household component started with 17,276 longitudinal respondents from the first cycle, and their cycle 1 and 2 responses are recorded in the longitudinal data file. The 17,276 longitudinal respondents from the first cycle are topped up with supplemental samples purchased by Ontario, Alberta, and Manitoba, resulting in a cycle 2 cross-sectional data file with approximately 82, 000 respondents. As a result, the household component contains cross-sectional data for cycle 1 (1994/95), cycle 2 (1996/97), and cycle 3 (1998/99), as well as longitudinal data from cycle 1 (1994/95) through to cycle 9 (2010/11). The master files of the cross-sectional and longitudinal data sets are confidential, and access requires Statistics Canada approval. However, Public Use Microdata Files (PUMFs) for the cross-sectional data of the first three cycles are publicly available.

[2]The target population of this component was long-term (expected stay of six months or more) residents of health care institutions with four beds or more in all provinces except Yukon and Northwest Territories

[3]The target population of this component was household residents in the Yukon and Northwest Territories except those living on Native Reserves, Canadian Forces Bases and some of the most remote areas of the Territories

Table 1: NPHS data features

Cycle	Year	Data.files	Components	PUMF.Availability
1	1994/1995	Cross-sectional	Households, H.I.s, N.Ts	Households & H.I.s cross sections
2	1996/1997	Cross-sectional, Longitudinal	Households, H.I.s, N.Ts	Households & H.I.s cross sections
3	1998/1999	Cross-sectional, Longitudinal	Households, H.I.s, N.Ts	Households cross section
4	2000/2001	Longitudinal	Households, H.I.s	NA
5	2002/2003	Longitudinal	Households, H.I.s	NA
6	2004/2005	Longitudinal	Households	NA
7	2006/2007	Longitudinal	Households	NA
8	2008/2009	Longitudinal	Households	NA
9	2010/2011	Longitudinal	Households	NA

Note:
H.I.= Healthcare Institutions
N.T.= Northern Territories
PUMF= Public Use Microdata File

The analysis presented in this paper uses the NPHS cycle 2 (1996/97) cross-sectional PUMF because the NPHS provides information about prescription opioid use in the Canadian population, cycle 2 provides the largest sample with which to conduct estimation (81, 800 observations) and the public use nature of the data greatly facilitates the reproducibility of the research in this chapter.

1.3.2 Study Variables

1.3.2.1 Dependent Variable The NPHS household component asks respondents if they have consumed codeine, Demerol, or morphine in the month prior to the interview. The respondent may answer yes, no, don't know (DK), or refuse to answer (RF). Observations with a DK/RF response are converted into missing values[4], and a binary variable for prescription opioid use is created. The prescription opioid use variable is equal to one if the respondent answered yes to having consumed codeine, Demerol, or morphine in the month prior to the interview and equal to zero if they answered no.

[4]Observations with missing values are removed.

$$Y = \begin{cases} 1 & \text{if answered Yes} \\ 0 & \text{if answered No.} \end{cases}$$

1.3.2.2 Regressors The socio-demographic variables included in the analysis are self-reported age, gender, race, immigrant status, marital status, rural vs. urban community resident, province of residence, education, household income, and prescription drug insurance. Physical and mental health variables included are: self-rated general health status, chronic conditions, serious injuries, self-rated pain, and an indicator of significant mental distress based on the respondent's six-item measure of non-specific psychological distress (K6) score (R. C. Kessler et al. 2002) A variable indicating likely alcohol dependence is included to try and capture substance abuse behavior. The healthcare utilization variables included in the analysis are self-reported overnight hospitalization and the number of consultations with a medical health professional. The details of these variables are presented in Table 2.

Table 2: Description of Variables

Variable	Name	Values	Data Type
age	Age group	On separate table	Ordered Categorical
sex	Gender	0: Female, 1: Male	Binary
race	Race	0: Other, 1: White	Binary
imm	Immigrant status	0: Non-immigrant, 1: Immigrant	Binary
ms	Maritial status	1: Single	Unorder Categorical
		2: Married/Common law/Partner	
		3: Widowed/Separated/Divorced	
res	Rural vs urban residence	0: Rural, 1: Urban	Binary
prov	Province	1: Ontario	Unorder Categorical
		2: Maritimes	
		3: Quebec	
		4: Praries	
		5: British Columbia	
educ	Education	1: No school/Some Secondary	Ordered Categorical

Table 2: Description of Variables *(continued)*

Variable	Name	Values	Data Type
		2: Secondar Grad	
		3: Other post-secondary	
		4: Diploma/Communtiy college course/GEGEP	
		5: Some university	
		6: Bachelors degree	
		7: Masters/PhD/Medicine	
income	Household Income Quintile	1: 1st quintile	Ordered Categorical
		2: 2nd quintile	
		3: 3rd quintile	
		4: 4th quintile	
		5: 5th quintile	
insured	Insurance status	0: No, 1: Yes	Binary
srhs	Self-rated health status	1: Poor	Ordered Categorical
		2: Fair	

Table 2: Description of Variables *(continued)*

Variable	Name	Values	Data Type
		3: Good	
		4: Very good/ Excellent	
cc	Chronic condition indicator	0: No chronic condition, 1: 1 or more chronic conditions	Binary
injury	Serious Injury	0: No , 1: Yes	Binary
pain	Pain	1: No pain or discomfort,	Ordered Categorical
		2: Mild pain	
		3: Moderate pain	
		4: Severe Pain	
distress	Significant distress	0: No , 1: Yes	Binary
alcdep	Alcohol dependence	0: No , 1: Yes	Binary
onhp	Over night hospital patient	0: No , 1: Yes	Binary
md_consult	Consultations with an MD	0	Ordered Categorical
		1: 1	
		2: 2-4	

Table 2: Description of Variables *(continued)*

Variable	Name	Values	Data Type
		3: 5-7	
		4: 8-10	
		5: 11 or more	

Table 3: Categorical Age Variable Categories

Age Category	Ages
1	15-19
2	20-24
3	25-29
4	30-34
5	35-39
6	40-44
7	45-49
8	50-54
9	55-59
10	60-64
11	65-69
12	70-74
13	75-79
14	80+

1.3.3 Analytical Sample

The analytical sample is restricted to respondents of age 12 or older because several variables of interest are only available for respondents of age 12 or older. If a respondent was not asked (NA), refused to answer (RF), did not state (NS), or did not know (DK) the answer to a question, the response is converted to a missing value. Omitting observations with missing values for any of the variables of interest resulted in an

analytic sample of 5959 observations. Subsamples of the analytic sample are examined throughout the analysis to gain further insight.

1.4 Methodology

As illustrated in the literature review, most papers seeking to identify the determinants of prescription opioid use measure prescription opioid use as a binary variable and use logistic regression to estimate a model of the binary outcome variable. This methodology section will first review the logistic regression approach by discussing its origin, estimation, strengths, and limitations. Then, I consider an alternative approach to modelling a binary indicator for prescription opioid use and similarly discuss its origin, estimation, strengths, and limitations. For both approaches, a method for identifying and analyzing key predictors is described. Finally, the methodology for how the two approaches will be compared is discussed.

1.4.1 The Parametric Approach

1.4.1.1 Parametric Binary Response Models The binary response models presented in this section follow the presentation style, and notation from Davidson and MacKinnon (2003).

In practice the binary variable is most often coded as either a 0 or 1, for example the variable will equal 1 if an individual answered yes when asked if they have taken prescription opioids and 0 otherwise. As opposed to regression models which estimate the conditional expectation of a continuous outcome variable, binary response models [5] seek to explain the probability that the individual will report yes (i.e., that the binary dependent variable will equal 1) as a function of some explanatory variables.

[5] Also known as binary choice models.

Let the binary dependent variable be denoted by y_t which can only take on two values 0 or 1. Let P_t denote the probability that $y_t = 1$ conditional on the information set Ω_t, which consists of predetermined variables. The binary response model models the conditional probability P_t as follows,

$$P_t \equiv Pr(y_t = 1|\Omega_t) \tag{1}$$

Note that since y_t can only take on the values are 0 or 1, P_t is also equivalent to the expectation of y_t conditional on Ω_t:

$$\begin{aligned} E(y_t|\Omega_t) &= 1\text{x}Pr(y_t = 1|\Omega_t) + 0\text{x}Pr(y_t = 0|\Omega_t) \\ E(y_t|\Omega_t) &= Pr(y_t = 1|\Omega_t) \\ E(y_t|\Omega_t) &= P_t \end{aligned} \tag{2}$$

Therefore, if $Y \in \{0, 1\}$, we can also think of the binary response model as modeling a conditional expectation.

$$P_t \equiv Pr(y_t = 1|\Omega_t) = E(y_t|\Omega_t); \iff y_t \in \{0, 1\} \tag{3}$$

Suppose we wanted to model this conditional expectation using the widely used linear probability model,[6] since after all, linear regression models are designed for estimating conditional expectations. Let X_t denote a row vector of length k of variables that belong to the information set Ω_t, plus a constant term. In such case the conditional expectation $E(y_t|\Omega_t)$ would be specified by the linear probability model as

[6]The linear probability model is the name given to the linear regression model when the outcome variable y_t is a binary variable with values 0 or 1

$$E(y_t|\Omega_t) = X_t'\beta, \tag{4}$$

which allows for a straightforward regression of y_t on X_t. However, the linear probability model does not impose a very important condition, namely that $E(y_t|\Omega_t) = X_t'\beta$ be bound between 0 and 1, since $E(y_t|\Omega_t)$ can take on values that are negative or greater than 1. Recall from (3) that $E(y_t|\Omega_t)$ is a probability; therefore, the condition $0 \leq E(y_t|\Omega_t) \leq 1$ is necessary. Thus, using the linear probability model is not a reasonable approach to estimating $E(y_t|\Omega_t)$ when y_t is binary because it can produce estimated probabilities that are statistically improper.

In order to avoid improper estimated probabilities, it is necessary that the model ensures that $0 \leq E(y_t|\Omega_t) \leq 1$. While there are several ways to impose this condition, the most commonly used approaches are to use either a probit or a logit model. As discussed in Section 1.2, the logit model is the most commonly used model for analyzing a binary prescription opioid use variable, thus in the following section the focus will be on exploring the important details of the logit model and I only make brief comments on how the probit model compares and contrasts to logit model. Both the logit and probit model begin by specifying P_t as

$$P_t \equiv E(y_t|\Omega_t) = F(X_t'\beta), \tag{5}$$

where $X_t'\beta$ is an index function and $F()$ is a transformation function which has the properties of a probability distribution CDF:

$$\begin{aligned} F(-\infty) &= 0, \\ F(\infty) &= 1, \\ f(x) &= \frac{dF(x)}{dx} > 0. \end{aligned} \tag{6}$$

The index function $X_t'\beta$ uses the explanatory variables and parameters to produce a scalar index which can be any real number. However since the scalar index goes into the transformation function $F()$, which is bound between 0 and 1, together the two functions $F(X_t'\beta)$ ensure that the estimated probabilities lie in the interval 0 to 1.

1.4.1.2 The Logistic Regression Model It is evident that the transformation function plays an important role in binary response models. Using a transformation function with the properties listed in (6) imposes the necessary condition that the linear probability model lacked, and the specification of $F()$ is the key difference between the two most commonly used binary response models, the probit and logit model. The probit model specifies the transformation function as the cumulative standard normal distribution function

$$F(X_t'\beta) = \Phi(X_t'\beta)$$

where,

$$\Phi(x) = \frac{1}{\sqrt{(2\pi)}} \int_{-\infty}^{x} e^{-\frac{1}{2}X^2} dX.$$

Alternatively, the logit model specifies the transformation function as the logistic cumulative distribution function

$$F(X_t'\beta) = \Lambda(X_t'\beta) \tag{7}$$

where

$$\Lambda(x) \equiv \frac{1}{1+e^{-x}} = \frac{e^x}{1+e^x}. \tag{8}$$

The first derivative of $\Lambda(x)$ is denoted by $\lambda(x)$ as

$$\lambda(x) \equiv \frac{e^x}{(1+e^x)^2} = \Lambda(x)\Lambda(-x), \tag{9}$$

or alternatively

$$\lambda(x) \equiv \frac{e^x}{(1+e^x)^2} = \Lambda(x)(1-\Lambda(x)), \tag{10}$$

since $\lambda(x)$ is symmetric around zero[7].

Recall from (4) that the linear probability model is derived by assuming that the conditional expectation of y_t, $E(y_t|\Omega_t) = Pr(y_t = 1|\Omega_t) \equiv P_t$, is linear in a set of parameters β. Similarly, to derive the logit model we assume that the logarithm of the odds[8] is linear in a set of parameters β,

$$log\left(\frac{P_t}{1-P_t}\right) = X_t'\beta. \tag{11}$$

[7]Implying that $\Lambda(-x) = 1 - \Lambda(x)$.

[8]The odds is a ratio of the two probabilities $\frac{P_t}{1-Pt}$. The numerator is the probability that y_t equals 1 and the denominator is the probability of the alternative, that y_t equals 0.

Solving for P_t, we find that

$$P_t = \frac{\exp(X_t'\beta)}{1+\exp(X_t'\beta)} = \Lambda(X_t'\beta). \tag{12}$$

This result is what we would get by letting $\Lambda(X_t'\beta)$ play the role of the transformation function $F(X_t'\beta)$ in (5).

1.4.1.2.1 Estimation From (12), the function $\Lambda(.)$ is known, and defined by (8), and X_t is observed. Thus, only the vector of parameters (β) needs to be estimated. For both the probit and logit model, the most common method to conduct this estimation is through Maximum Likelihood Estimation (MLE).

For observation t the probability that $y_t = 1$ is

$$Pr(y_t = 1|X_t, \beta) = F(X_t'\beta), \tag{13}$$

and the probability that $y_t = 0$ is

$$Pr(y_t = 0|X_t, \beta) = 1 - F(X_t'\beta). \tag{14}$$

For $y_t = 0, 1$, both outcomes can be included into one function

$$Pr(y_t|X_t'\beta) = F(X_t'\beta)^{y_i}(1 - F(X_t'\beta))^{1-y_i}. \tag{15}$$

Assuming independence across all t, the likelihood function of y, where y and X denote the full set of y_t and X_t values, is

$$L(\beta|y,X) = Pr(y|X,\beta) = \prod_{t=1}^{n} F(X_t'\beta)^{y_t}(1-F(X_t'\beta))^{1-y_t}. \tag{16}$$

Then by taking the log of the likelihood function $L(\beta|y,X)$ we obtain the loglikelihood function denoted $l(y,\beta)$,

$$l(y,\beta) = \log L(\beta|y,X) = \sum_{t=1}^{n} \Big(y_t \log F(X_t'\beta) + (1-y_t)\log(1-F(X_t'\beta)) \Big). \tag{17}$$

Note that the log-likelihood function is negative when the index $X_t'\beta$ is finite. When the index is finite ($-\infty < X_t'\beta < \infty$), that implies that $0 < F(X_t'\beta) < 1$.

In such case, if $y_t = 1$:

$$\Big(y_t \log F(X_t'\beta) + (1-y_t)\log(1-F(X_t'\beta)) \Big) = \Big(1\log F(X_t'\beta) + 0 \Big).$$

Since $0 < F(X_t'\beta) < 1$, then $\log F(X_t'\beta) < 0$, which results in

$$\Big(y_t \log F(X_t'\beta) + (1-y_t)\log(1-F(X_t'\beta)) \Big) = \Big(1\log F(X_t'\beta) + 0 \Big) < 0.$$

If $y_t = 0$

$$\Big(y_t \log F(X_t'\beta) + (1-y_t)\log(1-F(X_t'\beta)) \Big) = \Big(0 + 1\log(1-F(X_t'\beta)) \Big).$$

Since $0 < F(X_t'\beta) < 1$, then $0 < (1-F(X_t'\beta)) < 1$ and $\log(1-F(X_t'\beta)) < 0$ which also results in

$$\Big(y_t \log F(X_t'\beta) + (1-y_t)\log(1-F(X_t'\beta))\Big) < 0.$$

Therefore when $X_t'\beta$ is finite, the term in parentheses will be negative for either $y_t = 1$ or $y_t = 0$. Thus the log-likelihood function will be negative because it is the sum of negative values.

The log-likelihood function reaches its maximum of 0, under a special case where $X_t'\beta = \infty$ when $y_t = 1$, and $X_t'\beta = -\infty$ when $y_t = 0$.

In such case, $y_t = 1 \implies F(X_t'\beta) = 1$ and

$$\begin{aligned}\Big(y_t \log F(X_t'\beta) + (1-y_t)\log(1-F(X_t'\beta))\Big) &= \Big(1\log 1 + (1-1)\log(1-1)\Big) \\ &= 0.\end{aligned}$$

Similarly, $y_t = 0 \implies F(X_t'\beta) = 0$ and

$$\begin{aligned}\Big(y_t \log F(X_t'\beta) + (1-y_t)\log(1-F(X_t'\beta))\Big) &= \Big(0\log 0 + (1-0)\log(1-0)\Big) \\ &= 0.\end{aligned}$$

For this special case where the model has perfect fit, the term in the large parenthesis will equal 0 whether y_t equals 0 or 1. Thus the log-likelihood will equal zero, since it is the sum of zeros.

Beyond being non-positive for both the logit and probit models, the log-likelihood function is globally concave with respect to β (Pratt 1981), making the maximization of the likelihood function straightforward. When the first derivative of the log-likelihood function with respect to β is equated to 0 we obtain the maximization problem's first order conditions, also known as the likelihood equations, below

$$\frac{\partial l(y,\beta)}{\partial \beta} = \sum_{t=1}^{n} \left(\frac{y_t f(X_t'\beta) x_{ti}}{\log F(X_t'\beta)} + \frac{(1-y_t)(-f(X_t'\beta))x_{it}}{\log(1-F(X_t'\beta))} \right) = 0, i = 1, ..., k. \quad (18)$$

Which simplify to

$$\sum_{t=1}^{n} \left(\frac{(y_t - F(X_t'\beta)) f(X_t'\beta) x_{ti}}{F(X_t'\beta)(1-F(X_t'\beta))} \right) = 0, i = 1, ..., k. \quad (19)$$

The maximum likelihood estimate of β, is achieved by solving for the β that satisfies the likelihood equations. However, β appears in the likelihood equations in the $F(X_t'\beta)$ and $f(X_t'\beta)$ terms which are nonlinear, thus likelihood equations must be solved numerically.

1.4.1.2.2 Strengths Multivariate logistic regressions are commonly used because they are one of the simplest machine learning algorithms. The simplicity of logit regressions allows for a much faster training time than other machine learning algorithms and the computational power required to estimate the model parameters is low. The low computational intensity and fast training time allows researchers to quickly and easily update the model to reflect new data as it is obtained. As well, because the logit model is quick and easy to estimate, researchers often start by estimating a logit model to get a rough idea of the data's features, then estimate a more complex model and use the logit model as a benchmark to which the more complex model can be compared to using some measure of model performance. Proponents of the logit model point out that logit models can be very efficient if the data set is large and the underlying Data Generating Process (DGP) of the dependent variable is linear and additively separable. However, in applied work the true DGP of the dependent

variable is most often unknown and simply assuming that it is linear and additive in parameters can lead to problems of misspecification.

1.4.1.2.3 Limitations As mentioned in Section 1.4.1.2.2, an estimated logit model can serve as a relatively good approximation of the true model if the data set is large and the model has been correctly specified, however if that is not the case, problems of under/overfitting and misspecification may arise. When the logit model is estimated with many regressors and few observations the model is prone to being overfitted, meaning that the model close to perfectly fits the data used to estimate the model and, although the model may have strong in-sample predictive performance, it is likely to have low out-of-sample predictive accuracy. Regularization techniques can be used to mitigate issues of overfitting; however, over-regularization can result in the converse problem of underfitting the model. Thus, caution should be exercised when estimating and using a logit model with many predictors and a small sample.

Maximum Likelihood estimation of logit models almost always yields biased and inconsistent estimates if the form of the transformational function, that is $F(X_t'\beta)$, is misspecified. It is therefore very important to test whether this function has been specified correctly. This can be done using a parametric specification test, however parametric tests (including but not limited to functional form specification tests) are sometimes inconsistent, that is to say the test lacks power in the direction of certain alternatives. Inconsistent parametric tests arise because the user must specify the set of alternatives under which the null is rejected, and there may exist some alternatives that a particular test cannot detect. Traditionally, parametric model specification tests test the null hypothesis (H_0) that the model has been correctly specified against an alternative hypothesis (H_a) that specifies another functional form. If an inconsistent test is used, the probability of rejecting H_0 when H_0 is false does not approach 1 as

the sample size n tends to infinity, thus even with a large sample the researcher will likely fail to reject the null that the model has been correctly specified, although the model has in fact been misspecified. For such reasons, it is advised to use a consistent nonparametric specification test for binary choice models, such as the test proposed by Li, Lin, and Racine (2013).

If a model specification test rejects H_0, it informs the researcher that the data suggests that the specified parametric model under the null is not a good representation of the DGP and the model estimates are likely to be biased and inconsistent. Although the test informs the researcher that the model should be ruled out, it unfortunately does not inform the researcher of what model would best represent the DGP. As a result, the researcher is only able to rule out one of many potential parametric models to represent the DGP. Rather than repeatedly testing alternative parametric specifications, which can induce pre-testing bias into the model selection process (H. White 2000), the researcher may instead adopt a nonparametric approach.

1.4.2 The Nonparametric Approach

Recall that we are interested in modelling the probability that the binary dependent variable equals 1 conditional on a set of predetermined variables. For the binary dependent variable $Y \in \{0, 1\}$, the conditional probability of interest can be obtained from the conditional Probability Density Function (PDF) as follows:

$$Pr(Y = 1|X = x) = f(Y = 1|x) \tag{20}$$

Thus a nonparametric approach would be to model the conditional PDF $f(y|x)$ using a mixed-data kernel estimator of a conditional PDF. The estimated PDF $\widehat{f}(y|x)$ makes

obtaining $\hat{f}(Y=1|x) = \hat{Pr}(Y=1|X=x)$ straightforward. To estimate $f(y|x)$ the R package "np" is used, this is a package for Nonparametric Kernel Smoothing Methods for Mixed Data Types. From the "np" package, I make use of the npcdens() function to estimate the nonparametric conditional density of interest. The details of the mixed-data kernel PDF estimator are described in the next section and the model in the section thereafter.

1.4.2.1 Mixed-data Conditional Probability Density Function Estimation

The conditional PDF is defined as

$$f(y|x) = \frac{f(y,x)}{f(x)}, \tag{21}$$

where $f(y,x)$ denotes the joint density of (X,Y) and $f(x)$ denotes the marginal density of X. The dependent variable Y is a binary variable and the covariate vector X can consist of continuous and discrete (unordered and ordered) variables. Using $\hat{f}(y,x)$ and $\hat{f}(x)$ to denote kernel estimators of $f(y,x)$ and $f(x)$, the conditional density $f(y|x)$ is estimated by

$$\hat{f}(y|x) = \frac{\hat{f}(y,x)}{\hat{f}(x)}. \tag{22}$$

The estimator of $f(z) = f(y,x)$ is given by

$$\hat{f}(z) = \frac{1}{n}\sum_{i=1}^{n} K_{\gamma_z}(Z_i, z), \tag{23}$$

and the estimator of $f(x)$ is given by

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} K_{\gamma_x}(X_i, x). \tag{24}$$

It is very important to note that $\hat{f}(y|x)$ is *not* calculated using separate estimates of $\hat{f}(z)$ and $\hat{f}(x)$. The estimation of $\hat{f}(z)$ and $\hat{f}(x)$ is to be done jointly such that the estimated smoothing parameters are the same in $\hat{f}(z)$ and $\hat{f}(x)$.

The $K_{\gamma_z}()$ and $K_{\gamma_x}()$ in (23) and (24) are generalized multivariate mixed-data product kernel functions, more specifically

$$K_{\gamma_z}(Z_i, z) = \prod_{j=1}^{q} h_j^{-1} K\Big(\frac{z_j^c - z_{ij}^c}{h_j}\Big) \prod_{j=1}^{r} L(Z_{ij}^u, z_j^u, \lambda_j^u), \prod_{j=1}^{s} l(Z_{ij}^o, z_j^o, \lambda_j^o) \tag{25}$$

and

$$K_{\gamma_x}(X_i, x) = \prod_{j=1}^{q} h_j^{-1} K\Big(\frac{x_j^c - x_{ij}^c}{h_j}\Big) \prod_{j=1}^{r} L(X_{ij}^u, x_j^u, \lambda_j^u) \prod_{j=1}^{s} l(X_{ij}^o, x_j^o, \lambda_j^o), \tag{26}$$

where $\prod$ is the product operator. Continuous variables are identified using the superscript ^{c}, q denotes the number of continuous variables in X, and $K()$ is the kernel function for continuous variables. Similarly, unordered discrete variables are indicated by the superscript ^{u}, r denotes the number of unordered discrete variables in X, and $L()$ is the unordered kernel function. Finally, ordered discrete variables are indicated by the superscript ^{o}, s denotes the number of ordered discrete variables in X, and $l()$ is the ordered kernel function.

In the generalized product kernel functions (25) and (26), h, λ^u, and λ^o are vectors of smoothing parameters. As previously mentioned, $\hat{f}(y, x)$ and $\hat{f}(x)$ are jointly estimated and have the same smoothing parameters for X, thus the vectors h, λ^u

and λ^o in (25) are the same as those found in (26). The vector h is of length q and contains the smoothing parameters[9] for each of the q continuous covariates. For discrete variables, λ^u is of length r and contains the smoothing parameters of the r unordered covariates, while λ^o is of length s and contains the smoothing parameter of the s ordered covariates. The vector γ_x contains all the smoothing parameters of the covariates, the vector γ_z contains all the smoothing parameters of the covariates plus the smoothing parameter for the outcome variable Y[10]. The vectors of smoothing parameters γ_x and γ_z, further known as the bandwidths, are estimated via least squares cross-validation (Hall, Racine, and Li 2004). Before estimating γ_x and γ_z the kernel functions $K()$, $L()$, and $l()$ kernel functions in the product kernels (25) and (26) must be specified.

1.4.2.1.1 Data-Type Specific Kernel Functions $K(.)$ is a second-order kernel, thus for x (or z) $K(x)$ it is real-valued, non-negative, bounded and symmetric, and it satisfies $K(x) \geq 0$, $\int_{-\infty}^{\infty} K(x)dx = 1$, $\int_{-\infty}^{\infty} xK(x)dx = 0$ and $0 \leq \int_{-\infty}^{\infty} x^2K(x)dx = \kappa_2 < \infty$. The function npcdensbw() from the "np" package default uses a second-order Gaussian kernel but has the option to modify the kernel type to either Gaussian, Epanechnikov, or uniform and the kernel order to either 2, 4, 6, or 8.

For discrete unordered variables, the kernel $L(.)$ is used. The default is the Aitchison and Aitken (1976) kernel function, defined as

$$L(X_i^u, x^u, \lambda^u) = \begin{cases} 1 - \lambda^u & \text{if } X_i^u = x^u \\ \lambda^u/(c-1) & \text{if } X_i^u \neq x^u, \end{cases} \tag{27}$$

[9]For continuous variables a smoothing parameter is also referred to as a bandwidth.
[10]The length of γ_x is $q + r + s$, and γ_z is of length $q + r + s + 1$.

where c is the cardinality of $X^d \in D$, $\lambda^u \in [0, (c-1)/c]$, and $\sum_{X^d \in D} L(X^d, x^d, \lambda) = 1$. Alternatively, the discrete unordered kernel type can be set to the Li and Racine (2003) kernel, which is defined as

$$L(X_i^u, x^u, \lambda^u) = \begin{cases} 1 & \text{if } X_i^u = x^u \\ \lambda^u & \text{if } X_i^u \neq x^u, \end{cases} \tag{28}$$

where $\lambda^u \in [0, 1]$.

The kernel $l(.)$ is used for discrete ordered variables. The npcdensbw() function uses the Li and Racine (2003) ordered kernel function, which is defined as

$$l(X_i^o, x^o, \lambda^o) = \begin{cases} 1 & \text{if } X_i^o = x^o \\ \lambda^{o[X_i^o - x]} & \text{if } X_i^o \neq x^o, \end{cases} \tag{29}$$

where $\lambda^o \in [0, 1]$. Alternatively, the kernel function for ordered discrete variables may be changed to the M.-C. Wang and Van Ryzin (1981) kernel function,

$$l(X_i^o, x^o, \lambda^o) = \begin{cases} 1 - \lambda^o & \text{if } X_i^o = x^o \\ \frac{1}{2}(1 - \lambda^o)\lambda^{o|X_i^o - x|} & \text{if } X_i^o \neq x^o. \end{cases} \tag{30}$$

Again $\lambda^o \in [0, 1]$. For the analysis presented in this paper the conditional PDF was estimated using the Li and Racine (2003) kernel functions for ordered and unordered discrete variables. The continuous variable kernel type was set to a second-order Epanechnikov kernel function; however, ultimately no continuous variables were included in the estimate. Having selected the kernel types, the vector of smoothing parameters γ_z can now be computed by various methods, one of those being Least

Squares Cross-Validation (Hall, Racine, and Li 2004).

1.4.2.1.2 Least-Squares Cross-Validation Computing the smoothing parameter vector γ_z via least squares cross-validation involves selecting the vector γ_z that minimized the integrated square error. The weighted integrated square difference between $\hat{f}(y|x)$ and $f(y|x)$ is[11]

$$\begin{aligned} I_n &= \int \left(\hat{f}(y|x) - f(y|x)\right)^2 f(x)dz \\ &= \int \left(\hat{f}(y|x)\right)^2 f(x)dz - 2\int \hat{f}(y|x)f(y|x)f(x)dz + \int \left(f(y|x)\right)^2 f(x)dz \\ &\equiv I_{1n} - 2I_{2n} + I_{3n}. \end{aligned} \tag{31}$$

The third term, $\int \left(f(y|x)\right)^2 f(x)dz$, is not a function of estimated densities, therefore it is independent of γ_z. Thus the problem of obtaining the γ_z that minimizes I_n is equivalent to obtaining the γ_z that minimizes $I_{1n} - 2I_{2n}$.

1.4.2.1.3 Strengths The logit model and nonparametric model presented in this paper both aim to estimate the conditional probability $P_t = Pr(Y = 1|X = x)$. The logit model specifies P_t as $P_t = \frac{e^{(X_t'\beta)}}{1+e^{(X_t'\beta)}}$, and as noted in Section 1.4.1.2.3, if this specification is incorrect then the estimates will be biased and inconsistent. On the other hand, the nonparametric approach models P_t as $P_t = f(Y = 1|x)$ which is obtained by estimating $f(y|x)$ using a kernel-smoothed estimator of a conditional PDF. The nonparametric approach's estimate will be biased in finite samples; however, the finite sample variance of the estimate is reduced as the sample size increases and the estimator is asymptotically unbiased and consistent. Despite the downside of some finite sample

[11] To simplify notation $\int dz = \sum_{z^d} \int dz^c$.

bias, the nonparametric approach offers some estimator benefits (reduced finite sample variance and asymptotic unbiasedness and consistency) that a misspecified logit model cannot offer. Thus, if the logit model fails to pass a consistent model specification test, one may instead choose to undertake the nonparametric approach, rather than to continue guessing and testing different parametric specifications. Another favorable feature of the nonparametric approach is that when the optimal bandwidths are estimated via least-squares cross validation, as described in Section 1.4.2.1.2, covariates (components of X_t) that are independent of Y are smoothed out (and asymptotically removed) so that they do not contribute to the variance of the estimator or the predicted outputs (Hall, Racine, and Li 2004), thus this feature provides automatic dimensionality reduction when appropriate (Racine 2019).

1.4.2.1.4 Limitations Researchers are sometimes deterred from using nonparametric kernel estimation methods because such methods are numerically intensive. Unlike parametric models where the functional form is specified and only a finite number of parameters require estimation, nonparametric methods can be applied when the functional form is unknown and the number of parameters in the function is said to be infinite. Thus, computation time and intensity is often greater with nonparametric methods. However, rapid technological progress has brought forth large advancements in computer hardware and software that allows for increasingly complex numerical problems to be solved more rapidly. The computation time of nonparametric estimation can be minimized through efficient estimation programming available through statistical software packages like the "np" package in R which was used to estimate the nonparametric mixed-data kernel estimator of a conditional PDF presented in this paper. Computational time can also be reduced by splitting up the computational work among multiple cores on a computer and/or among multiple computers using

parallel computing. The nonparametric estimation required for this research made use of the parallel computing services available through the Shared Hierarchical Research Computing Network (SHARCNET) computer cluster "GRAHAM". The use of the "np" package and the "GRAHAM"" cluster greatly reduced the computing time so that it did not pose a significant limitation to the speed at which the research project progressed.

1.4.3 Identifying and Analyzing Key Predictors

The papers listed in Appendix 4.1.1 estimated a model of prescription opioid use to identify which variables are statistically significant predictors of prescription opioid use and then to analyze the direction and magnitude of the effects that each of those variables have on the outcome variable. In this paper, both of these steps are taken with each of the two models.

1.4.3.1 Statistically Significant Predictors Assessing if the variable i in a logit model is statistically significant follows the standard practice of conducting a two-sided t-test to test the null hypothesis $H_0 : \beta_i = 0$ versus the alternative $H_a : \beta_i \neq 0$. Conducting this test involves using the estimated parameter $(\widehat{\beta}_i)$ and standard error $(\text{S.E}(\widehat{\beta}_i))$ to compute the test statistic $(t = \widehat{\beta}_i/\text{S.E}(\widehat{\beta}_i))$ and p-value $(2\Phi(-|t|))$[12]. If the p-value is less than the alpha (α) value (commonly used are 0.05 or 0.01 for the 5% and 1% significance levels), then the null hypothesis is rejected and the variable is deemed statistically significant at the pre-specified significance level (e.g., 5% or 1%).

For the nonparametric approach, relevant predictors can be identified by analyzing the estimated bandwidths of each variable. Recall from Section 1.4.2.1.2, that the bandwidth vector γ_z contains the bandwidths/smoothing parameters for the outcome

[12]Where $\Phi(x) = \frac{1}{\sqrt{(2\pi)}} \int_{-\infty}^{x} e^{-\frac{1}{2}X^2} dX$.

variable Y and each of the variables in X. The greater the bandwidth the more that variable is smoothed out and the less it contributes to estimating the conditional density. When the bandwidth selection method is least-squares cross-validation, the irrelevant variables are smoothed out by assigning those variables a large bandwidth (Hall, Racine, and Li 2004). Thus, the relevant predictors are those that have not been identified as irrelevant and have been assigned moderate bandwidths (Racine 2019). Recall from Table 2 that the predictors entered into the model are a mix of ordered and unordered discrete variables and Section 1.4.2.1.1 described the Li and Racine (2003) kernel functions for order and unordered discrete variables. The smoothing parameter λ in the Li and Racine (2003) kernel functions has an upper bound of 1, therefore any variable that receives a smoothing parameter of 1 or close to 1 (e.g., 0.9997) has been smoothed out because it is independent of Y and is not useful in the estimation of $\hat{f}(y|x)$.

1.4.3.2 Marginal Effects Research aiming to identify the statistically significant predictors of prescription opioid use is most often also interested in analyzing the marginal effect that each of those variables have on the dependent variable. The marginal effect refers to the change in the dependent variable that occurs in response to a one-unit change in a given explanatory variable, while holding all other explanatory variables constant. For a binary dependent variable, the linear probability model provides the simplest interpretation of marginal effects. Recall from equations (3) and (4), that for the linear probability model $P_t \equiv Pr(y_t = 1|\Omega_t) = X_t'\beta$ and the predicted probability is estimated as $\hat{P}_t = X_t'\hat{\beta}$. For illustrative purposes, suppose that the vector X_t contains only two regressors x_{1t} and x_{2t}, plus a constant. Without introducing nonlinearity into the model by adding polynomials of x_{1t}, x_{2t} or interactions, then the probability that $y_t = 1$ conditional on x_{1t} and x_{2t} is modeled by the linear probability

model as:

$$P_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + e_t.$$

It is evident that the relationship between P_t and say x_{1t} is linear and the marginal effect $\partial P_t/\partial x_{1t}$ is a constant (β_1). Note that interpreting the partial derivative $\partial P_t/\partial x_{1t} = \beta_1$ as the marginal effect implies that the marginal effect depends neither on the value of x_{1t} nor the value of x_{2t}, this is a result of the linear and additive functional form. Depending on the research question at hand, it may be hard to justify the idea that the marginal effect is constant for all values of the regressor of interest and/or independent of the value of other covariates. The interpretation of β_1 depends on the data type of x_{1t}. If x_{1t} is a continuous variable, and changed by one unit while holding all other explanatory variables (x_{2t}) constant, the predicted probability that $y_t = 1$ (i.e. $\widehat{P}_t$) would change by β_1. When x_{1t} is binary, then β_1 is interpreted as the change in the predicted probability that $y_t = 1$ when x_{1t} changes from 0 to 1. If x_{1t} is a categorical variable, then a reference category is selected and β_1 is interpreted as the difference in $\widehat{P}_t$ for a given category relative to the reference category.

The linear and additive functional form of the linear probability model is what allows the marginal effect to be a constant and easily interpretable scalar, however when the model is nonlinear, as in the case of logit and probit models, the marginal effect is not constant across different values of X_t. Recall from equation (5), that for the logit and probit models $P_t = F(X_t'\beta)$ hence the marginal effect of the i^{th} element of X_t is

$$\frac{\partial P_t}{\partial x_{it}} = \frac{\partial F(X_t'\beta)}{\partial x_{it}}.$$

More specifically, for the logit it is

$$\begin{aligned}\frac{\partial P_t}{\partial x_{it}} &= \frac{\partial \Lambda(X_t'\beta)}{\partial x_{it}} \\ &= \Lambda(X_t'\beta)(1-\Lambda(X_t'\beta))\beta_i \\ &= \frac{\exp(X_t'\beta)}{1+\exp(X_t'\beta)}\left(1-\frac{\exp(X_t'\beta)}{1+\exp(X_t'\beta)}\right)\beta_i \\ &= \frac{\exp(X_t'\beta)}{(1+\exp(X_t'\beta))^2}\beta_i.\end{aligned} \tag{32}$$

From (32), it is evident that the marginal effect is no longer constant for all values of X_t, instead the marginal effect depends the values of all the regressors. If x^* and x^{**} are vectors of values for the regressors in X_t and $x^* \neq x^{**}$, the marginal effect evaluated at x^* will not be the same as the marginal effect evaluated at x^{**}.

There are two popular methods for describing the marginal effects for a nonlinear model in terms of a scalar: the marginal effect at the mean (MEM) and the average marginal effect (AME). The MEM approach computes the marginal effect of variable i as follows:

$$MEM_i = \frac{\exp(\bar{x}'\beta)}{(1+\exp(\bar{x}'\beta))^2}\beta_i, \tag{33}$$

where the vector $\bar{x}$ contains the sample mean value of each variable in X_t. A downside to the MEM approach is that if the model includes binary or categorical variables then evaluating the marginal effect at their mean values is not very intuitive. This problem can be easily overcome by having the elements of $\bar{x}$ equal the sample mean for continuous variables and the sample mode for binary and categorical variables. The average marginal effect (AME) of variable i is calculated by

$$AME_i = n^{-1} \sum_{t=1}^{n} \left(\frac{\exp(x_t'\beta)}{(1+\exp(x_t'\beta))^2} \right) \beta_i.$$

Thus the marginal effect of variable i ($\frac{\partial P_t}{\partial x_{it}}$) is evaluated at the observed variable values of observation t, this done for all observations $t = 1, ..., n$, then all n of the marginal effects of variable i are averaged to obtain the average marginal effect. Note that since the marginal effect is nonlinear, the marginal effect at the mean (MEM) and the average marginal effect (AME) are not equivalent.

1.4.3.3 Counterfactual Experiments Reducing a complicated nonlinear marginal effect function to a scalar may seem appealing, however in doing so some interesting features of the relationship between the dependent variable and the independent variable of interest may go unnoticed. In lieu of the commonly used MEM and AME approaches described above, this paper analyses the marginal effects by conducting counter-factual experiments. This is an approach that can be applied to either linear or nonlinear parametric or nonparametric models. The counter-factual experiment approach commences by first identifying an interesting individual, that is an individual that may be of particular relevance to the research topic at hand. The interest of the research presented in this paper is to identify the factors that determine prescription opioid use, thus a likely prescription opioid user would be an interesting individual to analyze. For the counter-factual experiments presented in this paper a likely prescription opioid user is defined as an individual with the characteristics most commonly observed among a sample of prescription opioid users. The interesting individual is created by creating an observation vector $\dot{x}$ in which for every regressor variable the value entered is the sample mode for that variable from a sample of prescription opioid users. Equipped with an interesting individual,

the counter-factual experiment proceeds to answer specific questions. For example, how would the probability of taking prescription opioids change for this individual if he/she were to obtain pharmaceutical insurance? In such case, the effect that having pharmaceutical insurance has on the probability of prescription opioid use is

$$\hat{Pr}(y = 1|\dot{x}, \text{insurance} = 1) - \hat{Pr}(y = 1|\dot{x}, \text{insurance} = 0).$$

Using either the logit or nonparametric model the two predicted probabilities can be estimated and the difference calculated. Confidence intervals can be computed and the null hypothesis that there is no significant difference ($H_0 : \hat{Pr}(y = 1|\dot{x}, \text{insurance} = 1) - \hat{Pr}(y = 1|\dot{x}, \text{insurance} = 0) = 0$) can be tested.

In the example presented above, the variable whose marginal effect is of interest is a binary variable (equals 1 for insured or 0 for uninsured); however, this approach can also be applied with a categorical or continuous variable of interest. In fact, the counter-factual experiment approach is a particularly insightful approach to use for continuous variables. When the counter-factuals are computed for the entire range of values of a continuous variable, they may be plotted and provide a visual tool to analyze the *partial marginal effect function*. The plotted function is a *partial* marginal effects function because the difference in probability is measured on the y-axis and the continuous variable of interest is measured on the x-axis, while holding all off-axis covariates constant.

1.4.4 Assessing and Comparing Model Performance

The logit model is parametrized by first specifying the functional form of the model, however if the specified functional form is incorrect then the estimated parameters

may be biased and inconsistent. The nonparametric approach discussed in Section 1.4.2 overcomes this limitation by avoiding model specification and instead uses a data-driven approach to estimating the conditional probability of interest. This does not suggest that the nonparametric approach should always be strictly preferred, as the logit model could be misspecified but still usefully accurate in its predictions. Thus, comparing the two models on the basis of predictive performance may be used as an approach to select which of the two models to use. The predictive performance of the logit and nonparametric model will be evaluated and compared using various measures and illustrative tools from the binary classification literature, including confusion matrices, correct classification ratios and ROC curves. The following section describes each of these measures and discusses how these measures are particularly insightful when the outcome variable is a highly imbalanced binary variable.

1.4.4.1 Confusion Matrices, Correct Classification and ROC curves Statistical models are often used to predict what the outcome variable is expected to be for a given vector of values of the model's covariate variables. Recall that the outcome variable of interest is a binary variable $Y \in \{0, 1\}$ and that both the logit and nonparametric model described in Section 1.4.1.2 and Section 1.4.2 are able to estimate the conditional probability of interest $Pr(Y = 1|X = x)$. The estimate $\hat{Pr}(Y = 1|X = x)$ informs the analyst of the probability that $Y = 1$, however it does not make a prediction about whether Y will be equal to 1 or 0. For a binary prediction, also known as classification, a cutoff $\tau \in (0, 1)$ must be indicated[13], such that the when $\hat{Pr}(Y = 1|X = x) > \tau$ the model predicts $Y = 1$, and when $\hat{Pr}(Y = 1|X = x) \leq \tau$ it predicts $Y = 0$.

[13] Conventionally $\tau = 0.5$ is chosen.

1.4.4.1.1 The Confusion Matrix The data used to estimate a model can also be used to analyze the accuracy of that model's predictions. For each observation $i = 1, ..., n_1$ where $n_1 \leq n$ (where n is the sample size), the vector of covariate values x_i can be used to obtain $\widehat{Pr}(y_i = 1|x_i)$ and, using a classification threshold (τ), to predict y_i. The prediction $\widehat{y}_i$ is then compared to the observed y_i in the data. The prediction can result in one of four outcomes:

- A *True Positive* (TP): When the model predicts $Y = 1$ and this is in fact true (i.e., both the predicted value and the observed value equal 1, $\widehat{Y} = 1$ & $Y = 1$)
- A *True Negative* (TN): When the model predicts $Y = 0$ and this is in fact true (i.e., both the predicted value and the observed value equal 0, $\widehat{Y} = 0$ & $Y = 0$)
- A *False Positive* (FP): When the model predicts $Y = 1$ but the observed value is in fact 0 (i.e., $\widehat{Y} = 1$ & $Y = 0$)
- A *False Negative* (FN): When the model predicts $Y = 0$ but the observed value is in fact 1 (i.e., $\widehat{Y} = 0$ & $Y = 1$)

By definition true positives and true negatives are correct predictions, whereas false positive and false negatives are incorrect predictions. When this procedure is done for all n_1 observations the results can be collected in a *confusion matrix*, which tabulates the actual outcomes versus those predicted by the model. Table 4 illustrates a confusion matrix and what is being tabulated in each element of the matrix. The correct predictions are tabulated in the diagonal elements and the incorrect (confused) predictions tabulated in the off-diagonal elements. The confusion matrix can be used to illustrate several terms, measures and ratios used to analyze classification accuracy. First is the term *positive* (P) which is the total number of actual positive ($Y = 1$) observations in the data. The positive is the sum of the second column of the confusion

Table 4: Confusion Matrix (actual in columns, predicted in rows)

	Actual 0	Actual 1
Predicted 0	TN	FN
Predicted 1	FP	TP

matrix, that is P=TP+FN. Similarly the *negative* (N), is the total number of actual negative ($Y = 0$) observations in the data, thus N=TN+FP which is the sum of the first column in the confusion matrix. The positive (P) and negative (N) values are necessary for calculating and interpreting four ratios:

- True Positive Rate: The proportion of actual 1's that are *correctly* predicted

$$TPR = P(\hat{Y} = 1|Y = 1) = \frac{TP}{P} = \frac{TP}{TP + FN} = 1 - FNR$$

- False Positive Rate: The proportion of actual 0's that are *incorrectly* predicted

$$FPR = P(\hat{Y} = 1|Y = 0) = \frac{FP}{N} = \frac{FP}{TN + FP} = 1 - TNR$$

- True Negative Rate: The proportion of actual 0's that are *correctly* predicted

$$TNR = P(\hat{Y} = 0|Y = 0) = \frac{TN}{N} = \frac{TN}{TN + FP} = 1 - FPR$$

- False Negative Rate: The proportion of actual 1's that are *incorrectly* predicted

$$FNR = P(\hat{Y} = 0|Y = 1) = \frac{FN}{P} = \frac{FN}{TP + FN} = 1 - TPR$$

As an illustrative example, the confusion matrix presented in Table 5 is for a model with no predictive power. The TPR, FPR, TNR and FNR are as follows:

Table 5: Confusion Matrix (actual in columns, predicted in rows, model has no predictive ability)

	Actual 0	Actual 1
Predicted 0	257	270
Predicted 1	239	234

Table 6: Confusion Matrix (actual in columns, predicted in rows, model has perfect predictive ability)

	Actual 0	Actual 1
Predicted 0	493	0
Predicted 1	0	507

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN} = \frac{234}{234 + 270} = 0.4642857$$

$$FPR = \frac{FP}{N} = \frac{FP}{FP + TN} = \frac{239}{239 + 257} = 0.4818548$$

$$TNR = \frac{TN}{N} = \frac{TN}{FP + TN} = \frac{257}{239 + 257} = 0.5181452$$

$$FNR = \frac{FN}{P} = \frac{FN}{TP + FN} = \frac{270}{234 + 270} = 0.5357143$$

Utilizing the confusion matrix in Table 5 and the rates listed above, the analyst can infer that the model used has no predictive power. This is evident by the fact that the probabilities of making a correct prediction ($P(\hat{Y} = 1|Y = 1) = TPR$ and $P(\hat{Y} = 0|Y = 0) = TNR$) for either case are close to 50%, as are the probabilities of making an incorrect prediction ($P(\hat{Y} = 1|Y = 0) = FPR$ and $P(\hat{Y} = 0|Y = 1) = FNR$). Thus, the model used does not perform any better than simply flipping a coin for

which heads predicts 1 and tails predicts 0. Alternatively, Table 6 shows the confusion matrix for a model with perfect predictive power. This is evident by the fact that only the diagonal elements, which represent correct predictions, have values and the off-diagonal elements, which represent incorrect predictions are empty. This result could also be inferred using the TPR, FPR, TNR, and FNR rates. The probabilities of making a correct prediction ($P(\hat{Y} = 1|Y = 1) = TPR$ and $P(\hat{Y} = 0|Y = 0) = TNR$) for either case are 100%, whereas the probabilities of making an incorrect prediction ($P(\hat{Y} = 1|Y = 0) = FPR$ and $P(\hat{Y} = 0|Y = 1) = FNR$) are 0.

1.4.4.1.2 The Correct Classification Ratio The classification rates (TPR, FPR, TNR, and FNR) inform the researcher of the model's probability of making a correct or incorrect prediction, given an outcome and prediction. For an overall measure of classification accuracy, the *Correct Classification Ratio (CCR)* is commonly used. The CCR is of the sum of the diagonal elements of the confusion matrix as a fraction of the sum of all the elements of the confusion matrix:

$$CCR = \frac{TN + TP}{TN + FN + FP + TP}$$

.

The CCR indicates the proportion of correct predictions (either correct $\hat{Y} = 1$ or $\hat{Y} = 0$), however this measure may be misleading if the data are imbalanced, that is there is large variation in the number of observations in each class. To illustrate, suppose the data contains 98 observations that reported "False" to a question regarding prescription opioid use and 2 observations reported "True". In such case, a classifier may classify all observations as "False", resulting in a CCR equal to 98%. However, with a thorough analysis of the confusion matrix it would become evident that the

classifier has a 100% recognition rate for "False" cases and 0% recognition for "True" cases. Therefore, the CCR of 98% may mislead the researcher to think the classifier is fairly accurate; however, when it comes to the population of interest (prescription opioid users) the classifier is completely inaccurate. The CCR is a measure of overall accuracy. To shift interest away from overall accuracy and place more focus on the correct prediction of one class (e.g., when Y=1 to indicate that an individual reported "True" to taking prescription opioids) it is advised to use Receiver Operating Characteristic (ROC) curve analysis.

1.4.4.1.3 The ROC Curve As previously noted, classification requires a cutoff $\tau \in (0,1)$. Commonly a cutoff of $\tau = 0.5$ is chosen such that $\hat{Y} = 1$ when $\hat{Pr}(Y = 1|X = x) \geq 0.5$ and $\hat{Y} = 0$ otherwise. However, $\tau = 0.5$ is most often chosen on an ad hoc basis and there may exist another value of τ that would result in superior classification performance. An optimal cutoff τ^* may be selected by allowing the cutoff to vary and analyzing how a classifier's accuracy changes in response to changes in τ. Instead of computing only one confusion matrix using a fixed threshold (e.g., $\tau = 0.5$), a range of confusion matrices are computed for a range of cutoff values $\tau \in (0,1)$. For each τ, and its associated confusion matrix, the TPR and FPR are calculated and used to select τ^*. The TPR and FPR are used because these two rates represent a trade-off that occurs when τ, and by extension the probability of predicting $\hat{Y} = 1$, changes. Recall that a perfect classifier like the one illustrated in Table 6 can perfectly distinguish $Y = 0$ and $Y = 1$ observations and will have a TPR=1 and FPR=0. Therefore, ideally we look for a τ that maximizes TPR while minimizing FPR. To illustrate how the balance of TPR and FPR changes as τ increases from 0 to 1, we explore the two extremes. Suppose we start the search for the optimal τ at the lower bound $\tau = 0$, then $\hat{Y} = 1$ if $\hat{Pr}(Y = 1|X = x) \geq 0$ and 0 otherwise, however since

$\hat{Pr}(Y = 1|X = x) \in [0, 1]$ that implies at all the prediction made will be $\hat{Y} = 1$. In such a case, for all the observations which were in fact $Y = 1$ the prediction will be correct and the TPR will equal 1. However, for all the observation which were $Y = 0$, the prediction will be incorrect and the FPR will also equal 1. Conversely at the upper bound $\tau = 1$, then $\hat{Y} = 1$ if $\hat{Pr}(Y = 1|X = x) \geq 1$ and 0 otherwise, resulting in all the predictions being $\hat{Y} = 0$, therefore, there are no positives and hence the TPR and FPR are both 0. As illustrated both the TPR and FPR decrease as τ increases, but the rates at which the TPR and FPR fall are not the same for both nor are they constant, and depend on the model's predictive ability.

The changes in TPR and FPR as τ changes can be summarized and illustrated with an ROC curve. The ROC curve serves as a tool to illustrate the diagnostic capability of a binary classification system. The ROC curve plots the TPR on the y-axis and the FPR on the x-axis for $\tau \in (0, 1)$. The ROC curve plots the classifier's correct predictions of $Y = 1$ versus its incorrect predictions as τ varies. Figure 4 is an ROC curve for a classifier with some predictive power and demonstrates the TPR and FPR values when τ ranges from $\tau = 0$ (top right in dark blue) to $\tau = 1$ (bottom left in red). Figure 5 illustrates three ROC curves; one with no predictive power (in red), one with some predictive power (in green), and one with prefect predictive power (blue). Note that the higher the predictive power of a model the greater the area below its ROC curve. The predictive performance of two models can be compared by comparing the Area Under the Curve (AUC) of the two models, with a higher AUC being preferred.

1.4.4.2 In-Sample and Out-of-Sample Performance The previous section discussed the various measures (FPR, TPR, CCR and AUC) that will be used to evaluate and compare the predictive performance of the logit and nonparametric model. The performance measures are computed for each model's in-sample and out-

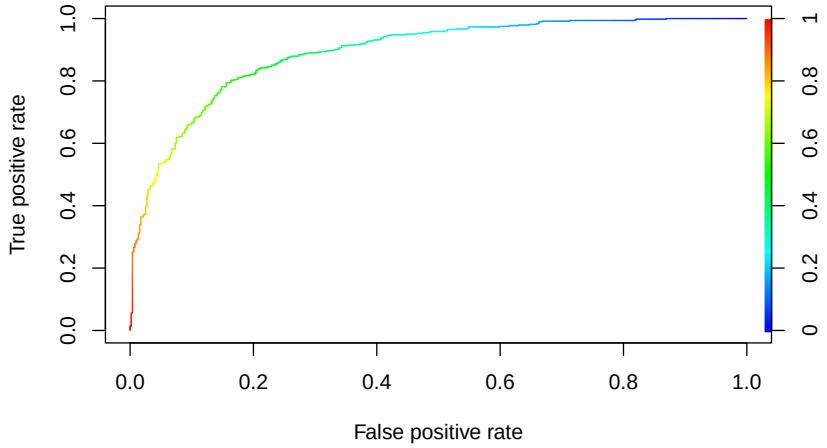


Figure 4: ROC Curve (as cutoff increases we move from upper right to lower left)

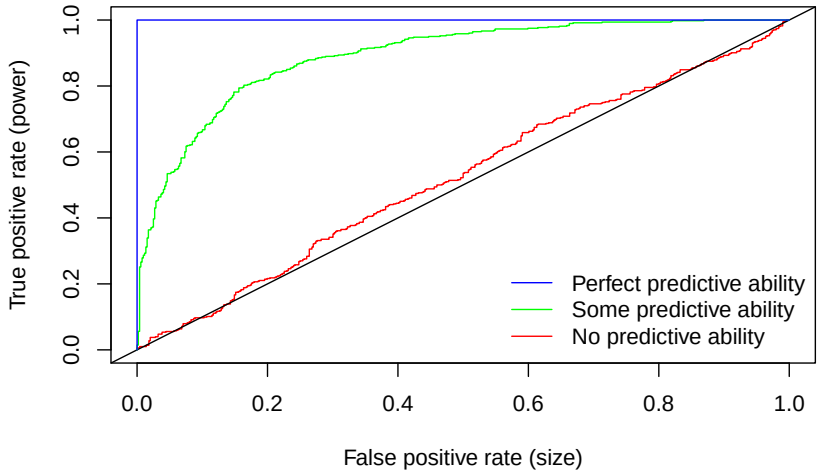


Figure 5: ROC Curves for Models with Varying Predictive Ability

of-sample predictions. For the in-sample evaluations, the complete data set, which has n observations, is used to estimate and evaluate the two models. For the out-of-sample evaluations, the total data is broken up into two independent samples with n_1 and n_2 observations respectively, such that $n = n_1 + n_2$. The first n_1 observations are referred to as the training data and the remaining n_2 observations are referred to as the testing, hold-out, or evaluation data. The training data are used to fit the models, and the evaluation data are used to evaluate the models' ability to make correct predictions for observations which were not used in the model's estimation. The out-of-sample

evaluation measure (e.g., the out-of-sample CCR) may be influenced by the cut-off point between the training data and evaluation data, depending on which observations lie in the training or evaluation data. To obtain a measure of out-of-sample predictive performance that is robust to the split of the data, an approach by Racine and Parmeter (2014) is used by applying the steps listed below.

1. The data of size n is divided into two independent samples. The first n_1 observations make up the training data and the remaining n_2 observations make up the evaluation data, such that $n_1 + n_2 = n$ and n_2 is, say, 10% of n.

2. The training data is used to fit the logit and nonparametric model.

3. For each observation in the evaluation data, the logit model and nonparametric model use the covariate data to produce predicted probabilities, $\hat{P}(y_i = 1|x_i)$. Using each model's optimal classification cutoff (τ^*) and the classification rule $\hat{y}_i = 1$ if $\hat{P}(y_i = 1|x_i) > \tau^*$ and $\hat{y}_i = 0$ otherwise, predictions are made for each of the observations in the evaluation data.

4. The models' predictions are compared to the observed outcomes in the evaluation data and the out-of-sample CCR for each model is collected.

5. The whole data set (all n observations) is then shuffled and steps 1 to 4 are repeated. This process is repeated, say, a thousand times, such that for each model (logit and nonparametric) a thousand CCRs are collected.

For each model, the one thousand corresponding CCRs serve to construct an empirical distribution function of the model's out-of-sample CCR and analyze whether that model's expected out-of-sample CCR is statistically larger than the other model's. Similarly, this approach is also used to compare other expected out-of-sample predictive performance measures such as the TPR and FPR.

1.5 Results

1.5.1 Model Comparison Results

The entire sample of data used for the analysis included 5959 observations, of which 214 reported taking prescription opioids. Thus, only 3.59% of observations belong to the sub-population of interest, resulting in a highly imbalanced binary outcome variable. This section illustrates the logit and NP models' ability to model and correctly predict this low probability event.

1.5.1.1 In-Sample Evaluations As discussed in Section 1.4.4.1, the logit and nonparametric model can each estimate the conditional probability of interest, $\hat{Pr}(Y = 1|X = x)$. Then, for a classification cutoff $\tau \in (0, 1)$, the prediction $y_i = 1$ is made if $\hat{Pr}(y_i = 1|x_i) > \tau$ and zero otherwise. This requires the value of τ to be determined; a popular approach to determining the optimal cutoff is to select the cutoff that maximizes overall prediction accuracy, in this case the CCR. Figure 6 illustrates for each of the models how the overall predictive accuracy (CCR) changes as τ changes, and the vertical lines indicate the optimal cutoff value that maximizes accuracy. For the logit model, a cutoff value of 0.5954 achieves a maximum CCR of 0.9643. For the nonparametric model, a cutoff value of 0.2218 achieves a maximum CCR of 0.9686.

Using the optimal cutoff values, the confusion matrices for the logit and nonparametric model are computed and presented respectively in Table 7 and Table 8. The logit model made 5954 (5743 + 211) $Y = 0$ predictions, 5743 of which were correct, leading to a high True Negative Rate (TNR) of 99.97%. However, the logit model leads to very few $Y = 1$ predictions, 3 correct, and 2 incorrect classifications. By making few $Y = 1$ predictions, the model makes few false positive misclassifications; thus, the FPR which captures the proportion of $Y = 0$ observations that were incorrectly predicted

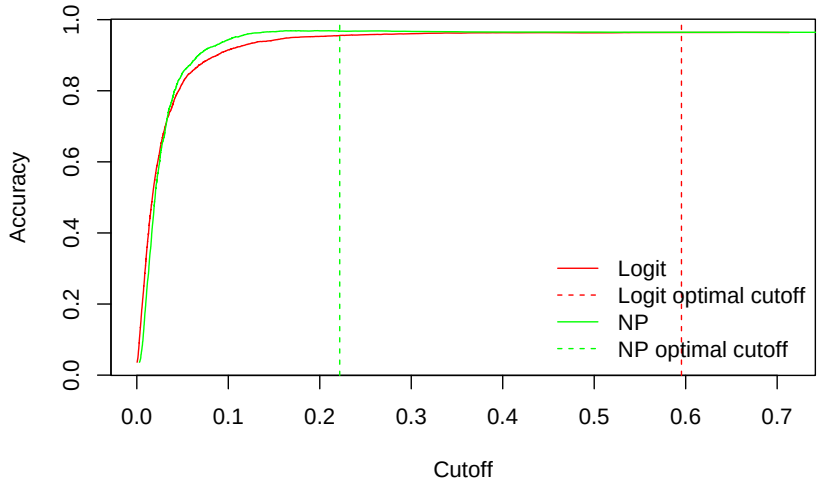


Figure 6: Classification Accuracy

to be $Y = 1$ is low (0.03%). Unfortunately, by making few $Y = 1$ predictions, the proportion of correctly predicted $Y = 1$ cases is also low and results in a low TPR (1.4%). Therefore, although the logit model achieves high overall accuracy (CCR= 96.43%), this measure is primarily driven by high predictive performance at classifying non-users of prescription opioids (Y=0). On the other hand, the model performs poorly at classifying the observations of interest, prescription opioid users (Y=1). From Table 8, it can be observed that the nonparametric model follows a similar pattern, where high overall accuracy (CCR=96.86%) is primarily driven by the high prediction accuracy of non-users (TNR=99.88%). However, the nonparametric model's predictive performance of prescription opioid users is noticeably different from that of the logit model. First, more $Y = 1$ predictions are made. The nonparametric model made 41 $Y = 1$ predictions, which is 8.2 times the number of $Y = 1$ predictions made by the logit model. More importantly, the accuracy of those predictions is 15.89%, which is 11.33 times better classification accuracy of prescription opioid users.

This result suggests that the nonparametric model is substantially better able to correctly classify prescription opioid users. To assure that this result is robust to the

Table 7: In-Sample Logit Confusion Matrix

	Predicted 0	Predicted 1
Actual 0	5743	2
Actual 1	211	3

Note:
Cutoff = 0.5954
CCR= 0.9643
TPR= 0.0140
FPR= 0.0003
AUC= 0.8104

Table 8: In-Sample NP Confusion Matrix

	Predicted 0	Predicted 1
Actual 0	5738	7
Actual 1	180	34

Note:
Cutoff = 0.2218
CCR= 0.9686
TPR= 0.1589
FPR= 0.0012
AUC= 0.8791

cutoffs selected, the TPRs and FPRs for all cutoff values are explored for both models. Figure 7 illustrates the TPR and FPR decrease as the cutoff increases because fewer positive ($Y = 1$) predictions are made. Recalling that higher values of TPR and lower values of FPR are desirable, the better the predictive ability of a model, the larger the space between the TPR curve and FPR curve. In this case, Figure 7 illustrates how the TPR curve of the nonparametric model is higher than the logit's for nearly all cutoff values. The FPR curves of the two models are plotted close together for most values, except for a small gap for cutoffs between 0.05 and 0.22, where the nonparametric model's FPR curve lies below that of the logit's. While Figure 7 plots the TPR and

FPR of each model separately, the ROC curve plots the TPR and FPR for all cutoff values. Figure 8 is the logit model's ROC curve which plots the FPR on the y-axis and FPR on the x-axis for each cutoff value ranging from 0 at the top-left in dark blue to 1 at the bottom right in red. The Area Under the Curve (AUC) is 0.8104, which lies between a model with no predictive ability (AUC=0.5) and a model with perfect predictive ability (AUC=1). Similarly, the nonparametric model's ROC curve is plotted in Figure 8. The nonparametric model's AUC is 0.8791, implying better predictive ability than the logit model. This result is visualized in Figure 10. The nonparametric model's higher ROC curve shows that the nonparametric model can achieve a high TPR than the logit for the same FPR cost. Because the ROC curve graphs the TPR and FPR for the full range of cutoff values from 0 to 1 it is clear that the better relative performance of the nonparametric model is due to the model's predictive ability and not the cutoff selected.

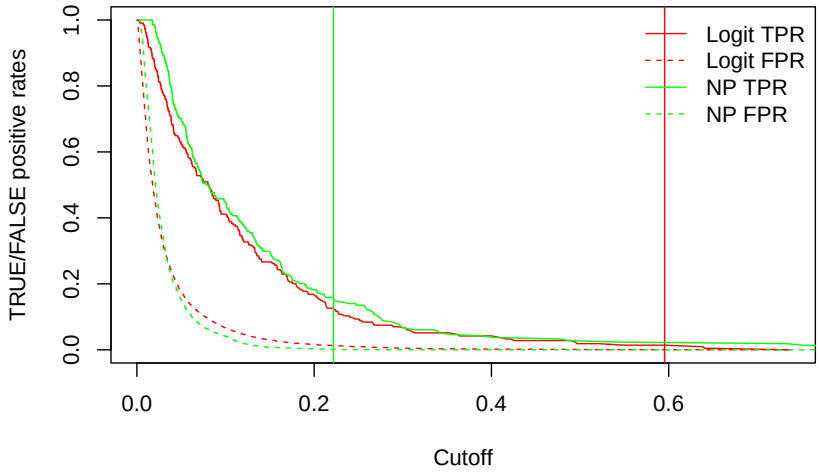


Figure 7: TPR/FPR Curves for Logit and NP

1.5.1.2 Out-of-Sample Evaluations In-sample evaluations of predictive performance can be overly optimistic about a model's predictive ability, as the model is being evaluated on its ability to predict the outcome of observations it was trained to fit. On

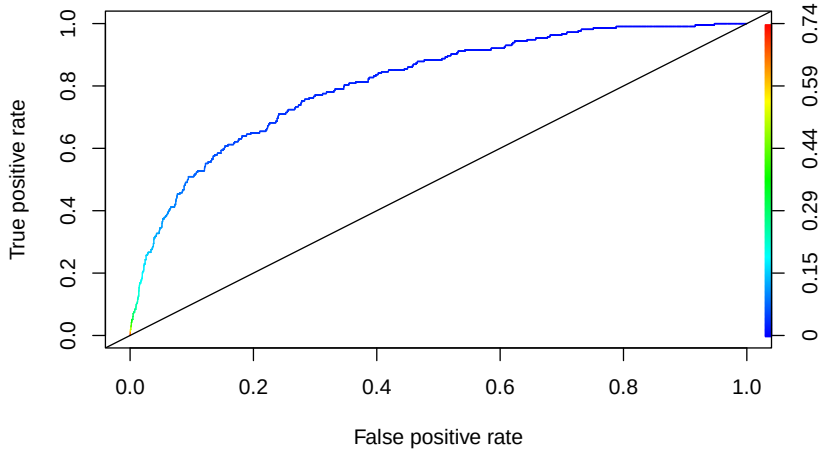


Figure 8: Logit ROC Curve

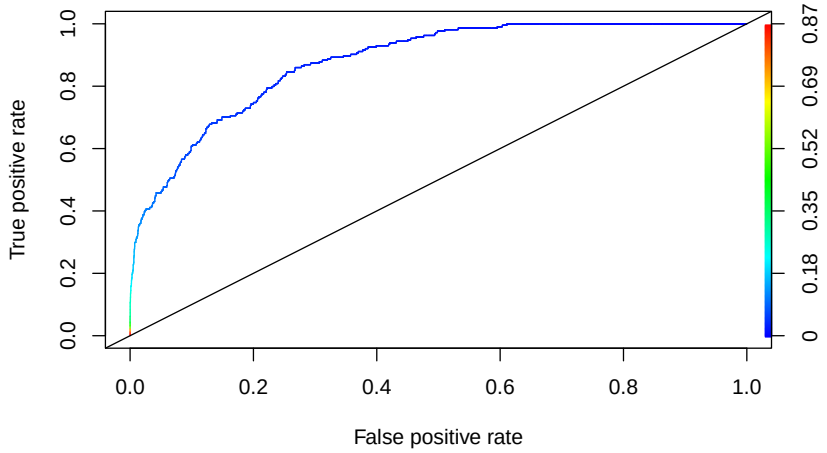


Figure 9: NP ROC Curve

the other hand, out-of-sample evaluations further test the model's predictive ability by evaluating the model's ability to predict observations the model has not "seen" before. Therefore, it can be expected that the out-of-sample predictive performance will be less than that of the in-sample evaluations. Table 9 summarizes the results of the out-of-sample evaluations by presenting the expected measures (CCR, TPR, TNR) from the one thousand shuffles and splits of the data. Similar to the in-sample results, Table 9 shows that the two models have high overall accuracy (Logit CCR=0.9636, NP CCR=0.9623), which is mainly attributable to very high accuracy at predicting

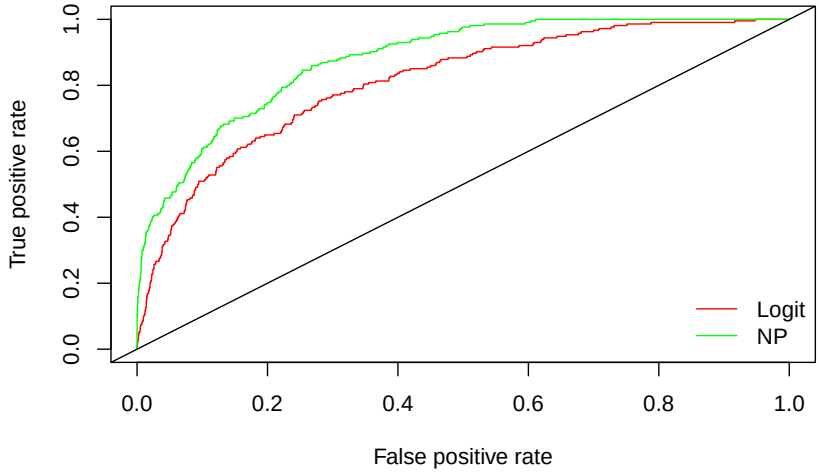


Figure 10: Logit and NP ROC Curves

non-users (Logit TNR=0.9992, NP TNR=0.9959). Both models are less able to classify users correctly than non-users, with a TPR of 0.0048 and 0.0567 for the logit and nonparametric models, respectively. As well, the out-of-sample predictive performance is less than the in-sample performance for both models. However, although the ability of the nonparametric model to correctly classify prescription users is less in the out-of-sample evaluations, it continues to be an 11.8 times better classifier than the logit model. To explore this out-of-sample result further, Figure 11 and Figure 12 present the boxplots of the CCRs and TPRs from each model for the thousand out-of-sample evaluations. Figure 11 shows that the CCR for both models is similarly distributed. Conversely, as shown in Figure 12, the two models have different TPR distributions, with most of the logit's TPR results being equal or close to 0. Many of the logit's out-of-sample evaluations resulted in a TPR of zero because the classification system hit a corner solution, whereby for all observations it predicted $Y = 0$. The fewer $Y = 1$ observations there were in the training data, the more likely the logit model's predictions would result in a corner solution. On the other hand, for the same few $Y = 1$ observations in the training data, the nonparametric model would make positive

predictions and have a non-zero TPR.

Table 9: Summary of Out-of-Sample Evaluations

Measure	Logit	NP
Expected CCR	0.9635787	0.9622802
Expected TPR	0.0048170	0.0567358
Expected TNR	0.9992059	0.9959360

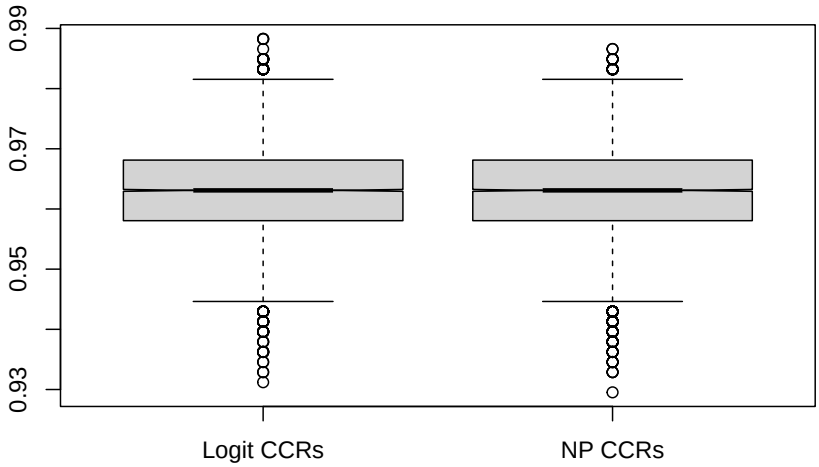


Figure 11: CCRs from One Thousand Out-of-Sample Evaluations

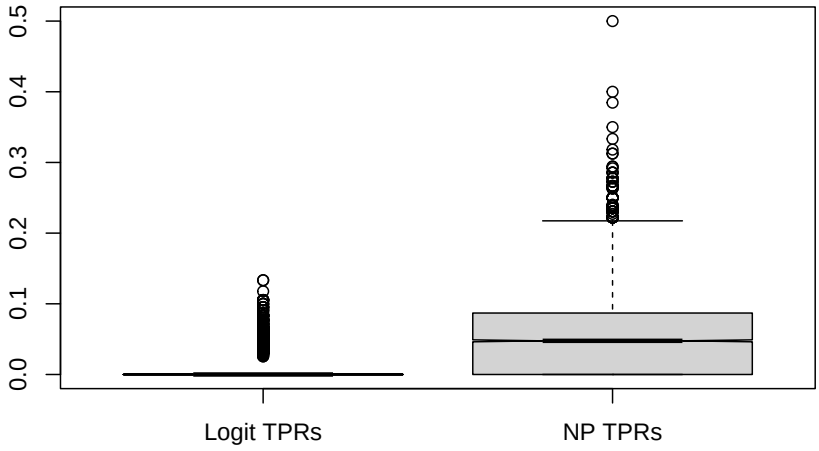


Figure 12: TPRs from One Thousand Out-of-Sample Evaluations

1.5.2 Analysis of Key Predictors

The previous section demonstrates how the nonparametric model can achieve superior predictive performance relative to the logit model. However, logistic regression is often used for analysis because it facilitates identifying the statistically significant predictors in the model and interpreting the relationship between those variables and the response variable. This section illustrates how analysis of key predictors can be easily achieved with the nonparametric model as well. Appendix 4.1.2 presents the model results of the logit and nonparametric models, respectively. Analyzing the logit model results and following the standard practice of using coefficient p-values to determine statistical significance, the coefficients on the following indicator variables are found to be statistically different from zero ($\alpha = 0.05$) age group 12 - 14 years, age group 15 - 19 years, British Columbia residence, one or more chronic conditions, mild pain, alcohol dependence and having 1 MD visit. As discussed in Section 1.4.3.1, the nonparametric conditional density model is estimated via least-squares cross-validation, which smooths out irrelevant predictors by assigning them a large bandwidth. The variables included in the nonparametric model are a mix of ordered and unordered discrete variables for which the Li and Racine (2003) kernel is used. The covariates with a bandwidth of 1 (rounded to the fifth decimal place) are variables that were deemed independent of the outcome variable. The variables smoothed out are sex, race, immigrant status, marital status, province, past-year serious injury, and distress. The relevant predictors in the nonparametric model are (in order of least smoothed out): alcohol dependence, chronic condition, urban/rural residence, self-rated pain, number of MD visits, age, insurance status, education, overnight hospitalization, and income.

The relationship between these relevant predictors and prescription opioid use can

be analyzed via a counter-factual experiment as described in Section 1.4.3.3. Recall that the interesting individual, in this case, is a likely prescription opioid user, with right-hand side variable values chosen as the modal values for prescription opioid users. A counter-factual experiment is conducted to estimate the effect that having pharmaceutical insurance has on that individual's probability of taking prescription opioids. Table 10 presents the results of such an experiment. Using the logit model (in the first row) and the nonparametric model (in the second row), the predicted probabilities of a likely prescription opioid user taking prescription opioids are computed if they have insurance, and if they do not. The final column labeled "Difference" displays for each model the difference in the probability of taking opioids under the two scenarios. Thus, the logit model predicts that having pharmaceutical insurance increases a likely prescription opioid user's probability by 2.42%. In contrast, the nonparametric model predicts that having pharmaceutical insurance increases the probability by only 0.38%. This presents an interesting result; in the logit model, insurance status is not deemed a statistically significant predictor, yet the estimated effect on the predicted probability is 2.42%, whereas, in the nonparametric model, it is a relevant predictor but the magnitude of the effect less than 1 percent. This can have important implications for prediction; if a regressor is independent of the outcome variable, it should not contribute to the predicted outcome as it will increase the variance of the prediction without improving prediction accuracy. Table 10 presents the counter-factual results of the pharmaceutical insurance variable; however, this same approach can be used to explore the relationship between prescription opioid use and the other relevant variables.

Table 10: Predicted probability of taking POs

	Model	Insured	Not.Insured	Difference
1	Logit	0.1363318	0.1121020	0.0242298
	Nonparametric	0.0973774	0.0935658	0.0038116

1.6 Conclusions

Canada and the U.S have seen a steady rise in the use of prescription opioids for the treatment of chronic non-cancer pain, as well as opioid-related harms, including misuse, abuse, dependence, and overdose. Prescription opioids provide pain relief and improved quality of life to individuals suffering from mild to severe, acute or chronic pain and are potent medications available for clinical treatment. However, prescription opioid use involves a risk of prescription opioid-related morbidity and mortality, with some patients being at higher risk of prescription opioid misuse, abuse, dependence, or overdose.

This paper demonstrates that most often, measures of prescription opioid use are captured using a binary variable and use a logit model to identify key predictors. In most data sets, the prevalence of prescription opioid use (use, misuse, abuse, etc.) is very infrequent, resulting in a highly imbalanced binary outcome variable. Highly imbalanced data pose classification limitations for the logit model. This paper presents an alternative approach to modeling a binary prescription opioid use measure, that is, to use a nonparametric conditional mode model. The logit model and the nonparametric model are compared using ROC curve analysis, and the results show that the nonparametric model has 11 times better classification accuracy of prescription opioid users. The results are consistent in-sample and out-of-sample and robust to the classification cutoff selected. The nonparametric approach can be used for more

accurate classification or screening of individuals. It can also identify critical predictors and analyze their relationships with the outcome variable through a counter-factual experiment. Future work on this topic would involve analyzing how this nonparametric method compares to other machine learning methods that have shown predictive improvements over the logit, such as random forest algorithms.

2 Chapter 2: The Impact of Mandatory Universal Pharmaceutical Insurance on Prescription Opioid Use: Evidence from Canada

2.1 Introduction

Canada is internationally known for its universal health insurance system. However, it is less commonly known that Canada is the only OECD country with a universal healthcare system that does not provide universal coverage for prescription drugs (Health Canada 2019). Unlike physician and hospital services, which are fully covered through provincial universal public health insurance plans, coverage for prescription drugs dispensed outside of hospitals falls outside of the Canada Health Act and is not covered by provincial universal public health insurance plans. There exists public provincial pharmaceutical programs for seniors, social-assistance recipients, and individuals whose medication expenses threaten their financial security (Daw and Morgan 2012). Most Canadians with private pharmaceutical insurance obtain it as a part of their employee or professional association benefits plans. Kapur and Basu (2005) find that 60% of Canadians are covered by a private plan, 25% are covered by a public plan, and the remaining 15% of Canadians are uninsured. As a result, many Canadians are uninsured or under-insured and face rising medication costs (OECD 2019). For uninsured or under-insured individuals, the cost of prescription medications can be a barrier to receiving necessary treatment. Roughly 10% of Canadians who receive a prescription do not adhere to the treatment for cost-related reasons, primarily lack of insurance (Law et al. 2012). Among OECD countries, Canada has the second highest cost-related medication non-adherence rate (Morgan and Lee 2017). Rising national pharmaceutical costs (OECD 2019) and a high cost-related non-adherence

rate suggests that the financial burden of prescription medications can be a barrier for individuals seeking medical treatment, particularly for "working poor" Canadians who are more likely to be uninsured (Kapur and Basu 2005) and to report cost-related non-adherence (Law et al. 2012).

The financial barriers to obtaining necessary prescription medications have raised policy concerns about the design of Canada's pharmaceutical insurance system and how it can be reformed to align with the Canada Health Act's mission to "protect, promote and restore the physical and mental well-being of residents of Canada and to facilitate reasonable access to health services without financial or other barriers" (Health Canada 2020). Several recommendations for a national pharmacare program have been proposed, including the publicly popular proposal to expand the universal public health insurance system to include prescription drugs (Health Canada 2019; Brandt, Shearer, and Morgan 2018).

Much of the debate regarding a national pharmacare program has focused on the merits of implementing a program and on how such a program should be structured and financed. However, the discussion should also be informed by evidence regarding potential negative and unintended consequences arising from expanding drug insurance coverage. Canada is facing a prescription opioid crisis, the crisis being the rapid rise in the rates of prescription opioid dependence, abuse, and overdose that have accompanied the steady rise in prescription opioid use starting in the early 1990s (Health Canada 2017). If pharmaceutical insurance coverage is a significant determinant of prescription opioid use, then implementing a national pharmacare program could exacerbate existing prescription opioid problems.

To better inform the pharmacare debate, this paper aims to resolve the question "does expanding pharmaceutical insurance coverage lead to an increase in prescription

opioid use"? This research question is explored using longitudinal data from Canada's National Population Health Survey (NPHS) to conduct a policy evaluation of a 1997 drug insurance reform in the province of Quebec, Canada, that mandated pharmaceutical insurance coverage. Quebec's 1997 drug insurance reform serves as a natural experiment that may be exploited to evaluate the causal effects of a mandatory universal drug program on prescription opioid use. The compulsory nature of the province-wide reform serves as a source of exogenous variation in pharmaceutical insurance status and, using longitudinal data, its dynamic effect on prescription opioid use can be analyzed. Previous studies have estimated multivariate models of prescription opioid use to evaluate whether pharmaceutical insurance status is a statistically significant variable in the model and have provided evidence of an association between the two variables (Carmona et al. 2020; Schepis et al. 2020; Becker et al. 2008; Sullivan et al. 2006). This paper contributes to the literature with evidence of a causal relationship.

2.2 Background Information

2.2.1 The Canadian Healthcare System

Canada's Federal healthcare insurance legislation is governed by the Canada Health Act (CHA). The CHA sets the national objective for the 13 provincial and territorial healthcare insurance plans, and that objective is to "protect, promote and restore the physical and mental well-being of residents of Canada and to facilitate reasonable access to health services without financial or other barriers" (Health Canada 2020). More specifically, the CHA aims to ensure that all Canadian residents have access to medically necessary hospital and physician services free of charges at the point of care. Although, at the federal level, the CHA determines the objective for healthcare in

Canada and provides federal funding to provinces who comply with the conditions of the act, each province or territory has the jurisdiction to determine how healthcare is administered and delivered (Health Canada 2020). As a result, all 13 provinces and territories have a universal publicly financed health insurance plan covering medically necessary hospital and physician services. These universal public health insurance plans are publicly funded (from federal and provincial tax revenue), but services are privately delivered (by private non-profit hospitals and physicians who participate in a private solo or inter-professional practice)[14]. Families are allowed to choose their family physician, and although they are not prohibited from accessing a specialist directly, it is the norm that the family physician refers their patients to a specialist. During the study period analyzed in this paper (1994-2003), Canada's primary healthcare system did not experience any major reforms (Hutchison et al. 2011). The recession in the early 1990s did lead to a temporary decrease in public healthcare spending; however, by the late 1990s public healthcare spending had begun to rise again (Hutchison et al. 2011). Overall, during the study period, Canada's healthcare system is essentially unchanged.

2.2.2 The Canadian Pharmaceutical Insurance Setting

Medications dispensed outside of hospitals are not covered under the CHA and therefore are not covered under each province's or territory's universal public health insurance plan. During the study period, the absence of a national legislative framework guiding public pharmaceutical insurance resulted in a mix of private and public drug insurance programs that varies across provinces (Health Canada 2019; Brandt, Shearer, and Morgan 2018; Kapur and Basu 2005). The federal government provides prescription drug programs for six specific population groups; First Nations, Inuit and Innu people,

[14]The most common physician compensation method is fee-for-service.

members of the Department of National Defense, some veterans, members of the RCMP, some incarcerated individuals in federal correctional facilities, and some immigrants. Provincial/territorial governments provide public drug insurance to the elderly, social assistance recipients, and in some provinces to residents with serious illnesses that require expensive prescription medications (often referred to as catastrophic drug plans) (Kapur and Basu 2005). Private drug plans are obtained through employee group benefit plans, individual private group insurance, or professional association benefit plans. When Quebec implemented the Mandatory Universal Drug Insurance Program (1996/1997), it was estimated that 26% of Canadian were covered by a conventional public drug plan[15] and 58.4% were covered by a conventional private drug plan (Kapur and Basu 2005). Between 1990 and 2003, the pharmaceutical insurance setting described above remained unchanged for all provinces except Quebec, which underwent a major pharmaceutical insurance reform in 1996/1997.

2.2.3 Quebec's Pharmaceutical Insurance Setting

Prior to 1996, the drug insurance setting in Quebec was almost identical to the drug insurance setting in all other provinces, with a federal public plan for select population groups, provincial public plans for seniors (65+) and social assistance recipients, and private plans available through employee/professional association benefit plans. In 1996 the Act Respecting Prescription Drug Insurance (ARPDI) was passed into legislation to establish a basic prescription drug insurance plan that ensures "all persons in Quebec have reasonable and fair access to the medications required by their state of health" (Legis Quebec 2020). As a provision of the ARPDI, the Regie de l'Assurance Maladie du Quebec (RAMQ) established the Public Prescription Drug Insurance Plan;

[15]Drug plans which are not catastrophic drug expense plans are referred to as conventional drug plans.

coverage for this plan is provided by the RAMQ and provides a minimum level of coverage for the cost of pharmaceutical services and medications (Legis Quebec 2020). Hereinafter the RAMQ's Public Prescription Drug Insurance Plan will be referred to as "the public plan." Quebec's elderly and social assistance recipients who were already insured by a public plan continue to be insured by the public plan; however, beginning in August 1996, the user fees for these two population groups increased. Table 11 demonstrates how the public plan's fees and coverage changed once the reform took place and reveals how this made the plan more costly for seniors and social assistance recipients.

The second stage of the implementation of the ARPDI began on January 1st, 1997, when the Mandatory Universal Drug Program was implemented, which mandated that all Quebec residents were required by law to have drug insurance coverage. Some relevant details of the Mandatory Universal Drug Program are listed below.

- Mandatory nature of the program
  - All Quebec residents, as defined by the Act Respecting Prescription Drug Insurance, must have some form, either private or public, of pharmaceutical insurance coverage.
  - Any Quebec resident under the age of 65 with access to a private pharmaceutical insurance plan, through employment or profession, must enroll in the private plan. Additionally, they must also provide coverage under that private plan for their spouse and children.
  - Any Quebec resident without access to a private plan must register for the public plan.
  - Quebec residents aged 65 and older with access to a private plan can choose to enroll in either the private plan, the public plan, or both (using the

public plan for basic coverage and private plan for supplementary coverage).

  - Financial penalties are in place for individuals who do not have any pharmaceutical insurance coverage or registered with the public plan even though they are eligible for a private plan.

- Eligibility for RAMQ public plan
  - Persons without access to a private plan.
  - Persons age 65 or older who have not joined a private plan.
  - Social assistance recipients and their families.

- Coverage
  - Private plan coverage varies across plans; however, all private insurance providers are required by law to provide coverage that is at least equivalent to that offered by the provincial public plan.
  - An overview of the public plan's coverage is illustrated in Table 11.

- Public plan financing
  - Income-dependent premiums are charged and collected through the provincial tax authority Revenue Quebec.
  - Cost-sharing is implemented through monthly deductibles and coinsurance rates.

2.3 Literature Review

2.3.1 Pharmaceutical Insurance and Medication Use

The theory regarding pharmaceutical insurance and moral hazard suggests that an increase in pharmaceutical insurance coverage will lead to an increase in the utilization

Table 11: Pharmaceutical insurance changes due to Quebec's Mandatory Universal Pharmaceutical Insurance Plan

Population group	Dates	Annual premium	Coinsurance	Monthly deductible	Max. monthly contribution
Welfare recipients	Prior to Aug 1996	Full coverage			
	Aug 1996 to Dec 1996	None	25%	None	$16.66
	Jan 1997 to 2003	None	25%	$8.33	$16.66
Low income seniors	Prior to Aug 1996	Full coverage			
	Aug 1996 to Dec 1996	None	25%	None	$16.66
	Jan 1997 to 2003	None	25%	$8.33	$16.66
Other seniors	Prior to Aug 1996	None	$2/prescription	None	$100
	Aug 1996 to Dec 1996	$0-$175	25%	None	$41.66/$62.50
	Jan 1997	$0-$175	25%	$8.33	$41.66/$62.50
	2003	$0-$460	25%/28%	$8.33/$9.60	$16.66/$46.17/$69.92
General population	Before 1997	No public coverage			
	1997 to 1999	$0-$175	25%	$8.33	$62.49
	2000	$0-$350	25%	$8.33	$62.49
	2001	$0-$385	25%	$8.33	$62.49
	2002	$0-$422	27.4%	$9.13	$68.5
	2003	$0-$460	28%	$9.6	$69.92

Note:
General population refers to the adult non-elderly (age 18-64) population
Source: Regie de 'Assurance Maladie du Quebec (RAMQ) and Wang et al. (2015)

of medications (Pauly 2012; Danzon and Pauly 2002). More specifically, the theory states that the increase in the volume of medications consumed (ΔQ) can be predicted by $\Delta Q = E \times \Delta P$, where ΔP is the reduction in out-of-pocket price and E is the demand price elasticity, other things being equal (Danzon and Pauly 2002). Empirical evidence supports this theory and illustrates that expanding coverage (i.e., more people having coverage) and increasing depth of coverage (i.e., policyholders having lower out-of-pocket costs) results in increased medication use (Danzon and Pauly 2002). The literature exploring the association between pharmaceutical insurance cost-sharing features (i.e., the coinsurance rate, co-payment, and deductible) and medication utilization is extensive. In most cases, the literature finds evidence of a negative relationship between cost-sharing and medication use; thus, insurance plans with higher out-of-pocket costs are associated with lower medication use (Goldman, Joyce, and Zheng 2007). Several studies have explored the causal impact of pharmaceutical insurance coverage expansion on medication use. Studies which have analyzed the

impact of the 2006 implementation of Medicare Part D, a U.S federal entitlement benefit for prescription drugs for Medicare beneficiaries[16], found it to have had a positive and statistically significant effect on medication use (Yin et al. 2008; Lichtenberg and Sun 2007; Liu et al. 2011; Kaestner and Khan 2012). However, one study did not find Medicare Part D to significantly affect medication use (Basu, Yin, and Alexander 2010). The effects of Quebec's 1997 implementation of the Mandatory Universal Pharmaceutical Insurance Program on medication use were analyzed by C. Wang et al. (2015), who found the program led to a 13% increase in the number of distinct medications taken (the number of medications taken combines prescription and nonprescription medications; therefore, the measured effect is net of substitutions between prescription and nonprescription medication).

2.3.2 Pharmaceutical Insurance and Cost-Related Non-Adherence (CRNA)

A closely related topic is the literature that explores the relationship between pharmaceutical insurance coverage and Cost-Related Non-Adherence (CRNA). CRNA refers to when individuals who have been prescribed medication do not fill out the prescription for cost-related reasons. The most commonly reported reason for CRNA is that the individual does not have pharmaceutical insurance (Law et al. 2012). Among 11 OEDC countries, CRNA was found to be significantly correlated with prescription drug coverage and was highest in the U.S. and Canada, respectively (Morgan and Lee 2017). A study comparing CRNA in the U.S. and Canada found large differences in CRNA between and within countries, with the lowest CRNA reported in Quebec, Canada (Kennedy and Morgan 2009). In the U.S., expanding pharmaceutical insurance cover-

[16]All Medicare Beneficiaries gained access to the Part D prescription drug benefit; however, enrollment was voluntary.

age through Medicare Part D expansions reduced CRNA and the use of pharmaceutical cost-saving strategies[17] (Wei, Lloyd, and Shrank 2013; Musich et al. 2015). It is estimated that 10% of Canadians do not fill prescriptions for cost-related reasons (Law et al. 2012). Gupta et al. (2018) reviewed Canadian studies of CRNA to find strong evidence that being uninsured/under-insured leads to CRNA. Quebec's mandate that all residents obtain pharmaceutical insurance led to lower rates of reported CRNA in the Quebec population, relative to other Canadian provinces. However, the depth of coverage still has an effect on CRNA for some Quebec residents. For the privately insured non-elderly population (18-64 years old), the level of out-of-pocket expense is the strongest predictor of CRNA (Després et al. 2016).

2.3.3 Pharmaceutical Insurance and Prescription Opioid Use

As outlined above, there exists ample evidence of a strong relationship between pharmaceutical insurance coverage and medication use behavior[18]; however, the strength of this relationship varies by drug class (Goldman et al. 2004). An analysis of how medication use responds to changes in co-payment found that doubling co-payment was associated with decreased medication use ranging from as high as a 45% decrease for non-steroidal anti-inflammatory drugs (NSAIDs) and as low as an 8% decrease for anti-depressants (Goldman et al. 2004). To estimate the responsiveness of prescription opioid use to changes in pharmaceutical insurance coverage, researchers have analyzed the effects of pharmaceutical insurance provisions under the Affordable Care Act. In 2010, the U.S. passed the Affordable Care Act, a comprehensive healthcare reform providing healthcare access for millions who previously lacked coverage. From the Affordable Care Act came the implementation of a Medicaid expansion and a Young

[17] Pharmaceutical cost-saving strategies are when individuals ration or do not use medications as prescribed to save costs.

[18] Either increased medication use or CRNA.

Adult provision. The Medicaid expansion involved expanding the Medicaid insurance program for low-income individuals. It was optional for states to partake in the expansion and, for the states that did, Medicaid beneficiaries gained prescription drug coverage which provided access to prescription opioids[19]. The Medicaid expansion did not lead to a significant increase in prescription opioid use (Saloner et al. 2018), prescription opioid prescriptions (Sharp et al. 2018), or prescription opioid overdose deaths (Averett, Smith, and Wang 2019). The Affordable Care Act Young Adult provision mandated that insurers allow family policyholders to include their children in the coverage up to age 26; previously, children were only covered until the age of 18. Analyses found the provision reduced mortality among young adults aged 19-25 (Wettstein 2019). For young adults aged 23-25, Coupet et al. (2020) found no significant effect on emergency department encounters or out of hospital mortality due to overdoses. In the Canadian context, there is limited research on the relationship between pharmaceutical insurance and prescription opioid use. By analyzing a quasi-experiment to gain insight into the dynamic relationship between pharmaceutical insurance and prescription opioid use, Auld et al. (2020) found that a pharmaceutical insurance plan with restrictions surrounding the prescribing of Oxycontin was effective in reducing Oxycontin prescriptions and use in Manitoba, Canada.

Theory and empirical analysis provide strong evidence that expanding pharmaceutical insurance coverage leads to increased medication use. However, when the medication class of interest is prescription opioids, some U.S. studies suggest that this relationship does not hold true. This paper aims to explore, in the Canadian context, if expanding pharmaceutical insurance coverage leads to an increase in prescription opioid use.

[19]It is important to note that under the expansion Medicaid beneficiaries also gained access to medication-assisted treatment (MAT) for addiction, which can be used to treat prescription opioid addictions.

2.4 Data

2.4.1 Data Source

The data used for the analysis presented in this paper comes from the National Population Health Survey (NPHS) household component, a nationally representative interview survey conducted biennially by Statistics Canada. The survey was designed to collect information related to health status, use of health services, determinants of health, a health index, chronic conditions, activity restrictions, and related socio-demographic variables. The NPHS survey spanned the time period 1994 to 2011, was conducted every two years, and would take a year to collect the data from the whole sample; as a result, NPHS data was collected in nine survey cycles, as shown in Table 12[20]. The NPHS has a household component for all nine cycles, a healthcare institutions (H.Is) component[21] for the first five cycles, and a Northern Territories (N.Ts) component[22] for the first three cycles. The NPHS household component's target population includes community-based household residents in the ten provinces, excluding communities on Native Reserves, Canadian Force Bases, and some remote areas in Quebec and Ontario.

In the first cycle (1994/1995), an initial sample of approximately 20,000 households was gathered. For each household, a limited amount of information (i.e, demographic, socio-economic, and basic health information) was collected on all household members; then, one household member was randomly selected for a more in-depth interview.

[20]This table was first presented in Chapter 1. However, for readability purposes, it is presented here as well.

[21]The target population of this component was long-term (expected stay of six months or more) residents of health care institutions with four beds or more in all provinces except Yukon and Northwest Territories.

[22]The target population of this component was household residents in the Yukon and Northwest Territories except those living on Native Reserves, Canadian Forces Bases and some of the most remote areas of the Territories.

Table 12: NPHS data features

Cycle	Year	Data.files	Components	PUMF.Availability
1	1994/1995	Cross-sectional	Households, H.I.s, N.Ts	Households & H.I.s cross sections
2	1996/1997	Cross-sectional, Longitudinal	Households, H.I.s, N.Ts	Households & H.I.s cross sections
3	1998/1999	Cross-sectional, Longitudinal	Households, H.I.s, N.Ts	Households cross section
4	2000/2001	Longitudinal	Households, H.I.s	NA
5	2002/2003	Longitudinal	Households, H.I.s	NA
6	2004/2005	Longitudinal	Households	NA
7	2006/2007	Longitudinal	Households	NA
8	2008/2009	Longitudinal	Households	NA
9	2010/2011	Longitudinal	Households	NA

Note:
H.I.= Healthcare Institutions
N.T.= Northern Territories
PUMF= Public Use Microdata File
NA= Not Available
The cycle 1 cross-sectional and longitudinal file are the same.

The longitudinal aspect of the study follows up with the randomly selected individual every cycle to conduct the in-depth interview, meanwhile still collecting limited data on his/her household members.

The analysis presented in this paper uses the NPHS longitudinal square data file, which contains a sample of 17 276 respondents of all ages[23], who participated in all nine cycles of the survey (from cycle 1 (1994/95) through to cycle 9 (2010/11)). This data was accessed at McMaster University's Statistics Canada Research Data Centre, with the approval of the Social Science and Humanities Research Council (SSHRC) and Statistics Canada.

2.4.2 Study Sample

A subsample from the NPHS longitudinal data is used for the policy analysis. The subsample uses the data from the first five cycles, which allows for an analysis of data from before, during, and after the policy is implemented, as listed below:

[23]Data of individuals under the age of 12 is collected from the Canadian National Longitudinal Survey of Children and Youth.

- Cycle 1 (1994/1995) Before the policy
- Cycle 2 (1996/1997) Policy implemented
- Cycle 3 (1998/1999) After policy implementation
- Cycle 4 (2000/2001) After policy implementation
- Cycle 5 (2002/2003) After policy implementation.

The later cycles (cycle 6 (2004/2005) through to cycle 9 (2010/2011)) are omitted from the analysis because, starting in 2003, major changes in the pharmaceutical insurance setting and primary healthcare system in provinces beyond Quebec begin to occur (C. Wang et al. 2015). In 2003, the province of British Columbia implemented the Fair PharmaCare Plan[24]. In the same year, the First Ministers[25] reached an accord to reform primary healthcare, home-care, and catastrophic drug coverage across Canada. The accord led to some reform implementations beginning in 2004, and the most extensive reforms took place in Canada's most populous provinces (British Columbia, Alberta, Ontario, and Quebec) (Hutchison et al. 2011). On the other hand, during the cycles 1 to 5 time frame there is minimal change in the primary healthcare system, and Quebec's passing of the Act Respecting Pharmaceutical Insurance is the only major pharmaceutical drug coverage reform (Brandt, Shearer, and Morgan 2018). Thus, by omitting the data from the later cycles, the analysis can be conducted over a time period that is more stable in terms of the healthcare and pharmaceutical insurance environment. Using a more stable time period prevents the estimated effect of Quebec's reform from being confounded by the effects of other reforms occurring in the same period.

Next, the elderly (65+) and welfare recipients are removed from the sample. These two groups are removed because the policy had a differential impact on them versus

[24]A public income-based program to assist families with the cost of prescription medications.
[25]The prime minister and the provincial/territorial premiers.

others in the data. The elderly and welfare recipients already had a public pharmaceutical insurance plan prior to the policy implementation that allowed them to obtain medications at little ($2/prescription) or no out-of-pocket cost. For these two population groups, the policy introduced co-insurance rates, deductibles, and or insurance premiums; the policy did not expand coverage for the better but increased the cost of obtaining medication. The analysis presented in this paper aims to evaluate the effect of expanding pharmaceutical coverage on prescription opioid use, and so it focuses on the non-elderly non-welfare recipient population for whom the program expanded coverage. In order to remove the elderly population from the sample, any observation age 56 or older in the first cycle is removed. The first five survey cycles span a period of 8 years, so removing individuals over age 55 in the first cycle ensures that at no point in the study period are these individuals age 65 or older. To remove social assistance recipients, any observation which reported welfare as their source of income in any of the five cycles is removed.

If a respondent was not asked (NA), refused to answer (RF), did not state (NS), or did not know (DK) the answer to a question, the response is converted to a missing value. Observations with missing values for key variables of interest were removed. This resulted in the removal of many respondents, including all respondents age 18 or younger, because several of the variables of interest were not collected for this group. The resulting study sample is a balanced longitudinal sample of non-elderly (18-64) survey respondents who did not receive welfare and whose data of key variables is gathered for survey cycles 1 (1994/1995) through to cycle 5 (2002/2003).

2.4.3 Variables

2.4.3.1 Response Variable The NPHS household component asks respondents if they have consumed codeine, Demerol, or morphine in the month prior to the interview. The respondent may answer yes, no, don't know (DK), or refuse to answer (RF). Observations with a DK/RF response are converted into missing values and a binary variable for prescription opioid use (Y_c) is created as follows,

$$\mathrm{Y}_c = \begin{cases} 1 & \text{if answered Yes} \\ 0 & \text{if answered No,} \end{cases}$$

where c={1,2,3,4,5} denotes the survey cycle from which the response was collected.

This variable measures self-reported prescription opioid use and can be utilized to estimate the proportion of the population taking three of the most commonly used prescription opioids (International Narcotics Control Board 2019), the factors associated with their use, and the impact of Quebec's pharmaceutical insurance reform had on the number of people taking them. However, this variable is subject to three limitations worth mentioning. The first is that the intensity of use cannot be measured, as that would require a more detailed questionnaire with questions regarding the quantity (e.g., in morphine equivalent milligrams) and frequency (e.g., dosage taken per day or week) of use. Second, although codeine, Demerol, and morphine are among the six most commonly used prescription opioids (International Narcotics Control Board 2019), respondents could be taking another popular prescription opioid such as fentanyl, hydrocodone, Oxycodone, or Hydromorphone, and their use of prescription opioids not be captured[26]. Lastly, the survey question asks whether the medications

[26]For ease of description the response variable is said to measure prescription opioid use, though we acknowledge that it is specifically measuring just codeine, Demerol, and morphine use.

were consumed in the month prior to the interview; thus, any use that occurred more than a month prior is not captured.

2.4.3.2 Treatment vs. Control Group Variable To estimate the impact of a policy, it is necessary to distinguish the individuals who were affected by the policy (the treatment group) from those who were not affected by the policy (the control group). In the case of the Mandatory Universal Prescription Drug Insurance Program, the policy was implemented province-wide in Quebec; therefore, the treatment group is Quebec residents. The control group consists of all non-Quebec Canadian residents (i.e., the rest of Canada). The variable QB is created to distinguish between observations from Quebec and those from the rest of Canada.

$$\text{QB} = \begin{cases} 1 & \text{if from Quebec} \\ 0 & \text{Otherwise} \end{cases}$$

Note that the QB variable does not have a subscript c indicating the cycle because this variable is constant for each individual. The NPHS longitudinal square data has very few observations that indicate inter-provincial migration, and the province of residence variable provided with the data assigns a missing value to observations who moved across provinces during the survey duration. By removing observations with missing values in the process of creating the study sample, the few observations with inter-provincial migration are removed. Therefore, in the analyzed sample, the province of residence is fixed for each individual.

2.4.3.3 Controls When estimating the policy effect, the models presented in the following section control for a series of demographic, socio-economic, health, and

healthcare utilization variables. The demographic variables included are age, gender, race, and marital status. Education and household income variables capture socio-economic status. Physical health indicators used are self-rated health, self-rated pain disability, an indicator for having one or more chronic conditions, and an indicator of having experienced a serious injury in the past year. Anxiety and depression are captured using an indicator of significant mental distress based on the respondent's six-item measure of non-specific psychological distress (K6) score (R. C. Kessler et al. 2002) and an indicator for a probable case of depression based on the Composite International Diagnostic Interview (CIDI) short-form screening measure for depression (Robert C. Kessler et al. 1998). Since a prescription from an MD is required to obtain prescription opioids from a pharmacist, a variable capturing the number of visits/consultations with a medical doctor is included in the model to measure healthcare utilization. For details on the control variables used, see the Appendix, Table 28.

2.5 Methods

2.5.1 The Average Treatment Effect on the Treated

The effect of Quebec's Mandatory Universal Drug Insurance Program on prescription opioid use in Quebec is estimated using a popular estimand from the program evaluation literature called the Average Treatment Effect on the Treated (ATET). The ATET estimates the average magnitude of the program's effect on the treatment group. Note that the ATET is different from the Average Treatment Effect (ATE), which estimates the average effect the program had on the entire study population, which includes both the treatment and control group. Recalling that the outcome variable of interest is a binary variable for prescription opioid use, the ATET is used to estimate by how much on average did the Mandatory Universal Drug Insurance Program increase

the probability of taking prescription opioids for Quebec residents. Similarly, the conditional Average Treatment Effect on the Treated (ATET(X)) estimates the average effect of the policy on the treated group, while controlling for covariates (X).

Before presenting a general definition of the ATET(X), some notation needs to be introduced. Let $D = \{0, 1\}$ be an indicator variable for treatment, where $D = 0$ indicates no treatment is received and $D = 1$ indicates that treatment is received. The time variable $t = \{0, 1\}$ indicates if the time period is before ($t = 0$) or after ($t = 1$) the treatment is administered. Using the indicator variables D and t, the outcome variable is denoted by $Y^D(t)$. Combinations of t and D result in four potential outcomes:

- Prior to treatment administration
  - $Y^0(0)$: The pre-treatment administration outcome of an individual who *will not* receive treatment
  - $Y^1(0)$: The pre-treatment administration outcome of an individual who *will* receive treatment
- After treatment administration
  - $Y^0(1)$: The post-treatment administration outcome of an individual who *did not* receive treatment
  - $Y^1(1)$: The post-treatment administration outcome of an individual who *did* receive treatment

An individual who receives treatment ($D = 1$) will have two possible observable outcomes, $Y^1(0)$ and $Y^1(1)$. Similarly, for an individual who does not receive treatment ($D = 0$), the two observed outcomes are $Y^0(0)$ and $Y^0(1)$. Given this notation, under

the unconfoundedness assumption[27], the ATET(X) is defined as follows:

$$\begin{aligned}\text{ATET(X)} &= E[Y^1(1) - Y^0(1)|X, D = 1] \\ &= \Big[E[Y(1)|X, D = 1] - E[Y(1)|X, D = 0]\Big] - \Big[E[Y(0)|X, D = 1] - E[Y(0)|X, D = 0]\Big]\end{aligned} \tag{34}$$

When the outcome variable is a binary variable $Y \in \{0, 1\}$, the ATET(X) can be expressed in terms of conditional probabilities as follows:

$$\begin{aligned}\text{ATET(X)} = &\Big[E[P(Y(1) = 1|X, D = 1)] - E[P(Y(1) = 1|X, D = 0)]\Big] \\ &- \Big[E[P(Y(0) = 1|X, D = 1)] - E[P(Y(0) = 1|X, D = 0)]\Big].\end{aligned} \tag{35}$$

The ATET(X) for a binary $Y \in \{0, 1\}$ can be applied to evaluate the effect of Quebec's pharmaceutical insurance reform on the probability of Quebec residents taking prescription opioids, and can be estimated using either a parametric or nonparametric approach.

2.5.2 Parametric Approach

A parametric difference-in-differences approach is commonly used to estimate the ATET(X), and can be applied to evaluate the effects of Quebec's Mandatory Universal Drug Insurance Program by estimating the model below,[28]

$$y_{ipc} = \alpha + \delta_1 \text{QB}_i + \delta_2 t_c + \beta(t \times QB)_{ic} + \gamma X_{ipc} + \epsilon_{ipc}, \tag{36}$$

[27] $E[Y^0(1) - Y^0(0)|X, D] = E[Y^0(1) - Y^0(0)|X]$

[28] This model follows the approach used by C. Wang et al. (2015) in their evaluation of the Mandatory Universal Drug Insurance Program, with some differences in the variables included in the model.

where y_{ipc} is an indicator for prescription opioid use for individual i, in province p, in survey cycle c. QB is an indicator which equals one if individual i is from Quebec and zero otherwise, t_c is an indicator that equals one for survey cycles after the policy is implemented (cycles 3, 4, and 5) and zero otherwise, and X_{ipc} is a vector of covariates to control for individual characteristics[29]. Using this model, the parameter β can be interpreted as the ATET(X): more precisely, it estimates the change from before to after the reform in the probability of consuming prescription opioids for Quebec residents relative to residents from other provinces, net of the difference in pre-treatment trends. The parametric difference-in-differences approach is appealing because the linear probability model in Equation (36) can be estimated quickly using Ordinary Least Squares (OLS) and the ATET(X) is easily summarized by the estimate of β. However, this approach relies on correct model specification, that is, that the additive and linear model in Equation (36) correctly represents the underlying data generating process (DGP). If the model is not correctly specified (i.e., it is misspecified), the estimated parameters, including the estimated parameter of interest $\hat{\beta}$, will be in general biased and inconsistent. Parametric and nonparametric tests for model specification were conducted and reject the null hypothesis that the model presented in Equation (36) is correctly specified; thus, model (36) should be ruled out. To avoid repeatedly testing alternative parametric specifications, which can induce pre-testing bias into the model selection process, a flexible nonparametric approach that does not rely on model specification is undertaken.

2.5.3 Nonparametric Approach

Recalling that cycle 1 is the pre-treatment period and cycles 3, 4, and 5 are post-treatment periods, the ATET(X) in Equation (35) which uses t to distinguish if the

[29]Section 2.4.3.3 lists the control variables included.

time period is before ($t = 0$) or after ($t = 1$) the treatment can be written as three separate ATET(X)s:

$$\begin{aligned}\text{ATET}(X_1, X_3) = &\Big[E[P(\text{Y}_3 = 1|X_3, \text{QB} = 1)] - E[P(\text{Y}_3 = 1|X_3, \text{QB} = 0)]\Big] \\ &-\Big[E[P(\text{Y}_1 = 1|X_1, \text{QB} = 1)] - E[P(\text{Y}_1 = 1|X_1, \text{QB} = 0)]\Big],\end{aligned}$$

$$\begin{aligned}\text{ATET}(X_1, X_4) = &\Big[E[P(\text{Y}_4 = 1|X_4, \text{QB} = 1)] - E[P(\text{Y}_4 = 1|X_4, \text{QB} = 0)]\Big] \\ &-\Big[E[P(\text{Y}_1 = 1|X_1, \text{QB} = 1)] - E[P(\text{Y}_1 = 1|X_1, \text{QB} = 0)]\Big],\end{aligned}$$

$$\begin{aligned}\text{ATET}(X_1, X_5) = &\Big[E[P(\text{Y}_5 = 1|X_5, \text{QB} = 1)] - E[P(\text{Y}_5 = 1|X_5, \text{QB} = 0)]\Big] \\ &-\Big[E[P(\text{Y}_1 = 1|X_1, \text{QB} = 1)] - E[P(\text{Y}_1 = 1|X_1, \text{QB} = 0)]\Big].\end{aligned}$$

The nonparametric approach inspects the ATET(X)s and recognizes that each ATET(X) is simply a linear function of four unknown conditional probabilities and each conditional probability can be obtained from the conditional probability density function (PDF) $f(y_c|x_c, D)$ of the binary outcome variable $Y \in \{0, 1\}$. More precisely,

- $P(Y_1 = 1|X_1 = x_1, QB = 1)$ is obtained from $f(y_1|x_1, QB = 1)$
- $P(Y_1 = 1|X_1 = x_1, QB = 0)$ is obtained from $f(y_1|x_1, QB = 0)$
- $P(Y_3 = 1|X_3 = x_3, QB = 1)$ is obtained from $f(y_3|x_3, QB = 1)$
- $P(Y_3 = 1|X_3 = x_3, QB = 0)$ is obtained from $f(y_3|x_3, QB = 0)$
- $P(Y_4 = 1|X_4 = x_4, QB = 1)$ is obtained from $f(y_4|x_4, QB = 1)$
- $P(Y_4 = 1|X_4 = x_4, QB = 0)$ is obtained from $f(y_4|x_4, QB = 0)$

- $P(Y_5 = 1|X_5 = x_5, QB = 1)$ is obtained from $f(y_5|x_5, QB = 1)$
- $P(Y_5 = 1|X_5 = x_5, QB = 0)$ is obtained from $f(y_5|x_5, QB = 0)$

To estimate each $f(y_c|x_c, QB)$ the full study sample is compartmentalized into subsets that are conditional on c and QB as follows:

- Subset 1: observations for which C=1 & QB=1
- Subset 2: observations for which C=1 & QB=0
- Subset 3: observations for which C=3 & QB=1
- Subset 4: observations for which C=3 & QB=0
- Subset 5: observations for which C=4 & QB=1
- Subset 6: observations for which C=4 & QB=0
- Subset 7: observations for which C=5 & QB=1
- Subset 8: observations for which C=5 & QB=0

For each subset, estimating $f(y|x)$ is equivalent to estimating $f(y_c|x_c, QB)$ from the study sample[30]. From each subset, $f(y|x)$ is estimated using a nonparametric mix-data kernel PDF estimator (Hall, Racine, and Li 2004).

The conditional PDF is defined as

$$f(y|x) = \frac{f(y,x)}{f(x)}, \tag{37}$$

where $f(y,x)$ denotes the joint density of (X,Y) and $f(x)$ denotes the marginal density of X. The dependent variable Y is a binary variable and the covariate vector X can consist of continuous and discrete (unordered and ordered) variables. Using $\hat{f}(y,x)$ and $\hat{f}(x)$ to denote kernel estimators of $f(y,x)$ and $f(x)$, the conditional density

[30]For example, if a subset containing all the observation for which c=1 and QB=1 is created and used to estimate $f(y|x)$, the result is the same as estimating $f(y_1|x_1, QB = 1)$ from the full sample.

$f(y|x)$ is estimated by

$$\hat{f}(y|x) = \frac{\hat{f}(y,x)}{\hat{f}(x)}. \tag{38}$$

The estimator of $f(z) = f(y,x)$ is given by

$$\hat{f}(z) = \frac{1}{n}\sum_{i=1}^{n} K_{\gamma_z}(Z_i, z), \tag{39}$$

and the estimator of $f(x)$ is given by

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} K_{\gamma_x}(X_i, x). \tag{40}$$

It is important to note that $\hat{f}(y|x)$ is *not* calculated using separate estimates of $\hat{f}(z)$ and $\hat{f}(x)$. The estimation of $\hat{f}(z)$ and $\hat{f}(x)$ is to be done jointly such that the estimated smoothing parameters for X are the same in $\hat{f}(z)$ and $\hat{f}(x)$. The $K_{\gamma_z}(\cdot)$ and $K_{\gamma_x}(\cdot)$ functions in (39) and (40) are generalized multivariate mixed-data product kernel functions (Li and Racine 2003). In particular,

$$K_{\gamma_z}(Z_i, z) = \prod_{j=1}^{q} h_j^{-1} K\Big(\frac{z_j^c - z_{ij}^c}{h_j}\Big) \prod_{j=1}^{r} L(Z_{ij}^u, z_j^u, \lambda_j^u) \prod_{j=1}^{s} l(Z_{ij}^o, z_j^o, \lambda_j^o) \tag{41}$$

and

$$K_{\gamma_x}(X_i, x) = \prod_{j=1}^{q} h_j^{-1} K\Big(\frac{x_j^c - x_{ij}^c}{h_j}\Big) \prod_{j=1}^{r} L(X_{ij}^u, x_j^u, \lambda_j^u) \prod_{j=1}^{s} l(X_{ij}^o, x_j^o, \lambda_j^o), \tag{42}$$

where $\prod$ is the product operator. Continuous variables are identified using the superscript ^{c}, q denotes the number of continuous variables in X, and $K(\cdot)$ is a kernel function appropriate for continuous variables. Similarly, unordered discrete variables are indicated by the superscript ^{u}, r denotes the number of unordered discrete variables

in X, and $L(\cdot)$ is an unordered kernel function. Finally, ordered discrete variables are indicated by the superscript ^{o}, s denotes the number of ordered discrete variables in X, and $l(\cdot)$ is an ordered kernel function. In the ATET(X) estimates, X is composed of 1 continuous variable, 7 unordered discrete variables, and 5 ordered discrete variables; for details on these variables see the Appendix, Table 28.

For the continuous variable kernel function $K(\cdot)$ a second-order Epanechnikov kernel function is used, this function is real-valued, non-negative, bounded and symmetric, and it satisfies $K(x) \geq 0$, $\int_{-\infty}^{\infty} K(x)dx = 1$, $\int_{-\infty}^{\infty} xK(x)dx = 0$ and $0 \leq \int_{-\infty}^{\infty} x^2K(x)dx = \kappa_2 < \infty$. For unordered discrete variables the Li and Racine (2003) kernel function $L(X_i^u, x^u, \lambda^u)$ defined below is used,

$$L(X_i^u, x^u, \lambda^u) = \begin{cases} 1 & \text{if } X_i^u = x^u \\ \lambda^u & \text{if } X_i^u \neq x^u, \end{cases} \tag{43}$$

where $\lambda^u \in [0, 1]$. The Li and Racine (2003) kernel function for ordered discrete variables is used and defined as

$$l(X_i^o, x^o, \lambda^o) = \begin{cases} 1 & \text{if } X_i^o = x^o \\ \lambda^{o[X_i^o - x]} & \text{if } X_i^o \neq x^o, \end{cases} \tag{44}$$

where $\lambda^o \in [0, 1]$.

In the generalized product kernel functions (41) and (42) h, λ^u, and λ^o are vectors of smoothing parameters. As previously mentioned, $\widehat{f}(y, x)$ and $\widehat{f}(x)$ are jointly estimated and have the same smoothing parameters for X; thus, the vectors h, λ^u and λ^o in Equation (41) are the same as those found in Equation (42). The vector h is of length

q and contains the smoothing parameters[31] for each of the q continuous covariates. For the discrete variables, λ^u is of length r and contains the smoothing parameters of the r unordered covariates, while λ^o is of length s and contains the smoothing parameters of the s ordered covariates. The vector γ_x contains all the smoothing parameters of the covariates, the vector γ_z contains all the smoothing parameters of the covariates plus the smoothing parameter for the outcome variable Y[32]. The vectors of smoothing parameters γ_x and γ_z, further known as the bandwidths, are estimated via least squares cross-validation (Hall, Racine, and Li 2004).

Hall, Racine, and Li (2004) demonstrate that

$$\sqrt{n \prod_{j=1}^{q} h_j} \left(\hat{f}(y|x) - f(y|x) - \text{Bias}\, \hat{f}(y|x) \right) \xrightarrow{d} N\left(0, \text{AVar}\, \hat{f}(y|x)\right), \qquad (45)$$

where $\prod_{j=1}^{q} h_j$ is the product of bandwidths for the q continuous control variables in $Z = (X, Y)$. Note that $\text{AVar}\, \hat{f}(y|x)$ denotes the pointwise variance less the $n \prod_{j=1}^{q} h_j$ terms that appear in the denominator of $\text{Var}\, \hat{f}(y|x)$. The interested reader may find detailed formulas for the bias and variance in Hall, Racine, and Li (2004) and Li and Racine (2007), along with additional technical details and definitions that lie beyond the scope of this paper. In the results section that follows, the ATET(X) estimates are presented along with robust bootstrap-based 95% confidence intervals rather than relying on the limiting asymptotic distribution outlined in Equation (45), which is undertaken simply to ensure that the results are robust to both functional form specification and to limiting distributional assumptions.

[31] For continuous variables, a smoothing parameter is also referred to as a bandwidth.
[32] The length of γ_x is $q + r + s$ and γ_z is of length $q + r + s + 1$.

2.6 Results

2.6.1 Descriptive Statistics

2.6.1.1 Characteristics of Prescription Opioid Users and Non-users An analysis of the mean characteristics of survey respondents that reported taking prescription opioids (users) and of those who reported not taking them (non-users) shows that the two groups are demographically very similar; both groups are majority white, non-immigrant, married, have completed post-secondary education and are in the high-middle income group. There are demographic differences between these two groups; the first is that the sample of prescription opioid users is majority female whereas the sample of non-users is majority male, while the second is that the sample of prescription opioid users is slightly older with an average age of 34.7 years whereas the average age of non-users is 34.5 years. However, the demographic differences between the two groups are not significantly different from zero. In terms of health and healthcare utilization variables, the two groups typically report being in very good/excellent health, having one or more chronic conditions, did not experience a serious injury in the past year, are pain-free, do not have a probable case of distress or depression, and visit a medical doctor 2-4 times per year. See the Appendix, Table 26 and Table 27, for more details.

2.6.1.2 Trends in Key Variables Starting in cycle 2, the NPHS asked respondents whether they had some form of pharmaceutical insurance. Figure 13 plots the proportion of Quebec and non-Quebec ("Rest of Canada") residents who reported having pharmaceutical insurance coverage. It is evident that in cycle 2 (1996/1997), when the policy was implemented, Quebec started with a lower proportion of self-reported coverage of 67.6% compared to 70.9% by the rest of Canada. By cycle 3

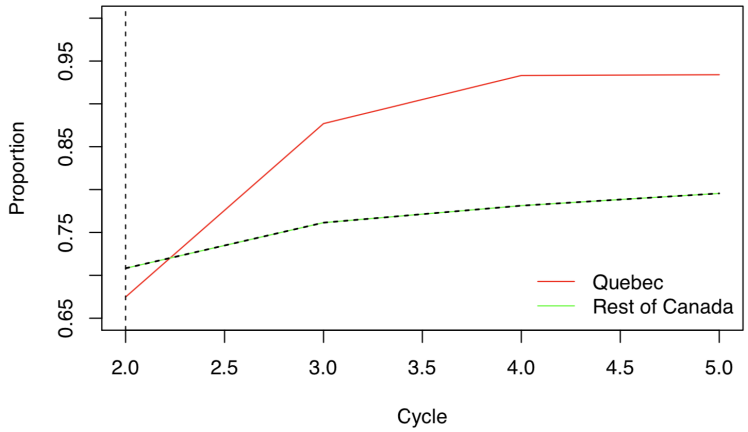


Figure 13: Proportion with pharmaceutical insurance

(1998/1999), the proportion of self-reported coverage had increased to 87.8% and had largely surpassed the rate reported by the rest of Canada (76.2%). Quebec's pharmaceutical insurance coverage rate increased at a decreasing rate up to a high of 93.5% in cycle 5. It may have been expected that the proportion of Quebec residents with pharmaceutical insurance would have spiked to 100% at or shortly after cycle 2, when pharmaceutical insurance coverage was made mandatory for all Quebec residents. A coverage of 100% may not have been captured because of survey self-report bias and confusion around the word "insurance" (Grootendorst, Newman, and Levine 2003).

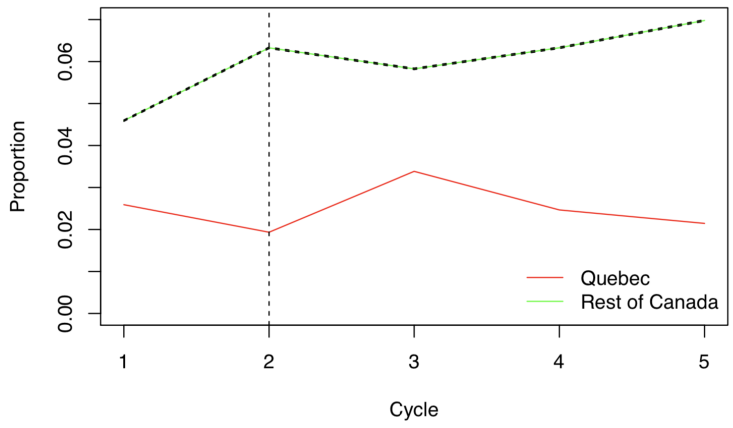


Figure 14: Proportion taking prescription opioids

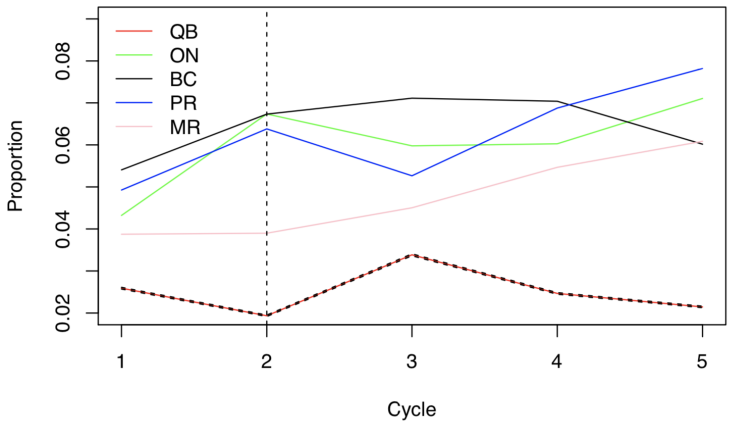


Figure 15: Proportion taking prescription opioids by province/province group

Figure 14 and 15 plot the proportion of residents reporting taking prescription opioids. These figures illustrate Quebec's low rate of self-reported prescription opioid use relative to the rest of Canada, when non-Quebec residents are pooled together or separated into provinces/province groups. In cycle 1, 2.6% of Quebec residents reported taking prescription opioids. This proportion decreased to 1.9% when the policy is implemented in cycle 2, before peaking in cycle 3 at 3.4% and then gradually decreasing to below the initial proportion (2.2%). Figure 14 demonstrates that the rest of Canada exhibits a somewhat opposite trend in prescription opioid use behavior, with the proportion reporting use peaking in cycle 2 (6.3%) and then dipping down in cycle 3 (5.8%). Unlike Quebec, which reported a small decrease over the five cycles, the proportion using prescription opioids in the rest of Canada increased overall by 2.3 percentage points. The upward trend in prescription opioids use in the rest of Canada, as shown in Figure 14, closely resembles the trend for the Prairie (PR) provinces[33] shown in Figure 15, which exhibit an overall upward trend from 4.9% in cycle 1 to 7.8% in cycle 5, with a peak and drop in cycles 2 and 3 respectively. The Maritime (MR) provinces[34] experienced a steady increase in prescription opioid use over the

[33]The Prairie provinces include Alberta, Saskatchewan, and Manitoba.

[34]Maritime provinces include New Brunswick, Nova Scotia, Prince Edwards Island, and Newfound-

five cycles. The Maritime provinces had the second-lowest rate of prescription opioid use of all other provinces/province groups until cycle 5 when it surpassed British Columbia (BC). For the first four cycles, BC has higher prescription opioid use than all other provinces/province groups, while cycle 5 shows a rapid drop to 6% reported prescription opioid use. Ontario (ON), the most demographically similar province to Quebec, experienced a large rise in prescription opioid use from cycle 1 to cycle 2 before decreasing for two cycles and then rising once again to 7.1% in cycle 5.

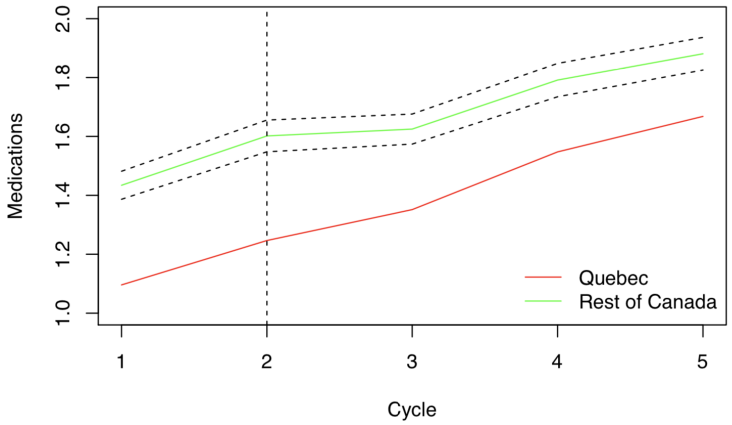


Figure 16: Average number of medications taken

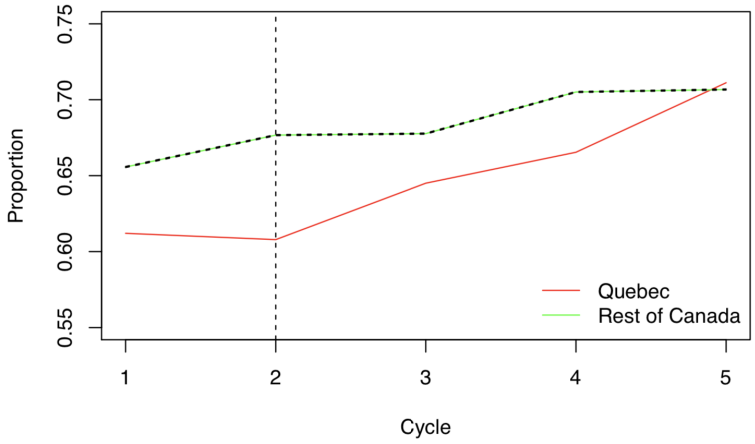


Figure 17: Proportion taking over-the-counter pain medication

land and Labrador.

2.6.1.3 Trends in Related Variables Figure 16 and Figure 17 illustrate the trends of other medication use measures captured by the NPHS. Figure 16 plots the average number of distinct medications (including prescription and nonprescription medication) respondents reported taking. The average number of medications taken rose from 1.1 to 1.67 for Quebec; similarly, the average number of medications taken in the rest of Canada rose from 1.43 to 1.88 over the study period. C. Wang et al. (2015) used a difference-in-differences approach to analyze the effect of Quebec's Mandatory Universal Pharmaceutical Insurance Program on the average number of distinct medications taken by Quebec residents relative to residents from the rest of Canada, while controlling for individual fixed-effects, and found that the program led to a 13% increase in medication use, net of substitutions between prescription and nonprescription medications. The rest of Canada's medication use behavior presented in Figure 16 resembles its prescription opioid use behavior plotted in Figure 14. The two trends involve an overall increase over the five cycles, with a rise in cycle 2 followed by a drop in cycle 3. Interestingly, although the average number of distinct medications taken steadily increased in Quebec during the study period, the proportion of respondent taking prescription opioids did not, suggesting that the rise in the average number of medications taken is due to an increase in the consumption of other prescription drugs, over-the-counter medications, or both. For example, the rise in the average number of medications taken in Quebec may be partially driven by the rise in the consumption of over-the-counter pain medications, an imperfect substitute for prescription opioids, as illustrated in Figure 17.

The consumption of prescription opioids may increase in response to an increase in pain-related injuries and conditions. Figure 18 shows how the proportion of Quebec and non-Quebec residents reporting a serious injury in the past year rapidly decreased

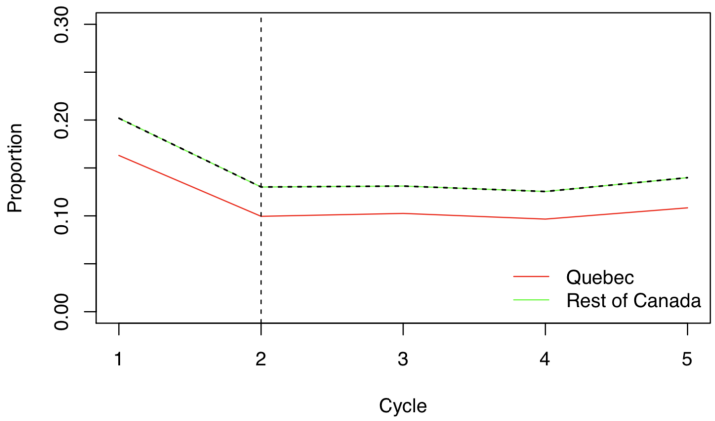


Figure 18: Proportion with a serious injury

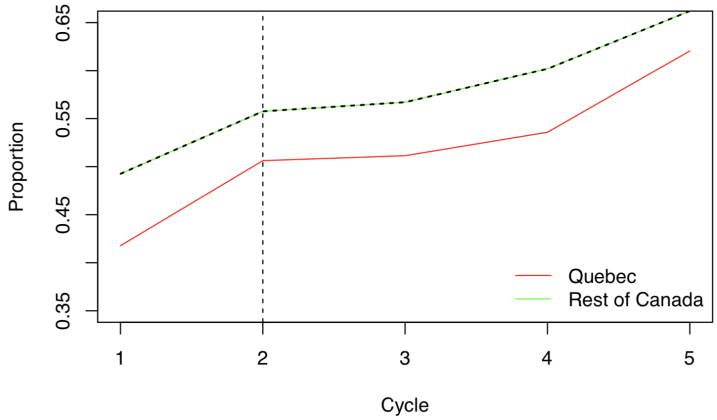


Figure 19: Proportion with one or more chronic conditions

from cycle 1 to cycle 2, before remaining relatively constant for the following three cycles, with the proportion reporting a serious injury in the rest of Canada being close to 4% higher than in Quebec for all cycles. Conversely, Figure 19 presents the proportion of respondents with one or more chronic conditions sharply increasing from cycle 1 to cycle 2, before increasing at a slower rate for cycles 3 and 4, only to then rapidly increase again in cycle 5. Prescription opioid use may also increase if individuals visit medical doctors (MD) more often since doctor visits are an intermediary service required to obtain prescription opioids. Figure 20 illustrates that after cycle 2 Quebec experienced an increase in MD visits over cycles 3 and 4 and later decreased in cycle

5. Figures 18, 19 and 20 plot variables related to prescription opioid use and depict a trend break for Quebec when the policy was implemented in cycle 2. Changes in these variables may result in changes in prescription opioid use that are independent of the policy implementation; thus, the estimated ATET(X) controls for these variables, among other observed characteristics.

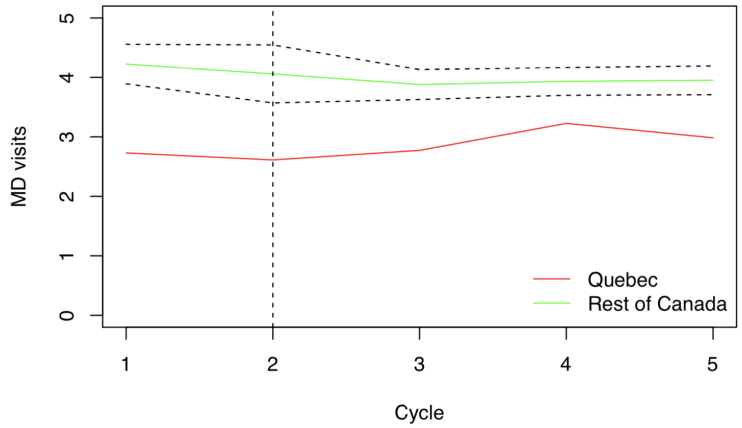


Figure 20: Average number of MD visits

2.6.2 The Average Treatment Effect on the Treated (ATET(X))

Table 13: Average Treatment Effect on the Treated (QB vs Rest of Canada)

Cycle	C3	C4	C5
ATET(X)	-0.0013	-0.0065	-0.0196
95% CI	(-0.0081, 0.0057)	(-0.0115, -0.0016)	(-0.024, -0.0155)

2.6.2.1 Quebec Relative to the Rest of Canada Table 13 reports the estimated ATET(X) and 95% bootstrap confidence intervals when the post-policy period is cycle 3, 4, or 5 in columns 1, 2, and 3, respectively. When cycle three is used as the post-policy period, the ATET(X) estimates that the policy implementation led to a 0.13 percentage point decrease in the probability of Quebec residents taking prescription

opioids relative to non-Quebec residents. Similarly, when cycle 4 or 5 are used as the post-policy periods, the policy is estimated to have led to a decrease of 0.65 and 1.96 percentage points, respectively. The confidence intervals indicate that the ATET(X) is only significantly different from zero when cycle 4 or 5 is used as the post-policy period. Overall, these results indicate that the policy had a negative effect on prescription opioid use and that the magnitude is increasing over time and remains statistically significant.

Table 14: Average Treatment Effect on the Treated (QB vs ON)

Cycle	C3	C4	C5
ATET(X)	0.0073	0.008	-0.021
95% CI	(-0.002, 0.0157)	(0.0023, 0.0158)	(-0.0306, -0.011)

Table 15: Average Treatment Effect on the Treated (QB vs PR)

Cycle	C3	C4	C5
ATET(X)	0.0076	-0.0072	-0.0114
95% CI	(-0.0022, 0.0164)	(-0.0151, -2e-04)	(-0.0179, -0.0044)

Table 16: Average Treatment Effect on the Treated (QB vs MR)

Cycle	C3	C4	C5
ATET(X)	0.0022	-0.0193	-0.021
95% CI	(-0.0057, 0.012)	(-0.0277, -0.0117)	(-0.0272, -0.0136)

Table 17: Average Treatment Effect on the Treated (QB vs BC)

Cycle	C3	C4	C5
ATET(X)	-0.0278	-0.0232	-0.0061
95% CI	(-0.0407, -0.0123)	(-0.0353, -0.0096)	(-0.0161, 0.0043)

2.6.2.2 Quebec Relative to Other Provinces In Table 13, the treatment group is Quebec residents and the control group is non-Quebec Canadian residents. In Tables 14 to 17, the treatment group remains the same; however, the control group is residents of Ontario (ON), the Prairies (PR) or the Maritimes (MR) and British Columbia (B.C), respectively. As shown in Table 14, when compared to Quebec's most demographically similar province, Ontario, the estimated ATET(X) of the policy increases from 0.0073 in cycle 3 to 0.008 in cycle 4 but later decreases to -0.021 in cycle 5. The interpretation of the ATET(X) estimates which are significantly different from zero (that is the ATET(X)s using cycle 4 and 5 as the post-policy periods) suggest that the policy initially resulted in a 0.8 percentage point increase in the probability of Quebec residents consuming prescription opioids, but later led to a decrease in the probability of prescription opioid use of 2.1 percentage points. Tables 15 and 16 present similar results, where the ATET(X) is positive but not significantly different from zero in cycle 3; however, in cycles 4 and 5 the ATET(X) is significantly different from zero and increasingly negative. Overall, the results from Tables 14 to 16 are consistent with the results obtained in Table 13, finding that the ATET(X) is increasingly negative at cycles more distant from the time of policy implementation and the effect is significantly different from zero when the post-policy period used to estimate the ATET(X) is cycle 4 or 5, but not when it is cycle 3. As shown in Table 17, when British Columbia residents make up the control group the results differ slightly from the results obtained using the alternative control groups. As was the case for the results presented in Table 13, the ATET(X) is negative regardless of the post-policy period used, however, unlike the results when other control groups are used where the ATET(X)s using cycles 4 and 5 as the post-policy periods are significantly different from zero, when the control group is B.C the cycle 5 ATET(X) is not significantly different from zero. This result may be driven by British Columbia's implementation

of the Fair PharmaCare Plan in 2003, a public income-based pharmaceutical insurance plan for B.C families. If the implementation of the Fair PharmaCare Plan in the later part of cycle 5 (2002/2003) affected the prescription opioid use behavior of B.C residents, then the estimated ATET(X) using cycle 5 as the post-policy period will also be affected because it measures the difference in the change in prescription opioid use by Quebec residents relative to B.C residents.

2.6.3 Treatment Effect on the Treated Individual of Interest (TETII)

Table 18: Treatment Effect on the Treated Individual of Interest (QB vs Rest of Canada)

Cycle	C3	C4	C5
TETII	-0.0057	-0.0284	-0.0178

Table 18 presents the estimated Treatment Effect for the Treated Individual of Interest (TETII), which in this case is a likely prescription opioid user[35]. For the likely prescription opioid user in Quebec, the implementation of the Mandatory Universal Pharmaceutical Insurance Program decreased their probability of taking prescription opioids. The magnitude of the estimated effect ranges from a 0.57 to 2.84 percentage point decrease depending on which cycle (3, 4, or 5) is used as the post-policy period. The estimated magnitude of the effect is largest when cycle 4 is used as the post-policy period and can be interpreted as follows: the policy led to an estimated 2.84 percentage point decrease in the probability of a likely prescription opioid user in Quebec consuming prescription opioids, relative to someone with the same characteristics living outside of Quebec.

[35]A likely prescription opioid user in this scenario is defined as an individual whose characteristics are the mode characteristics in a sample of prescription opioid users.

2.6.4 Substitution Effects

It is of interest to assess if the policy led to a substitution effect away from over-the-counter (OTC) pain medications and towards prescription opioids for pain treatment. A substitution of pain medications is defined as observations that reported taking OTC medications but not prescription opioids prior to the policy, but after the policy is implemented reported taking prescription opioids and not OTC medications. The proportion of Quebec and non-Quebec respondents whose medication use responses matched the substitution definition above was tabulated and the two proportions were compared to assess if they statistically differ from zero. Using this approach, it is found that less than 1% of Quebec residents substitute, less than 1% of Non-Quebec residents substitute, and the difference in substitution proportions between the two groups is not significantly different.

2.7 Conclusion and Discussion

Canada has experienced continuously increasing prescription opioid use, morbidity, and mortality since the early 1990s. Despite efforts to reduce prescription opioid-related hazards, rates of prescription opioid addiction and overdoses continued to rise to the point of being declared a national public health crisis by Health Canada (Health Canada 2017). During the same time period, increasing political and public interest in reforming Canada's healthcare insurance system to improve access to necessary medications has stirred up debate about whether Canada should implement a National PharmaCare Program (Morgan and Boothe 2016). The pharmacare debate needs to be informed about the potential effect expanding pharmaceutical insurance coverage could have on the use of prescription opioids in order to address concerns about a potential exacerbation of the prescription opioid crisis in Canada. The analysis presented here

utilizes Quebec's implementation of a Mandatory Universal Pharmaceutical Insurance Program as a natural experiment to explore if expanding drug insurance coverage led to an increase in the use of prescription opioids (i.e., codeine, Demerol, and morphine). The results show that the policy led to a statistically significant, although small in magnitude, negative effect on prescription opioid use. More importantly, the evidence presented in this paper does not suggest that expanding pharmaceutical insurance coverage leads to a rise in the consumption of prescription opioids. Even for a likely prescription opioid user, the model predicts that the program did not lead to an increase in their probability of taking prescription opioids. Additionally, this study does not find significant evidence that the policy caused a substitution effect away from over-the-counter pain medications and towards prescription opioid pain relievers. These findings are consistent with U.S. studies that do not find statistically significant evidence that the Affordable Care Act provisions expanding pharmaceutical insurance coverage had an effect on prescription opioid use (Saloner et al. 2018), prescriptions written (Sharp et al. 2018) or related harms (Wettstein 2019; Coupet et al. 2020; Averett, Smith, and Wang 2019).

Previous analysis of the effects of Quebec's Mandatory Universal Pharmaceutical Insurance Program found that it had a significant effect on increasing access to medications, increasing general practitioner visits, and it led to substantial health gains for the chronically ill and less healthy people (C. Wang et al. 2015). Quebec's private-public mixed approach to ensuring universal pharmaceutical insurance coverage has been shown to have positive health and healthcare system effects without increasing the use of prescription opioids. Additionally, the mixed private-public approach implies less public costs and minimal disruption to the private insurance industry relative to a purely public plan. Policymakers may consider Quebec's approach to expand-

ing pharmaceutical insurance coverage as a template for increasing pharmaceutical insurance coverage nationally. This study did not find evidence that expanding pharmaceutical insurance increases prescription opioid use as measured by the proportion of individuals reporting taking codeine, Demerol, or morphine. If the data becomes available, future research could expand on this study's results by analyzing the effects of the pharmaceutical insurance expansion on the intensity of prescription opioid use, to assess whether or not individuals consuming prescription opioids before the policy increased the quantity consumed in response to the policy implementation. Future work could also explore the policy effect when more types of prescription opioids, beyond codeine, Demerol, and morphine, are analyzed.

3 Chapter 3: The Effects of the COVID-19 Pandemic on the Labour Market Outcomes of Canadian Immigrants

3.1 Introduction

The year 2020 was undoubtedly marked by the surge of the global COVID-19 pandemic. The infectious disease COVID-19 (which is caused by the Severe Acute Respiratory Syndrome Corona Virus 2 (SAR-CoV2)) spread across the globe and many government bodies were forced to implement restrictions to slow down the spread of the virus. In mid-March 2020, Canada implemented policies aimed at increasing physical distancing; this included the shutdown of any non-essential businesses and services, the cancellation of in-person events and entertainment, school closures, and the start of work-from-home orders. As a result, economic activity plunged and job losses occurred. Some early analyses have shown that the economic effects of the lockdown have had a larger effect on sub-groups of the population, such as women (Beland, Fakorede, and Mikola 2020; Qian and Fuller 2020), parents of young children (Qian and Fuller 2020), aboriginal people (Bleakney, Masoud, and Robertson 2020), low wage workers (Koebel and Pohler 2020; Beland, Fakorede, and Mikola 2020), and self-employed workers (Beland, Fakorede, and Mikola 2020). However, there has been limited analysis on the economic impact of the COVID-19 pandemic and the associated lockdowns on immigrants, a group known to be economically sensitive to recessions (Hou and Picot 2022; Zhang and Gunderson 2022; Lamb, Banerjee, and Emanuel 2022). This paper uses Canadian microdata to explore the labor market effects that the COVID-19 pandemic has had on Canadian immigrants.

3.2 Literature Review

The academic literature analyzing the effects of the COVID-19 pandemic on the Canadian population has rapidly developed. An early analysis of the labour market effects at the start of the COVID-19 pandemic explored changes in employment and aggregate hours worked from February 2020 to April 2020 (Lemieux et al. 2020). This study found that the start of the pandemic led to a 15 percent decrease in employment and a 32 percent decrease in aggregate hours worked by adults ages 20-64 (Lemieux et al. 2020). It was also found that the start of the pandemic had a much larger effect on workers in the accommodation and food services industry, young workers, paid hourly employees, and non-unionized workers (Lemieux et al. 2020).

More analyses on the labour market effects of the pandemic followed. These analyses focused their attention on analyzing the effects of the pandemic on population groups which may have been disproportionately affected by the pandemic or are traditionally more economically sensitive to recessions. Such analyses found that the pandemic led to a larger than average effect for women (Beland, Fakorede, and Mikola 2020; Qian and Fuller 2020), parents of young children (Qian and Fuller 2020), aboriginal people (Bleakney, Masoud, and Robertson 2020), low wage workers (Koebel and Pohler 2020), and self-employed workers (Beland, Fakorede, and Mikola 2020)

Although immigrants make up a significant proportion of the population and are a group traditionally acknowledged to be economically sensitive to recessions, the existing research on this group is limited (Hou and Picot 2022; Zhang and Gunderson 2022; Lamb, Banerjee, and Emanuel 2022). Descriptive analyses of changes in the employment rate have found that the pandemic has led to decreases in employment for both immigrants and non-immigrants, however the decrease has been larger for immigrants, particularly immigrant females (Hou, Picot, and Zhang 2020; Hou and

Picot 2022; Mo et al. 2020; Nardon et al. 2021).

Beland, Fakorede, and Mikola (2020) compared the rates of small business ownership and aggregate hours worked by self-employed workers in February 2020 to April 2020 and found the pandemic lead to a substantial decrease in ownership and aggregate hours worked. The decrease in ownership was larger for immigrants (-16.1%) than it was for non-immigrants (-10.6%). Similarly, the decrease in aggregate hour was larger for immigrants (44.3%). Assessing a longer period (January 2016 to December 2020) than previous studies, Beland et al. (2022) conducted a simple pre/post analysis to analyze the labour market and mental health effects of the pandemic on the Canadian population. The authors do not find large differential effects in labour market outcomes by immigrant status but do find that compared to non-immigrants, immigrants were much more likely to fear losing their job, the latter result being consistent with the findings of other studies analyzing economic perceptions during the COVID-19 pandemic (Beland et al. 2022; Mo et al. 2020; LaRochelle-Côté and Uppal 2020).

This paper builds on the literature of the effects of the COVID-19 pandemic on the labour market outcomes of Canadian immigrants. Using nationally representative microdata, this paper analyzes changes in employment and aggregate hours worked using descriptive statistics and regression analysis. This paper extends previous analysis to include data up to December 2021, which allows for analysis of the effects of later waves of infection brought forth by variants of the virus (i.e., gamma, delta and omicron).

3.3 Data and Descriptive Statistics

3.3.1 Data

The data used for the analysis presented in this paper comes from the Canadian Labour Force Survey (LFS), a monthly household survey conducted by Statistics Canada. The LFS samples approximately 54,000 households each month and collects information relevant to measuring the current state of the Canadian labour market. Monthly Public Use Microdata Files (PUMFS) of the LFS from January 2017 to December 2021 are used. The analysis presented in this paper focuses on the impact of the COVID-19 pandemic on immigrant labour market outcomes for the 21 months after the first restrictions were implemented in Canada in March 2020 (that is data for the period March 2020 - December 2021). The sample used for analysis consists of individuals of ages 20-64 who are not full-time students and are residents of Canadian provinces[36]. The analysis is weighted to be representative of the Canadian population.

3.3.2 Outcome Variables

To analyze the effect of the COVID-19 pandemic on Canadian labour supply, we focus on analyzing individuals who are employed and at work, and aggregate hours worked. The employment rate and aggregate hours worked are at the forefront of most analyses of the COVID-19 pandemic and labour supply for several contextual reasons.

Traditionally, analyses of recessions focus on changes in unemployment. Although unemployment did in fact increase throughout the COVID-19 pandemic (Hou and Picot 2022), the unemployment rate does not fully encapsulate all forms of job loss or reduction in work that occurred during the pandemic (Lemieux et al. 2020). Many workers who were employed and at work faced job loss but did not lose their

[36]Does not include residents of Canadian Territories.

employment entirely. Workers who were furloughed, on-sick leave, or had their work hours reduced[37], transitioned from being employed and at work to being employed but absent from work for at least several days per week. Thus, a reduction in at work employment in many cases did not translate to an increase in unemployment, but instead to an increase in absent from work employment. To analyze the multiple dimensions of job loss that occurred during the pandemic, we focus our attention on changes in *at work employment*, while also analyzing absent from work employment, unemployment, and not in the labour force status. The LFS definition of each of the four employment statuses analyzed in this paper are listed below. The LFS's labour force status definitions are based on the definitions endorsed by the International Labour Organization.

3.3.2.1 Employment Status

- **Employed (at work)** persons are those who, during the reference week:
  - Did any work at all at a job or business, that is, paid work in the context of an employer-employee relationship, or self-employment.
  - It also includes persons who did unpaid family work, which is defined as unpaid work contributing directly to the operation of a farm, business or professional practice owned and operated by a related member of the same household.
- **Employed (absent from work)** persons are those who, during the reference week:
  - Had a job but were not at work due to illness or disability, personal or

[37]As decided by their employer or by their household (e.g., to provide care their children during school closures).

family responsibilities, vacation or labour dispute.

  - This category excludes persons not at work because they were on layoff or between casual jobs, and those who did not then have a job (even if they had a job to start at a future date).

- **Unemployed** persons are those who, during the reference week:

  - were without work, but had looked for work in the past four weeks ending with the reference period and were available for work;
  - were on temporary layoff due to business conditions, with an expectation of recall, and were available for work; or
  - were without work, but had a job to start within four weeks from the reference period and were available for work.

- **Not in the Labour Force**: Persons who were neither employed, nor unemployed during the reference period.

  - This includes persons who, during the reference period, were either unable to work or unavailable for work.
  - It also includes persons who were without work and who had neither looked for work in the past four weeks, nor had a job to start within four weeks of the reference period.

3.3.2.2 Total Hours Worked To capture changes in aggregate hours worked, the LFS variable for total actual hours worked (ATOTHRS) is used and described below.

- **Actual Total Hours Worked**: Number of hours actually[38] worked by the respondent during the reference week, at all jobs including paid and unpaid

[38]The term *actual* is used to distinguish from another variable collected in the LFS which captures *usual* hours worked per week at all jobs. The Usual Total Hours (UTOTHRS) variable is not used in the analysis presented in this paper.

hours. These hours reflect temporary decreases or increases in work hours (for example, hours lost due to illness, vacation or holidays, or more hours worked due to overtime).

Individuals who were unemployed or not in the labour force were coded to have zero total hours worked. Thus, the total hours worked variable can capture the multiple ways work hours could have been impacted by the pandemic. Table 19 summarizes the possible transitions from at work employment and how the change would be observed in the total hours worked variable. Workers who remained employed and at work could have had their total hours worked either unchanged[39], decreased[40], or increased[41]. Being employed and at work implies that the lower bound of total hours worked is positive, whereas total hours worked is zero for the other labour force statuses (which are employed (absent from work), unemployed, and not in the labour force). To summarize, the total hours worked variable measures the total hours worked by each individual in the sample (i.e., non-full-time students aged 20-64). Thus, it captures the hours worked by individuals who are employed (either at work or absent), unemployed or not in the labour force. Total hours worked for the unemployed and not in the labour force are equal to zero. Imputing zero hours for the unemployed and those not in the labour force avoids endogeneity/selection into labour force status. This avoids having to do selection corrections as Lamb et al. (2022), which is hard to do convincingly. In what follows, total hours worked and aggregate hours worked are used interchangeably.

[39] E.g., workers who were working from home before the pandemic.

[40] E.g., essential workers whose employment hours of operation were reduced for efficiency reasons or to comply with lockdown policies.

[41] E.g., healthcare workers working extended hours to provide care during an epidemic.

Table 19: Possible Transitions From At Work Employment

Pre-Pandemic Labour Force Status	Pandemic Labour Force Status	Effect on Total Hours Worked	Total Hours Worked
Employed (at work)	Employed (at work)	Unaffected	>0
Employed (at work)	Employed (at work)	Increased	>0
Employed (at work)	Employed (at work)	Decreased	>0
Employed (at work)	Employed (not at work)	Decreased	0
Employed (at work)	Unemployed	Decreased	0
Employed (at work)	Not in the Labour Force	Decreased	0

3.3.3 Descriptive Statistics

3.3.3.1 At Work Employment Figures 21 to 24 depict trends in the employment status (employed (at work), employed (absent from work), unemployed, and not in the labour force) of adults ages 20-64 who are not full-time students, broken up by gender and immigrant status. In each figure, the dashed vertical line marks March of 2020 and the onset of COVID-19 related restrictions in Canada. Following convention from the existing literature on the COVID-19 pandemic and the Canadian labour market, March 2020 is referred to as the start of the COVID-19 pandemic in Canada. However, it is acknowledged that the spread of the virus (SAR-CoV2) had been rapidly spreading internationally prior to March 2020.

Two features of the at work employment trends stand out in Figure 21. First, Figure 21 shows that soon after the start of COVID-19 related restrictions, there was a drop in the at work employment rate for all four gender-immigrant status groups. Another notable feature of Figure 21 is the noticeable seasonality in the summer months. In the years prior to the COVID-19 pandemic, each June, July and August there is a drop in at work employment. The seasonality is common to all four gender-immigrant status groups plotted in Figure 21; however, it is more pronounced for the non-immigrant females.

Analyzing the at work employment trends by gender highlights some differences

between immigrants and non-immigrants. Figure 21 shows that before COVID-19 related restrictions, the at work employment rate is consistently higher for immigrant males compared to non-immigrant males; however, with the start of restrictions and closures, the at work employment rate dropped by a larger amount for immigrant males than it did for non-immigrant males, resulting in the two groups having the same at work employment rate in April 2020. For females, non-immigrants have a higher at work employment rate for most of the year, with the exception of the summer months when at work employment drops to a rate similar to the immigrant female at work rate. The start of the COVID-19 pandemic brought forth a drop in at work employment for both immigrant and non-immigrant females alike.

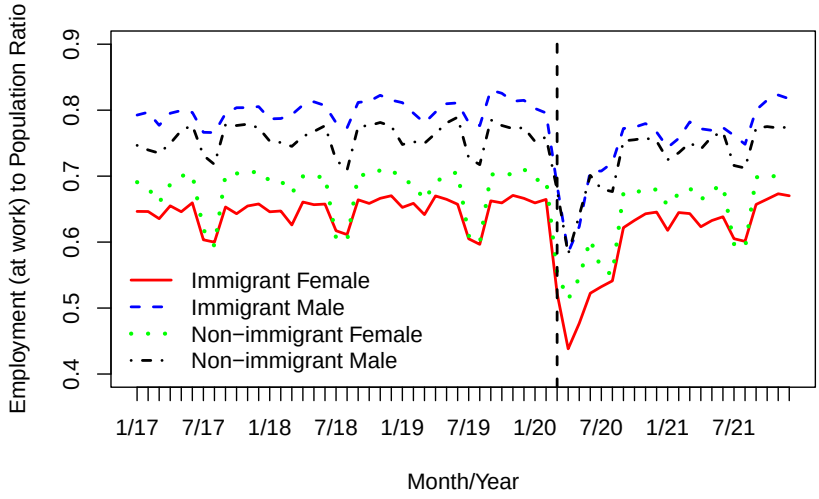


Figure 21: Employed (at work) to Population (immigrant status-gender group) Ratio

3.3.3.2 Absent From Work Employment Figure 22 illustrates the trends in absent from work employment for each of the four gender-immigrant status groups. Recall that the employed but absent from work status includes individuals who had a job but were not at work due to illness or disability, personal or family responsibilities, vacation or labour dispute. Figure 22 shows a seasonal increase in absent from work employment in the months of June, July and August. The rise in absent from work

employment coincides with the timing of the seasonal drop in at work employment shown in Figure 21, suggesting that some of the individuals who are not at work in the summer months are not unemployed but instead taking time away from work. Some individuals who are not at work in the summer usually do not work in summer.

The education sector plays a large role in the seasonality of absent from work employment for two reasons. First, during the summer months when primary and secondary schools are closed, educators are employed but not at work. Second, parents employed in other sectors are more likely than workers without children to take vacation time during the summer months when kids are not in school.

The influence of the educational sector on the absent from work employment rate helps explain why the seasonality of absent from work employment is greater for non-immigrant females. Non-immigrant females are more likely to be absent from work in the summer compared to the other three gender-immigrant groups because they are more likely to be employed in the education sector (Qian and Fuller 2020) or take time off in the summer to look after children since household childcare is asymmetrically distributed by gender (Moyser 2017).

Similarly, each March, when kids are out of school for the spring school break, there is a rise in absent from work employment. In the years prior to the COVID-19 pandemic the March rise in absent from work employment is small relative to the large increase in the summer months; however, Figure 22 shows that with the initial implementation of COVID-19 related restrictions in March 2020 there was a much higher than usual rate of absent from work employment for all four gender-immigrant status groups. In fact, the March 2020 increase in absent from work employment exceeds the regular summer increase.

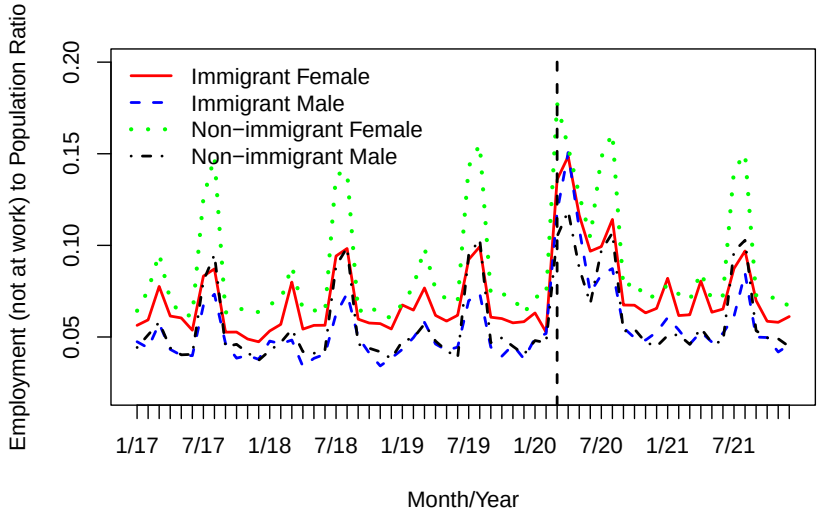


Figure 22: Employed (not at work) to Population (immigrant status-gender group) Ratio

3.3.3.3 Unemployment Traditionally, labour market analyses of recessions focus primarily on changes in the unemployment rate. However, as discussed in Lemieux et al. (2020) , the unemployment rate is not well suited in the context of the COVID-19 pandemic. Instead, we analyze the unemployment-to-population ratio, using the traditional definition of unemployment in the numerator but the population in the denominator. For the purposes of this analysis, we do not explore alternative definitions of unemployment. Figure 23 plots the unemployment-to-population ratio for each of the four gender-immigrant status groups. In the three years prior to the pandemic, the unemployment-to-population ratios for all four gender-immigrant groups were gradually decreasing year-over-year. By 2019, the annual average unemployment-to-population ratio of males (immigrant and non-immigrant) was about 5%, and just below 4% for females. At the time of the implementation of COVID-19 related restrictions, the unemployment-to-population ratios of all four groups spiked, and then peaked in the spring and early summer (unemployment peaked in April 2020 for non-immigrant males, in May 2020 for immigrant males and non-immigrant females, and in June

2020 for immigrant females). Figure 23 illustrates that after peaking in the spring and summer of 2020 the decrease in the unemployment-to-population ratios of the four gender-immigrant status groups was gradual and long-lasting (one year after the unemployment-to-population ratios peaked, they remained well above the pre-COVID unemployment-to-population ratios for those months). Hou, Picot, and Zhang (2020) and Hou and Picot (2022) provide further analysis of immigrant unemployment during the COVID-19 pandemic and how it compares to previous recessions.

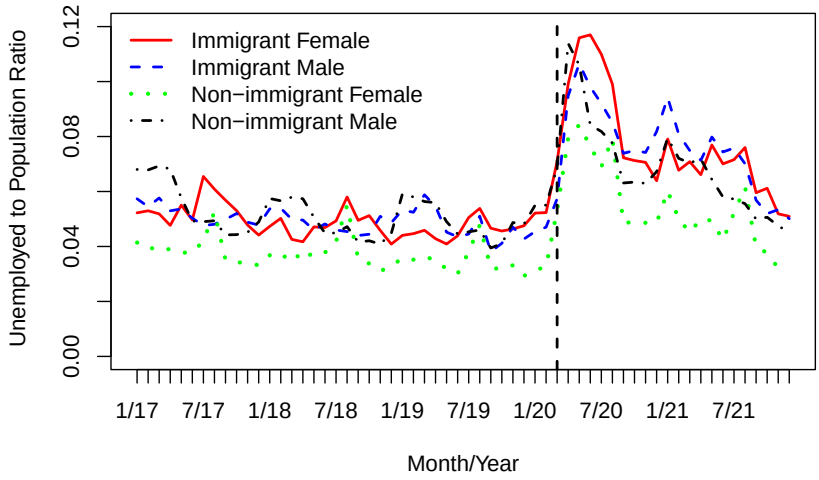


Figure 23: Unemployed to Population (immigrant status-gender group) Ratio

3.3.3.4 Not in the Labour Force Figure 24 illustrates the not in the labour force rate for each of the four gender-immigrant status groups. In the three years prior to the start of the pandemic, the trends in the rates of not in the labour force were stable and not trending upwards or downwards. A notable feature of Figure 24 is that the trends are clearly separated by gender; females have a higher not in the labour force rate than males. This feature is not surprising; the not in the labour status is largely composed of stay-at-home parents, and females are more likely to be stay at home parents (Moyser 2017). The not in the labour force rate is highest for immigrant females, followed by non-immigrant females, non-immigrant males and

immigrant males, respectively. Figure 24 shows that when the pandemic began, there was a rise in all four not in the labour force rates; however, by the start of autumn 2020 the not in the labour force rates had decreased back to near their pre-pandemic levels.

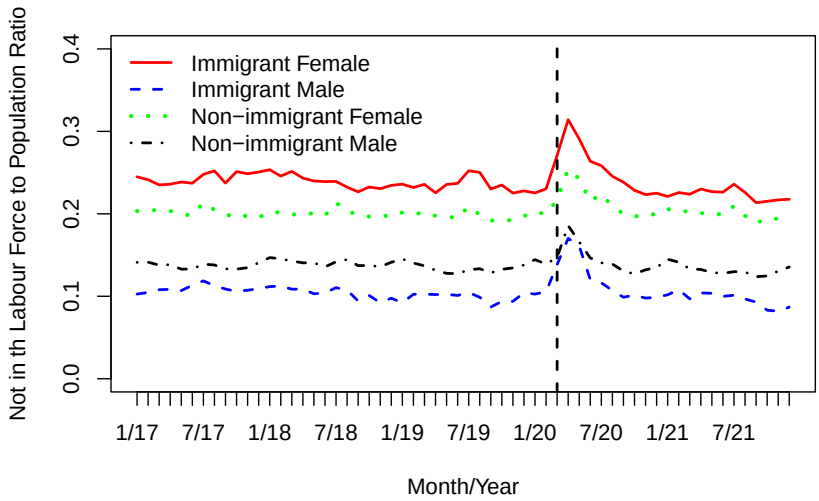


Figure 24: Not in the Labour Force to Population (immigrant status-gender group) Ratio

3.3.3.5 Average Total Hours Worked Figures 21 to 24 illustrate that at the time of the implementation of COVID-19 related restrictions, the population groups of interest (the four gender-immigrant groups) had a decrease in at work employment which resulted not only in an increase in unemployment but also in increases in absent from work employment and not in the labour force status. As noted in Table 19, the total hours worked variable summarizes the different changes in total hours worked that could arise due to changes in labour force status, as well as changes in hours worked by workers who remained employed and at work but had their hours increased or decreased due to the pandemic and pandemic related restrictions. Recalling that the total hours worked variable is equal to zero for not in the labour force and unemployed, Figure 25 presents the trends in average total hours worked by each of the gender-

immigrant status groups. In the period from 2017 to 2019, average total hours worked for the four gender-immigrant status groups show seasonal patterns but no upward or downward trend. On average, males worked more total hours than females. Before 2020 (i.e., 2017, 2018 and 2019) the average total hours worked by immigrant males was 32.01 hours and 30.67 hours for non-immigrant males. For females, the average total hours worked was 22.74 hours and 23.5 hours for immigrant and non-immigrant females, respectively.

At the beginning of the pandemic, the average total hours worked drastically dropped from February 2020 to April 2020 for all four gender-immigrant status groups; however, the percent decrease in average total hours worked was larger for immigrants than their non-immigrant counterparts. From February 2020 to April 2020 average total hours worked decreased by 27.3% for non-immigrant males, whereas they decreased by 30.55% for immigrant males. Similarly, the decrease in hours from February to April in 2020 was 27.9% for non-immigrant females and 36.44% for immigrant females.

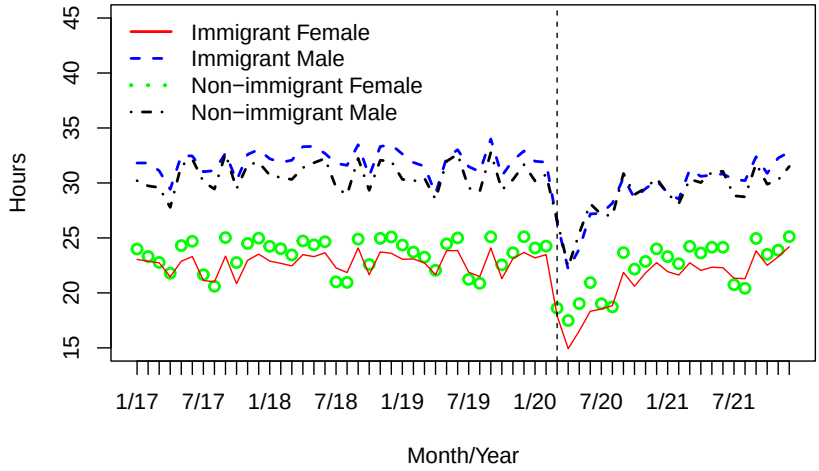


Figure 25: Actual hours worked per week at all jobs

3.4 Methods

3.4.1 Deseasonalizing Total Hours Worked

The figures presented in Section 3.3.3 illustrate that prior to the start of the pandemic there existed seasonal patterns in labour force status and total hours worked, and that the extent of the seasonality varied across the different gender-immigrant status groups. Thus, conducting a relative comparison of the effects of COVID-19 related restriction on the total hours worked requires that the total hours worked variable be deseasonalized, otherwise the analysis may systematically overstate or understate the effects of the start of the pandemic on aggregate hours worked. For example, overlooking the seasonality in absent from work employment of non-immigrant females would make the recovery in aggregate hours worked appear slow, when it is very likely aggregate hours would have been lower in the summer months in the absence of the pandemic.

Since the seasonality differs across the four gender-immigrant groups, the deseasonalization of total hours worked was done separately for each gender-immigrant status group. Appendix 4.3 presents the results of tests of seasonality in the total hours worked, and the results of the falsification tests verifying the correct deseasonalization of the aggregate hours worked variable.

3.4.2 The Model

Let H_i denote the deseasonalized total hours worked per week at all jobs by individual i. The following equation is used to analyze the effects of the start of the pandemic on the total deseasonalized hours worked by immigrants and non-immigrants of the same gender[42].

[42]The model is estimated for females and males separately.

$$\begin{aligned} H_i =& \alpha_1 \text{Immigrant}_i + \alpha_2 \text{Non-Immigrant}_i \\ &+ \beta \text{COVIDmonth}_i + \delta \text{Immigrant}_i \times \text{COVIDmonth}_i + \epsilon_i, \end{aligned} \tag{46}$$

where Immigrant_i is an indicator variable which is equal to one if immigrant and zero otherwise. Similarly, Non-Immigrant_i is an indicator variable which is equal to one if not an immigrant and zero otherwise. When estimating the model, which includes both the immigrant and non-immigrant indicators, the constant term (the intercept) is suppressed which has implications for the interpretation of the estimated coefficient parameters. COVIDmonth is a set of indicator variables for each month since the start of the pandemic, staring with March 2020 and ending with the last month in the data (December 2021). The immigrant indicator variable is interacted with each of the COVIDmonth indicator variables. Equation (47) is an expanded version of the model in Equation (46).

$$\begin{aligned} H_i =& \alpha_1 \text{Immigrant}_i + \alpha_2 \text{Non-Immigrant}_i \\ &+ \beta_1 \text{Mar2020}_i + ... + \beta_{21} \text{Dec2021}_i \\ &+ \delta_1 \text{Immigrant}_i \times \text{Mar2020}_i + ... + \delta_{21} \text{Immigrant}_i. \times \text{Dec2021}_i + \epsilon_i \end{aligned} \tag{47}$$

This model allows for an analysis of the effect of the pandemic on aggregate hours worked by immigrants and non-immigrants, as well as the relative differences between the two.

The parameter α_1 captures the average pre-pandemic deseasonalized hours worked by immigrants. Similarly, α_2 captures the average pre-pandemic deseasonalized hours worked by non-immigrants. The β parameters capture the difference in hours worked

by non-immigrants in each month after the start of the pandemic. For example, the predicted deseasonalized hours worked per week at all jobs in March 2020 by a non-immigrant is given by Equation (48):

$$\hat{H}_i = \hat{\alpha}_2 + \hat{\beta}_1. \tag{48}$$

Equation (49) predicts the deseasonalized hours worked per week at all jobs in March 2020 by an immigrant:

$$\hat{H}_i = \hat{\alpha}_1 + \hat{\beta}_1 + \hat{\delta}_1. \tag{49}$$

The δ parameters capture how much more/less the hours worked by immigrants were affected relative to non-immigrants for each month since the start of the pandemic. To illustrate, consider Equation (49) and suppose that both $\hat{\beta}_1$ and $\hat{\delta}_1$ are negative. In this case, $\hat{\beta}_1$ is the estimated March 2020 reduction in deseasonalized hours for non-immigrants, and $\hat{\delta}_1$ is the estimated March 2020 reduction in deseasonalized hours worked by immigrants above and beyond the reduction in deseasonalized hours worked by non-immigrants conditional on the pre-COVID gap between the two groups. Thus the total March 2020 reduction in deseasonalized hours worked by immigrants is given by $\hat{\beta}_1 + \hat{\delta}_1$.

3.5 Results

3.5.1 Female Results

The model in Equation (46) is estimated using the female observations from the sample and the estimated coefficients are presented in Table 20. The average deseasonalized

hours worked per week at all jobs by non-immigrant females before the pandemic was 23.51 hours, and was 22.76 hours by immigrant females. The coefficients for the month indicator variables (i.e., Mar.2020, …, Dec.2021) estimate the difference in deseasonalized hours that month compared to the pre-pandemic average for non-immigrant females. For example, the coefficient of the Mar.2020 variable indicates that, after adjusting for seasonality, in the first month of the pandemic (i.e., March 2020) non-immigrant females worked 4.56 fewer hours than the pre-pandemic average.

The pandemic month coefficients (i.e., the coefficients on Mar.2020 to Dec.2020), show that for the first year of the pandemic (i.e., March 2020 to February 2021) there was a statistically significant (at the 1% significance level) reduction in hours worked, after adjusting for seasonality. Further, the reduction in deseasonalized hours was largest in April and May of 2020, with an average reduction of 5.38 and 5.36 hours per week, respectively.

The coefficients on the interactions between the immigrant indicator variable and the pandemic month indicators (i.e., Immigrant in Mar.2020,…, Immigrants in Dec.2021) estimate how many more/less deseasonalized hours immigrant women worked in that month compared to non-immigrant women conditional after controlling for pre-COVID gap between the two groups. For example, in April 2020, immigrant women worked 1.47 hours less per week less than normal at all jobs than non-immigrant women, after adjusting for seasonality.

For the first four months after the start of the pandemic (i.e., April, May, June and July of 2020) the reduction in deseasonalized hours worked by immigrant women was significantly larger than the reduction in deseasonalized hours worked by non-immigrant women. The reductions in deseasonalized hours worked was largest in April and May of 2020, with immigrant women working 1.92 and 1.47 fewer deseasonalized

hours that non-immigrant women in April and May. Thus, immigrant women had a total reduction of 6.85 and 6.83 deseasonalized hours worked per week in April and May 2020, respectively.

The third wave of the virus (i.e., the gamma variant) took place during March, April and May of 2021 (Statistics Canada 2022), and as Table 20 shows, there was a statistically significant (at the 5% significance level) differential reduction in the deseasonalized hours work by immigrant women compared to non-immigrant women; however, the magnitude of the difference is less than one hour and not as large as in the first wave.

Table 20: Coefficient Estimates For Model of Total Actual Hours at All Jobs for Females

term	estimate	std.error	statistic	p.value
Non-Immigrant	23.5119686	0.0246293	954.6354398	0.0000000
Immigrant	22.7584913	0.0499041	456.0444950	0.0000000
Mar.2020	-4.5607592	0.1747079	-26.1050587	0.0000000
Apr.2020	-5.3774666	0.1742736	-30.8564651	0.0000000
May.2020	-5.3629747	0.1752822	-30.5962291	0.0000000
Jun.2020	-3.8620837	0.1757873	-21.9702059	0.0000000
Jul.2020	-2.2920578	0.1789073	-12.8114287	0.0000000
Aug.2020	-2.0909314	0.1803539	-11.5934913	0.0000000
Sep.2020	-1.3529203	0.1827982	-7.4011684	0.0000000
Oct.2020	-0.4846273	0.1753224	-2.7642072	0.0057062
Nov.2020	-1.5213558	0.1810314	-8.4038210	0.0000000

Table 20: Coefficient Estimates For Model of Total Actual Hours at All Jobs for Females *(continued)*

term	estimate	std.error	statistic	p.value
Dec.2020	-1.0670771	0.1880011	-5.6759076	0.0000000
Jan.2021	-0.9001223	0.1875729	-4.7987875	0.0000016
Feb.2021	-1.0376820	0.1754189	-5.9154516	0.0000000
Mar.2021	1.0601998	0.1824433	5.8111198	0.0000000
Apr.2021	0.7590046	0.1830021	4.1475182	0.0000336
May.2021	-0.2392115	0.1768930	-1.3522944	0.1762813
Jun.2021	-0.6488592	0.1755734	-3.6956578	0.0002193
Jul.2021	-0.5649841	0.1795361	-3.1469113	0.0016501
Aug.2021	-0.4015195	0.1795117	-2.2367321	0.0253040
Sep.2021	-0.0651851	0.1779479	-0.3663156	0.7141296
Oct.2021	0.8628879	0.1710147	5.0456958	0.0000005
Nov.2021	-0.4977089	0.1708993	-2.9122928	0.0035879
Dec.2021	0.0490587	0.1707910	0.2872443	0.7739253
Immigrant in Mar.2020	-0.1810094	0.3725681	-0.4858424	0.6270789
Immigrant in Apr.2020	-1.9181640	0.3658369	-5.2432219	0.0000002
Immigrant in May.2020	-1.4714312	0.3784395	-3.8881541	0.0001010
Immigrant in Jun.2020	-1.4379870	0.3846711	-3.7382251	0.0001853
Immigrant in Jul.2020	-0.9680725	0.3980511	-2.4320305	0.0150145
Immigrant in Aug.2020	-0.5319283	0.3972553	-1.3390086	0.1805680
Immigrant in Sep.2020	-0.6541704	0.3997748	-1.6363472	0.1017671

Table 20: Coefficient Estimates For Model of Total Actual Hours at All Jobs for Females *(continued)*

term	estimate	std.error	statistic	p.value
Immigrant in Oct.2020	-0.1964850	0.3838236	-0.5119148	0.6087107
Immigrant in Nov.2020	0.0515778	0.4025120	0.1281399	0.8980383
Immigrant in Dec.2020	0.1899486	0.4134135	0.4594640	0.6459010
Immigrant in Jan.2021	-0.1902963	0.4094728	-0.4647348	0.6421215
Immigrant in Feb.2021	-0.2500231	0.3810647	-0.6561172	0.5117488
Immigrant in Mar.2021	-0.9837596	0.4010232	-2.4531239	0.0141622
Immigrant in Apr.2021	-0.9321714	0.3961990	-2.3527857	0.0186335
Immigrant in May.2021	-0.8009916	0.3861083	-2.0745258	0.0380306
Immigrant in Jun.2021	-0.6903922	0.3798710	-1.8174386	0.0691501
Immigrant in Jul.2021	0.1130635	0.3866039	0.2924531	0.7699402
Immigrant in Aug.2021	0.2208158	0.3871877	0.5703068	0.5684697
Immigrant in Sep.2021	0.0186118	0.3906998	0.0476371	0.9620055
Immigrant in Oct.2021	0.3547399	0.3678676	0.9643141	0.3348886
Immigrant in Nov.2021	0.4952465	0.3621228	1.3676204	0.1714311
Immigrant in Dec.2021	0.5195444	0.3677129	1.4129079	0.1576830

Note:

n=1974426. Horvitz-Thompson-type standard errors are presented in the second column.

3.5.2 Male Results

The model in Equation (46) is estimated using the male observations from the sample and the estimated coefficients are displayed in Table 21. The average deseasonalized hours worked per week at all jobs by non-immigrant men before the pandemic was 30.68 hours, and 32 hours by immigrant men. Similar to the female results, the coefficients on the set of pandemic month indicator variables show that, for the first year of the pandemic, non-immigrant men had significantly lower than average deseasonalized hours worked per week at all jobs. The reduction in deseasonalized hours worked by non-immigrant men was largest in April and May of 2020, with an average reduction of 6.88 and 6.39 deseasonalized hours per week, respectively. Additionally, for the entire first year after the start of the pandemic (i.e., March 2020 to February 2021) the reduction in deseasonalized hours worked by immigrant men was significantly larger than the reduction in deseasonalized hours worked by non-immigrant men. The reductions in deseasonalized hours worked by immigrant men was also largest in April and May of 2020, with an average reduction of 8.42 and 8.81 deseasonalized hours worked per week, respectively.

Table 21: Coefficient Estimates For Model of Total Actual Hours at All Jobs for Males

term	estimate	std.error	statistic	p.value
Non-Immigrant	30.6828862	0.0264917	1158.2083963	0.0000000
Immigrant	31.9991280	0.0518579	617.0539110	0.0000000
Mar.2020	-3.5158425	0.1889327	-18.6089670	0.0000000
Apr.2020	-6.8763703	0.1931517	-35.6008820	0.0000000
May.2020	-6.3899460	0.1925065	-33.1934048	0.0000000

Table 21: Coefficient Estimates For Model of Total Actual Hours at All Jobs for Males *(continued)*

term	estimate	std.error	statistic	p.value
Jun.2020	-4.2364080	0.1914738	-22.1252598	0.0000000
Jul.2020	-2.6270657	0.1966115	-13.3617074	0.0000000
Aug.2020	-2.2076509	0.1974183	-11.1826066	0.0000000
Sep.2020	-1.7063073	0.1948693	-8.7561612	0.0000000
Oct.2020	-0.4540912	0.1882421	-2.4122729	0.0158535
Nov.2020	-1.8199724	0.1944839	-9.3579579	0.0000000
Dec.2020	-1.4278961	0.1984060	-7.1968395	0.0000000
Jan.2021	-1.4208257	0.1973374	-7.1999808	0.0000000
Feb.2021	-2.0280441	0.1877003	-10.8046902	0.0000000
Mar.2021	0.2188242	0.1911162	1.1449800	0.2522176
Apr.2021	0.7997577	0.1934642	4.1338794	0.0000357
May.2021	-0.8324469	0.1875049	-4.4395993	0.0000090
Jun.2021	-1.2866738	0.1845103	-6.9734515	0.0000000
Jul.2021	-0.9293173	0.1925206	-4.8271055	0.0000014
Aug.2021	-0.4726424	0.1940407	-2.4357899	0.0148594
Sep.2021	-0.7995477	0.1884053	-4.2437631	0.0000220
Oct.2021	0.4834689	0.1819573	2.6570459	0.0078829
Nov.2021	-1.0642550	0.1801099	-5.9089200	0.0000000
Dec.2021	-0.3579119	0.1771157	-2.0207808	0.0433026
Immigrant in Mar.2020	-1.6187907	0.4090230	-3.9577005	0.0000757

Table 21: Coefficient Estimates For Model of Total Actual Hours at All Jobs for Males *(continued)*

term	estimate	std.error	statistic	p.value
Immigrant in Apr.2020	-1.5480858	0.4206781	-3.6799771	0.0002333
Immigrant in May.2020	-2.3170737	0.4283166	-5.4097223	0.0000001
Immigrant in Jun.2020	-1.3002350	0.4198572	-3.0968505	0.0019559
Immigrant in Jul.2020	-1.5734119	0.4303572	-3.6560605	0.0002561
Immigrant in Aug.2020	-0.8787181	0.4353056	-2.0186237	0.0435265
Immigrant in Sep.2020	-1.2293320	0.4258469	-2.8867933	0.0038919
Immigrant in Oct.2020	-1.4217806	0.4177916	-3.4030860	0.0006663
Immigrant in Nov.2020	-1.3389202	0.4252859	-3.1482829	0.0016424
Immigrant in Dec.2020	-1.5002656	0.4383945	-3.4221816	0.0006212
Immigrant in Jan.2021	-1.6963529	0.4369149	-3.8825709	0.0001034
Immigrant in Feb.2021	-1.2900229	0.4135413	-3.1194533	0.0018119
Immigrant in Mar.2021	-0.5640929	0.4151972	-1.3586143	0.1742690
Immigrant in Apr.2021	-0.7693994	0.4079927	-1.8858167	0.0593198
Immigrant in May.2021	-1.1453946	0.4033450	-2.8397393	0.0045151
Immigrant in Jun.2021	-0.6190258	0.3975735	-1.5570097	0.1194684
Immigrant in Jul.2021	-0.1842318	0.4119177	-0.4472539	0.6546918
Immigrant in Aug.2021	-0.5625163	0.4219438	-1.3331547	0.1824812
Immigrant in Sep.2021	-0.2188434	0.3987318	-0.5488486	0.5831094
Immigrant in Oct.2021	-0.1091711	0.3824407	-0.2854588	0.7752927
Immigrant in Nov.2021	0.6898725	0.3771251	1.8292936	0.0673558

Table 21: Coefficient Estimates For Model of Total Actual Hours at All Jobs for Males *(continued)*

term	estimate	std.error	statistic	p.value
Immigrant in Dec.2021	0.0272937	0.3732969	0.0731151	0.9417145

Note:

n=1915826. Horvitz-Thompson-type standard errors are presented in the second column.

3.6 Conclusions

Immigrants represent a significant proportion of the Canadian population and labour force. However, due to their over-representation in jobs that were disproportionately affected by the COVID-19 pandemic, immigrants were differentially affected compared to their Canadian-born counterparts (Hou and Picot 2022). Conducting an extended (i.e., 21 months since the start of the pandemic) analysis of trends in labour force status, this paper finds results consistent with previous analyses; at work employment sharply decreased at the start of the pandemic resulting in a rapid increase in unemployment, which peaked at the end of spring/beginning of summer 2020. Furthermore, the decrease in at work employment also resulted in increases in absent from work employment and leaving the labour force. These findings were more prominent for immigrants, especially immigrant females. After adjusting for seasonality in total hours worked per week at all jobs, the labour supply effects of the first year of the COVID-19 pandemic were widespread, having a statistically significant (at the 1% significance level) reduction in deseasonalized hours worked by women and men. The first and third wave of the pandemic had a significantly larger negative effect on the

average deseasonalized hours worked by immigrant women compared to non-immigrant women, whereas for immigrant men, they worked significantly fewer deseasonalized hours per week than non-immigrant men for the entire first year of the pandemic (March 2020 to March 2021).

Although the results of the descriptive analysis of changes in the employment and unemployment status are consistent with the results of previous studies, the analysis and corresponding results of the aggregate hours worked analysis differ from those reported in a similar previous study. Beland et al. (2022) conduct a pre-post pandemic analysis of aggregate hours worked by immigrant status and average the effect of all the post COVID-19 months (i.e., March 2020 to December 2020), and do not find large differential effects by immigrant status. In contrast, the analysis presented in this paper estimates the regression model described in Section 3.4.2 with data up to December 2021, which allows for a month-by-month analysis of the effects of the pandemic on deseasonalized hours worked by immigrants and non-immigrants of each gender separately, and relative to their counterparts. The difference in our empirical strategy allows us to detect significant differential differences in deseasonalized hours worked by immigrants and non-immigrants in the initial months of the pandemic and then again in 2021 for women, an effect masked by the analysis of Beland et al. (2022).

Future analysis will utilize this empirical strategy to assess at a provincial level, the effects on the different COVID-19 waves on the hours worked by immigrants. Conducting the analysis at a national level highlights the significant effects at the start of the pandemic and not at later stages, with the exception of the third wave effect on immigrant women. However, at the start of the pandemic the provinces acted uniformly to implement policies to reduce the spread of the virus. But at later stages of the pandemic, the policies implemented and timeline of implementation

varied substantially by province (Cotton et al. 2022). Conducting the analysis at a provincial level may identify prolonged differential effects for immigrants in provinces which implemented longer-lasting or more restrictive policies. Future analysis should also seek to quantify the financial loss incurred[43] by hourly-paid workers due to the reduction in total hours worked. The results of such analysis would help inform policies aimed at mitigating the potentially financially scarring effects of the pandemic and designing targeted publicly financed social benefits.

[43]Net of financial benefits, such as CERB, received.

4 Appendix

4.1 Chapter 1 Appendix

4.1.1 Literature Review Appendix

Papers with prescription opioid use coded as a binary variable

Type of use	Country	Reference
P.O use	USA	Carmona et al. (2020)
P.O use initiation	USA	Dobscha et al. (2013)
Prescription	USA	Olfson et al. (2013), Asfaw, Alterman, and Quay (2020)
Medical Use	USA	McCabe, West, and Boyd (2013b)
Regular P.O use	USA	Sullivan et al. (2006)
Persistent P.O use	AUS	Lalic et al. (2018)
Prolonged P.O use	USA	Lanzillotta-Rangeley et al. (2020)
Prolonged P.O use	CAN	Clarke et al. (2014)
Long-term P.O use	USA	Dobscha et al. (2013)
Chronic P.O use	CAN	Cuthbert et al. (2020)
P.O dependence	USA	Back et al. (2010), Becker et al. (2008), Edlund et al. (2007)
Medical misuse	USA	McCabe, West, and Boyd (2013b), McCabe, West, and Boyd (2013c)

Type of use	Country	Reference
Non-Medical P.O Use	USA	Olfson et al. (2018), Tetrault et al. (2008), Back et al. (2010), McCabe, West, and Boyd (2013a), McCabe et al. (2012a), McCabe, West, and Boyd (2013b), McCabe et al. (2007), Martins et al. (2012), Becker et al. (2008), Sung et al. (2005), McCabe et al. (2005), Carmona et al. (2020)
Non-Medical P.O Use	CAN	Shield et al. (2011), Fischer, Ialomiteanu, et al. (2013)
P.O use disorder	USA	Olfson et al. (2018), Dobscha et al. (2013), Cochran et al. (2014), Martins et al. (2012), Carmona et al. (2020)
P.O abuse	USA	A. G. White et al. (2009), Back et al. (2010), Becker et al. (2008), Fiellin et al. (2013), Edlund et al. (2007), Reid et al. (2002), Reps, Cepeda, and Ryan (2020), Green et al. (2009)
P.O & other drug co-ingestion	USA	McCabe et al. (2012b)
P.O overdose	USA	Sun et al. (2017)

Papers with prescription opioid use coded as a categorical variable

Type of use	Country	Reference
P.O use	USA	Seal et al. (2012)
P.O misuse	USA	Schepis et al. (2020)
P.O overdose	USA	Seal et al. (2012)

Papers with prescription opioid use coded as a continous variable

Type of use	Country	Reference
Medical P.O use	USA	McCabe et al. (2017)
Non-medical P.O use	USA	McCabe et al. (2017)
P.O misuse	USA	West et al. (2015)
Abuse	USA	West et al. (2015)
Overdose	USA	West et al. (2015)

4.1.2 Identifying Key Predictors Appendix

Table 25: Logit Regression Results

	Estimate	Std. Error	z value	Pr(>|z|)	OR	
(Intercept)	-4.1585	0.5397	-7.7046	<0.001	0.0156	***
age: .L	-3.0829	0.7509	-4.1058	<0.001	0.0458	***
age: .Q	-1.9701	0.7530	-2.6162	0.009	0.1394	**
age: .C	0.6812	0.7209	0.9450	0.345	1.9763	
age: ^4	-0.6685	0.6538	-1.0224	0.307	0.5125	
age: ^5	0.3437	0.5502	0.6248	0.532	1.4102	

Table 25: Logit Regression Results *(continued)*

	Estimate	Std. Error	z value	Pr(>|z|)	OR	
age: ^6	-0.6604	0.4974	-1.3277	0.184	0.5167	
age: ^7	-0.1969	0.4596	-0.4284	0.668	0.8213	
age: ^8	-0.5164	0.3904	-1.3228	0.186	0.5967	
age: ^9	0.1382	0.3654	0.3782	0.705	1.1482	
age: ^10	0.4606	0.4071	1.1313	0.258	1.5850	
age: ^11	0.6306	0.4012	1.5718	0.116	1.8788	
age: ^12	0.4078	0.3482	1.1711	0.242	1.5035	
age: ^13	0.4443	0.2927	1.5182	0.129	1.5595	
age: ^14	0.2667	0.2655	1.0043	0.315	1.3056	
sex: Male	-0.0632	0.1602	-0.3944	0.693	0.9388	
race: White	-0.0558	0.3929	-0.1419	0.887	0.9458	
imm: Immigrant	0.2615	0.3452	0.7577	0.449	1.2989	
ms: Marr/CLaw/Partner	0.1100	0.2221	0.4950	0.621	1.1162	
ms: Widow/Sep/Div	0.3318	0.2823	1.1754	0.24	1.3935	
res: Urban	0.1156	0.1657	0.6975	0.485	1.1225	
prov: Quebec	-0.3337	0.2249	-1.4837	0.138	0.7163	
prov: Prairies	0.2688	0.2198	1.2228	0.221	1.3084	
prov: British Columbia	0.5308	0.2016	2.6332	0.008	1.7004	**
income: .L	-0.1606	0.2571	-0.6245	0.532	0.8517	
income: .Q	0.2032	0.2089	0.9727	0.331	1.2253	
income: .C	0.1200	0.1741	0.6897	0.49	1.1276	

Table 25: Logit Regression Results *(continued)*

	Estimate	Std. Error	z value	Pr(>|z|)	OR	
income: ^4	-0.1041	0.1482	-0.7029	0.482	0.9011	
educ: .L	0.4278	0.3041	1.4069	0.159	1.5339	
educ: .Q	0.2114	0.2791	0.7577	0.449	1.2355	
educ: .C	0.4723	0.2558	1.8467	0.065	1.6037	.
educ: ^4	-0.0350	0.2222	-0.1574	0.875	0.9656	
educ: ^5	0.2128	0.2216	0.9604	0.337	1.2371	
educ: ^6	0.1553	0.2036	0.7627	0.446	1.1680	
insured: Yes	0.2234	0.1626	1.3736	0.17	1.2503	
srhs: .L	-0.1424	0.3501	-0.4068	0.684	0.8672	
srhs: .Q	0.2792	0.2692	1.0372	0.3	1.3221	
srhs: .C	-0.2108	0.2031	-1.0379	0.299	0.8099	
cc: 1(plus) chronic cond.	0.8440	0.1990	4.2420	<0.001	2.3256	***
injury: Yes	0.2602	0.1998	1.3026	0.193	1.2972	
pain: .L	0.8602	0.2040	4.2167	<0.001	2.3636	***
pain: .Q	0.0388	0.2388	0.1625	0.871	1.0396	
pain: .C	0.1672	0.2836	0.5895	0.555	1.1820	
distress: Yes	-0.1221	0.4524	-0.2699	0.787	0.8851	
alcdep: Yes	1.1770	0.3175	3.7072	<0.001	3.2447	***
onhp: Yes	0.2161	0.2123	1.0178	0.309	1.2412	
md_consults: .L	1.3299	0.2401	5.5382	<0.001	3.7808	***
md_consults: .Q	0.1646	0.1903	0.8650	0.387	1.1789	

Table 25: Logit Regression Results *(continued)*

	Estimate	Std. Error	z value	Pr(>|z|)	OR
md_consults: .C	-0.1103	0.2180	-0.5061	0.613	0.8955
md_consults: ^4	0.2916	0.2197	1.3274	0.184	1.3385
md_consults: ^5	0.0734	0.1794	0.4093	0.682	1.0762

```
Conditional density data (5959 observations, 19 variable(s))
(1 dependent variable(s), and 18 explanatory variable(s))

Bandwidth Selection Method: Maximum Likelihood Cross-Validation
Formula: po_use ~ age + sex + race + imm + ms + res + prov + income +
    educ + insured + srhs + cc + injury + pain + distress + alcdep +
    onhp + md_consults
Bandwidth Type: Fixed
Objective Function Value: -815.0179 (achieved on multistart 24)

Exp. Var. Name: age         Bandwidth: 0.608885   Lambda Max: 1
Exp. Var. Name: sex         Bandwidth: 0.9999999  Lambda Max: 1
Exp. Var. Name: race        Bandwidth: 0.9999991  Lambda Max: 1
Exp. Var. Name: imm         Bandwidth: 0.9999997  Lambda Max: 1
Exp. Var. Name: ms          Bandwidth: 0.9999999  Lambda Max: 1
Exp. Var. Name: res         Bandwidth: 0.1784411  Lambda Max: 1
Exp. Var. Name: prov        Bandwidth: 0.9999999  Lambda Max: 1
Exp. Var. Name: income      Bandwidth: 0.9251652  Lambda Max: 1
Exp. Var. Name: educ        Bandwidth: 0.7427634  Lambda Max: 1
Exp. Var. Name: insured     Bandwidth: 0.6116871  Lambda Max: 1
Exp. Var. Name: srhs        Bandwidth: 1          Lambda Max: 1
Exp. Var. Name: cc          Bandwidth: 0.1099255  Lambda Max: 1
Exp. Var. Name: injury      Bandwidth: 0.9999997  Lambda Max: 1
Exp. Var. Name: pain        Bandwidth: 0.2552425  Lambda Max: 1
Exp. Var. Name: distress    Bandwidth: 1          Lambda Max: 1
Exp. Var. Name: alcdep      Bandwidth: 0.01983635 Lambda Max: 1
Exp. Var. Name: onhp        Bandwidth: 0.9159593  Lambda Max: 1
Exp. Var. Name: md_consults Bandwidth: 0.3459083  Lambda Max: 1

Dep. Var. Name: po_use      Bandwidth: 0.0002274408 Lambda Max: 0.5

Unordered Categorical Kernel Type (Exp. Var.): Li and Racine (normalized)
Unordered Categorical Kernel Type (Dep. Var.): Aitchison and Aitken
No. Unordered Categorical Explanatory Vars.: 12
No. Unordered Categorical Dependent Vars.: 1
```

Figure 26: Nonparametric Model Bandwidths

4.2 Chapter 2 Appendix

Table 26: Sample of Prescription Opioid Users (sample means)

Variable	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Sex:F	0.5729	0.6048	0.5973	0.5995	0.5786
Sex:M	0.4271	0.3952	0.4027	0.4005	0.4214
Race:Minority	0.0451	0.0327	0.0665	0.0523	0.0414
Race:White	0.9549	0.9673	0.9335	0.9477	0.9586
Imm:Non-Immigrant	0.9111	0.9068	0.9067	0.9123	0.9305
Imm:Immigrant	0.0889	0.0932	0.0933	0.0877	0.0695
Age	34.7331	36.3389	38.8807	39.2783	41.2206
MS:Single	0.2692	0.2624	0.2564	0.2566	0.2358
MS:Prev.Married	0.1202	0.1158	0.1393	0.1063	0.1039
MS:Married	0.6106	0.6218	0.6043	0.6370	0.6603
Educ:Less than Secondary	0.1539	0.1172	0.0992	0.1280	0.0892
Educ:Secondary	0.1317	0.1704	0.1544	0.1376	0.1413
Educ:Some Post-Secondary	0.3234	0.3205	0.3373	0.3310	0.3794
Educ:Post-Secondary	0.3910	0.3920	0.4091	0.4033	0.3901
Income:Low	0.0552	0.0515	0.0599	0.0539	0.0355
Income:Lower Middle	0.2686	0.2356	0.1834	0.1555	0.1171
Income:Higher Middle	0.4142	0.4120	0.4190	0.4120	0.4129
Income:High	0.2621	0.3009	0.3377	0.3786	0.4345
Health:Poor	0.0381	0.0487	0.0374	0.0419	0.0388

Table 26: Sample of Prescription Opioid Users (sample means) *(continued)*

Variable	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Health:Fair	0.1017	0.0718	0.1195	0.1274	0.1280
Health:Good	0.2715	0.3149	0.3269	0.3660	0.3302
Health:Very Good/Excellent	0.5887	0.5646	0.5162	0.4647	0.5030
Chronic Conditions:None	0.2816	0.2381	0.2260	0.2102	0.1852
Chronic Conditions: 1 or more	0.7184	0.7619	0.7740	0.7898	0.8148
Injury:No	0.7331	0.7644	0.7533	0.7522	0.7862
Injury:Yes	0.2669	0.2356	0.2467	0.2478	0.2138
Pain:None	0.6979	0.7556	0.7289	0.6958	0.6588
Pain:Doesn't prevent activities	0.0809	0.0259	0.0323	0.0252	0.0355
Pain:Prevents few activities	0.0831	0.0674	0.1079	0.1150	0.1183
Pain:Prevents some activities	0.0876	0.1061	0.0768	0.0959	0.1257
Pain:Prevents most activities	0.0505	0.0450	0.0541	0.0681	0.0616
Distress:No	0.9627	0.9614	0.9537	0.9525	0.9761
Distress:Yes	0.0373	0.0386	0.0463	0.0475	0.0239
Depression:No	0.8820	0.8505	0.8632	0.8590	0.9292
Depression:Yes	0.1180	0.1495	0.1368	0.1410	0.0708
MDvisits:0	0.0457	0.0990	0.0895	0.0533	0.0740
MDvisits:1	0.1196	0.0741	0.0571	0.0805	0.0873
MDvisits:2-4	0.3637	0.4240	0.3717	0.3431	0.2585
MDvisits:5-7	0.1503	0.1160	0.1608	0.1641	0.2077

Table 26: Sample of Prescription Opioid Users (sample means) *(continued)*

Variable	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
MDvisits:8-10	0.1039	0.0721	0.0959	0.0776	0.1068
MDvisits:11+	0.2167	0.2149	0.2250	0.2813	0.2656

Table 27: Sample of Prescription Opioid Non-Users (means)

Variable	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Sex:F	0.5068	0.4956	0.4922	0.4947	0.4919
Sex:M	0.4932	0.5044	0.5078	0.5053	0.5081
Race:Minority	0.0854	0.0838	0.0809	0.0830	0.0858
Race:White	0.9146	0.9162	0.9191	0.9170	0.9142
Imm:Non-Immigrant	0.8509	0.8462	0.8465	0.8444	0.8464
Imm:Immigrant	0.1491	0.1538	0.1535	0.1556	0.1536
Age	34.5030	36.5425	38.4967	40.9097	42.3602
MS:Single	0.2930	0.2732	0.2484	0.2127	0.2050
MS:Prev.Married	0.0594	0.0667	0.0774	0.0946	0.1012
MS:Married	0.6477	0.6601	0.6742	0.6927	0.6937
Educ:Less than Secondary	0.2316	0.1892	0.1511	0.1105	0.1024
Educ:Secondary	0.1592	0.1565	0.1542	0.1507	0.1410
Educ:Some Post-Secondary	0.2437	0.2691	0.2873	0.2896	0.2787

Table 27: Sample of Prescription Opioid Non-Users (means) *(continued)*

Variable	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Educ:Post-Secondary	0.3655	0.3852	0.4074	0.4491	0.4778
Income:Low	0.0808	0.0652	0.0474	0.0430	0.0374
Income:Lower Middle	0.2564	0.2510	0.2014	0.1471	0.1406
Income:Higher Middle	0.4417	0.4765	0.4301	0.4221	0.3736
Income:High	0.2211	0.2073	0.3210	0.3878	0.4484
Health:Poor	0.0040	0.0042	0.0053	0.0109	0.0090
Health:Fair	0.0405	0.0317	0.0307	0.0512	0.0478
Health:Good	0.2142	0.2247	0.2204	0.2428	0.2808
Health:Very Good/Excellent	0.7413	0.7394	0.7436	0.6951	0.6625
Chronic Conditions:None	0.5298	0.4652	0.4568	0.4211	0.3600
Chronic Conditions: 1 or more	0.4702	0.5348	0.5432	0.5789	0.6400
Injury:No	0.8092	0.8818	0.8827	0.8906	0.8700
Injury:Yes	0.1908	0.1182	0.1173	0.1094	0.1300
Pain:None	0.8767	0.9161	0.9023	0.9018	0.8884
Pain:Doesn't prevent activities	0.0535	0.0312	0.0318	0.0291	0.0343
Pain:Prevents few activities	0.0401	0.0294	0.0414	0.0361	0.0419
Pain:Prevents some activities	0.0186	0.0152	0.0181	0.0236	0.0264
Pain:Prevents most activities	0.0110	0.0081	0.0064	0.0094	0.0089
Distress:No	0.9831	0.9914	0.9880	0.9909	0.9903
Distress:Yes	0.0169	0.0086	0.0120	0.0091	0.0097

Table 27: Sample of Prescription Opioid Non-Users (means) *(continued)*

Variable	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Depression:No	0.9529	0.9628	0.9638	0.9582	0.9583
Depression:Yes	0.0471	0.0372	0.0362	0.0418	0.0417
MDvisits:0	0.2180	0.2215	0.2098	0.1895	0.2035
MDvisits:1	0.2174	0.2416	0.2300	0.2280	0.2260
MDvisits:2-4	0.3445	0.3397	0.3478	0.3647	0.3543
MDvisits:5-7	0.1011	0.1019	0.1102	0.1113	0.1127
MDvisits:8-10	0.0455	0.0339	0.0413	0.0431	0.0386
MDvisits:11+	0.0734	0.0613	0.0609	0.0633	0.0649

Table 28: Description of Control Variables

Variable	Name	Values	Data Type
age	Age group	Range: 18-64	Continuous variable
sex	Gender	0: Female	Unordered discrete variable
		1: Male	
race	Race	0: Other	Unordered discrete variable
		1: White	
ms	Maritial status	1: Single	Unordered discrete variable
		2: Married/Common law/Partner	
		3: Widowed/Separated/Divorced	
educ	Education	1: Less than secondary-school graduation	Ordered discrete variable
		2: Secondary-school graduation	
		3: Some post-secondary	
		4: Post-secondary graduation	
income	Household Income Quintile	1: Low-income	Ordered discrete variable
		2: Lower middle-income	

Table 28: Description of Control Variables *(continued)*

Variable	Name	Values	Data Type
		3: Higher middle-income	
		4: High income	
srhs	Self-rated health status	1: Poor	Ordered discrete variable
		2: Fair	
		3: Good	
		4: Very good/ Excellent	
cc	Chronic condition indicator	0: No chronic condition	Unordered discrete variable
		1: One or more chronic conditions	
injury	Serious Injury	0: No	Unordered discrete variable
		1: Yes	
pain	Pain	1: No pain or discomfort	Ordered discrete variable
		2: Mild pain	
		3: Moderate pain	
		4: Severe Pain	

Table 28: Description of Control Variables *(continued)*

Variable	Name	Values	Data Type
distress	Significant distress	0: No	Unordered discrete variable
		1: Yes	
depression	Probable case of depression	0: No	Unordered discrete variable
		1: Yes	
md_consult	Consultations with an MD	0: None	Ordered discrete variable
		1: 1	
		2: 2-4	
		3: 5-7	
		4: 8-10	
		5: 11 or more	

4.3 Chapter 3 Appendix

4.3.1 Checking for Seasonality

Test for seasonality in total hours worked per week at all jobs by females

```
## Working (Rao-Scott+F) LRT for factor(imm):factor(SURVMNTH)
##  in svyglm(formula = frml.checksea, design = wpre.pooledF, na.action = na.omit)
## Working 2logLR =  132.2743 p= < 2.22e-16
## (scale factors:  1.1 1.1 1 1 1 1 1 1 0.99 0.93 0.89 );  denominator df= 1271858
```

Test for seasonality in total hours worked per week at all jobs by males

```
## Working (Rao-Scott+F) LRT for factor(imm):factor(SURVMNTH)
##  in svyglm(formula = frml.checksea, design = wpre.pooledF, na.action = na.omit)
## Working 2logLR =  132.2743 p= < 2.22e-16
## (scale factors:  1.1 1.1 1 1 1 1 1 1 0.99 0.93 0.89 );  denominator df= 1271858
```

4.3.2 Deseasonalization Falsification Tests

Table 29: Falsification Test for the Deasonalization of Actual Total Hours, for Immigrant Females

term	estimate	std.error	statistic	p.value
(Intercept)	22.7371	0.1798941	126.3915	0
factor(SURVMNTH)2	0.0000	0.2535484	0.0000	1
factor(SURVMNTH)3	0.0000	0.2558221	0.0000	1
factor(SURVMNTH)4	0.0000	0.2492599	0.0000	1
factor(SURVMNTH)5	0.0000	0.2529613	0.0000	1
factor(SURVMNTH)6	0.0000	0.2539097	0.0000	1
factor(SURVMNTH)7	0.0000	0.2547749	0.0000	1

Table 29: Falsification Test for the Deasonalization of Actual Total Hours, for Immigrant Females *(continued)*

term	estimate	std.error	statistic	p.value
factor(SURVMNTH)8	0.0000	0.2543345	0.0000	1
factor(SURVMNTH)9	0.0000	0.2551676	0.0000	1
factor(SURVMNTH)10	0.0000	0.2459601	0.0000	1
factor(SURVMNTH)11	0.0000	0.2522000	0.0000	1
factor(SURVMNTH)12	0.0000	0.2529403	0.0000	1

Table 30: Falsification Test for the Deasonalization of Actual Total Hours, for Non-Immigrant Females

term	estimate	std.error	statistic	p.value
(Intercept)	23.49978	0.0881009	266.7372	0
factor(SURVMNTH)2	0.00000	0.1244218	0.0000	1
factor(SURVMNTH)3	0.00000	0.1255829	0.0000	1
factor(SURVMNTH)4	0.00000	0.1216232	0.0000	1
factor(SURVMNTH)5	0.00000	0.1233942	0.0000	1
factor(SURVMNTH)6	0.00000	0.1235735	0.0000	1
factor(SURVMNTH)7	0.00000	0.1256686	0.0000	1
factor(SURVMNTH)8	0.00000	0.1260684	0.0000	1
factor(SURVMNTH)9	0.00000	0.1254012	0.0000	1
factor(SURVMNTH)10	0.00000	0.1204899	0.0000	1

Table 30: Falsification Test for the Deasonalization of Actual Total Hours, for Non-Immigrant Females *(continued)*

term	estimate	std.error	statistic	p.value
factor(SURVMNTH)11	0.00000	0.1242312	0.0000	1
factor(SURVMNTH)12	0.00000	0.1249467	0.0000	1

Table 31: Falsification Test for the Deasonalization of Actual Total Hours, for Immigrant Males

term	estimate	std.error	statistic	p.value
(Intercept)	32.00511	0.1859306	172.1347	0
factor(SURVMNTH)2	0.00000	0.2638692	0.0000	1
factor(SURVMNTH)3	0.00000	0.2668757	0.0000	1
factor(SURVMNTH)4	0.00000	0.2610902	0.0000	1
factor(SURVMNTH)5	0.00000	0.2619176	0.0000	1
factor(SURVMNTH)6	0.00000	0.2617055	0.0000	1
factor(SURVMNTH)7	0.00000	0.2652205	0.0000	1
factor(SURVMNTH)8	0.00000	0.2646065	0.0000	1
factor(SURVMNTH)9	0.00000	0.2619270	0.0000	1
factor(SURVMNTH)10	0.00000	0.2547306	0.0000	1
factor(SURVMNTH)11	0.00000	0.2599293	0.0000	1
factor(SURVMNTH)12	0.00000	0.2613392	0.0000	1

Table 32: Falsification Test for the Deasonalization of Actual Total Hours, for Non-Immigrant Males

term	estimate	std.error	statistic	p.value
(Intercept)	30.67267	0.0949549	323.0236	0
factor(SURVMNTH)2	0.00000	0.1343926	0.0000	1
factor(SURVMNTH)3	0.00000	0.1348280	0.0000	1
factor(SURVMNTH)4	0.00000	0.1319175	0.0000	1
factor(SURVMNTH)5	0.00000	0.1334813	0.0000	1
factor(SURVMNTH)6	0.00000	0.1325073	0.0000	1
factor(SURVMNTH)7	0.00000	0.1355191	0.0000	1
factor(SURVMNTH)8	0.00000	0.1361937	0.0000	1
factor(SURVMNTH)9	0.00000	0.1338852	0.0000	1
factor(SURVMNTH)10	0.00000	0.1304918	0.0000	1
factor(SURVMNTH)11	0.00000	0.1330598	0.0000	1
factor(SURVMNTH)12	0.00000	0.1340044	0.0000	1

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