Essays in Environmental and Labour Economics

by

Philippe Kabore

A thesis submitted in partial fulfillment of the requirements for the Doctorate in Philosophy degree in Economics

Department of Economics
Faculty of Social Sciences
University of Ottawa

Abstract

Chapter 1 – This paper analyzes the effects of extreme temperature on manufacturing output using a dataset covering the universe of manufacturing establishments in Canada from 2004 to 2012. Extreme temperature can affect manufacturing activity directly through its impact on labour productivity and indirectly through a change in demand for products. Using a panel fixed effects method, our results suggest a non linear relationship between outdoor extreme temperature and manufacturing output. Each day where outdoor mean temperatures are below -18°C or above 24°C reduces annual manufacturing output by 0.18% and 0.11%, respectively, relative to a day with mean temperature between 12 to 18°C. In a typical year, extreme temperatures, as measured by the number of days below -18°C or above 24°C, reduce annual manufacturing output by 2.2%, with extreme hot temperatures contributing the most to this impact. Given the predicted change in climate for the mid and end of century, we predict annual manufacturing output losses due to extreme temperature to range between 2.8 to 3.7% in mid-century and 3.7 to 7.2% in end of century.

Chapter 2 – In May 2011, the municipality of Slave Lake, Alberta was hit by a devastating wildfire; the second costliest natural disaster in Canada at the time. In this study, we use longitudinal income tax data from 2004-2018, to analyze the short, medium, and long-term effect of this wildfire on incomes, and related outcomes. This paper contributes to the very limited literature examining the economic effects of natural disasters on individuals. It also contributes to the discussion about the cost of natural disasters and highlights an important cost often excluded in published reports of natural disasters. Our results suggest that this event led to a decrease in total income mainly explained by a drop in employment income. Evidence of an intensive margin effect, whereby individuals are more likely to report lower earnings conditional on paid employment, is found. We also find evidence for an extensive margin effect, in which the employment rate falls for individuals over 55 years old.

Chapter 3 – How do firms in the manufacturing sector respond to voluntary energy conservation program? Using data covering the universe of manufacturing firms in Canada over the period 2004 to 2012, we estimate the effectiveness of the Canadian Industry Program for Energy Conservation, the flagship federal government energy conservation program targeted at large industrial firms. We use a difference-in-difference approach, coupled with coarsened exact matching, to estimate the effect of this program on firms energy intensity, output, as well as productivity. Our results suggest that the program does not significantly affect the energy intensity of participating firms compared to non-participating firms. We also find no evidence that participant firms perform differently from non-participant firms in term of total productivity or total production. Our study results add to the evidence that voluntary programs play a limited role in transforming energy and environmental outcomes.

Declaration of Authorship

All chapters of this thesis are self-containing research articles. Chapters 1, 2 and 3 are from joint research. The first and third chapter is co-authored with Nicholas Rivers. My contribution is equal to his. The second chapter is co-authored with Nicholas Rivers and Catherine Deri Armstrong. My contribution is also equal to theirs. The first chapter has been accepted in the *Canadian Journal of Economics*.

I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ____________________________________

Date: October 23, 2021

General Introduction

This thesis explores three different questions in environmental economics using business and social confidential micro-data. The essays presented in the different chapters also contribute to labour economics. The first chapter examines the causal effect of extreme temperature on manufacturing establishments' performance in Canada. The second chapter analyzes the causal effect of wildfire in Slave Lake, Alberta, on individuals' well-being. The third chapter tackles a different question by analyzing the effectiveness of a long standing voluntary energy program in Canada.

Understanding the potential costs of climate change, through extreme temperature or natural disasters, will increase policy makers awareness and stimulate better climate policy. Policy makers can help mitigate the negative effects of climate change by designing information-based programs that allow firm and individuals to adopt avoidance behaviour.

In the first chapter, we estimate the causal effect of extreme temperature on establishments' activity in Canada, using confidential business data linked to detailed weather information. The causal interpretation comes from the assumption that year-to-year temperature fluctuations experienced by establishments are exogenous once fixed effects for facility, province-by-year, and industry-by-year are conditioned on, as in Deryugina & Hsiang (2017); Zhang et al. (2018)

Our result show that each day where outdoor mean temperatures are below -18°C or above 24°C reduces annual manufacturing output by 0.18% and 0.11%, respectively, relative to a day with mean temperature between 12 to 18°C. In a typical year, extreme temperatures, as measured by the number of days below -18°C or above 24°C, reduce annual manufacturing output by 2.2%, with extreme hot temperatures contributing the most to this impact.

The second chapter analyzes how natural disasters affect individuals outcomes. In particular, we study the effect of wildfire disaster, that affected the entire municipality of Slave Lake, Alberta, on individuals economic and non-economic performance. We use an administrative tax data to answer our question of interest. We estimate the causal effect of wildfire using a difference-in-difference estimation coupled with a matching technique. The matching covariates are pre-event variables including incomes, age, gender, and 3-digit industry.

We find that exposure to the wildfire decreases affected individuals total income by more than $3,500 on average per person per year, representing almost 8.5% of pre-event average total income. The drop in total income is mostly driven by the decrease in affected individuals employment income by more than $3,200 on average. The results suggest that the drop in incomes occurs in the medium and long-term while we find no significant effect in the short-term.

Evidence for intensive margin effects, whereby individuals are less likely to report lower earnings conditional on paid employment, report , is found. We also find that the affected individuals over 55 years old are particularly vulnerable to the wildfire in term of employment loss and employment income drop compared to the other age group. Similarly, women are the ones experiencing the drop in employment income while men are unaffected.

The third chapter is a program evaluation analysis. It discusses the effectiveness of a long standing Canadian energy conservation program at reducing manufacturing firms energy intensity and improving their economic performance. For this analysis, we collect information of the program's participants over the period 2004-2012 which is merged to a confidential longitudinal data on manufacturing sector combined to tax data. The final data provide various information at the firm level including energy consumption and its components, total output, total employment, capital stock, industry and province of operation, and the entry year to the program.

We estimate the effect of this program, on firms' energy efficiency and economic performance, using a difference-in-difference approach with a matching technique. We match the non participants to the participants using pre-event covariates as suggested in the literature (Kube et al., 2019; Richter & Schiersch, 2017). These covariates include total energy, total output, total employment, generating own energy, multi-establishment firm, exporter status, industry and province of operation.

The headline result suggest that the energy conservation program has a zero and non significant effect on manufacturing firm energy efficiency. We find that the estimated coefficient for energy intensity varies between -0.15 and 0.32%. Similarly, we find no significant effect on electricity intensity and natural gas intensity. Therefore, it is not surprising that we also find no significant effect of the program on firms' total factor productivity nor their production. Nonetheless, this study highlights firms' characteristics that explain the adoption of the energy conservation program. We find that energy consumption, total production, multi-establishment firm, size, exporter, generating own energy, industry and province of operation, contribute to explain the program adoption.

Acknowledgments

I am sincerely grateful to my two co-supervisors, Nicholas Rivers and Catherine Deri Armstrong, for countless hours of guidance and their exercise in limitless patience. They have been very supportive in helping me morally and financially and also in critical thinking. I found myself luckiest to have Nicholas as my supervisor. The joy and enthusiasm you have for your research inspired me a lot. A special thank to my thesis committee members Carolyn Fischer and Maya Papineau for their time, interest and for providing insightful comments for this research. Lastly, I am grateful to many others, far too numerous to name, for the time and effort they have generously given me.

I want to thank the entire Economic Department of the University of Ottawa and all its professors and staff for their support. A great thank to Jason Garred for his guidance and his sharp insights that helped me in more ways than one.

This experience would not have been nearly as good without the friendships I made with my fellow graduate students. To Nabil Afodjo, Farzaneh Davarzani, Fabien Forge and Joanne Haddad: it has been interesting sitting together to discuss research ideas, ways to solve some issues encountered in our papers, and helping each other moving forward. I look forward to collaborate with you all in another context. I am also thankful to my friend Julia Dicum for encouraging me since the beginning of my thesis.

Last but not least, I want to thank my wife Hayazouma Fati Machelle Ye and my parents Michel Moussa Kabore and Rosalie Basga Ouedraogo for trusting and supporting me. A lot of what I achieved was because of Machelle. Thank you so much for your sacrifices and everlasting support.

To Machelle and Nathan

Contents

List of Tables

List of Figures

Chapter 1

Manufacturing Output and Extreme Temperature: Evidence from Canada

1.1 Introduction

Climate change will affect the prevalence of extreme temperatures worldwide. Extreme temperatures can have a number of impacts on humans, including on behaviour, productivity, cognitive ability, mood, health, and well-being. This paper aims to evaluate the effect of extreme temperatures on economic activity in Canada. We find that extreme temperatures – both cold and hot – reduce economic activity. Our results suggest that output losses from extreme temperatures are caused by a combination of impacts of temperature on consumer demand and on labour productivity. We estimate that extreme weather currently reduces Canadian manufacturing output by 2.2% per year, and that this impact will likely grow with future climate change.

Our study builds on a body of recent work that links economic activity to temperature and weather. Many studies focus on the agricultural sector (Deschênes & Greenstone (2007), Schlenker & Roberts (2009), Burke & Emerick (2016)) because of its direct link with atmospheric conditions. However, the agricultural sector in developed countries such as the United States and Canada represents only 1-2% of gross domestic product.[1] Little in known about how extreme temperatures affect other economic sectors, especially in developed countries. Our study is one of the first that aims to estimate the impact of extreme temperatures on economic activity in Canada. This type of research is critical for understanding potential economic impacts that may result from unabated climate change.

There is a growing body of evidence that relates short-term weather realizations to socio-economic impacts outside of the agricultural sector (for recent reviews, see Auffhammer (2018); Carleton & Hsiang (2016)). This research has uncovered links between extreme temperatures and impacts on performance such as cognitive tasks, physical tasks, as well as overall workplace tasks and productivity. For example, an early study in the laboratory by Mackworth (1946) shows that higher temperatures caused an increase in the number of transcription mistakes made by wireless operators, thus reducing productivity. The low performance is explained by a rapid increase of fatigue and discomfort during prolonged activities in hot environments (González-Alonso et al., 1999; Galloway & Maughan, 1997). These findings are also supported by a meta-analysis of Hancock et al. (2007) who find that thermal stressors (heat and cold stress) affect individual psychomotor and perceptual tasks.

Outside of the lab, studies also link cognitive performance to temperatures. For example,

[1] https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/farming-and-farm-income/ and https://www.canada.ca/en/agriculture-agri-food/news/2017/11/canada_s_agriculturalsectorcontinuestoseeeconomicgrowth.html

Park (2017) links examination records for New York students with outside temperatures, and finds that hot temperatures cause substantial declines in academic performance. Cook & Heyes (2020) uses a similar approach to find a strong negative impact of cold weather on university student examination outcomes in Ottawa, Canada. Graff Zivin et al. (2018) show that short-run exposure to hot temperature leads to significant declines in math scores.

Other studies show that these impacts on cognitive performance are not limited to schooling outcomes, but also affect labour market outcomes, including labour productivity (Heal & Park, 2016). In a meta-analysis, Seppanen et al. (2006) find that the average individual work performance decreases by almost 2% per degree Celcius above the temperature of 25°C in a work office environment. These findings are supported by Somanathan et al. (2021) who find a decrease in labour productivity in garment manufacturing plants during days with mean temperature above 25°C.

Empirical studies have also shown that labour supply, as determined by the number of hours worked or absenteeism, is negatively affected by hot outdoor temperatures (Behrer & Park, 2017; Somanathan et al., 2021; Graff Zivin & Neidell, 2014). There is also some evidence (in the Canadian context, which we study) that shirking increases when hot outdoor temperatures fall on a Friday or Monday (Shi & Skuterud, 2015). The negative effects are at least three times higher in industry sectors highly exposed to outside temperature than those less exposed to outside hot temperature.[2]

Like the present study, existing research has also estimated the link between outdoor temperature and overall economic output, which captures the effect of temperature on both labour supply and labour productivity (Zhang et al., 2018; Chen & Yang, 2019; Somanathan et al., 2021). These studies provide evidence that hot temperatures reduce industrial output in emerging countries. For example, annual manufacturing output in China is estimated to fall by 0.45% for each day with mean temperature above 32°C, and daily manufacturing output in India is estimated to fall by 3.1% when mean temperature is above 25°C. In contrast, Addoum et al. (2020) find no evidence that extreme temperatures affect industrial sales in US. At a more aggregate level, several studies find a negative impact of hot temperatures on economic activity at the country or sub-national level. For example, Dell et al. (2009) find that higher temperatures reduce gross domestic product in poor countries, and Burke et al. (2015) find a global non-linear relationship between temperature and gross domestic product. These findings are in line with Newell et al. (2021); Deryugina & Hsiang (2017) who find a non-linear relationship between income and temperature in US counties.

[2]The literature does not provide a unique definition of extreme temperature. A maximum daily temperature of 85°C (30°C) and 95°C (32°C) is considered as hot day by respectively (Graff Zivin & Neidell, 2014; Behrer & Park, 2017) while Deschênes & Moretti (2009) consider a daily mean temperature above 80°F (26°C) as hot days and daily mean temperature below 30°F (-1°C) as cold days.

Economists have developed techniques for using these estimated relationships to forecast future impacts of climate change (Carleton & Hsiang, 2016; Kolstad & Moore, 2020). Briefly, the approach is to use empirically estimated temperature-outcome relationships along with forecasts of future temperature outcomes in order to generate empirically-derived predictions of the impact of climate change on the outcome of interest. This approach is used by, for example, Deschênes & Greenstone (2007); Deryugina & Hsiang (2017); Zhang et al. (2018).

Our study estimates the impact of extreme temperatures on manufacturing output in Canada.[3] Like prior studies, we use the estimated relationship to draw predictions about the impact of future climate change on this outcome. We conduct the empirical analysis in five steps. First, we estimate the causal effect of extreme temperature on manufacturing output using data from the universe of manufacturing establishments in Canada combined with local daily weather from 2004 to 2012.[4] We use a panel fixed effect method to identify a non linear causal effect of daily mean temperature on manufacturing output. We rely on the same identifying assumption as in prior literature, which is that after conditioning on establishment, year-by-province, and year-by-industry fixed effects, remaining daily temperature variation is quasi-random (Chen & Yang, 2019; Zhang et al., 2018; Somanathan et al., 2021). Causal identification resides in the intuition that day-to-day variation in temperature is not correlated with unobserved determinants of manufacturing production.

We find that both cold and hot temperatures negatively affect annual manufacturing output. In our preferred specification, an extra day with mean temperature below -18°C decreases establishment annual output by 0.18% while an extra day with mean temperature above 24°C lowers annual establishment output by 0.11% relative to a day with mean temperature between 12-18°C.[5] On average during the 2004-2012 period, Canadian manufacturing establishments experience an annual loss of total output by 1% as a result of days with temperatures below -18°C and another 1.2% for days with mean temperatures above 24°C. In total, manufacturing establishments in Canada experience an output loss of 2.2% in a typical year due to extreme temperatures (relative to a hypothetical counterfactual with no extreme temperatures).

Second, to understand the factors driving the temperature-output relationship, we esti-

[3]Manufacturing output is defined as the current value of goods produced within a year.

[4]As shown later in the data section, we transformed the daily data into an annual data by counting the number of days, within a given year, in which the mean temperature falls inside a predetermined temperature bins.

[5]Daily mean temperature 'above 24°C' or 'below -18°C' refers to a 24-hour period. We use the daily mean temperature because many manufacturing plants operate 24/7. We do not have information on establishments operating the entire day or half of the day. We also analyze the output-temperature relationship using minimum and maximum temperature and we find a similar effect. In our data, on days where the daily mean temperature is above 24°C, the average daily maximum temperature is 32°C. On days where the daily mean temperature is below -18°C, the average daily minimum is -28°C.

mate the effects of extreme temperatures on annual manufacturing plant labour productivity, employment, domestic sales, and exports. The theoretical framework presented in Section 1.2 postulates that direct impacts of extreme temperatures on labour productivity or consumer demand may indirectly affect plant output and employment in equilibrium. Empirically, we find that an extra day with mean temperature below -18°C reduces labor productivity by 0.14% relative to a day with mean temperature between 12-18°C. We do not find any evidence that hot temperatures affect labour productivity. In addition to impacts on labour productivity, we find that manufacturing plants respond to short-term hot and cold temperature shocks by reducing equilibrium employment at the plant. Based on our conceptual framework, we take this as evidence that extreme temperatures reduce local demand in addition to their effects on labour productivity. We find no impacts of extreme temperatures on exports or inventory additions but do find that extreme temperatures reduce domestic sales.

Third, we divide our manufacturing sample into establishments operating in the warmest and coolest regions in order to understand potential adaptation to climate. Establishments operating in cooler areas experience on average 15 cold days (below -18°C) and 3 hot days (above 24°C) in a typical year while those operating in warmer areas face on average 0.2 cold days and 22 hot days within a year. Because they more regularly face hot (cold) temperatures, establishments in warm (cool) regions may be better adapted to hot (cold) temperatures. We estimate the temperature-output relationship in warm, mild, and cool regions across Canada. Our results do not provide evidence in favour of location-based adaptation – there are not statistically different relationships between temperature and output across climactic regions.

Fourth, we analyze the heterogeneity in the response of manufacturing output to extreme temperatures across several dimensions, including facility size and labour intensity. We find that small establishments are the most affected by the extreme temperatures. An extra day below -18°C or above 24°C reduces small-sized establishment output by respectively 0.22 and 0.08%. We find no evidence that hot temperatures have a negative effect on medium and large establishments (likely in part because we have fewer observations of large plants). Our results also show that labour intensive establishments are more affected by the extreme temperature than capital intensive establishments.

Finally, we predict the potential impact of climate change on Canadian manufacturing output using downscaled weather forecast from an ensemble of climate models for the mid (2050s) and end (2080s) of century along with our estimates of the temperature-output relationship. Like similar empirical studies, we assume no additional adaptation with the potential of lowering the sensitivity of output to extreme temperatures. Using medium and high greenhouse gas scenarios for 2050s and 2080s, we find that the annual losses of manufacturing output due to extreme temperature would go from 2.2% today to 2.8-3.7% in mid-century and to 3.7-7.2% in end of century.

Our study provides several contributions to the literature. We provide the first evidence about the effect of extreme temperatures on establishment performance in Canada, as well as new evidence of the potential economic impact of climate change in a cold environment. The paper highlights the importance of demand shifts as a main contributor to the temperature-output losses. We find no evidence that the manufacturing sector adapts to extreme temperatures. We also highlight the vulnerability establishments to extreme temperature regardless their size.

The remainder of this paper is organized as follows. In section 2, we present a conceptual framework to motivate our empirical approach. Section 3 describes the data and reports descriptive statistics. Section 4 presents the empirical strategy. Section 5 describes the results. Section 6 presents robustness checks. And finally section 7 concludes and discusses implications for policy.

1.2 Conceptual Framework

This section introduces a simple framework to help illustrate how extreme temperature realizations may affect annual manufacturing plant output, labour productivity, employment, domestic sales, exports and inventory additions – the variables we observe in our empirical analysis. We make the assumption that temperature shocks may directly affect labour productivity as well as potentially directly affect consumer demand. The existing literature reviewed in the prior section provides evidence to justify our assumption that extreme temperatures may affect labour productivity. There is also some evidence that weather may affect domestic demand for particular products (Li et al., 2017; Conlin et al., 2007; Agarwal et al., 2020; Busse et al., 2015), as well as evidence that extreme temperatures may reduce overall economic activity, which would also impact domestic demand (Burke et al., 2015; Dell et al., 2012).

We develop a model to show how these direct effects result in changes to equilibrium output as well as to labour demand. It is important to distinguish the time frame in which the shocks take place from the time frame in which we model equilibrium. The temperature shocks we model involve daily realizations of extreme hot or extreme cold temperature. In contrast, the establishment level outcomes we observe are at the annual level. In the model, we assume that the over the course of a year, the establishment takes account of the prices it faces and selects variable inputs accordingly. As a result, extreme temperature realizations can affect establishment input choices (and consumer demand) indirectly, as the market reaches equilibrium following a temperature shock, as well as directly and contemporaneously with the temperature shock.

Our empirical analysis is conducted at the level of manufacturing establishments, and so our theory focuses on a representative establishment. The representative establishment is assumed to take prices as given.

The representative establishment uses inputs of capital and effective labour to produce output. We treat capital as pre-determined and unaffected by temperature, consistent with the short-run focus of our empirical analysis, and denote it by $\bar{K}$.[6] Effective labour L is given by the number of employees N multiplied by their productivity A, such that $L = NA$. Given the short-term nature of temperature shocks that we analyze (daily variation in temperature), we assume that the number of employees in the establishment is not directly affected by temperature shocks.[7] However, although the number of employees is not directly affected by temperature shocks, the number of employees is endogenous and is chosen by the establishment in response to changes in prices or demand. Consistent with the empirical evidence summarized above, we treat labour productivity as a function of extreme temperature T, so that output is:

$$Y = Y(\bar{K}, L) = Y(\bar{K}, NA(T)) = Y(NA(T)).$$

We take the total derivative with respect to temperature to understand how extreme temperature affects output:

$$\frac{dY}{dT} = \frac{\partial Y}{\partial L}\frac{dL}{dN}\frac{dN}{dT} + \frac{\partial Y}{\partial L}\frac{dL}{dA}\frac{dA}{dT} = Y_L\left(A\frac{dN}{dT} + NA'\right) \tag{1.1}$$

where Y_L is the marginal product of effective labour and A' is the direct effect of extreme temperature on labour productivity (we assume that $A' < 0$, reflecting the evidence that extreme temperatures reduce productivity). This equation shows that changes in manufacturing plant output can be decomposed into an effect relating to changes in the number of employees, and an effect relating to changes in labour productivity.

[6] Zhang et al. (2018) provide some evidence that capital productivity may be affected by extreme temperatures. We treat capital productivity as fixed in our model because we do not observe capital productivity in the data and because adding capital productivity complicates the model without generating fundamental new insights. It is straightforward to modify the model such that capital productivity is affected by temperature, by treating the effective capital input as $K = \bar{K}B(T)$, where $\bar{K}$ is the fixed capital stock and $B(T)$ is the temperature-dependent capital productivity.

[7] The data for this project includes annual observations on the number of people employed by each manufacturing plant, and we assume that firms do not directly adjust employment levels in response to daily variation in weather experienced throughout the year.

Given these assumptions, and assuming constant returns to scale and a fixed wage rate and capital rental rate, the unit cost function for the firm can be expressed as:

$$C = C(A(T)).$$

Taking the derivative with respect to temperature yields:

$$\frac{dC}{dT} = \frac{\partial C}{\partial A} A'.$$

On the demand side, the establishment sells to a domestic consumer and also exports. The domestic consumer is exposed to the same temperature shocks as the manufacturing plant. Exports are consumed by a consumer that faces temperature shocks that are orthogonal to the domestic temperature and so we assume no direct response of exports to the domestic temperature shock. As a result, total firm sales S are given by:

$$S = D(P, T) + X(P),$$

where P is the price of the domestic good, D is domestic sales, and X is exports. The derivative of total sales with respect to temperature is given by:

$$\frac{dS}{dT} = \frac{\partial D}{\partial P}\frac{dP}{dT} + D' + \frac{\partial X}{\partial P}\frac{dP}{dT},$$

where D' is the direct effect of the temperature shock on demand. We lack evidence to sign D'. D' could be positive if extreme temperature events prompt consumers to purchase additional manufactured goods as adaptation investments – for example buying an air conditioner in response to a forecast or experienced hot day. D' could be negative if extreme temperatures reduce consumer incomes, as determined by Deryugina & Hsiang (2017) and Burke et al. (2015), among others. This expression shows that demand for the plant's output is a function of the equilibrium price as well as any direct impacts of temperature on demand.

The market clearance condition is $Y = S + I(P)$, where $I(P)$ is inventory additions (which we assume are a function by price and not directly affected by temperature), and the derivative of the market clearance condition is:

$$\frac{dY}{dT} = \frac{dS}{dT} + \frac{\partial I}{\partial P}\frac{\partial P}{\partial T}$$

Substituting the expressions above, we get:

$$Y_L \left(A \frac{dN}{dT} + NA' \right) = \frac{\partial D}{\partial P} \frac{dP}{dT} + D' + \frac{\partial X}{\partial P} \frac{dP}{dT} + \frac{\partial I}{\partial P} \frac{\partial P}{\partial T}$$

In equilibrium, $P = C$, so we can simplify to:

$$Y_L \left(A \frac{dN}{dT} + NA' \right) = \left(\frac{\partial D}{\partial P} + \frac{\partial X}{\partial P} + \frac{\partial I}{\partial P} \right) \frac{\partial C}{\partial A} A' + D'$$

We can now solve for $\frac{dN}{dT}$ to get:

$$\frac{dN}{dT} = \frac{1}{AY_L} \left[\left(\frac{\partial D}{\partial P} + \frac{\partial X}{\partial P} + \frac{\partial I}{\partial P} \right) \frac{\partial C}{\partial A} - NY_L \right] A' + \frac{1}{AY_L} D' \tag{1.2}$$

And we can substitute back into Equation 1.1 to get:

$$\frac{dY}{dT} = \underbrace{\left[\left(\frac{\partial D}{\partial P} + \frac{\partial X}{\partial P} + \frac{\partial I}{\partial P} \right) \frac{\partial C}{\partial A} \right] A'}_{\text{Productivity shock}} + \underbrace{D'}_{\text{Demand shock}} \tag{1.3}$$

Equation (1.3) makes clear that equilibrium output can be affected through two channels in our simple model. First, a shock to productivity (A') affects unit costs, and as a result affects demand for output by the price-sensitive domestic and foreign consumers (the first term on the right hand side). Second, equilibrium output can be directly affected if temperature affects the demand from the domestic consumer (D', the second term on the right hand side). A similar logic applies to the equilibrium number workers at the plant in Equation (1.2).

In our empirical analysis, we estimate the direct impact of temperature on productivity (A'), as well as the effect of temperature on output ($\frac{dY}{dT}$) and the number of employees ($\frac{dN}{dT}$).[8] As is made clear from the preceding model, the output of the firm, as well as the number of employees in the firm, are equilibrium outcomes. Because we do not observe the demand shock D' directly in our data, we are not able to attribute changes in output or the number of employees to each of these channels, but the framework makes clear that equilibrium impacts on labour demand and output are a function of two potential shocks – to demand and productivity – which helps explain our empirical findings.

[8] In the Section 2.3, we better expand on the empirical definition of extreme temperature as mean temperature below -18C or above 24C. In this setting, T means temperature which takes the value of 1 during extreme temperature and 0 otherwise.

1.3 Data

We use a confidential dataset that includes the universe of Canadian manufacturing establishments over the period 2004-2012. This section describes the data and their sources and the process of matching annual manufacturing data to daily weather variables.

1.3.1 Manufacturing Data

The data in our analysis come from a longitudinal file collected by Statistics Canada and called Annual Survey of Manufacturing and Logging (ASML) which covers the period 2004-2012.[9] Each year, ASML collects establishment level information including total output, total sales, total export, total employment, payroll, and etc.[10] The survey also provides information on whether manufacturing production activities were disrupted due to extreme weather or natural disasters.

The ASML has information on the industry sector in which establishments operate as well as geographical information including the province and census-subdivision (CSD) for each establishment. CSD is a general term for municipalities or areas treated as municipal equivalents for statistical purposes. CSD is the smallest geographical unit at which we observe the manufacturing establishments due to confidentiality. Each CSD covers approximately 10,000 people, such that urban CSDs cover small geographical areas while rural CSDs can cover larger geographical areas as shown in Figure 1-1. Importantly, ASML data contain a unique establishment identifier which allows us to follow each establishment over time.

Over the period 2004-2012, the initial dataset counts more than 72,000 establishments located in 10 provinces and 3 territories and 2168 CSDs. A large number of manufacturing establishments operate in Ontario and Quebec and account for almost 65% of the total

[9] Statistics Canada collects confidential data on manufacturing activities across Canada. This dataset contains the universe of establishments from 2000-2012. However, some changes happened in the data collection in 2003. From 2000 to 2003, Statistics Canada sent out a questionnaire to all establishments in Canada. Starting in 2004, ASML was redesigned to reduce respondent burden on very small establishments. In 2004, Statistics Canada decided to drop the bottom 10% of plants of each industry by geographical area from the survey. As a consequence, we observe a spike in the death or exit of firms in 2004 which in principle in not the case. In 2007, Statistics Canada realized that in some geographical areas the bottom 10% include both small, medium, and large establishments and decided to use Canada Revenue Agency information (administrative data) to fill that gap. Given the complexity of the business register, they were not successful at retracing back all the missing establishments. We keep the period 2004-2012 for our analysis as in Najjar & Cherniwchan (2018) and Yamazaki (2017). For more information on ASML data, see: http://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getInstanceList&Id=504733

[10] All monetary values are in current Canadian dollars. Total employment is defined as the sum of full time equivalent production workers and salaried employees (administrative/selling/operating staff). For example, if a firm hires two workers in 2012 where the first works half of year 2012 and the second works half of that year, then it would be counted as one employee in 2012. The ASML data does not contain information on short-term worker absences.

sample.[11] Using the raw data, nearly 2.2% of the establishments changed industry subsector, 0.6% move across provinces and more than 12% move across CSD.[12][13] In our study, we may have an issue of endogeneity if establishments are allowed to move across industry sectors. We address this by assigning each establishment to the first industry in which they started operating the first year we see them in our data. We drop establishments that move across provinces and CSDs.[14][15]

Finally, we clean the data by keeping positive values for the key variables of interest which include total output, total employment, and total sales. We retain observations that have annual total output values greater or equal to $1,000,000 and at least one employee.[16] We define the establishment size as follows: small establishments are those with total employees less than 50, medium establishments are those with total employees between 50 and 249, and large establishments are those with total employees greater or equal to 250.

Our final sample has 39,684 establishments. Table 1-1 panel A reports the manufacturing sector summary statistics.[17] A large number of establishments are small (76%), followed by medium establishments (20%), and large establishments (4%). The average annual manufacturing output is $19,800,000 per establishment.

[11]This result is in line with the table 36-10-0222-01 produced by Statistics Canada where Ontario and Quebec respectively represented 37.3% and 19.4% of Canada GDP in 2012.

[12]When an establishment operates in more than one industry, Statistics Canada assigns to the establishment the industry code corresponding to the sector where more than 50% of the establishment's revenue come from.

[13]According to experts at Statistics Canada, very small establishments are likely to easily move across CSDs because of the low fixed cost. We find that 86%, 12%, and 2% of movers across CSD are respectively small, medium, and large establishments.

[14]Assuming that an establishment has the possibility to move across CSDs or provinces without low costs. In presence of extreme temperature in province/CSD A, an establishment would be likely to move in province/CSD B with moderate temperature. Thus, allowing establishments to move across provinces/CSDs would bias the effect of extreme temperature.

[15]In the Appendix, we estimate our main regression specification (Equation (2.4)) without dropping establishments that move across CSDs/provinces (Figure 1-31 d).

[16]We find a similar pattern when we estimate the main model (Equation (2.4)) using the full sample without output and employment restriction (Figure 1-31 c). Finally, Figure 1-31 b presents similar result as in the main finding, when we restrict the sample to establishments with at least 10 employees and total output greater or equal to $1,000,000.

[17]The manufacturing sector is divided into 21 subsectors based on the NAICS classification system, https://www.ic.gc.ca/app/scr/app/cis/summary-sommaire/31-33.

Table 1-1: Summary Statistics

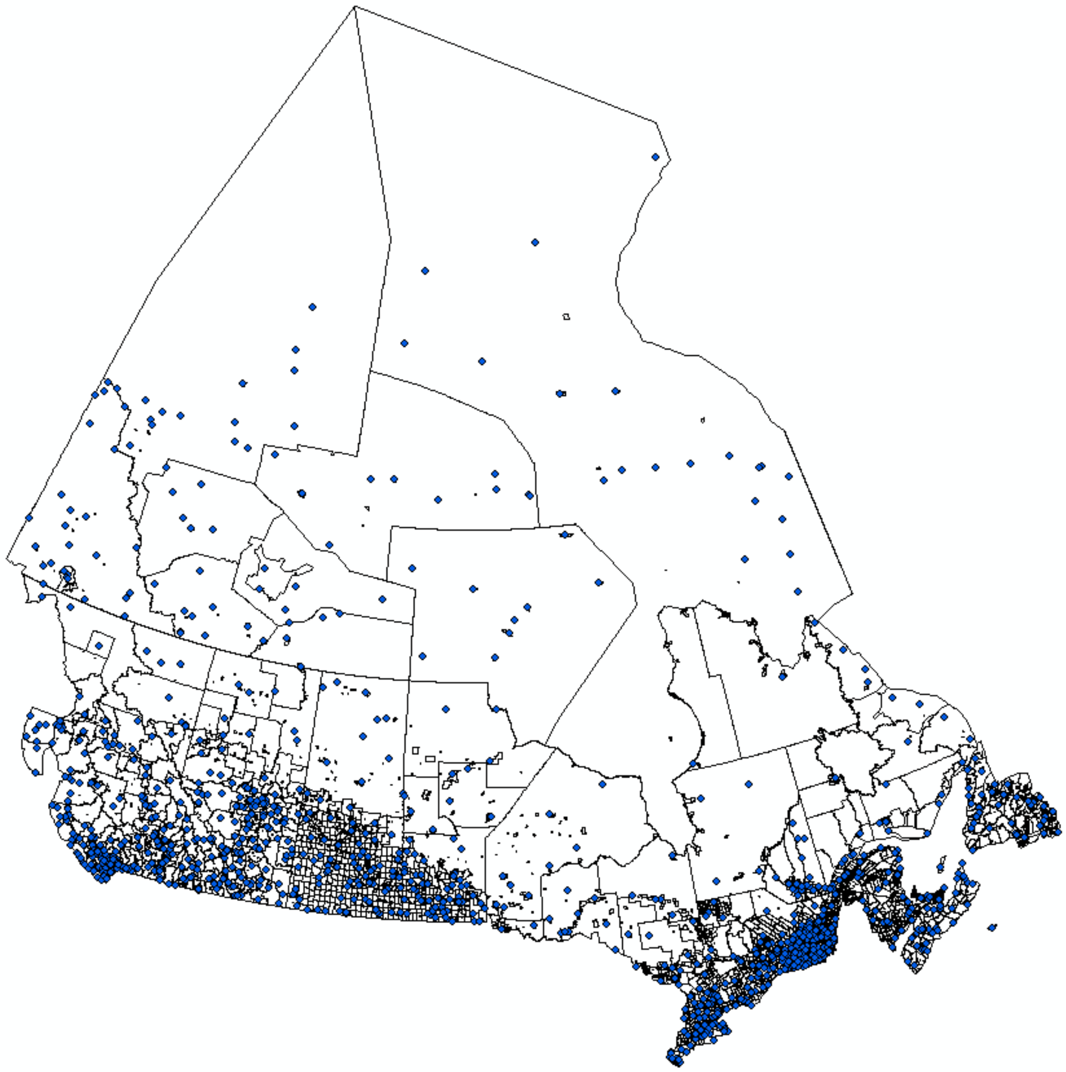
Panel A				
Manufacturing Data			Period 2004-2012	
	Observations	Firms	mean	sd
Output ($, in million)	235,683	39,684	19.8	169
Total employment	235,683	39,684	55	152
Labour productivity (in million)	235,653	39,684	0.39	0.78
Payroll ($, in million)	235,653	39,684	2.7	11
Total sales ($, in million)	232,904	39,476	19.8	170
Domestic sales ($, in million)	188,345	29,947	12.9	135
Export ($, in million)	106,136	15,614	14.4	138
Inventory ($, in million)	186,967	29,455	2.8	17
Small establishments	235,683	39,684	0.76	0.43
Medium establishments	235,683	39,684	0.2	0.4
Large establishments	235,683	39,684	0.04	0.19
Reduced activity (weather)	188,923	30,122	0.003	0.06
Panel B				
Weather data			Period 2004-2012	
	Observations	Firms	mean	sd
Mean temperature (°C)			7.28	2.3
Total rain (cm)			2.26	0.89
Total snow (cm)	235,683	39,684	0.45	0.25
Relative humidity (%)			0.71	0.05
Wind speed (m/s)			5.78	0.9
Panel C				
Predicted temperature	Mid century (2050s)		End century (2080s)	
	mean	sd	mean	sd
RCP45 (°C)	9.83	2.25	10.51	2.23
RCP85 (°C)	10.71	2.22	12.89	2.15

Notes: The unit of observation is establishment-year. This sample represents establishments with output greater or equal $1 million CAD. All monetary units are in current CAD.

1.3.2 Weather Data

The daily weather data come from Environment Canada monitoring stations across Canada. Figure 1-1 presents the location of monitoring stations across Canada used in the study. Most of the monitoring stations are located in the south of the country, where many cities are located and also where a large proportion of manufacturing establishments are operating. Over the period 2004-2012, we count 1,101 valid monitoring stations.[18] The Environment Canada weather data covers 759 out of 2168 CSDs where manufacturing plants are operating, which corresponds to a coverage rate of 35% of the manufacturing establishments. For CSDs that have multiple weather stations, we take the daily average of all the stations within a CSD. In order to obtain weather data for all establishments, we assign the value of the closest CSD to CSDs with no weather monitoring station. The weather data also contain missing value dues to the fact that they are turned off or sometimes values are simply not recorded. We fill the missing observations using an inverse distance weighting measure of the 10 closest monitoring stations.

[18] A monitoring station is valid when it provides daily weather data covering the entire period of study.



Source: Environment Canada. Each polygon represents the CSD borders. We observe large CSDs in the north of Canada because of its small population size while CSDs are smaller in the south of Canada with a high density of individuals. The blue dots are for the weather monitoring stations inside each CSD.

Figure 1-1: Dispersion of weather monitoring stations across Canada

Environment Canada weather data provides daily information on mean, minimum, and maximum daily temperature, total rain, total snow, and total precipitation.[19] The wind speed and relative humidity data come from the National Aeronautics and Space Adminis-

[19]Mean temperature is defined as the average of minimum and maximum temperature over 24 hours at a given location. See https://climate.weather.gc.ca/glossary_e.html

tration (NASA).[20] We derive these data from a gridded daily weather data using MERRA2 climate reanalysis.[21] The literature shows that weather variables such as wind speed, total rain, total snow, and relative humidity could be a confounder to the temperature effects (Deschênes & Greenstone, 2007; Deryugina & Hsiang, 2017; Zhang et al., 2018). Table 1-1 panel B presents the summary statistics of the weather data for our final sample.

1.3.3 Climate Change Prediction Data

In order to predict impacts from future climate change, we use downscaled climate predictions for North America with a resolution of 1km by 1km based on the Coupled Model Intercomparison Project phase 5 (CMIP5) database.[22] The data reflects and average of 15 CMIP5 models that were chosen as representative. The CMIP5 accounts for 4 global climate model scenarios (RCP2.6, RCP4.5, RCP6, and RCP8.5). Each scenario corresponds to a certain level of greenhouse gas (GHG) emission with RCP2.6 the lowest level of GHG emission and RCP8.5 the highest level of GHG emission. We focus on the moderate (RCP4.5) and high (RCP8.5) GHG emission and consider the mid century (2050s) and the end of century (2080s) projections in order to study the potential changes in manufacturing output resulting from future climate changes.

1.3.4 Matching Weather and Manufacturing Data

ASML data are annual observations while the weather data are observed daily. To retain the variability of the daily information while collapsing the weather data into annual data, we discretize the daily data into exhaustive bins that count the number of days within a year that daily mean temperature falls within each bin. We create 9 bins for daily (24-h) mean temperature as follows: $]\infty : -18[$, $[-18 : -12[$,...,$[24 : \infty[$ with each bin 6°C wide.[23] By year and CSD, we count the number of days the temperature falls inside each bin. This approach is used in a number of similar studies such as Deschênes & Greenstone (2007), Deryugina & Hsiang (2017), Zhang et al. (2018), and Addoum et al. (2020). We define T_{ct}^{b} as the number of days with temperature in bin b, at year t in the CSD c. We apply the same

[20] We do not use the wind speed data from Environment Canada because of its large proportion of missing observations; Environment Canada only records the maximum wind gust greater or equal to 29 km/h and otherwise wind speed data is missing.

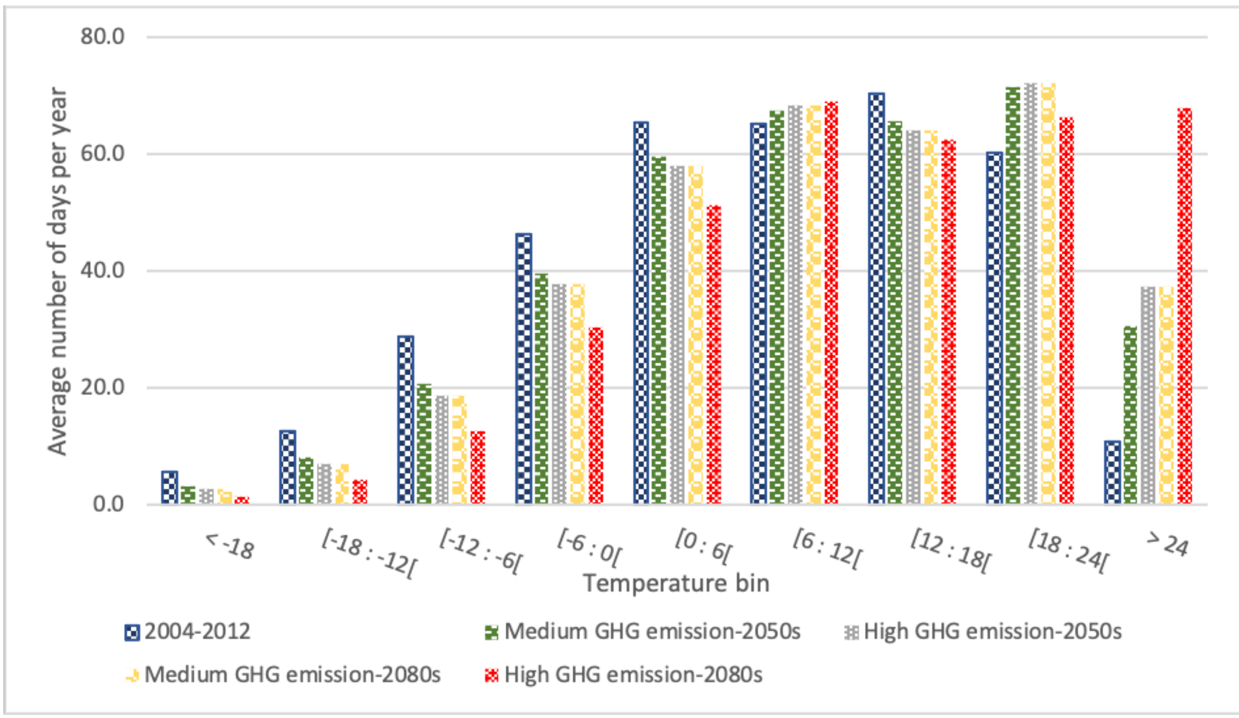
[21] MERRA-2 climate reanalysis data come from the file M2I3NPASM-5.12.4 with the grid 0.5 x 0.625 degree corresponding to almost 80 x 80 km.

[22] The data are made available by Adaptwest at `https://adaptwest.databasin.org/pages/adaptwest-climatena`

[23] We made a one-time choice of the temperature bins before being provided with access to the manufacturing data.

methodology to the other weather variables including relative humidity, wind speed, total snow, and total rain.

Figure 1-2 plots the distribution of daily mean temperature across CSDs.[24] The dark blue bars represent the daily mean temperature distribution over the period 2004-2012. The following bars represent the daily mean temperature distribution for mid and end of century projected under the scenarios RCP4.5 and RCP8.5. Under all the projected future climate scenarios, we observe a shift of daily mean temperature distribution to the right. Under the climate change scenarios, we observe that the number of days above 24°C will be 3 to 6 times higher than the current level in a typical year. Meanwhile the average number of days below -18°C is projected to decrease from 4 days annually for a typical manufacturing plant to 1-2 days annually.



Notes: The height of each bar represents the weighted daily mean temperature across all establishments and years. The weight used is the number of establishments in each CSD. The blue bar represents the period 2004-2012. The green and yellow bars respectively represent the mid (2050s) and end of century (2080s) temperature projection for medium GHG emission scenario. Finally, the grey and red bars represent the mid and end of century temperature projection for high GHG emission scenario.

Figure 1-2: Current and predicted daily temperature distribution.

[24]For this figure, we weight each CSD by the number of manufacturing establishments it contains, so the temperature distribution reflects the exposure of manufacturing establishments in Canada.

1.4 Empirical Approach

This section describes the reduced form approach used to estimate the effect of temperature on manufacturing output in Canada. Following other recent work outlined above, we use a panel fixed effects model for our analysis. We estimate the effect of extreme temperatures on manufacturing output by comparing the year-to-year within-establishment relationship between temperature and output. We control for province-by-time fixed effects and industry-by-time fixed effects. Equation (2.4) provides a standard formulation of the panel fixed effect method:

$$Y_{icpdt} = \sum_{b} \beta_b T_{ct}^{b} + \sum_{w} \sum_{q} \theta_b W_{ct}^{qw} + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{1.4}$$

where Y_{icpdt} is the inverse hyperbolic sine (IHS) of the total output of establishment i operating in census subdivision c, province p, and industry d at time t.[25] In addition to total output, we also estimate the effect of temperature on labor productivity, labor input, total sales, domestic sales, exports and inventory, as motivated in Section 1.2. T_{ct}^{b} is a count of the number of days in year t and census sub-division c that daily mean temperature falls within bin b. W_{ct}^{qw} is a count of the number of days in year t and census subdivision c that weather type w falls within bin q. The controlled weather variables (w) include relative humidity, total snow, total rain, and wind speed. For each of these weather variables, daily weather is discretized into 7 exhaustive bins (q=1..7). γ_i is the establishment fixed effect which captures all time invariant fixed characteristics of the establishment. ζ_{pt} is a province-by-year fixed effect. It accounts for annual shocks common to establishments within each province such as economic policy and energy prices. ψ_{dt} is the 3-digit industry sector-by-year fixed effect and it controls for annual shocks common to each manufacturing sector, such as input and output prices and technology change. Finally, ε_{icpdt} is the error term. The error term may be spatially correlated if there are common unobserved shocks that vary over space and may be serially correlated within a given establishment over time. We follow Zhang et al. (2018) and cluster the error terms at establishment and CSD-year levels to address potential spatial and serial correlation in the error terms.[26] In estimating Equation (2.4), we drop

[25] The IHS transformation is similar to the logarithm transformation (in interpretation). It accounts for zero or negative observations where the log transformation is undefined or missing as explained in Bellemare & Wichman (2020). We use the IHS because some variables, such as inventory and total export, have negative values or many zeros. While we use the IHS transformation throughout the analysis, our results are virtually unchanged when we instead use a log transformation.

[26] As an alternative approach to inference, we also implement a multi-way bootstrap as suggested in MacKinnon et al. (2019) in which we sample by province with replacement. This approach increases standard errors somewhat, such that our main coefficients are significant at $p < 0.1$ but no longer at $p < 0.05$ (Table 1-10). Our main results use a two-way cluster as described in the text and consistent with other similar papers. In the Appendix (Table 1-9), we also report standard errors with coarser clusters. Coarser clusters increase the size of standard errors somewhat.

1% of regression outliers using the approach proposed by Billor et al. (2000); Weber (2010). This is a typical approach in studies using self-reported manufacturing data (Fowlie et al., 2016; Ederington et al., 2005).

The coefficient of interest β_b is a semi-elasticity and is interpreted as the marginal effect of an extra day with temperature in bin b relative to a day with temperature in the reference bin (12 to 18°C) which is the omitted category. The causal interpretation comes from the assumption that year-to-year temperature fluctuations experienced by establishments are exogenous once fixed effects for establishment, province-by-year, and industry-by-year are conditioned on, as in Deryugina & Hsiang (2017), Addoum et al. (2020), Zhang et al. (2018), and other similar papers.

1.5 Results

In this section, we first describe our main findings relating to the temperature-output relationship. We also make use of an alternative measure of temperature to study the relationship between temperature and output. Secondly, we discuss the mechanism through which temperature affects manufacturing output. We then indirectly analyze whether manufacturing establishments adapt to their local temperature through investments in adaptation infrastructure such as buildings, air conditioner or heating systems. Later, we provide evidence on the heterogeneity of the temperature effects across establishments of different size and labour intensity. Finally, we combine our estimates on the impact of extreme temperature on output with downscaled climate projections to predict the effect of future climate change on manufacturing output.

1.5.1 Main results

Table 1-2 presents the effects of temperatures on manufacturing annual output, based on estimating Equation (2.4). We report the coefficients for the "extreme" temperatures – the two coldest and hottest temperature bins The full table with all temperature coefficients is in the Appendix in Table 1-7. This table presents the result in columns $A1$-$A4$, which test the robustness of our results to the inclusion of different sets of fixed effects. Column $A1$ includes only establishment and year fixed effects. The establishment fixed effects account for unobserved heterogeneity between establishments and the year fixed effects account for common shocks at the country level such as policy, technological, and price changes. In column $A2$, we replace year fixed effects with year-by-province fixed effect. This allows the shocks to be at the provincial level instead of country level. Since much economic policy is set at the provincial level, this specification may better account for confounders than the specification in column $A1$. In column $A3$, the year fixed effect is replaced by year-by-industry fixed effects, which control for shocks that are common within industry sub-sectors across the country. Unobserved changes in commodity prices, for example, have different effects on different sectors, and their confounding effect would be removed in this specification. In column $A4$, which is our preferred specification, the year fixed effect from column $A1$ is replaced by both year-by-industry fixed effects and year-by-province fixed effects, thus accounting for both sources of potential confounding described above.

Table 1-2: Estimated effects of temperature on total output

	log (output) x 100					
Variables	(A1)	(A2)	(A3)	(A4)	(B)	(C)
< -18	0.013	-0.19**	0.01	-0.19**	-0.23***	-0.19**
	(0.064)	(0.079)	(0.057)	(0.076)	(0.089)	(0.074)
[-18 : -12[	-0.145**	-0.14**	-0.06	-0.11*	-0.16**	-0.1*
	(0.06)	(0.061)	(0.053)	(0.059)	(0.07)	(0.056)
[18 : 24[	-0.04	-0.06**	-0.04	-0.05*	0	-0.05*
	(0.027)	(0.027)	(0.025)	(0.026)	(0.032)	(0.026)
> 24	-0.072*	-0.12**	-0.05	-0.11**	-0.16***	-0.12**
	(0.041)	(0.055)	(0.037)	(0.051)	(0.063)	(0.051)
Observations	235,683	235,683	235,683	235,683	112,140	235,683
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No
Year-province FE	No	Yes	No	Yes	Yes	Yes
Year-Industry FE	No	No	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	No

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

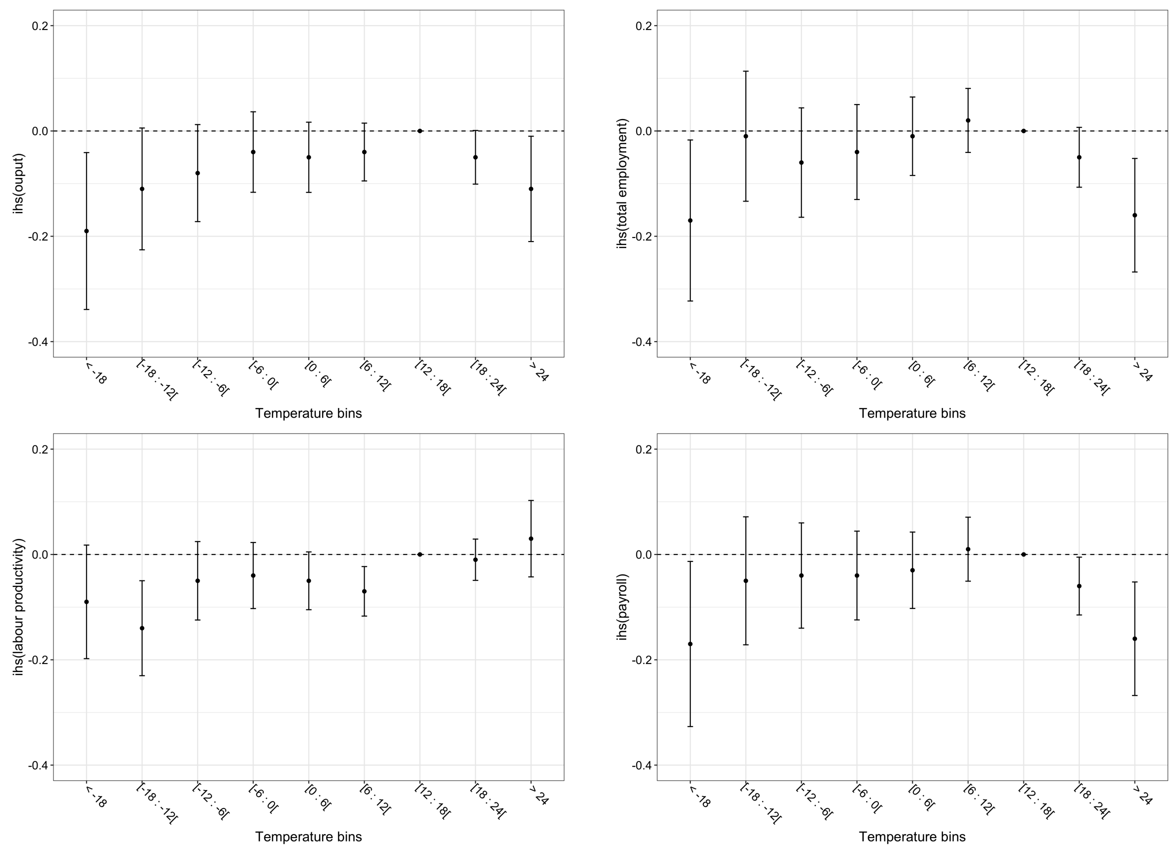
Notes: This table presents the effetcs of daily extreme temperature on manufacturing total output. Columns $A1$-$A4$ and B include weather controls which are total rain, total snow, relative humidity, and wind speed. For all estimations, the standard errors are clustered at the establishments and CSD-year levels. These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[.

Under the preferred specification, we find that both cold and hot temperatures have a negative effect on manufacturing establishment output. Other specifications yield similar results for hot days, however, in specifications $A1$ and $A3$, the effect of cold temperatures is no longer statistically significantly different from zero. Each day in which the mean daily temperature is below -18°C reduces annual manufacturing output by 0.19% relative to a day with mean temperature between 12 to 18°C. Similarly, an extra day with mean temperature above 24°C causes annual manufacturing output to be reduced by 0.11% compared to a day with mean temperature between 12 to 18°C. In our data set, manufacturing establishments in Canada experience on average 6 cold days with mean temperatures below -18°C, and 11 hot days with temperature above 24°C. Given the number of cold and hot days in a typical year, annual manufacturing output in Canada is reduced on average by 2.2% as a result of extreme temperatures, relative to a hypothetical counterfactual where the establishment experiences no extreme temperatures. This represents an annual output loss of $435,600 per establishment.

We visualize the relationship between manufacturing output and temperature using our preferred specification in the top-left panel of Figure 1-7. The figure shows an inverted U-shaped relationship between temperature and output, where extreme hot and cold temperatures both depress manufacturing output compared to more moderate temperatures. This inverted-U relationship is similar to findings in other papers that analyze the relationship in low-income and warmer countries, such as Zhang et al. (2018), who focus on Chinese manufacturing plants.

We provide two additional robustness checks in Table 1-2. In column B of Table 1-2, we run the analysis on a balanced sample of establishments–that is only the subset of establishments that are observed in every year of our data set. Restricting the sample to plants that always report ensures that our results are not driven by changing composition of establishments in the data. The results are very similar to our main specification, and confirm that the effect we observe is not related to plant entry and exit. In column C of Table 1-2, we run the model without the inclusion of other weather controls. We find that both cold or hot days reduce manufacturing annual output by a similar magnitude as in the main specification, suggesting that our main results are not affected strongly by the inclusion or exclusion of weather controls. The invariance of our results to weather controls provides suggestive evidence that inclusion of other weather controls would not substantially impact the results.

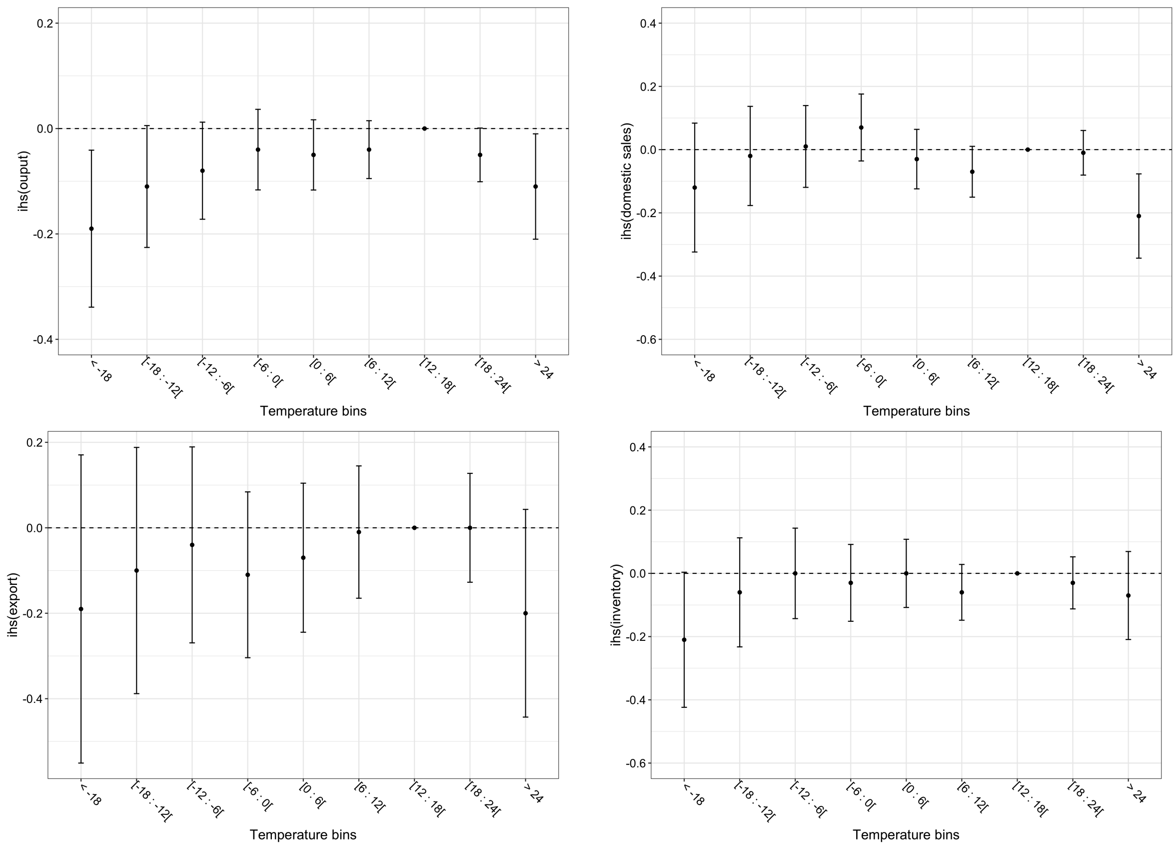
The conceptual framework presented in Section 1.2 decomposes changes in manufacturing plant output into changes in employment and changes in labour productivity (Equation 1.1). We create a labour productivity variable by dividing total output by number of employees, and conduct a similar regression as Equation (2.4) with labour productivity and number of employees as dependent variables (we use our preferred specification, corresponding to Column $A4$ in Table 1-2). We report the results as coefficient plots in Figure 1-7. For labour productivity, the results suggest that cold temperatures worsen labour productivity, but that labour productivity is unaffected by hot temperatures. This result stands in contrast to the results in Zhang et al. (2018), who find that hot temperatures worsen labour productivity in Chinese plants. However, the results are consistent with Addoum et al. (2020), who find no impact of (hot) temperature on labour productivity in US firms. For employment, the results suggest that both hot and cold temperatures reduce manufacturing employment. The conceptual framework (Equations (1.2) and (1.3)) shows that manufacturing plant employment and output are affected both by productivity shocks as well as by demand shocks. While we do not observe demand shocks directly, the results presented here suggest that for hot temperatures, (negative) demand shocks are the dominant channel impacting output and employment (since labour productivity effects appear muted). Figure 1-7 also shows the effect of extreme temperature on manufacturing payroll (i.e., total wage bill), as an alternative variable for measuring labour inputs. Unsurprisingly, we find that payroll is affected by extreme temperature similarly to the way employment is affected. Total annual payroll decreases by respectively 0.17 and 0.16% as a result of cold and hot days experienced during the year, again suggesting a decline in employment at manufacturing plants that face extreme temperatures.



Notes: These figures present the effect of daily mean temperature on manufacturing output (a), total employment (b), labour productivity (c), and payroll (d). The coefficients are multiplied by 100. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

Figure 1-7: Estimated effects of extreme temperatures on manufacturing activity

Manufacturing total output can be decomposed into domestic sales, exports, and inventories. We rerun Equation (2.4) with different dependent variables reflecting this decomposition. Figure 1-12 decomposes the effects of extreme temperatures on manufacturing output into these three demand components. We find that the reduction in total output resulting from extreme temperatures is mainly explained by the effects of cold and hot days on domestic sales. An extra day with temperature below -18°C and above 24°C decreases manufacturing domestic sales by respectively 0.12 and 0.21%. We also find some evidence that manufacturing closing inventory is negatively affected by cold temperature. We find no evidence that manufacturing total exports are affected by extreme temperatures.



Notes: These figures present the impact of daily mean temperature on manufacturing output (a), domestic sales (b), total export (c), and inventory (d). The coefficients are multiplied by 100. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

Figure 1-12: Estimated effect of extreme temperature on total sales and its components

Overall, our analysis provides robust evidence that manufacturing output in Canada is susceptible to both extreme hot temperatures and extreme cold temperatures. We provide evidence that labour productivity is reduced on extreme cold days, which reduces manufacturing plant output. In contrast, our analysis suggests that labour productivity is unaffected as a result of hot weather. Instead, as suggested by our theoretical framework, hot weather appears to reduce manufacturing output and employment by affecting demand from domestic consumers.

1.5.2 Perceived temperature

In this section, we consider alternative measures of temperature, which adjust for relative humidity and wind speed, in order to estimate the effect of temperature on manufacturing total output. A combination of outside negative temperature and wind speed is called wind chill temperature, while a combination of outside positive temperature and relative humidity is called wet-bulb temperature. These measures usually differ from the outside temperature measure, and may better capture how humans perceive the extreme outdoor temperatures.

Using daily weather variables, we compute daily mean wind chill temperature and wet-bulb temperature following Equations (3.1) and (1.11) in the Appendix. We then define three bins for perceived temperatures, based on extreme weather risk thresholds suggested by Environment and Climate Change Canada: low, medium, and high. For example, the wind chill temperature is considered to be high risk when the wind chill adjusted temperature falls below -28°C. Full definitions are provided in the Appendix. For each year, we count the number of days the perceived temperature lies inside the defined bins and then estimate the perceived temperature effect on manufacturing output as follows:

$$Y_{icpdt} = \sum_{b} \beta_b PT^b_{ct} + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{1.5}$$

where PT^b is the perceived temperature in bin b in CSD c at time t.

Table 1-3 shows the results of estimating Equation (1.5). We find that the high risk bin for both wind-chill temperature and wet-bulb temperature have a negative effect on manufacturing total output. An extra day of temperature in the high risk bin relative to the low risk bin, reduces manufacturing total output by 0.22% for wind-chill temperature and 0.14% for wet-bulb temperature. The magnitudes at which perceived temperatures affect manufacturing output are slightly higher than the ones found in our main result in Table 1-2. In particular, while we estimate that each day where mean daily temperature is below 24°C reduces annual output by 0.19% in Table 1-2, in Table 1-3 we find that a high risk wind-chill day reduces annual output by -0.22%. The results are similarly comparable for high-risk wet-bulb temperature and mean daily temperatures above 24°C. This result supports our main finding in section 1.5.1 and highlights the importance of factors such as wind speed or relative humidity in studies analyzing the economic effects of extreme temperatures.

Table 1-3: Estimated effect of wet-bulb and wind-chill temperature on total output

	Total output(x100)	Total output(x100)
Medium risk (wet bulb)	-0.07**	-
	(0.03)	-
High risk (wet bulb)	-0.15***	-
	(0.05)	-
Medium risk (wind-chill)	-	-0.03
	-	(0.03)
High risk (wind-chill)	-	-0.22***
	-	(0.06)
Observations	235,683	

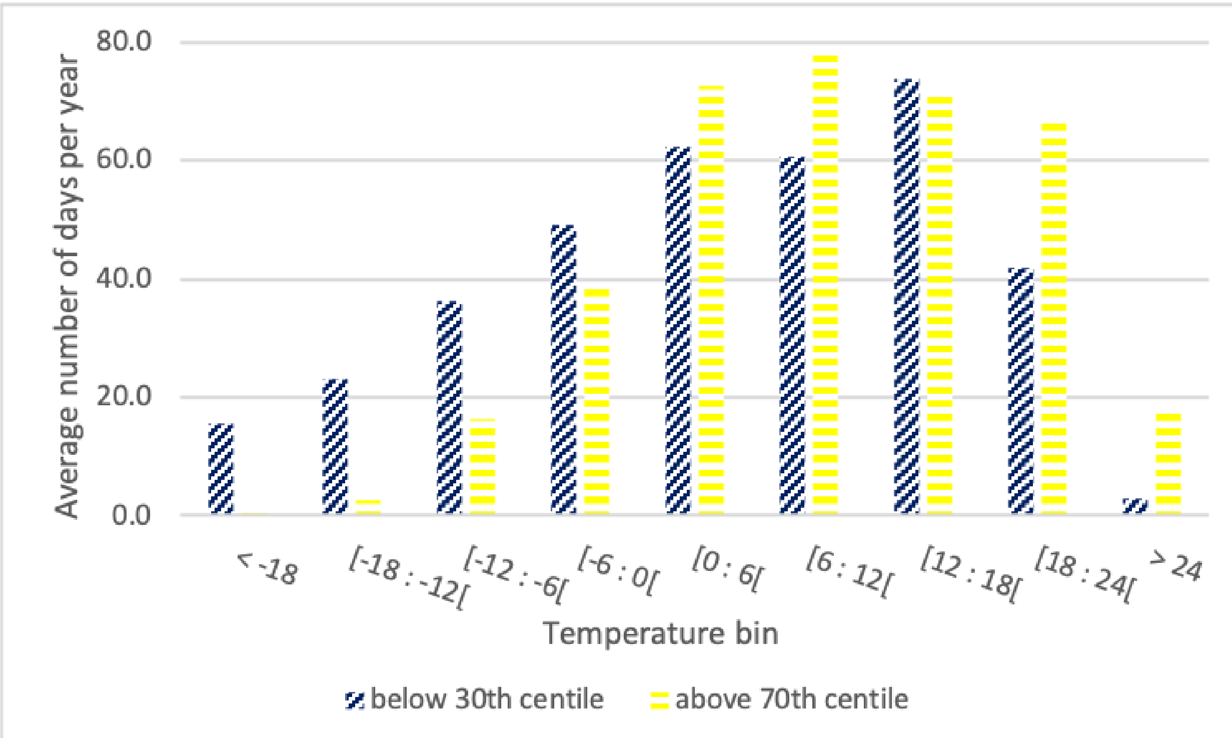
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: this table presents the effects of wet-bulb and wind-chill temperatures on manufacturing output. All the specifications include establishment, year-province, and year-industry three-digit FE. The standard errors are clustered at the CSD levels. The standard errors are clustered at the establishment and CSD-year levels.

1.5.3 Local adaptation

In this section, we analyze whether the temperature-output relationship depends on the local climate in which establishments are located. We test the hypothesis that establishments or consumers in relatively warm areas are less sensitive to hot temperature and vice-versa for those in relatively cool areas. For example, establishments might adopt some types of adaptation to mitigate the effect of the extreme temperature they experience the most as in Chen & Yang (2019), such as air conditioning or insulation. Alternatively, since our prior results point to the role of domestic consumer demand in affecting firm output, adaptation may occur on the consumer side. For example, Cook & Heyes (2020) find that people become acclimated to weather they most commonly face and are less impacted by temperature extremes they experience more regularly.

Using the distribution of the annual mean temperature by CSDs, we define coolest, mildest, and warmest climates as those respectively below 30th centile, between 30 and 70 centile, and above 70th centile of temperature annual temperature distribution. To better contrast the difference in temperature, Figure 1-13 presents the temperature distribution for establishments operating in areas below the 30th and above the 70th centile of annual temperature distribution (we do not show the distribution of temperatures for the plants located in mild locations, between the 30th and 70th centiles). On average, establishments operating below the 30th centile experience 15 cold days per year and 3 hot days. Similarly, establishments operating above the 70th centile, on average, experience 1 cold days and 18 hot days per year. We then test whether establishments operating in coolest or warmest areas react differently to extreme temperatures relative to establishments operating in areas with mild temperatures (between 30 and 70 centile of temperature annual temperature distribution).



Notes: Each height represents the weighted average daily temperature across all establishments and year. The weight used is the number of establishments in each CSD. The bar represents the average number of days per year over the period 2004-2012 for CSDs below the 30th centile (blue) and above the 70th centile (yellow) of mean temperature distribution.

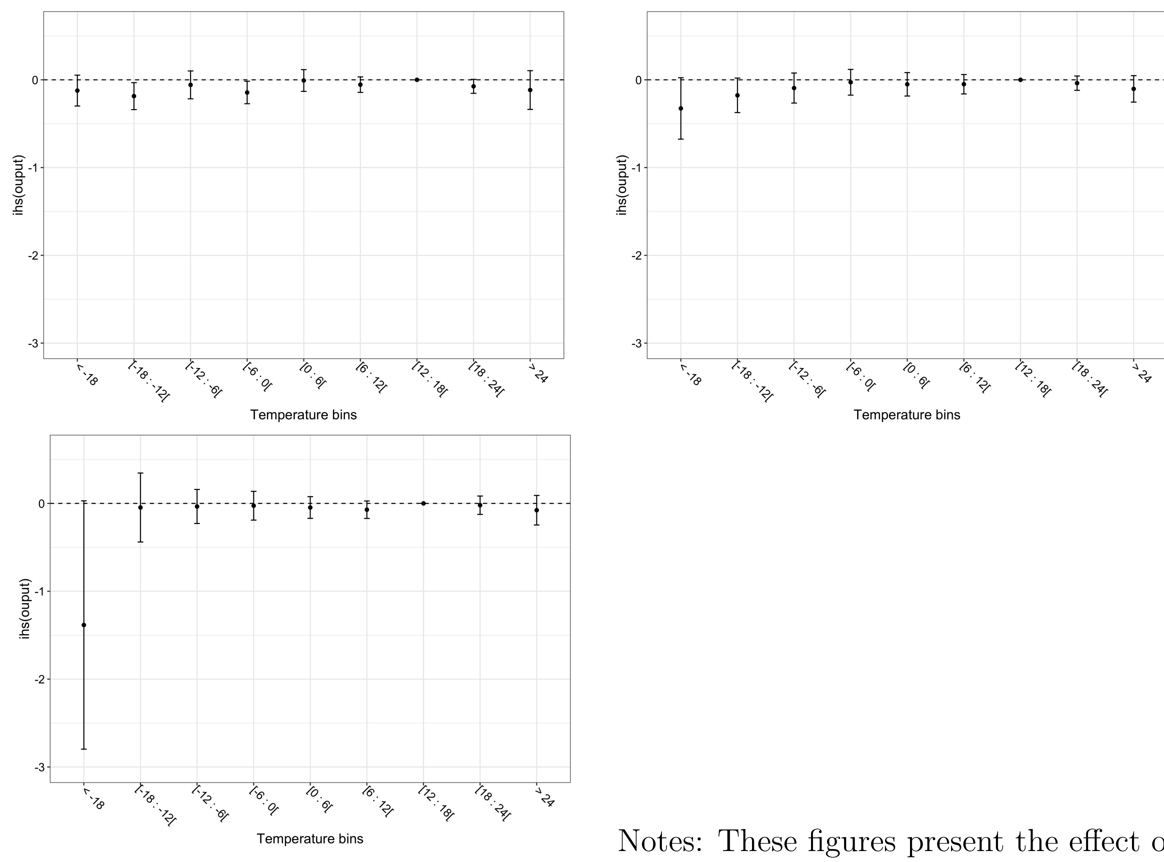
Figure 1-13: Daily temperature distribution in cooler and hotter CSDs.

We rerun equation (2.4) by interacting weather variables with warm/cool dummy variable as follows:

$$Y_{icpdt} = (\sum_b \beta_b T^b_{ct} + \sum_w \sum_q \theta_b W^{qw}_{ct}) \times adaptation + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \qquad (1.6)$$

where *adaptation* is a discrete variable that categorizes each region as (1) cool areas, (2) mild, or (3) warm. We also interact *adaptation* with both industry-year and province-year fixed effects.

Evidence of adaptation would be if establishments operating in areas below the 30th centile of the temperature distribution (above the 70th centile) respond differently to cold (hot) temperature. As shown in Figure 1-17, our results pertaining to local adaptation are inconclusive, but suggest limited adaptation to extreme temperatures. We do not find a statistically different response to extreme temperatures depending on the local climate (there is a large negative point estimate associated with extreme cold days in establishments operating in warmer climates, but with few instances of extreme cold in these regions the point estimate is very noisy). This may be in part because of our earlier finding that a key mechanism by which extreme temperatures impact plant output is not through productivity changes but as a result of local demand shifts.



Notes: These figures present the effect of extreme temperature on establishments output in cold, mild, and hot areas relative to establisments in mild areas. The coefficients are multiplied by 100. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

Figure 1-17: Estimated effect of extreme temperature on total output

1.5.4 Heterogeneity

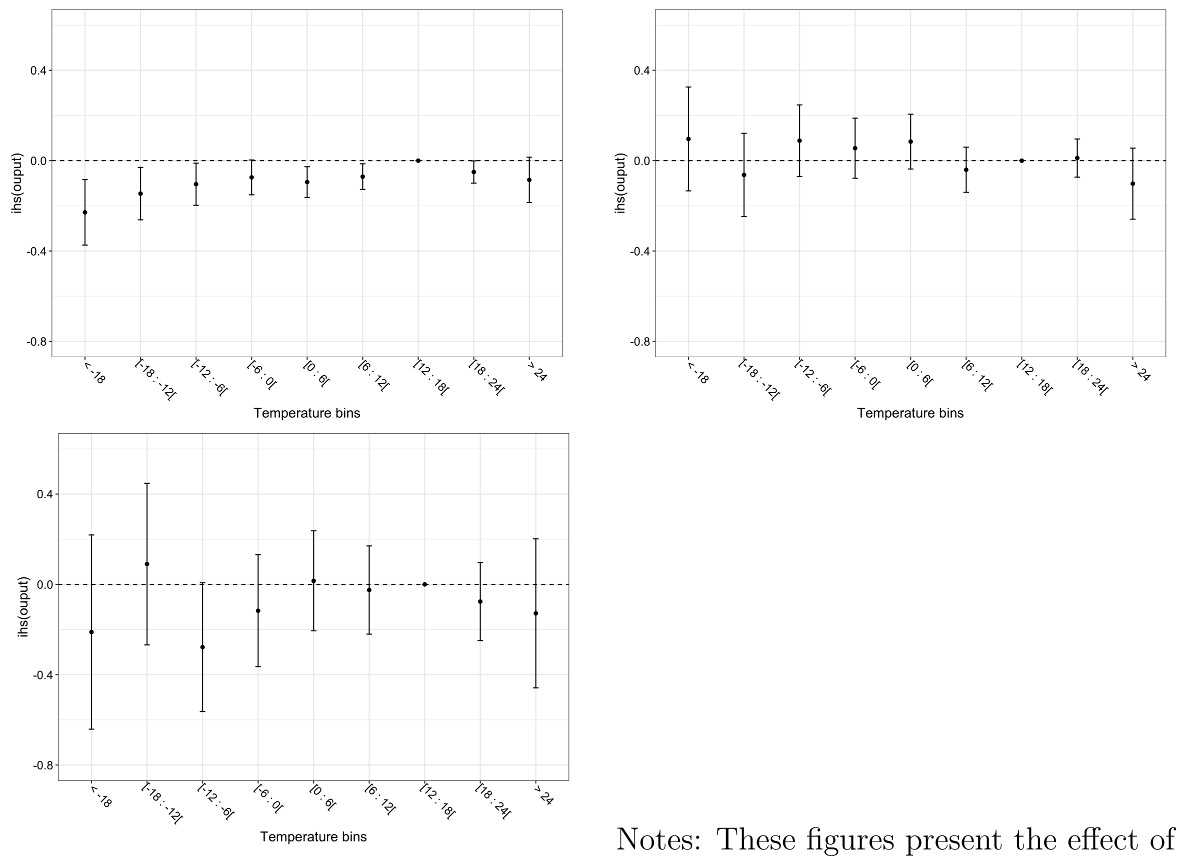
Establishment size

In this section, we study the effect of temperature on manufacturing output for small, medium, and large establishments. Our aim is to test the hypothesis that large establishments would have enough resources for adaptive investments compared to small or medium establishments that the effect of temperature would be more muted. We rerun (2.4) by interacting weather variables with a discrete variable representing establishments' size as follows:

$$Y_{icpdt} = (\sum_b \beta_b T^b_{ct} + \sum_w \sum_q \theta_b W^{qw}_{ct}) \times size + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{1.7}$$

where $size$ is a discrete variable that categorizes each establishment as (1) small, with less than 50 employees, (2) medium, with 50 to 250 employments, or (3) large, with more than 250 employees. We also interact $size$ with both industry-year and province-year fixed effects.

Figure 1-21 presents the effect of extreme temperature on small, medium, and large manufacturing output. We find a persistent negative effects of cold and hot temperature on small establishments output. An extra day with temperature below -18°C to 6-12°C decreases small establishments output by 0.07-0.23%. Similarly, an extra day with temperature above 24°C or between 18-24°C reduces small establishments output by 0.05-0.07%. Estimates for the effect of extreme temperatures on medium and large establishments are much noisier, owing to the much smaller number of establishments of this size. With imprecise estimates, it is difficult to determine whether larger establishments are differentially affected by extreme weather compared to smaller ones, but our results suggest there is no statistically significant differences in the response to extreme temperature by establishment size.



Notes: These figures present the effect of extreme temperature on small, medium, and large establishments output relative to meduim establisments output. The coefficients are multiplied by 100. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

Figure 1-21: Estimated effect of extreme temperature on total output

Labour intensity

In this section, we study the effect of temperature on manufacturing establishments with different input structures. In the conceptual framework presented in Section 1.2, impacts on labour productivity reflect a key determinant of how manufacturing plants respond to temperature shocks. As a result, we may expect labour intensive establishments to be more affected by extreme temperature compared to capital intensive establishments. We divide our sample into labour versus capital intensive establishments. We use two measures of labour intensity, respectively defined as the share of total wage in total output and the number of employee per output. An establishment is considered labor intensive when its share is above the median labour share in a given industry sector. We rerun (2.4) by interacting weather variables with a dummy variable representing labour intensity as follows:

$$y_{icpdt} = \sum_b \beta_a T^b_{ct} + (\sum_b \beta_b T^b_{ct} + \sum_w \sum_q \theta_b W^{qw}_{ct}) \times labourintensity + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \quad (1.8)$$

where *labourintensity* is a dummy variable taking the value of 1 when the establishment is labour intensive and 0 otherwise. We also interact *labourintensity* with both industry-year and province-year fixed effects.

Using the definition of labour intensity, as total employees over total sales (labour intensity 2), we find that labour intensive establishments suffer the most from cold and hot temperature compared to capital intensive establishments. An extra day with temperature below -18°C or above 24°C decreases labour intensive manufacturing output by respectively 0.31% and 0.14% as in Table 1-4. However, when we use another measure of labour intensity (total wages divided total output or labour intensity 1), we find no statistically significant difference between labour and capital intensive establishments (although the coefficients still point to more labour intensive establishments being more negatively affected by extreme temperatures).

Table 1-4: Estimated effects of temperature on total output by manufacturing intensity

	Output (x100) (A)	Output (x100) (B)
< -18	-0.14*	-0.01
	(0.08)	(0.07)
< -18 x labour intensity 1	-0.02	-
	(0.06)	-
< -18 x labour intensity 2	-	-0.31***
	-	(0.03)
[-18 : -12[	-0.11*	-0.0004
	(0.06)	(0.06)
[-18 : -12[x labour intensity 1	0.12**	-
	(0.05)	-
[-18 : -12[x labour intensity 2		-0.2**
		(0.07)
[18 : 24[	-0.02	-0.02
	(0.03)	(0.03)
[18 : 24[x labour intensity 1	-0.04	-
	(0.03)	-
[18 : 24[x labour intensity 2		-0.05
		(0.03)
> 24	-0.08	-0.06
	(0.05)	(0.06)
> 24 x labour intensity 1	-0.05	-
	(0.05)	-
> 24 x labour intensity 2	-	-0.14***
	-	(0.06)
Observations	235,672	232,891

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: The coefficients are multiplied by 100. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

1.5.5 Predicted impacts of climate change

Figure 1-2 shows the projected impacts of climate change on the distribution of temperatures that are likely to be experienced by manufacturing establishments in our sample. Climate change will increase the average temperature, and also shift the incidence of days with extreme temperatures. Climate models predict that the future holds more extremely hot days and less extremely cold days in places where manufacturing establishments are located. Under the moderate (RCP4.5) and the high (RCP8.5) scenarios of GHG emissions, the number of days with temperature greater or equal to 24°C would respectively increase from 14 days to 40 and 43 in the mid-century (2050s) for a typical manufacturing plant. At the end of century (2080s), climate change is expected to respectively increase the number of hot days experienced by a typical manufacturing plant to 43 and 80 under respectively medium and high scenarios of GHG emissions. These climate scenarios also predict a decrease in the number of days with mean temperature below -18°C from 4 to 1 in the mid and end of century.

To predict the impact of future climate change on manufacturing output, we multiply the regression coefficient estimates from Equation (2.4), which capture how annual output is affected by a change in daily weather, by the predicted difference of the number of days between the mid/end of century projection and the current period (2004-2012) for each temperature bin. We derive the standard error using the delta method.[27] Lemoine (2018) shows that using reduced form estimates of weather-output in combination with climate projections as we do here would recover the effects of climate change if establishments are myopic (i.e., do not change production in response to anticipated weather). This methodology assumes that the determinants of manufacturing output are fixed over the time which include the baseline productivity and technology. While this is a strong assumption, it is consistent with the limited adaptation we found in tests of Section 1.5.3.

[27] Our projections of the impact of future climate change on manufacturing output hold everything fixed except the temperature distribution. To the extent that technological change occurs concurrently with climate change, our projections may overstate the likely impact of climate change on output. For example, new technologies may be developed that help to attenuate the temperature-output relationship, and existing technologies such as air conditioning may become more widely adopted. Our data do not allow us to determine the prospects for technological change to compensate for future climate change.

Table 1-5: Predicted effects of climate change on manufacturing output by GHG emission scenarios

	Mid century (2050s)	End century (2080s)
Medium GHG emission (RCP45)	-2.8** (1.3)	-3.7** (1.7)
High GHG emission (RCP85)	-3.7** (1.7)	-7.3** (3.4)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

This table presents the annual impact of climate change on manufacturing output in percentage change relative to current temperature. We assume that the determinants of manufacturing output are fixed over the time which include the baseline productivity and technology. In parenthesis, we show the standard errors derived from the delta method.

Table 1-5 presents the predicted effect of climate change on manufacturing establishment output for temperatures below -18 °C and above 24 °C. The predicted mid century effect suggests that extreme temperature would annually reduce the manufacturing output by 2.8 and 3.7% under medium and high GHG emission scenarios, respectively, relative to today's climate. When we consider the predicted effect for the end of century, the medium and high GHG emission scenarios respectively suggest a decrease of manufacturing output by 3.7 and 7.3% as a result of extreme temperatures.

1.6 Extensions

This section presents two extensions to our basic approach that are aimed at increasing confidence in our results.

1.6.1 Reduced activity due to extreme temperature or natural disasters

In this section, we use self-reported information from manufacturing establishments which captures whether an establishment has experienced reduced activity due to extreme weather or natural disasters. While this is not a perfect parallel to the impact we estimate in the paper, it provides a useful check on how sensitive manufacturing output is to local shocks. In the ASML questionnaire, establishments were asked if they experienced a reduction of their activity due to extreme weather or natural disasters.[28] We then estimate the impact of

[28] This question has more than 21% missing values. Missing values are explained by both the non-response of some establishments and the use of tax file data to fill information of some establishments.

reduced activity due to extreme temperature or natural disasters on manufacturing output:

$$Y_{icpdt} = \beta R_{it} + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{1.9}$$

where R takes the value of 1 when establishment i experiences reduced activity due to extreme weather/natural disasters at time t and 0 otherwise.

Table 1-6 shows that manufacturing output is negatively affected by extreme weather/natural disasters realizations. Manufacturing total output is reduced by 5% for establishments that have experienced a reduction of their activity due to extreme weather/natural disasters. While not perfectly comparable to our main result, the result is in line with our main finding in 1.5.1 showing that manufacturing activity is adversely affected by extreme temperature. In terms of numerical magnitudes, our preferred model suggests that firm output would be reduced by 5% as a result of 26 days of extreme cold weather (daily mean below 18°C) or 45 days of extreme hot weather (daily mean above 25°C).

Table 1-6: Estimated effect of "reduced activity due to weather" on total output

	total output
Weather activity	-0.05***
	(0.018)
Observations	188,855
Establishment FE	Yes
Year-province FE	Yes
Year-industry FE	Yes

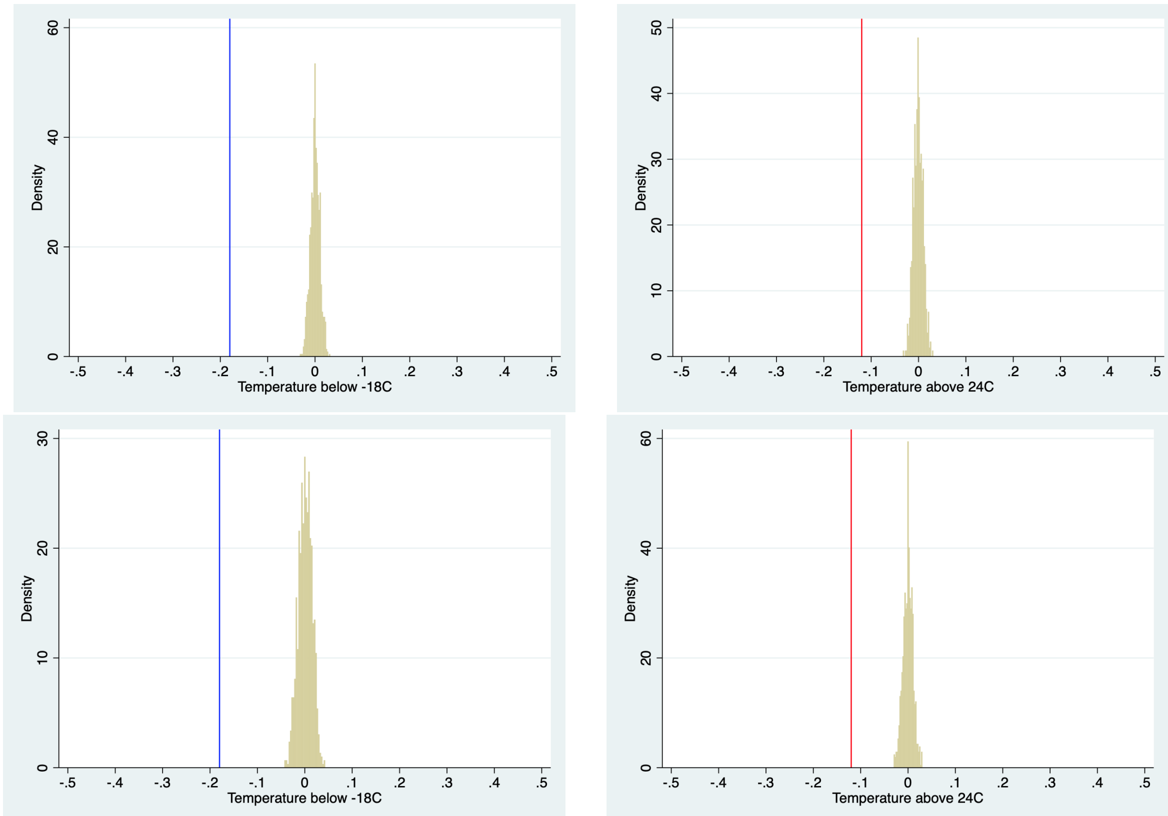
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: this table presents the efffects of reduced activity due to weather or natural disaster on manufacturing total output. The estimation includes establishment, year-province, and year-industry three-digit FE. The standard errors are clustered at the establishment and CSD-year levels.

1.6.2 Falsification test

In this section we report on a falsification test designed as a test of model specification to show that our results are not driven by spurious patterns. As in R. Fishman et al. (2019), we use a falsification test that consists of repeatedly and randomly "reshuffling" the weather data across time and location and estimating Equation (2.4) with the reshuffled data. We take two approaches to reshuffling the data. The first consists to randomly assign the temperature of another year to the current year within the same location. Similarly, the second consists to randomly assign the temperature of another location to a given location in a given year. We expect to see no relation between the randomly assigned temperature and manufacturing output. We repeat this process 1000 times, and report the coefficient estimates from these falsification tests, along with our real coefficients in Figure 1-26.

Figure 1-26 plots the coefficient distribution for temperature below -18°C and above 24°C. When the weather variables are randomly assign across location, we find that the coefficients estimates are not statistically significant in 94.7% and in 94% of cases for respectively temperature below -18°C and above 24°C. All the coefficients are centered around 0. We also randomly assign weather variables across year and we find that in 95.2% and 93.3% of cases the estimates are not statistically significant. We find that all the estimate coefficients from the falsification test are centered around 0. As expected, the random assignment weather variables across location or year are likely to lead to no significance effect of extreme temperature and are centered around 0 whenever significant. This result validate our empirical strategy in 2.4 and the data used in our study.



Notes: These figures present the effect of random assigned temperature on manufacturing output. The blue line represents the preferred estimate of temperature below -18°C while the red line represents the preferred estimate of temperature above 24°C. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

Figure 1-26: Estimated effect of extreme temperature on output by manufacturing output

1.7 Summary and concluding remarks

This paper analyzes the effect of extreme temperature on manufacturing output in Canada. We find that extreme temperatures, as represented by mean temperature below -18°C and above 24°C, have a negative impact on manufacturing output. Our finding is robust to the use of alternative measures of temperature, controlling for other weather covariates, and establishments' fixed effects. Overall, we find that the manufacturing sectors in Canada are vulnerable to extreme temperatures realizations in the short-term. Our estimates suggest that in a typical year, manufacturing output in Canada is reduced by almost 2.2% due to extreme temperatures.

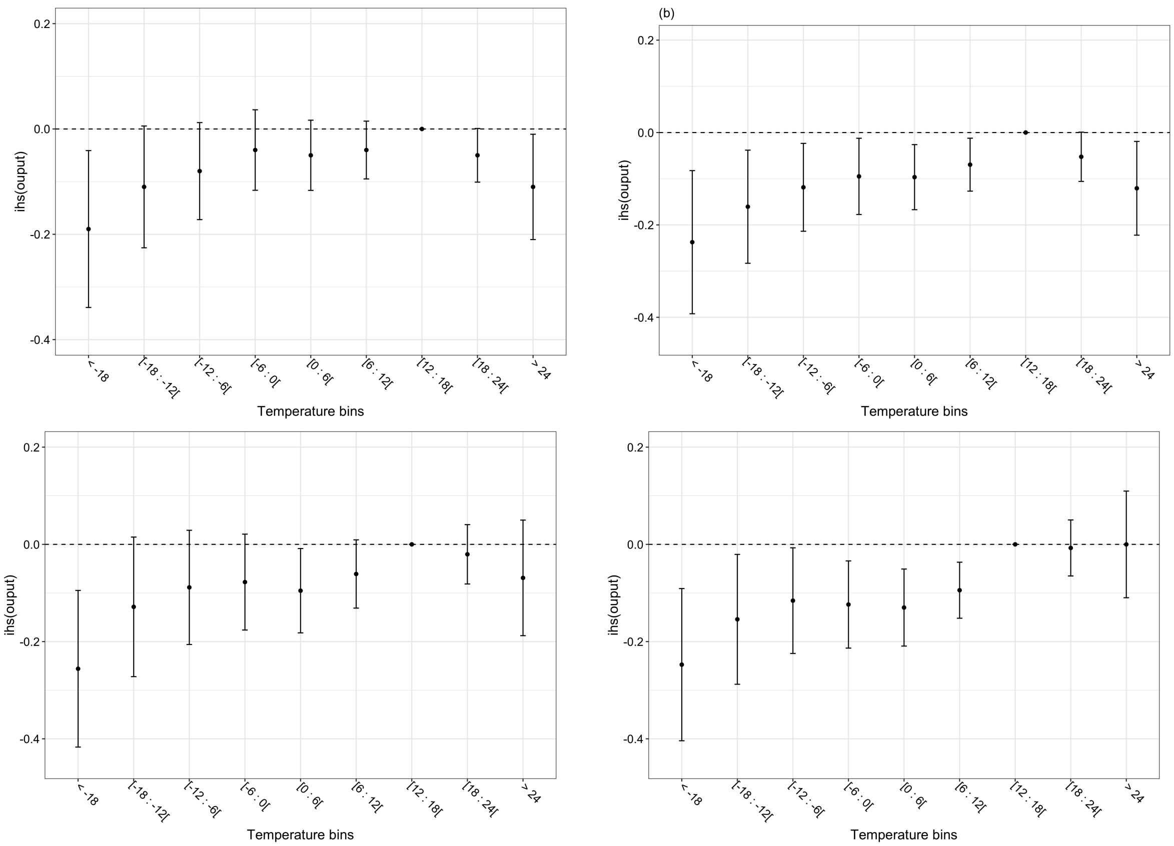
The temperature-output relationship is mainly driven by the negative effect of temperature on manufacturing sales. We find some evidence that labour intensive establishments are the most exposed to the temperature-output relationship compared to capital intensive establishments. Our findings also show that cold day has an extra negative effect on small and large establishments compared to medium establishments. We study whether establishments adapt to their local temperatures by considering those operating in cool and warm areas versus mild areas. We find no evidence that establishments operating in cold areas adapt to cold temperatures and those operating in hot areas adapt to hot temperatures.

Using downscaled climate change projections, we predict that the losses of manufacturing output in Canada would almost double in the mid century and quadruple by the end of the century, as a result of an increase in the number of extremely hot days.

There are three main limitations in this study. First, our data are missing estimates of capital stock in manufacturing plants which prevents us from analyze the impact of temperature on total factor productivity (TFP). TFP, which represents the efficiency of employment of both labour and capital inputs to production, can be used to estimate welfare impacts of extreme weather shocks. Zhang et al. (2018) find some evidence that the capital stock is affected during extreme temperatures realization, which we cannot validate in our sample, given the missing information. The second limitation is the missing information on establishments' investments in equipment related to extreme temperatures. The investment variable would shed light on establishments' efforts to minimize the effect of extreme temperatures and potential for adaptation. The final limitation comes from the predicted climate impact because establishments are likely to engage in variety of investments or actions in the long-run in response to the climate change. As the result, we may overestimate the effect of climate change on manufacturing output in the mid and end of century.

1.8 Appendix

1.8.1 Estimated effect of extreme temperature on manufacturing output using full sample



Notes: Figure *a* represents the main sample used in our analysis. Figure *b* is the main sample restricted to establishments with at least 10 employees. Figure *c* includes all observations without output and employment restrictions but exludes movers across industry, CSD, and province. Finally, figure *d* represents all observations including movers. The coefficients are multiplied by 100. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

Figure 1-31: Estimated effect of extreme temperature on total output

1.8.2 Extreme temperature and manufacturing output - all bins

Table 1-7: Estimated effects of temperature of total output

	log (output) x 100					
Variables	(A1)	(A2)	(A3)	(A4)	(B)	(C)
< -18	0.013	-0.19**	0.01	-0.19**	-0.23***	-0.19**
	(0.06)	(0.08)	(0.06)	(0.08)	(0.09)	(0.07)
[-18 : -12[	-0.145**	-0.14**	-0.06	-0.11*	-0.16**	-0.1*
	(0.06)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)
[-12 : -6[	-0.12***	-0.07	-0.08**	-0.08	-0.14**	-0.06
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
[-6 : 0[	-0.12**	-0.05	-0.07	-0.04	-0.09**	-0.03
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
[0 : 6[	-0.15***	-0.02	-0.11***	-0.05	-0.07*	-0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
[6 : 12[	-0.16***	-0.04	-0.11***	-0.04	-0.03	-0.04
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
[18 : 24[	-0.04	-0.06**	-0.04	-0.05*	0	-0.05*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
> 24	-0.07*	-0.12**	-0.05	-0.11**	-0.16***	-0.12**
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)
Observations	235,683	235,683	235,683	235,683	112,140	235,683
Establishments FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No
Year-province FE	No	Yes	No	Yes	Yes	Yes
Year-Industry FE	No	No	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	No

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table presents the effects of daily extreme temperature on manufacturing total output. Column A1 controls for establishment and year FE. In column A2, we replace the year FE by year-province FE. In column A3, we replace the year FE by year-industry three-digit FE. Column A4 includes both establishment, year-province, and year-industry FE. Column B represents the estimations of balanced panel. Finally, column C represents the estimations without weather controls. Columns A1-A4 and B include weather controls which are total rain, total snow, relative humidity, and wind speed. For all estimations, the standard errors are clustered at the establishments and CSD-year levels. These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[.

1.8.3 Temperature and relative humidity

Table 1-8 shows the result of interacting the temperature bins with an indicator for above-median humidity. We find no difference in the effect of extreme (hot) temperature, depending on whether it is humid or not.

Table 1-8: Estimated effects of combined temperature-humidity of total output

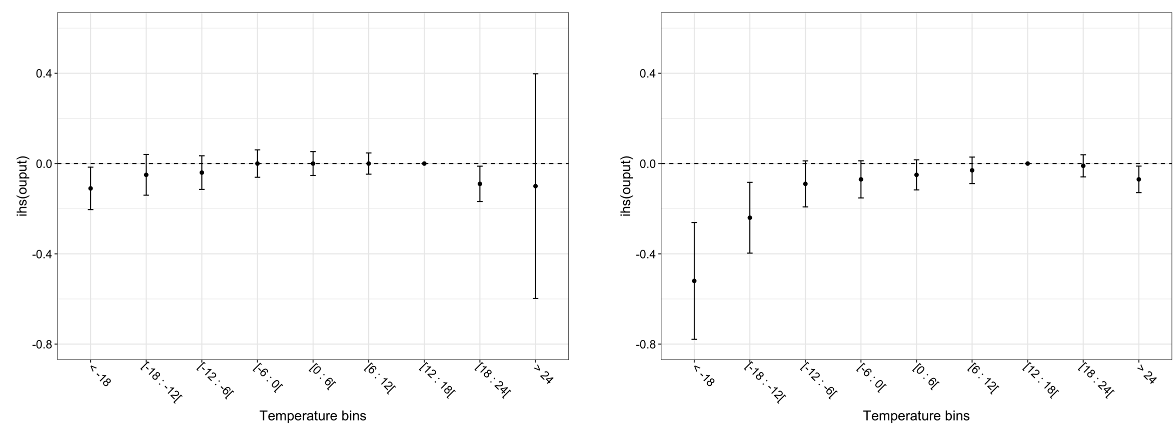
Variables	Output (x100)
< -18	-0.176**
	(0.084)
[-18 : -12[	-0.113
	(0.069)
[-12 : -6[	-0.08
	(0.056)
[-6 : 0[	-0.014
	(0.045)
[0 : 6[	-0.047
	(0.043)
[6 : 12[	-0.025
	(0.037)
[18 : 24[	-0.065*
	(0.034)
> 24	-0.140**
	(0.06)
< -18 x humidity	0.035
	(0.065)
[-18 : -12[x humidity	-0.023
	(0.072)
[-12 : -6[x humidity	0.033
	(0.055)
[-6 : 0[x humidity	-0.095**
	(0.039)
[0 : 6[x humidity	0.038
	(0.036)
[6 : 12[x humidity	-0.019
	(0.044)
[18 : 24[x humidity	0.03
	(0.036)
> 24 x humidity	-0.015
	(0.052)
Observations	235,673

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table presents the effects of daily extreme temperature and combined daily extreme temperature and relative humidity on manufacturing total output. We include weather controls which are total rain, total snow, and wind speed. This specification includes establishment, year-province, and year-industry three-digit FE. The standard errors are clustered at the establishments and CSD-year levels. These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[.

1.8.4 Minimum and maximum temperatures

In the literature, other measures of temperature such as minimum or maximum temperature have been used as an alternative to mean temperature, to capture the exposure degree as in (Deschênes & Greenstone, 2007; Graff Zivin & Neidell, 2014). As a robustness test, we estimate the effect of maximum and minimum temperature of manufacturing output. The minimum temperature represents the lowest temperature faced in any given day while the maximum temperature captures the highest temperature experiences in any given day. For example, a day with minimum temperature between 18 to 24°C might represent a really hot day while a day with maximum temperature between -12 to -6 °C might indicate a very cold day. We estimate (2.4) by replacing mean temperature by respectively minimum and maximum temperature.



Notes: These figures present the effect of daily minimum/maximum temperature on manufacturing output. The coefficients are multiplied by 100. All the specifications include establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the establishment and CSD-year levels.

Figure 1-34: Estimated effect of extreme minimum/maximum temperature on total output

Figure 1-34 presents the effect of minimum and maximum temperatures on manufacturing output. We find a persistent negative impact of maximum temperature on manufacturing output during cold days while not having any impact during cold day. An extra day with maximum temperature less than -18°C or between -18 and -12°C reduces manufacturing output by respectively 0.52 and 0.24%. Using minimum temperature, we find that both cold and hot days have a negative impact on manufacturing output. An extra day with minimum temperature less than -18°C or between 18-24°C reduces manufacturing output by respectively 0.11 and 0.1% compared to a day with minimum temperature between 12-18°C.

This result is consistent with our main finding showing that extreme temperatures have an adverse effect on manufacturing activity.

1.8.5 Wind chill temperature

Wind chill temperature is the combination of mean temperature and wind speed and represents the perceived temperature during cold days. We derive this variable following the index computed by Canada, United States, and United Kingdom experts as follows:[29]

$$windchill = 13.12 + 0.6215 * T - 11.37 * V^{0.16} + 0.3965 * T * V^{0.16} \tag{1.10}$$

Where T is the mean temperature in °C and $windkmh$ is the wind speed in kilometers per hours. When wind chill index is below 0, it has no effect. A wind chill index between 0 and -10 means a slight increase of discomfort. A day is called uncomfortable with moderate risk when the wind chill index is between -10 and -28. Finally, the wind chill index is qualified as high risk when its index is below -28.[30]

1.8.6 Wet-bulb temperature

Wet-bulb temperature is a combination of temperature and relative humidity and represents the perceived temperature during hot days. It has been computed as follows:

$$\begin{aligned} Wetbulb = T * atan(0.151977 * (RH * 8.313659)^{1/2}) + atan(T + RH) \\ -atan(RH - 1.676331) + 0.00391838 * ((RH)^{3/2}) * atan(0.023101 * RH) - 4.686035 \end{aligned} \tag{1.11}$$

Where T is the mean temperature in °C, RH is for relative humidity in percentage. A wet-bulb index lower than 24.5 means normal day for normal activities. For wet-bulb index between 24.5 and 27.3, it is advised to use discretion for intense and prolonged activities. A wet-bulb index between 27.3 and 29 implies a maximum of 2h activities outside. Finally, a wet-bulb index above 29 means high discomfort and a maximum of 1h outside activities are advised.

[29] https://en.wikipedia.org/wiki/Wind_chill

[30] https://www.canada.ca/en/environment-climate-change/services/weather-health/wind-chill-cold-weather/wind-chill-index.html

1.8.7 Alternative standard errors

We rerun our preferred estimation with various approaches to two-way clustering. We report these results in Table 1-9 below. In column (a), we report the main results of our preferred regression of output on temperature, where we cluster the error terms at the establishment and census-subdivisions×year level. In column (b) , we implement a two way cluster at the establishment and province×year level. This approach allows for correlation of observations within a province in a year, as well as allowing for serial correlation of observations within an establishment. Standard errors increase slightly compared to our main specification, but we still reject hypotheses of no impact of temperature on output for both hot and cold temperatures. Finally, in column (c), we cluster the error terms at the establishment and year level. Note that our data only contains 9 years, and so standard errors using this approach are likely to be incorrect (MacKinnon et al., 2019). We report here for completeness only. Standard errors using this approach are somewhat larger, and the point estimate on the coefficient for the effect of hot temperatures on output is no longer statistically significant at conventional levels.

Table 1-9: Estimated effects of temperature on total output

	Output * 100		
Variables	(a)	(b)	(c)
< -18	-0.19**	-0.19**	-0.19*
	(0.076)	(0.079)	(0.086)
[-18 : -12[	-0.11*	-0.11*	-0.11*
	(0.059)	(0.061)	(0.059)
[-12 : -6[	-0.08	-0.08*	-0.08
	(0.047)	(0.041)	(0.051)
[-6 : 0[	-0.04	-0.04	-0.04
	(0.039)	(0.043)	(0.046)
[0 : 6[	-0.05	-0.05	-0.05
	(0.034)	(0.033)	(0.034)
[6 : 12[	-0.04	-0.04	-0.04
	(0.028)	(0.026)	(0.028)
[18 : 24[	-0.05*	-0.05**	-0.05
	(0.026)	(0.022)	(0.032)
> 24	-0.11**	-0.11*	-0.11
	(0.051)	(0.064)	(0.073)
Observations		235,683	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[. Column (a) reports standard errors clustered by establishment and CSD×year; column (b) reports standard errors clustered by establishment and province×year; column (c) reports standard errors clustered by establishment and year.

1.8.8 Multi-way bootstrap

Table 1-10: Estimated effects of temperature on total output using multi way bootstrap

Variables	Output (x100)
< -18	-0.19*
	[0.08]
[-18 : -12[	-0.11*
	[0.08]
[-12 : -6[	-0.08
	[0.07]
[-6 : 0[	-0.04
	[0.43]
[0 : 6[	-0.05
	[0.26]
[6 : 12[	-0.04
	[0.34]
[18 : 24[	-0.05*
	[0.09]
> 24	-0.11*
	[0.08]
Observations	235,683

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[. In brackets, we report the p-value attached to each coefficient.

Chapter 2

Natural disasters and economic performance: Evidence from the Slave Lake wildfire

2.1 Introduction

Destructive natural disasters are expected to increase in frequency and intensity due to climate change (Field et al., 2012). This paper focuses on the Slave Lake wildfire, a significant natural disaster which occurred in central Alberta in May 2011. During the wildfire in Slave Lake, all 6,782 residents were forced to evacuate for nearly four weeks, and the fire caused significant damage to property. The wildfire was the second costliest disaster at that time in Canadian history with estimated economic losses of more than $1.1 billion.[1] Existing estimates of costs of natural disasters, however, tend to focus on costs of property damage, contemporaneous damage to health and economic opportunities, and costs associated with disaster suppression and recovery, and do not typically include potentially long-run costs associated with changes in economic opportunity.[2] This paper aims to first evaluate the effect of the Slave Lake wildfire on long-run economic outcomes for affected individuals. Based on our estimates of economic impacts of the wildfire, we estimate the amount of economic activity displaced by the wildfire. We find that, in the seven years following the fire, affected individuals experience a decrease in total income by more than $3,500 per person per year on average as a result of the wildfire, representing almost 8.5% of pre-event average total income for affected individuals.[3]

Our study builds on a body of recent work examining the economic consequences of natural disasters. Some studies analyze the economic costs of natural disasters on affected countries (Cavallo et al., 2013; Hsiang & Jina, 2014) or counties (Belasen & Polachek, 2008, 2009; Xiao, 2011; Strobl, 2011; Coffman & Noy, 2012; Mu & Chen, 2016; Tran & Wilson, 2020). These studies are facilitated by data availability at the country or county level. The existing literature is conflicting on the economic impacts of natural disasters, with results ranging from no effects to persistent negative effects at different geographical levels. However, these analyses provide no information on individuals' capabilities to cope with

[1]The most costly disaster in Canada was the 1998 ice storm that affected the south of Quebec and Ontario. The 2011 wildfire costs comes from the Insurance Bureau of Canada, http://www.ibc.ca/nu/disaster/fire/slave-lake

[2]In their evaluation of the cost of natural disasters, Natural Resources Canada includes costs of fire preparedness, mitigation, and response. It also includes damage costs of fire including insured and uninsured property losses, business interruptions, and recovery and rebuilding. https://www.nrcan.gc.ca/climate-change/impacts-adaptations/climate-change-impacts-forests/forest-change-indicators/cost-fire-protection/17783

[3]The total amount of economic activity displaced by the wildfire, considering the working-age population in Slave Lake, is estimated at more than $104 million over the period 2012-2018. This cost is derived by timing the average cost per person per year to the working age population of Slave Lake in 2011 over the period 2012-2018.

natural disasters.

In this paper, we analyze the effects of the 2011 Slave Lake wildfire on individuals' outcomes using the Canadian Longitudinal Administrative Databank (LAD), which ensures that we can follow affected individuals before and after the event. We rely on individuals' postal code in their tax declaration to determine both treatment and control groups. The comparison or control group is constructed in two steps. First, we select municipalities of similar size as Slave Lake before 2011 that are between 100-200km away. Second, we perform a matching strategy using Coarsened Exact Matching (CEM) to identify individuals for the control group that are comparable to individuals in the treatment group based on pre-fire incomes, gender, age, and industry. Causal identification relies on the assumption that without the disaster, residents of Slave Lake would have experienced similar trends in outcomes as matched residents in control municipalities.

We conduct the empirical analysis in four steps. First, we estimate the causal effect of the Slave Lake wildfire on individuals' total income and its main components including employment income, self-employment income, investment income, and total government transfers. We use a difference-in-difference approach to determine the average effect over the period 2012-2018 and also implement an event-study analysis to distinguish the short-, medium-, and long-term effect of the disaster. We find that exposure to the wildfire decreases affected individuals total income by more than \$3,500 on average, representing almost 8.5% of pre-event average total income. Affected individual employment and investment incomes fall by more than \$3,200 and \$166 respectively while they experience an increase in government transfers of more than \$400 on average over the period 2012-2018. Compared to the pre-event average income, this represents respectively 8.4 and more than 14.8% decreases in employment and investment income while government transfer increases by more than 9.6%. The event study results suggest that the drop in incomes occurs in the medium and long-term while we find no statistically significant effect in the short-term.

To understand the income effects, we analyze the effect of the wildfire on both the extensive margin–focusing on participation in the labour market–and the intensive margin–focusing on how the wildfire affects income conditional on participation in the labour market. On average, we find no significant evidence that the wildfire affects employment, self-employment, and the number of individuals receiving employment insurance or classified as low income earners. We also find that for wildfire victims who were employed in each year in our sample, employment income fell by more than \$3,400 on average. These results show that the wildfire negatively impacted overall income on the intensive margin. Although our data do not provide information on individuals' wages or hours worked, our results suggest that the event negatively affected incomes conditional on working while the decision to participate in the labour market is unaffected.

Second, we analyze how the wildfire affected the industry composition in Slave Lake. We find that the event reduced the number of people employed in information, finance and real estate sector. This sector is plausibly directly impacted by the fire given the damages to property that occurred with the wildfire. Conditional on working in a given industry sector in 2010, we find a decrease in employment income by more than $47,000 and $13,000 for affected individuals working respectively in agriculture and forestry sector and service and adminsitration sector, suggesting particularly pronounced impacts in these two sectors.

Third, we analyze whether the wildfire caused out-migration from Slave Lake. We find evidence of migration in the short, medium and long run. Our estimates suggest that migration out of Slave Lake increased by almost 6 percentage points compared to the matched control group. The fact that people did migrate also implies that the costs of relocation are outweighed by the returns.

Fourth, we examine how the wildfire affected individuals differently by age and gender in order to understand vulnerability to climate-related disasters. Our most significant finding is that the largest economic impacts of the wildfire are concentrated in older individuals. Individuals aged more than 55 years, at the time of the disaster, experience an employment income drop of more than $27,000 on average and an employment drop of 18 percentage points on average following the wildfire, compared to similar individuals in control communities. In contrast, individuals aged 40 to 54 at the time of the disaster, experience an employment income drop of about $12,000 on average with no decrease in employment. We find an increase in employment incomes for young people following the wildfire. Our results also suggest that women are the ones suffering from the employment income drop. They experience a drop in employment income by more than $7,200 on average. However, employment is unaffected for both women and men.[4]

Finally, we conduct different robustness exercises to assess the importance of our choice of the control group. We first expand the control group by including all municipalities with population between 5-10 thousand individuals that are 100-300 km radius away from Slave Lake. Second, we expand the control group by considering all municipalities/cities with population between 5-50 thousand that are 100-200 km radius away from Slave Lake. Third, we consider all the municipalities in the same economic region as Slave Lake. Lastly, we include all municipalities with population between 5-10 thousand across Alberta. In each case, we estimate our difference-in-difference model both with and without matching

[4]One possible explanation is that older individuals are less attached to the labour market than other groups. It is also possible that women are over-represented in the older group. We suspect that younger individuals benefit the most from the rebuilding of the city, which explains their gain. In future work, we plan to explore these possibilities.

individuals on pre-wildfire covariates, and we find similar results as in our main finding.

Few studies analyze the effects of natural disasters on individual-level economic outcomes (Groen et al., 2020; Deryugina et al., 2018; Groen & Polivka, 2008; McIntosh, 2008). Groen et al. (2020) and Deryugina et al. (2018) analyze both short-, medium-, and long-term effects of hurricanes on individuals' outcomes using administrative datasets. Groen et al. (2020) combine the Longitudinal Employer-Household Dynamics data (LEHD) and US census data to hurricanes Katrina and Rita data and compare the evolution of wage earnings before and after the hurricanes. Similarly, Deryugina et al. (2018) analyze the long-term effect of hurricane Katrina on individuals' incomes using individual tax data. They both find that hurricane Katrina led to an increase in labour income following the storm for affected individuals. The rise in income is explained by the possibility for displaced people to relocate to other locations with better economic opportunities or an improvement in the New Orleans labour market due to the disaster.

Our study contributes to the literature investigating the long-term effect of natural disasters on economic outcomes of individuals. We provide the first evidence on the economic effects of wildfires on individuals in Canada, and use our results to highlight an additional cost of natural disasters that is often omitted in accounting for the costs of natural disasters. This paper also highlights the particular vulnerability of older individuals and women to natural disasters. Climate change is expected to increase the frequency and intensity of natural disasters, including wildfires, so our results may be useful in providing more accurate estimates of the costs of natural disasters as well as in preparing for such disasters.

The remainder of this paper is organized as follows. In Section 2.2, we describe the Slave Lake wildfire. In Section 2.3, we describe the data that we use to estimate the impact of the wildfire. In Section 2.4, we present the empirical strategy, we well as the results of our analysis. Finally, in Section 2.5 we conclude and discusses implications for policy.

2.2 Background: The Slave Lake wildfire

On May 14th, 2011, a wildfire started in the rural communities of Canyon Creek, Widewater and Wagner in Alberta, which led to an evacuation a few hours later to Slave Lake, the regional centre for the area. The day after, Slave Lake itself was threatened by the devastating wildfire which forced authorities to issue a mandatory evacuation order. All 6,782 residents evacuated for nearly 4 weeks to the closest unaffected municipalities/cities such as Westlock, Athabasca, Edmonton, and other areas in Alberta. This was the first time the Slave Lake community was forced to evacuate because of life threatening danger. At this time, the wildfire was considered as the costliest disaster in the province of Alberta and has lead to the largest displacement of individuals.[5]

The wildfire is attributed to the unusual hot and dry weather of the previous days in this region of Alberta.[6] In addition to weeks of warm and dry weather, forest greening in the region of Slave Lake was delayed, and aspen trees were at their most flammable point of the season. While arson is believed to be the principal cause of the wildfire, hot, dry, and windy conditions proved perfect for allowing the fire to spread quickly and uncontrollably. When the fire started in the region, it quickly threatened the town of Slave Lake and neighbour areas due to the 100 km/h wind gusts.

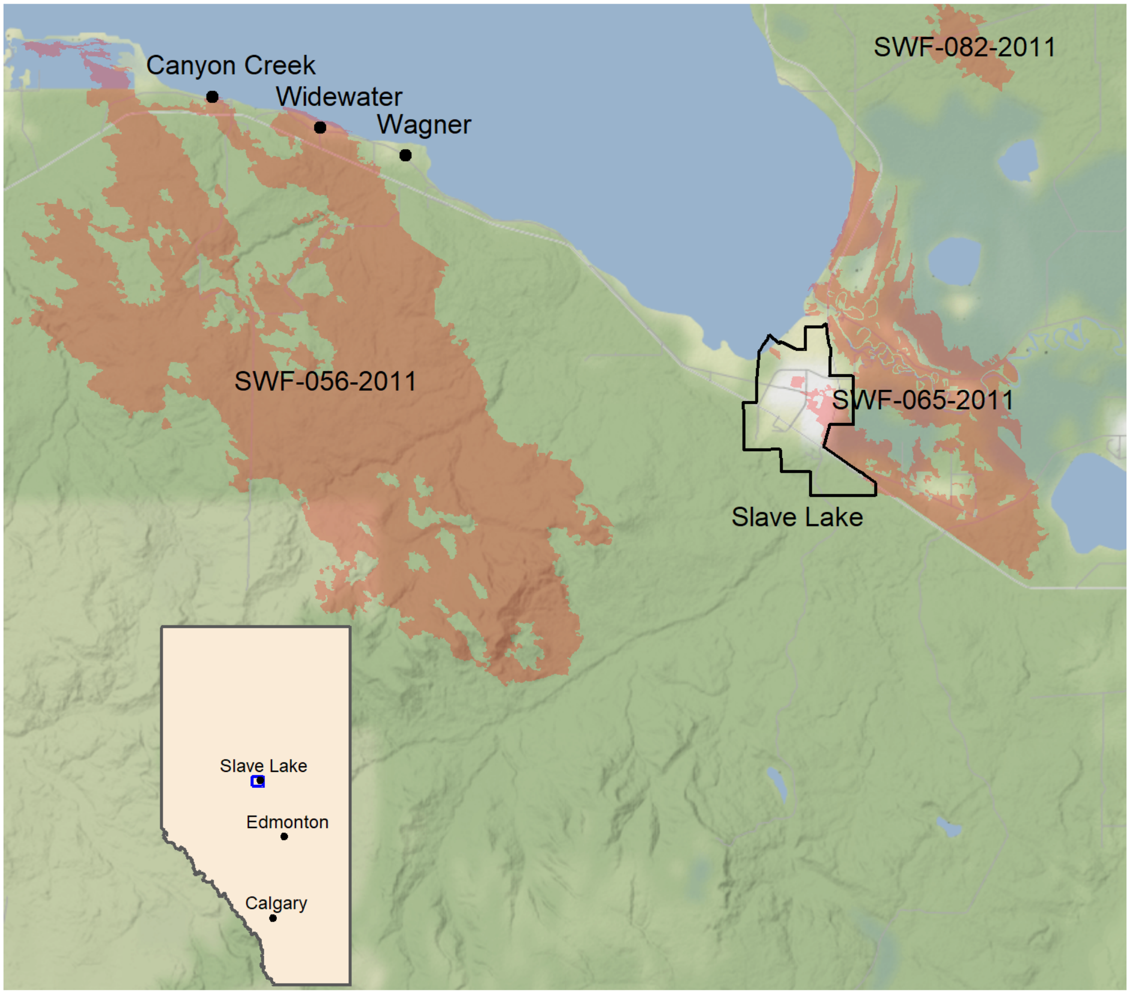
At the time it occurred, the Slave Lake wildfire was the second costliest natural disaster in the history of Canada after the 1998 ice storm. The fire was estimated to inflict a cost of $1.1 billion including $400 million in uninsurable losses at that time according to the Insurance Bureau of Canada.[7] The wildfire devastated an estimated area of $47km^2$ as in Figure 2-1. The fire ravaged more than 30% of Slave Lake destroying the town hall, along with businesses, the library, dozens of houses and the radio station.[8]

[5] KPMG (2012), https://open.alberta.ca/publications/lesser-slave-lake-regional-urban-interface-wildfire-lessons-learned

[6] Fire weather forecasters in Alberta foresaw this climate as a perfect breeding conditions for a firestorm. phttps://www.ec.gc.ca/meteo-weather/meteo-weather/default.asp?lang=En&n=EE2A47F9-1

[7] http://www.ibc.ca/nu/disaster/fire/slave-lake

[8] https://edmontonjournal.com/news/one-third-of-slave-lake-destroyed-in-massive-wildfire-mayor-says



The three brown shaded areas are the fire permiters from the Flat Top Complex fire, available from the Government of Alberta (https://wildfire.alberta.ca/resources/historical-data/spatial-wildfire-data.aspx). Fire SWF-065-2011 affected the town of Slave Lake which is the only urban area in the region. Fire SWF-056-2011 affected rural areas including Canyon Creek, Widewater, and Wagner

Figure 2-1: Areas affected by the 2011 Slave Lake wildfire

In response to the victims' needs, the Alberta government provided emergency funds on their debit cards. The victims also received money and goods from non-governmental organizations and local communities. Some companies supported their employees by continuing to pay salaries while their businesses were closed. The Government of Alberta supported the affected Slave Lake by implementing a revenue stabilization program. It approved $50 million early in the response to the disaster, and followed over the next three months with additional amounts of $239 million to support recovery for damaged infrastructures.[9]

The town of Slave Lake, as a regional centre for the area, provides services such as retail, education, health, financial, government, and transportation. The main industries in the affected area are oil and gas, and forestry. Oil and gas companies did not suffer any direct damages but they reduced the oil production due to the wildfires threatening shipping routes and construction sites as well as facilities in northern Alberta.[10] The losses of oil and gas companies due to the wildfire were estimated at more than $300 million. The forest industry however incurred a direct loss with more than 790,000 hectares of forested land burned by the fire.[11]

2.3 Data

This section describes the main data source used in this study. It also explains how the treatment and control groups are constructed.

2.3.1 Administrative Tax Database

We use the Longitudinal Administrative Databank (LAD) from Statistics Canada. It is a longitudinal sample of tax filers since 1982. LAD represents a randomly selected 20% sample of all tax filers and their families in the annual T1 family file. Every year, LAD is augmented with a 20% sample of new tax filers which makes it a representative sample of tax filers in Canada.[12] LAD provides information on individual annual incomes including total income, employment income, self-employment income, and government transfers. It also has information on individual social characteristics including gender, age, number of kids, and marital status.[13] Finally, LAD provides information on individual geographical location including six digit postal code, census-subdivision, and province of residence which are used to determine exposure to the 2011 Slave Lake wildfire and to select a control group.

Using the income variables, we derive individual employment status as follows: an individual is considered employed if her/his employment income in a given year is greater than $0. We adopt a similar definition to define an individual as self-employed. Similarly, we define a dummy variable for individuals receiving employment insurance, contributing to

[9] https://open.alberta.ca/publications/9781460102732

[10] https://www.theglobeandmail.com/globe-investor/oil-production-tanks-in-alberta-as-wildfires-threaten-facilities/article4262917/

[11] https://open.alberta.ca/publications/9781460102732

[12] Newly added individuals are followed back to 1982 where possible.

[13] One limitation of this data, as it pertains to this project, relates to the fact that it does not have information on other potential outcomes such as house ownership, and health.

RRSP, and claiming medical expenditure. The low income variable is provided by Statistics Canada and is defined as one-half of the adjusted median family income, where 'adjusted' indicates a consideration of family size. We also derive a variable called 'investment income', which is the sum of rental income and interest and investment income.[14] Using the variable number of kids, we define a categorical variable called new kid which take the value of one when an individual experience an increase in the number of children compared to previous year and zero otherwise.[15]

Migration is one potential response to a natural disaster. Deryugina et al. (2018) find that evacuees from hurricane Katrina migrated to new location with better economic opportunities, which helped to mitigate the negative economic effect of the disaster. We create a dummy variable that takes the value 1 when an individual municipality of residence in year t is different from his/her municipality in 2010 (before the wildfire) and 0 otherwise.

2.3.2 Treatment and control groups

When filling their tax form, individuals provide information on their residence address including the postal code, the city, and the province. Using this information, we identify individuals exposed to the 2011 Slave Lake wildfire as those with a residence in Slave Lake in 2010. This approach is similar to the one used in Deryugina et al. (2018). The event affected all the residents of Slave Lake as all residents were forced to evacuate the city for at least one month. Once the treatment group is identified, the longitudinal data allow us to follow this group before and after the event across Canada.

We construct the control group in three steps. We first keep all the individuals living in municipalities of similar size as Slave Lake i.e a municipality with a population between 5 to 10 thousand. Second, we restrict our sample to all individuals living in the municipalities that are 100-200 km radius away from Slave Lake as in Figure 2-2. The retained municipalities are Peace River, Whitecourt, and Morinville. These municipalities are near enough to serve as a good control group, but far enough that they are unlikely to be directly impacted by the fire. By restricting our analysis to individuals living in this area at the time of the disaster, we expect the treatment and the control group to share similarities on incomes and labour patterns and social characteristics before the event.

[14]Interest and investment income represent an income earned from interest and other investments during the tax year. This type of income results from savings bonds, corporate bonds, trusts, bank or other deposits, mortgages, notes, foreign interest, foreign dividend income and other property.

[15]According to LAD dictionary, a child is defined as someone who is single and living with one or both parents. It is also noted that children may be any age, i.e. a 40-year-old child may be living with a 60-year-old parent. As a consequence, this definition does not uniquely refer to new-born kid but also includes a kid who is back in the family house.

Despite the geographical matching, Table 2-1 described further below, shows difference in level on incomes and social characteristics between the treatment and the unmatched control group. As a result, our third step in the construction of the control group is to use CEM methodology, a matching strategy/algorithm to identify individuals in the pool of the control group who are most similar to the treatment group before the wildfire takes place.[16] CEM method divides each covariate into bins where each treated unit gets a weight of one and control units get varying weights. Although CEM is called Coarsened Exact Matching, it is a hybrid between matching and reweighting methods (Black et al., 2020).[17]

Following Deryugina et al. (2018), we first start by selecting a limited number of covariates to match on for each year between 2004 and 2010. The matching covariates include total income, employment income, self-employment income, employment insurance, age, gender, and 3-digit industry sectors.[18] Second, we apply the CEM technique on the matching covariates for each year over the period 2004-2010.[19] We then get a matched control group comparable to the treatment group for each year over the period 2004-2010.[20] Each matched observation is given a weight greater than zero while the unmatched unit is given a weight of zero.[21] Third, for each individual, we compute the average weight over the period 2004-2010. We then assign to each individual the corresponding average weight over the period 2004-2018.

[16]The CEM approach was developed by Iacus et al. (2011, 2012) and it provides appropriate weights to the control group in order to make them comparable to the treated unit. CEM yields strong balance in covariates and lower root mean square error than other matching techniques

[17]Treated (control) units are kept if they can be matched, after coarsening, to one or more control (treated) units.

[18]We define the incomes bins with a $20,000 range.

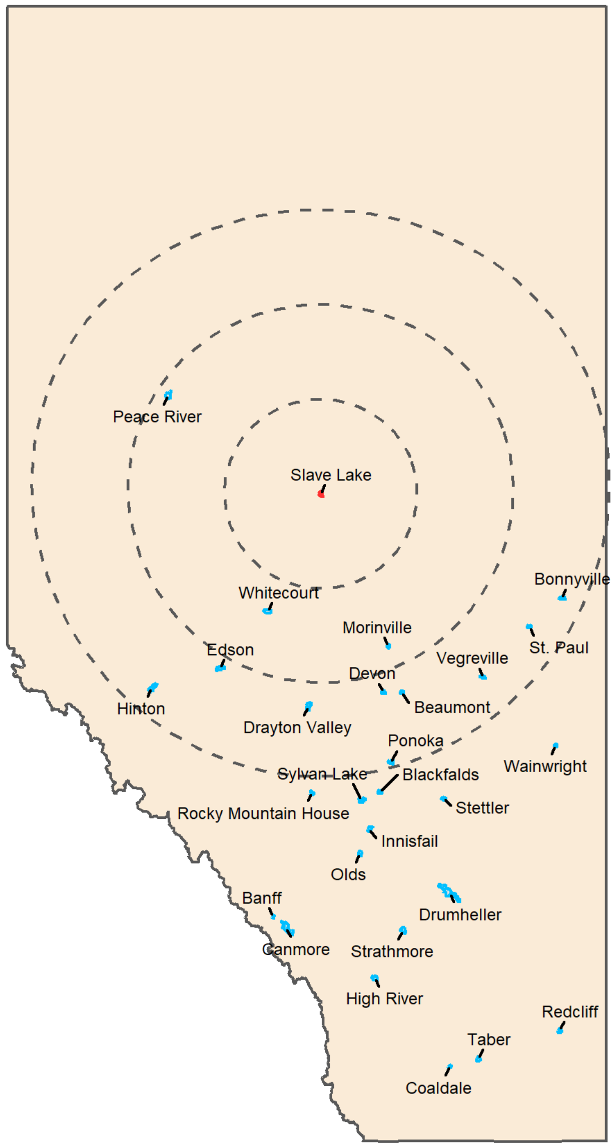
[19]The CEM matching on panel data can be implemented in different ways. a) An alternative way to implement the matching is to give the 2010 value to each individual over the period 2011-2018 and runs the CEM algorithm for each year over the period 2004-2018. b) Another alternative way could be to only match the treatment and control group on selected covariates in 2010 and assign the corresponding CEM weight to each individual over the period 2004-2018. In appendix, we estimate (2.1) using the matching weights from (a) and find almost similar results as in our main finding in Table 2-5.

[20]We lose 7 individuals from the treatment group and 188 individuals from the control group.

[21]As explained in (Iacus et al., 2012), after coarsening, the CEM algorithm creates a set of strata where units that have at least one treated and one control unit are retained and the other units are drop from the sample. Therefore, to each matched unit i in a given stratum s, CEM assigns weights as follows:

$$w_i = \begin{cases} 1, i \in T^s \\ \frac{m_C}{m_T}\frac{m_{T^s}}{m_{C^s}}, i \in C^s \end{cases}$$

Where T^s is the number of treated units in the stratum and C^s the number of control units in the stratum. m_T and m_s respectively represent the number of matched and control units in the sample. The unmatched units are assigned a weight (w_i) of zero. The use of weights in the regression analysis facilitates the estimation of the average treatment effect on the treated in a weighted least squares regression program. For more information, see https://docs.google.com/document/d/1xQwyLt_6EXdNpA685LjmhjO20y5pZDZYwe2qeNoI5dE/edit



The dashed lines represent 100, 200, and 300 km radius buffers around Slave Lake, which is represented by the red dot. Blue dots represent potential control municipalities, which (like Slave Lake) have population between 5,000 and 10,000 individuals, based on the 2016 Census. The control group in our main specification is drawn from municipalities with 5,000-10,000 individuals between 100 and 200 km from Slave Lake.

Figure 2-2: Location of treatment and control municipalities

For this analysis, we consider the period 2004 to 2018 which represents 7 years before and after the 2011 Slave Lake wildfire.[22] We restrict our sample to tax filers who were above 16 and below 65 years old at the time the disaster occurred and follow them across Canada. Our main control groups are individuals living in a similar municipalities as Slave Lake within 100-200km radius.[23]

2.3.3 Summary Statistics

Table 2-1 describes individual characteristics prior to the 2011 Slave Lake wildfire.[24] This table includes information on incomes, employment status, and social characteristics for the treatment, matched and unmatched control groups over the period 2004-2010. We also perform a t-test that compares the treatment group to the matched and unmatched control group for each variable. We find that the matched control group and the treatment group are similar in mean on many variables. This similarity is confirmed through the use of the t-test that shows no statistically significant difference between the treatment and the matched control groups except for the variables self-employment income, employment insurance, investment income, migrant, self-employed, and new kid. In contrast, the unmatched group is different from the treatment across a number of dimensions.

Most of individuals in our data were employed before the event with respectively 89% in both treatment and matched control group. Low income individuals represent almost 13% of Slave Lake population before the event and more than 12% for the matched control group. Table 2-1 also shows that the probability to move out of municipality before the disaster is almost 21% for the treatment group and 19% for the matched control group.

[22] The currently available LAD covers the period 1982 to 2018. https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=4107

[23] In the Robustness Section 2.4.4, we perform various analyses using alternative control groups that differ from the main control group.

[24] The information for the treated and matched control group are weighted. The treated unit has always a weight of one.

Table 2-1: Summary statistics of individuals' characteristics over the period 2004-2010

Variables	Treatment		Matched control			Unmatched control		
	mean	sd	mean	sd	t-test (p-value)	mean	sd	t-test (p-value)
Total income ($)	41,425	(38,104)	42,327	(40,278)	0.23	50,556	(96,957)	0.00
Employment income ($)	38,331	(37,301)	38,554	(39,003)	0.76	44,236	(88,399)	0.00
Self-employment income ($)	307	(4,059)	495	(6,058)	0.02	1,036	(10,959)	0.00
Government transfer ($)	1,963	(4,254)	1,874	(4,277)	0.28	1,862	(4,404)	0.04
Investment income ($)	143	(1,117)	246	(2,380)	0.00	382	(3,919)	0.00
Employment insurance ($)	617	(2,340)	529	(2,244)	0.05	577	(2,330)	0.01
Age	36	(12)	36	(12)	0.94	36	(12)	0.05
Female	0.54	(0.50)	0.54	(0.50)	1.00	0.49	(0.50)	0.02
Migrant	0.21	(0.40)	0.19	(0.39)	0.01	0.19	(0.39)	0.01
Employed	0.89	(0.31)	0.89	(0.31)	0.90	0.89	(0.32)	0.21
Self-employed	0.04	(0.19)	0.06	(0.24)	0.00	0.10	(0.29)	0.00
Receiving employment insurance	0.11	(0.31)	0.09	(0.29)	0.00	0.10	(0.30)	0.00
Low-income earner	0.13	(0.33)	0.12	(0.33)	0.61	0.11	(0.31)	0.11
Medical expense claim	0.12	(0.33)	0.11	(0.31)	0.02	0.11	(0.32)	0.07
New child at home	0.12	(0.32)	0.09	(0.28)	0.00	0.09	(0.28)	0.00
Newly divorced	0.01	(0.11)	0.01	(0.10)	0.48	0.01	(0.10)	0.16
Newly married	0.02	(0.16)	0.02	(0.14)	0.24	0.02	(0.15)	0.25
RRSP contribution	0.30	(0.46)	0.31	(0.46)	0.74	0.33	(0.47)	0.15
Individuals	583		1,953			2,141		
Observations	3,687		12,327			13,491		

Notes: These descriptive statistics cover the period 2004-2010. All the monetary values are in current dollar. The descriptive statistics for the matched control group are weighted using the CEM weights.

Similarly, Table 2-2 presents individual characteristics after the disaster over the period 2012-2018. Compared to Table 2-1, we find an increase in income gap between the treatment and control group regarding employment income, self-employment income, government transfer, and investment income. Similarly, we observe an increase in mean difference between the treatment and matched control group. On average, the treatment group is more likely to move out of city (33 versus 26%) , be low-income earner (11% versus 9%), and claim medical expenses (22% versus 18%) compared to the matched control group.

Table 2-2: Summary statistics of individuals' characteristics over the period 2012-2018

Variables	Treatment		Matched control		Unmatched control	
	mean	sd	mean	sd	mean	sd
Total income ($)	58,753	(53,908)	63,048	(64,887)	70,604	(89,237)
Employment income ($)	49,727	(46,074)	53,198	(60,107)	57,233	(68,438)
Self-employment income ($)	694	(6,649)	938	(8,611)	1,301	(11,123)
Government transfer ($)	3,969	(7,476)	3,434	(6,945)	3,310	(6,579)
Investment income ($)	201	(2,049)	463	(3,487)	531	(3,890)
Employment insurance ($)	897	(3,201)	767	(3,028)	749	(3,031)
Age	42	(13)	42	(13)	43	(13)
Female	0.55	(0.50)	0.55	(0.5)	0.50	(0.50)
Migrant	0.34	(0.47)	0.26	(0.44)	0.27	(0.44)
Employed	0.81	(0.39)	0.83	(0.38)	0.83	(0.38)
Self-employed	0.06	(0.25)	0.08	(0.27)	0.10	(0.30)
Receiving employment insurance	0.12	(0.32)	0.10	(0.30)	0.09	(0.29)
Low-income earner	0.12	(0.32)	0.09	(0.29)	0.08	(0.28)
Medical expense claim	0.22	(0.42)	0.19	(0.39)	0.19	(0.39)
New child at home	0.09	(0.29)	0.07	(0.26)	0.07	(0.26)
Newly divorced	0.01	(0.10)	0.01	(0.11)	0.01	(0.11)
Newly married	0.02	(0.13)	0.02	(0.14)	0.02	(0.14)
RRSP contribution	0.30	(0.46)	0.35	(0.48)	0.35	(0.48)
Individuals	581		1,943		2,130	
Observations	3,835		12,925		14,186	

Notes: These descriptive statistics cover the period 2004-2010. All the monetary values are in current dollar. The descriptive statistics for the matched control group are weighted using the CEM weights.

Table 2-3 compares the industry of occupation in the treatment group and the matched control group before the wildfire. The table shows that the treatment and matched control group are well balanced by industry of occupation, with the exception that a slightly greater fraction of individuals in the control group are employed in the agriculture and forestry sector than in the treatment group prior to the wildfire.

Table 2-3: Summary statistics for industry sectors over the period 2004-2010

Variables	Treatment		Matched control			Unmatched control		
	mean	sd	mean	sd	t-test (p-value)	mean	sd	t-test (p-value)
Agriculture forestry	0.008	(0.089)	0.012	(0.108)	0.03	0.018	(0.134)	0.00
Mining, oil, gas	0.082	(0.275)	0.083	(0.276)	0.87	0.091	(0.288)	0.11
Construction	0.067	(0.251)	0.065	(0.246)	0.59	0.069	(0.254)	0.89
Manufacturing	0.085	(0.278)	0.080	(0.271)	0.37	0.091	(0.287)	0.46
Trade, retail, & wholesale	0.172	(0.378)	0.162	(0.368)	0.16	0.144	(0.351)	0.00
Transportation & warehousing	0.031	(0.174)	0.037	(0.188)	0.10	0.044	(0.206)	0.01
Information, finance, & real estate	0.036	(0.185)	0.036	(0.185)	0.98	0.046	(0.210)	0.44
Professional, management, & administrative support	0.071	(0.257)	0.070	(0.256)	0.89	0.074	(0.261)	0.55
Education health	0.096	(0.294)	0.095	(0.293)	0.84	0.079	(0.270)	0.00
Accommodation & other services	0.129	(0.335)	0.131	(0.337)	0.83	0.121	(0.326)	0.97
Individuals	583		1,953			2,141		
Observations	3,687		12,327			13,491		

Notes: These descriptive statistics cover the period 2004-2010. The descriptive statistics for the matched control group are weighted using the CEM weights.

In table 2-4, we now compare the industry of occupation in the treatment group and the matched control group after the wildfire over the period 2012-2018. We find an increase in the gap between the treatment and matched control group regarding information, finance, real estate sector, professional, management, and administrative support sector, accommodation and other services sector, manufacturing sector and mining, oil, and gas sector.

Table 2-4: Summary statistics for industry sectors over the period 2012-2018

Variables	Treatment		Matched control		Unmatched control	
	mean	sd	mean	sd	mean	sd
Agriculture forestry	0.004	(0.060)	0.010	(0.101)	0.014	(0.116)
Mining, oil, gas	0.085	(0.278)	0.073	(0.260)	0.084	(0.278)
Construction	0.072	(0.259)	0.073	(0.260)	0.075	(0.264)
Manufacturing	0.069	(0.253)	0.059	(0.235)	0.062	(0.241)
Trade, retail, wholesale	0.133	(0.339)	0.115	(0.319)	0.108	(0.311)
Transportation & warehousing	0.041	(0.199)	0.043	(0.202)	0.047	(0.211)
Information, finance, & real estate	0.033	(0.178)	0.046	(0.210)	0.050	(0.219)
Professional, management, & administrative support	0.067	(0.250)	0.090	(0.286)	0.091	(0.288)
Education health	0.101	(0.302)	0.106	(0.308)	0.095	(0.293)
Accommodation & other services	0.075	(0.263)	0.087	(0.282)	0.085	(0.279)
Individuals	581		1,943		2,130	
Observations	3,835		12,925		14,186	

Notes: These descriptive statistics cover the period 2012-2018. The descriptive statistics for the matched control group are weighted using the CEM weights.

2.4 Empirical Approach

In this section, we first describe the estimation strategy used to answer our main question. Second, we discuss the findings and their implications. Third, we analyze the effect of the event on individuals' non-economic outcomes. Finally, we estimate the effect of the wildfire using various sets of controls group as a robustness check.

2.4.1 Estimation strategy

To estimate the average causal effect of the 2011 Slave Lake wildfire on individual incomes, we run a difference-in-difference estimation with CEM weights as follows:

$$y_{imt} = \theta D_{mt} + \gamma_i + \omega_t + \epsilon_{imt} \tag{2.1}$$

Where i represents the individual, m the municipality, and t the time. The unit of analysis is the individual.[25] y is the outcome of interest including total income, employment and self-employment incomes, investment income, and government transfers. D_{mt} is a dummy variable equal to 1 for $t >= 2012$ for individuals exposed to the wildfire–i.e., were living in Slave Lake at the time the fire took place and 0 otherwise.[26] Our coefficient of interest θ captures the causal effect of the event on affected individuals' incomes over the period 2012-2018. γ_i is the individual fixed effect which controls for time-invariant characteristics of individuals that may affect the dependent variable. ω_t is the year fixed effect and it controls for annual shocks common to all individuals such as provincial policies and oil prices. Finally, ϵ_{imt} the error term. The error term may be spatially correlated if there are common unobserved shocks that vary over space but are serially correlated at the individual level over time. We cluster the error terms at the 6 digit postal code level in 2010 to address potential spatial and serial correlation in the error terms, similarly to Deryugina et al. (2018); Groen et al. (2020).[27]

In estimating the difference-in-difference regression using Equation (2.1), we use data from seven years before and after the 2011 wildfire. However, we drop the year 2011 in conducting the difference-in-difference regression. The wildfire occurred in May 2011, and as a result, the year 2011 spans the pre- and post-treatment periods. We drop all observations in this year to obtain a clean separation of treatment and control periods.[28]

In addition to the difference-in-difference analysis, we run an event-study analysis with CEM weights (Equation (2.2)) which is used to estimate the effect of the wildfire over time. This technique also offers the opportunity to check for potential differences in trends in the dependent variables in control and treatment municipalities before the wildfire takes place. The event-study equation can be written as:

$$y_{imt} = \sum_{k=2004, k\neq 2010}^{2018} \theta_k D_m^k + \gamma_i + \omega_t + \epsilon_{imt} \tag{2.2}$$

[25]We do not control for industry or municipality fixed effects because they are endogenous to our variable of interest. Our results, represented in Figures 2-14 and 2-15, suggest that the event has a significant effect on migration across municipalities and on industry sectors.

[26]There is one main caveat to this definition. We may mis-classify individuals who move out of Slave Lake after their 2010 tax declaration but before the disaster. Similarly, we may mis-classify individuals who move to Slave Lake after their 2010 tax declaration but before the disaster. The time period, between the wildfire and the time individuals might move in or move out of Slave Lake, corresponds to a period of almost three months (mid-February to mid-May 2011).

[27]We also rerun (2.1) using a two-way cluster at the individual and postal code levels. Table 2-15, in the appendix, shows that standard errors are similar to those in Table 2-5.

[28]In the appendix, we rerun Equation (2.1) on individuals' income while keeping the year 2011. We find similar results as in Table 2-5.

D_{im}^k is a dummy variable that equals 1 if individual i is in the treatment group and the period k before or after the disaster happened. The coefficient of interest, θ_k, captures the average difference between individuals in the treatment and matched control group as of kth period before and after the disaster compared to the difference in the year before the wildfire (2010).

2.4.2 Main results

Using Equation (2.1), we analyze the average causal effect of the wildfire on affected individuals' incomes, and present the results in Table 2-5.[29] We find that the wildfire cause a decrease in individual total income by more than \$3,500 on average per year compared to the matched control group. Employment income is the main factor explaining the drop in total income. The affected individuals experience a drop in employment income by more than \$3,200 which represents more than 92% of total income drop. We also find a slightly significant decrease in investment income for affected individuals by more than \$166 on average per year which represents almost 5% of total income drop. The result also shows a decrease in self-employment income by more than \$60 but the coefficient estimate is not statistically significant. Our table shows that the fire led to a significant increase in government transfers of more than \$400 on average.

Table 2-5: Estimated average effect of the Slave Lake wildfire on individual incomes

Variables	Total income	Employment income	Self-employment income	Government transfer	Investment income
Treatment	-3,517**	-3,238**	-63.79	409.9**	-166.2*
	(1,487)	(1,462)	(256.1)	(177.5)	(87.93)
Mean dependent variable, pre-event	41,425	38,331	307	1,963	142
Observations			32,773		

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

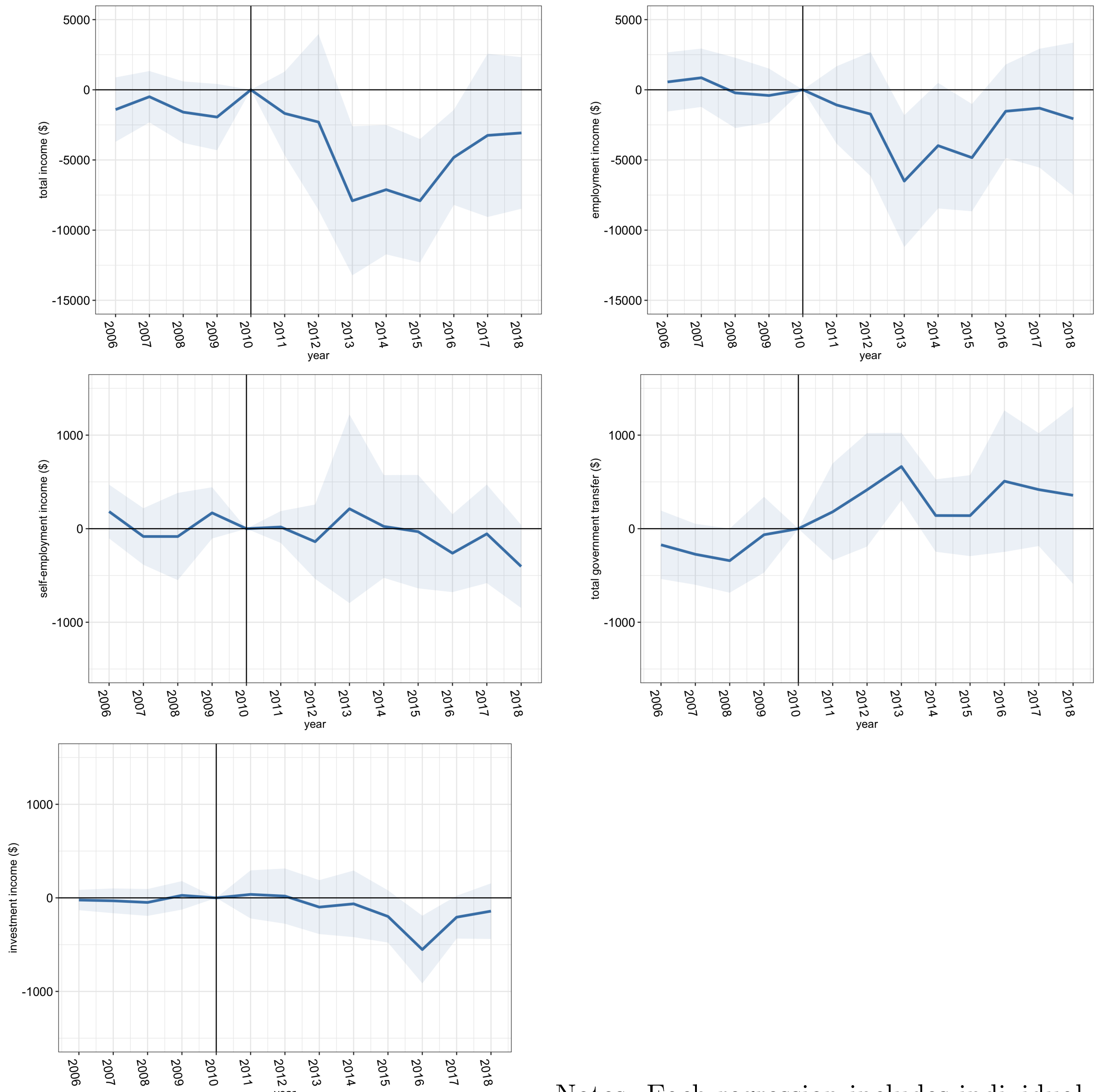
Table 2-5 shows average effects of the wildfire on incomes in the seven years following the disaster. To understand dynamic effects, we estimate equation (2.2). Figure 2-8 presents the causal effect of the wildfire on individuals' incomes over the period 2004-2018. We find

[29] We add in this table the prefire average of the dependent variables for the treatment group to help with the interpretations.

no statistically significant pretrend for most of the variables of interest which indicates that the treated and the matched control group are likely comparable on both the observable and unobservable factors. In the short-term (i.e the first two years after the event), we find a small but statistically insignificant effect of the wildfire on employment income, self employment income, investment income, and government transfer. In total, we find no statistically significant effect of the event on individual total income. On possible reason for the limited short-term impact is that the help provided by non-government and government organizations to affected individuals mitigated the potential negative effect of the wildfire. For example, the Agriculture Financial Services Corporation waived application fees for small businesses in the disaster area, and offered interest-free loans for 24 months and up to 24 months without payments to help businesses establish, rebuild and/or expand. The government of Alberta in conjunction with Slave Lake forgave 2011 property taxes that would have been owed by residents who owned destroyed or uninhabitable property.[30]

In the medium term (i.e the third and fourth year after the event), we observe a decrease in total income by more than \$5,800 on average. This drop is explained by the reduction of employment income by more than \$4,400 on average over that period. The results also suggest an increase in government transfer to affected individuals by more than \$480 the third year of the disaster. One potential reason for larger impacts in this period is that most of the direct disaster support stopped 1-2 years after the disaster. In the long-term (i.e fifth year and more after the event), we find a decrease in affected individual total income by almost \$2,000 on average. This is explained by the decrease in employment income and investment income by respectively \$1,800 and \$170 on average. Overall, the results show that the 2011 wildfire in Slave Lake had a negative effect on affected individuals' incomes in the medium and long-term.

[30]http://www.municipalaffairs.alberta.ca/documents/The-Lesser-Slave-Lake-Region-One-Year-Stronger-Together.pdf



Notes: Each regression includes individual and year fixed effects. The standard errors are clustered at the 2010 six digit postal code level. The vertical line represents the year before the disaster happened. We also plot the upper and lower bound associated to each coefficient at the 5% significant level.

Figure 2-8: Estimated average effect of the Slave Lake wildfire on individual incomes in the short, medium, and long term

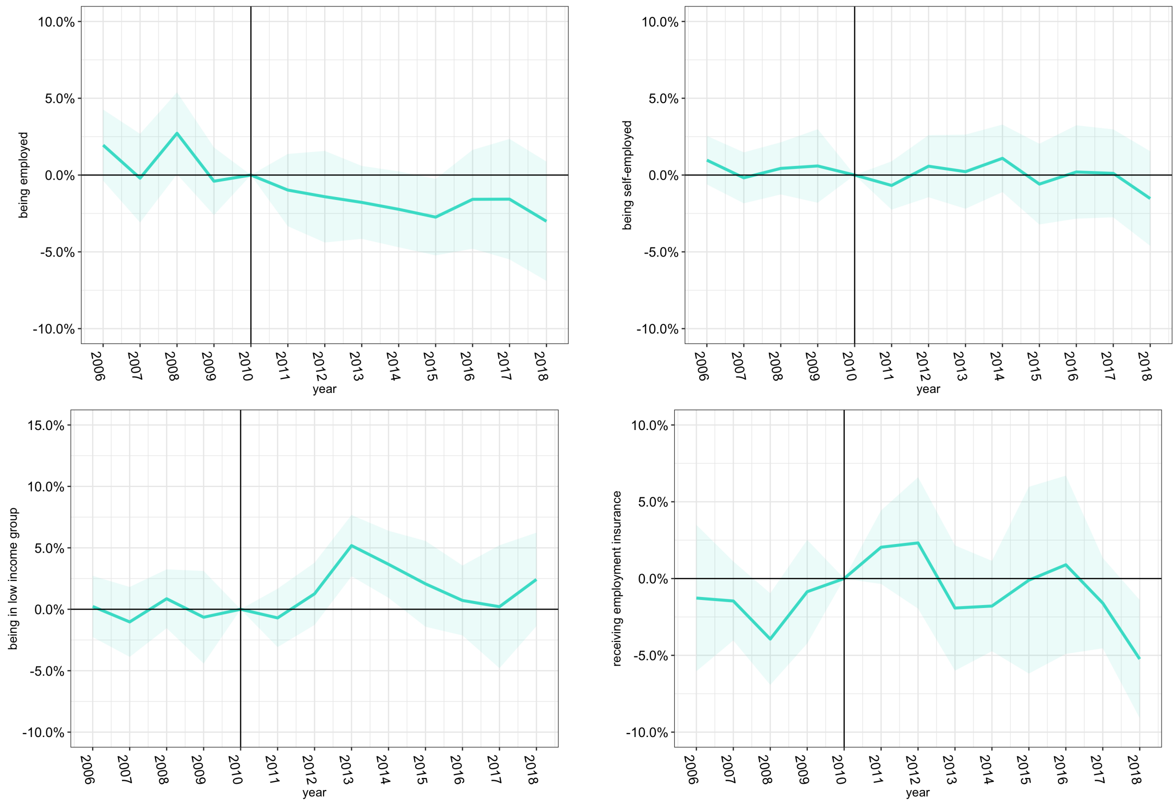
To provide further insight about the factors leading to the reduction in income estimated in Table 2-5 and Figure 2-8, we analyze the extensive and intensive margins in the labour market. To highlight the extensive margin effect, ie the movements in and out of the labour market, we estimate the effect of the wildfire on employment status, self-employment status, whether an individual receives employment insurance, and whether an individual is in the low income group, using Equations (2.1) and (2.2).

Table 2-6: Estimated average effect of the Slave Lake wildfire on individuals' labour outcomes

Variables	Employed (x 100)	Self-employed (x 100)	Classified low income (x 100)	Receiving employment insurance (x 100)
Treatment	-1.40	1.20	1.56	-0.11
	(1.01)	(0.82)	(1.03)	(0.77)
Mean dependent variable, pre-event	89.25	3.67	12.79	11.07
Observations	32,773	32,773	32,756	32,773

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

Table 2-6 presents the average effect of the event on affected individual labour market outcomes over the period 2004-2018. We estimate that being exposed to the wildfire reduces the employment rate by 1.4 percentage points on average, although our estimate is not precise and we are not able to reject the null hypothesis of zero impact on employment at conventional significant levels Table 2-6 also shows that exposure to the wildfire increases the share of affected individuals in the low income group by almost 1.5 percentage points but the coefficient estimate is not statistically significant. However, we find a significant increase in the share of individuals that are in the low income group the third and fourth year after the wildfire, where the share of low income people increases by 3.9 and 3.2 percentage points, respectively (Figure 2-13). We find no evidence that this event significant affects the likelihood of receiving employment insurance or being self-employed individuals.



Notes: Each regression includes individual and year fixed effects. The standard errors are clustered at the 2010 six digit postal code level. The vertical line represents the year before the disaster happened. The light-shaded areas in each figure are 95% confidence intervals.

Figure 2-13: Estimated average effect of the Slave Lake wildfire labour outcomes in the short, medium, and long term

To highlight the labour intensive margin, we estimate the effect of the event on individuals' employment income using Equation (2.1). We restrict our sample to all individuals who are employed in every year. A direct estimation of the intensive margin is tricky because the disaster affects employment in Slave Lake but not in the control locations. The employed population is then likely to differ in Slave Lake relative to control locations, before the disaster relative to afterwards. We therefore acknowledge that this estimation raises the issues of selection bias. However, we do not find a better way to reflect the labour intensive margin.

Table 2-7 shows that affected employed individuals experience a decrease in employment income by more than $3,400 on average as a result of the wildfire. We find no significant evidence that they experience a drop in investment income. We also find no significant evidence of the disaster on government transfer for this group. This result suggests that employed affected individuals, are the ones suffering from the disaster.

Table 2-7: Estimated average intensive margin effect of the Slave Lake wildfire

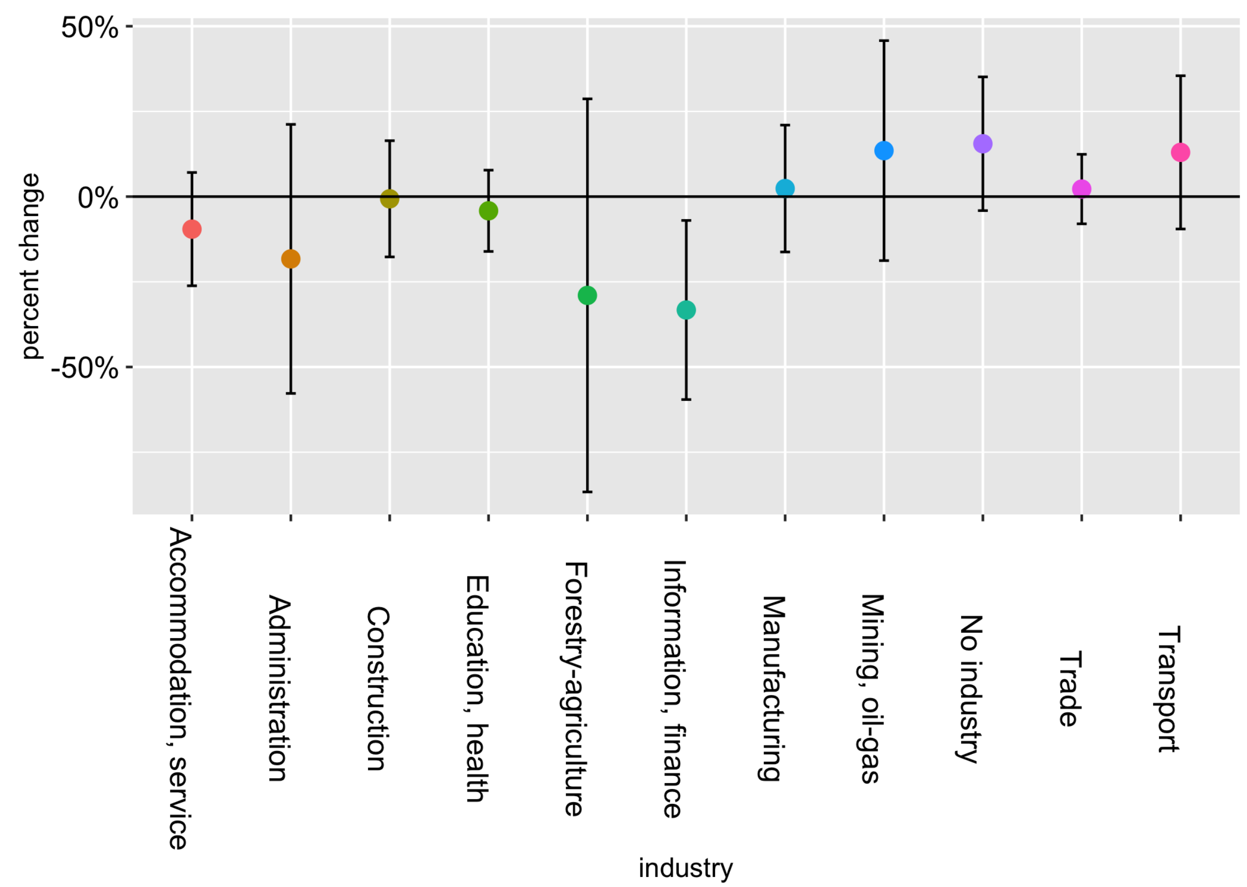
Variables	Total income	Employment income	Government transfer	Investment income
Treatment	-4,140**	-3,480**	252.1	-153.0
	(1,829)	(1,556)	(262.6)	(104.1)
Observations		28,067		

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. In this analysis, we restrict the sample to individuals employed every year over the period 2004-2018. These results do not include the year 2011.

Overall, we find that the 2011 Slave Lake wildfire has a negative but no significant effect the rate of employment while it significantly decreases affected individuals employment income conditional on being employed. Unfortunately, the LAD does not provide information on either wages and hours worked, and so while our results show that the wildfire reduce employment incomes, we are unable to determine exactly how these reductions in wages arise.

To better highlight the effect of the event on affected individuals employment, we analyze the effect of the event on employment in each industry 3-digit sector using Equation (2.1). The dependent variable in each regression is a dummy variable that takes the value of 1 if an individual is employed in a given sector in a given year and 0 otherwise. To account for the size of each industry sector, we divide the estimated coefficient by the corresponding size of each sector over the period 2004-2010. Figure 2-14 presents the effect of the event on each industry sector relative to each sector size over the period 2004-2010. We find that the event has strong negative effect on finance and information sector in Slave Lake. This sector experience a drop by more than 33%. The wildfire also have a negative but no significant effect on service-accommodation sector, education and health sector, and forestry and agriculture sector. However, other sectors, including transport sector and mining sector' are positively but not significantly affected by the wildfire. This results is in line with our finding in Table 2-13 where we find a non-significant decrease in employment among the affected individuals. [31]

[31] The decrease in information and finance sector does not seem to be big enough to significantly affect the overall employment rate in Slave Lake.



Each regression includes individual and year fixed effects. The standard errors are clustered at the 2010 six digit postal code level. We also plot the upper and lower bound associated to each coefficient at the 5% significant level. These results do not include the year 2011.

Figure 2-14: Estimated average effect of the Slave Lake wildfire on employment by industry sector.

Figure 2-14 shows how the wildfire affected the propensity of individuals to be employed in different sectors, and illustrated that the wildfire changed the sectoral composition of employment in Slave Lake. In order to determine how these sectoral impacts affected incomes for individuals, we analyze the employment income conditional of being in a given industry in 2010 using (2.3) below.

$$y_{imt} = \sum_{d=1}^{11} \theta_d D_{mt} \times industry_d^{2010} + \gamma_i + \omega_t + \epsilon_{imt} \tag{2.3}$$

Table 2-8 shows that, conditional on being employed in the forestry or agriculture sector in 2010 (before the wildfire), employment income fell for exposed individuals by more than \$47,000. This dramatic reduction in employment income shows that the impact of the wildfire is highly concentrated in sectors that are directly exposed to the fire. We also find that individuals in Slave Lake who were employed in administration sector and with no industry in 2010, experience an employment income decrease by respectively $13,000 and $6,000.[32]

Table 2-8: Estimated average effect of the Slave Lake wildfire on employment income by 2010 industry

Variables	Employment income
Treatment * no industry in 2010	-6,232***
	(1,574)
Treatment * forestry-agriculture in 2010	-47,041***
	(1,045)
Treatment * oil, gas in 2010	-7,902*
	(4,060)
Treatment * construction in 2010	3,177
	(4,750)
Treatment * manufacturing in 2010	3,212
	(6,786)
Treatment * trade in 2010	-250.5
	(3,807)
Treatment * transportation in 2010	-6,520
	(4,271)
Treatment * information, finance in 2010	643.8
	(2,902)
Treatment * administration in 2010	-13,458***
	(2,219)
Treatment * education, health in 2010	-4,370
	(2,972)
Treatment * accommodation in 2010	-3,407
Observations	32,773

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

[32] Almost 75% of individuals, in no industry group, are not employed or self-employed. The other 25% of individuals are either employed or self-employed but their industry sector is unknown or not reported.

2.4.3 Additional results

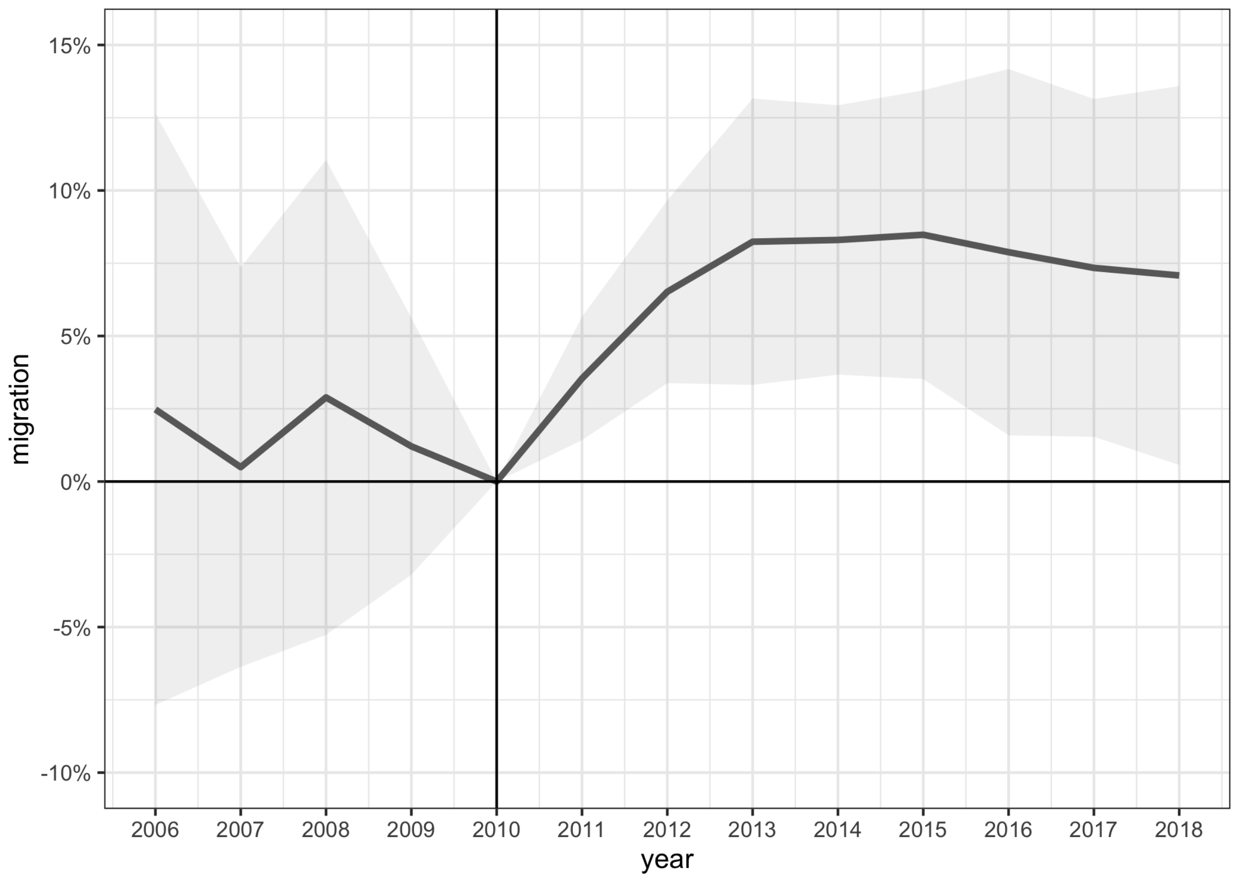
In this section, we first analyze the effect of the wildfire on individuals' migration. Second, we estimate the event effect of individuals non-monetary outcomes.[33] Third, we analyze the effect of the event of individuals' incomes by age group. Finally, we estimate the effect of the event on individuals' incomes by gender.

Migration

We begin by estimating how the wildfire affected individuals' out-migration from Slave Lake compared to the matched control group as in previous papers (Strobl, 2011; Deryugina et al., 2018).[34] We then estimate the effect of the event on migration using Equation (2.2).

[33]We are interested in the long run impact of individuals' well-being which includes both economic and non-economic outcomes.

[34]We recall that migration is defined as a dummy variable that takes the value 1 if an individual's municipality at time t is different from her residence municipality in 2010 and 0 otherwise. Note that the migration definition covers the period 2004-2018 which allows us to check for pre-trend.



This regression includes individual and year fixed effects. The standard errors are clustered at the 2010 six digit postal code level. The vertical line represents the year before the disaster happened. The light-shaded areas in each figure are 95% confidence intervals.

Figure 2-15: Estimated average effect of the Slave Lake wildfire on migration.

We find an increase in affected individual migration patterns after the wildfire compared to the matched control group. In Figure 2-15, we observe an increase in affected individual migration right after the disaster until the fifth year from 3.5 to 8.5 percentage points. Starting the sixth year, we see a slight decline in the migration rate. Overall, this represents an average increase in migration by 6 percentage points among the affected individuals compared to the matched control group. This result is in line with Statistics Canada census profile showing a decrease in Slave Lake population change between 2011 and 2016 by 1.9% while the rest of Alberta was experiencing an increase in population change by 11.6%.[35]

[35] https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/index.cfm?Lang=E

Non-monetary outcomes

We now estimate the effect of the event on other non-monetary outcomes, including marital status, the number of new kid, and the number people claiming medical expenses as a deduction, using (2.1). Table 2-9 shows that the event increases the number of affected individuals claiming medical expenses by almost 2.1 percentage points. We also find a decrease in the number of new kid by 1.9 percentage points due to this event. We also find a reduction in the number of affected individuals contributing to their saving plan by more than 4.6 percentage points compared to the matched control group. Finally, our result shows a slight significant decrease in the number of people newly married by 0.6% while the number of people newly divorced is unaffected.

Table 2-9: Estimated average effect of the Slave Lake wildfire on non monetary outcomes

Variables	Medical expense claim (x 100)	Newly divorced (x 100)	Newly married (x 100)	New child at home (x 100)	RRSP contributing (x 100)
Treatment	2.13**	-0.39	-0.67**	-1.89***	-4.61***
	(0.97)	(0.25)	(0.33)	(0.47)	(1.76)
Mean dependent variable, pre-event	12.37	1.16	2.48	11.89	3.04
Observations	32,773	30,720	30,720	30,720	32,773

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

Income by age and gender

In this section, we first estimate the effect of the event on outcomes by age group using the following equation:

$$y_{imt} = \sum_{age=1}^{4} \theta_{age} D_{mt} * age_i + \gamma_i + \omega_t + \epsilon_{imt} \tag{2.4}$$

We define four age groups, based on the ages of individuals immediately before the wildfire (in 2010). The first group comprises individuals below 25, the second group includes individuals between 25 to 40, the third group comprises individuals between 40 to 55 and the last group includes individuals over 55. Table 2-10 presents the effect of the wildfire on affected individuals incomes and employment status by age group. We find a decrease in employment income for individuals between 40 to 55 and over 55 at the time of the disaster by respectively more than \$12,500 and \$27,200. We also find that affected individuals over 55 experience a large decrease in the number of employed by 18.1 percentage points. We also find that the disaster decreases the self-employment income for this age group by more than \$700 on average. Our results suggest that the effects of the wildfire are particularly concentrated on older individuals, some of whom likely exited the labour market prematurely in response to the disaster. In contrast, affected individuals below 25 and between 25 and 40 experienced an increase in employment income by respectively more than \$11,600 and \$6,200. In one side, these results suggests that the 2011 event has a detrimental effect on affected individuals in the middle age especially the seniors. They suffer from both employment and employment income reduction. This might explain the large government transfer to the affected senior by more than \$5,500.

Table 2-10: Estimated effect of the Slave Lake wildfire on income and other outcomes by age group

Variables	Employment income	Employed (x 100)	Self-employment income	Self-employed (x 100)	Government transfer	Investment income	Individuals contributing to RRSP (x 100)
Treatment * below 25	11,698***	0.09	27.71	0.008	1,524***	-287.8***	0.142***
	(2,318)	(2.63)	(412.6)	(1.11)	(311.2)	(83.61)	(0.0186)
Treatment * 25-40	6,248***	1.81	-91.00	3.13***	-572.4	-213.6**	-0.00660
	(2,106)	(2.24)	(246.3)	(0.92)	(352.6)	(91.12)	(0.0230)
Treatment * 40-55	-12,469***	0.74	154.1	0.16	-1,123***	-54.61	-0.124***
	(2,295)	(1.36)	(316.3)	(1.39)	(179.2)	(103.7)	(0.0208)
Treatment * above 55	-27,280***	-18.10***	-700.1***	0.37	5,516***	-149.1	-0.228***
	(2,009)	(2.90)	(180.2)	(1.72)	(658.8)	(97.77)	(0.0179)
Mean dependent variable, pre-event	38,331	89.25	307	3.67	1,963	143	3.04
Observations	32,773	32,773	32,773	32,773	32,773	32,773	32,773

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

Second, we analyze the effect of the event on individuals by gender using (2.4) where age_i is replaced by $female_i$. Table 2-11 presents these results. We find a significant evidence that women are the ones experiencing the decrease in employment income compared to men with an average decrease of employment income by more than \$7,000. However, we find no significant effect in the number of employed women which indicate that women suffer mostly from an employment income drop. This event has led to a decrease in investment income for men by more $200 while women investment income is unaffected. We also find that both women and men are less likely to contribute to their RRSP with a 2.8 and 6.7 percentage points decrease respectively.

Table 2-11: Estimated effect of the Slave Lake wildfire on affected individuals' income and other outcomes by gender

Variables	Employment income	Employed	Self-employment	Self-employed	Government transfer	Investment income	Individuals contributing to RRSP (x 100)
Treatment * female	-7,206***	-2.81	-194.70	1.70	668.60	-83.10	-2.82**
	(1,787)	(1.85)	(172.70)	(1.12)	(413.10)	(102.30)	(1.30)
Treatment * male	1,612	0.32	96.25	0.58	93.67	-267.8***	-6.79**
	(1,627)	(1.14)	(411.6)	(1.17)	(304.9)	(92.51)	(2.65)
Mean dependent variable, pre-event	38,331	89.25	307	3.67	1,963	143	3.04
Observations				32,773			

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

2.4.4 Robustness Checks

In this section, we discuss alternative ways to evaluate the causal effect of the 2011 Slake Lake wildfire on individuals incomes. Using Figure 2-2, we define different set of control groups including individuals living between 100-300 km radius away from Slave Lake or all individuals living in similar municipalities (5,000-10,000 populations) as Slave Lake across Alberta. We also construct two additional control groups. The first consists of all the municipalities and cities in the same economic region as Slave Lake (based on the Statistics Canada definition of Economic Regions). The second group includes municipalities and cities with 5,000-50,000 individuals within 100-200 km radius from Slave Lake. Table 2-12 presents the effect of Slave Lake wildfire on individuals incomes running Equation (2.1). We consider both unmatched and matched control groups for this analysis.

Table 2-12: Average effect of the Slave Lake wildfire on affected individuals' incomes using various control groups

	(a)	(b)		(c)		(d)		(e)	
	Municipalities 5K-10K, radius 100-200 km	Municipalities 5K-10K, radius 100-300 km		Population 5K-50K, radius 100-200 km		Cities and municipalities, same economic regions		Municipalities 5K-10K, Alberta	
	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched
Total income	-3,644***	-2,820**	-2,211**	-3,353**	-3,406***	-3,115***	-2,446***	-1,663*	-1,177
	(1,301)	(1,169)	(884.5)	(1,474)	(1,284)	(1,126)	(931.3)	(1,006)	(878.1)
Employment income	-2,443	-1,548	619.6	-3,019**	-2,224	-1,740	-560.0	-898.3	1,290
	(1,565)	(1,324)	(1,078)	(1,469)	(1,544)	(1,077)	(1,067)	(1,224)	(998.8)
Self-employment income	1.566	-49.52	-10.98	-77.35	-7.467	108.2	280.7	-40.46	9.573
	(304.7)	(199.8)	(246.3)	(254.0)	(301.5)	(219.0)	(250.5)	(217.2)	(239.0)
Government transfer	478.3***	329.2**	185.8*	400.6**	454.1***	280.9**	298.2***	288.6**	73.40
	(142.5)	(134.2)	(110.9)	(178.7)	(141.3)	(109.2)	(108.0)	(135.8)	(104.1)
Investment income	-105.4	-117.1***	-172.0***	-152.1*	-101.2	-133.6***	-150.1***	-99.53***	-192.6***
	(79.65)	(42.45)	(44.44)	(87.10)	(77.83)	(32.62)	(37.98)	(33.91)	(28.17)
Observations	35,328	123,277	136,677	33,443	36,021	183,762	203,179	244,006	274,830

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

Table 2-12 presents the effect of the event on affected individuals compared to the matched and unmatched control group. We find almost similar results as in our main result Table 2-5 for columns (b), (c), and (d). Table 2-12 column (a) presents the incomes effect of the event using the unmatched control group in our main analysis. The results are in line with our main finding using the matched control group. Similarly, the results, using the unmatched control in columns (b), (c), and (d), are close to the findings with the unmatched control group in column (a).

2.5 Summary and concluding remarks

This paper investigates the economic effects of the 2011 wildfire in Slave Lake, Alberta, Canada. We find that this event reduces employment opportunity and employment income for the affected individuals. This results in a 10% drop of total income on average, compared to the pre-event average total income. We find evidence of both extensive and intensive margin effects. Our results suggest that information/finance sector suffers from an employment drop while affected individuals in agriculture/forestry sector and administration sector before the disaster, suffer from an employment income drop.

We find also that individuals aged over 55 suffer the most from this disaster. They experience the largest decrease in employment income and in employment. They also experience a drop in self-employment income. We observe women are the ones suffering the most from the decrease in employment income. We also provide a suggestive evidence that the wildfire affects individuals' health.

This study suggests that some industry sectors are somehow exposed to the negative effect of the wildfire, regardless the degree of exposure. The industries directly affected by the disaster bear the heavy cost in term of employment income drop. Given the expected increase of major natural disasters, due to climate change, governments should design a short, medium, and long term plan to support vulnerable individuals and sectors and thus improve the local labour market responses.

The non-significant effect of the disaster on employment outcomes might be explained by various types of aid provided by the provincial and federal governments and other agencies. These aid packages include the cancellation of application fees for small businesses and the interest-free loans for 24 months and up to 24 months without payments in order to help businesses establish, rebuild and/or expand, by the Agriculture Financial Services Corporation, the forgiveness of 2011 property taxes by both the municipality of Slave Lake and the government of Alberta.

This paper contributes to the literature by first analyzing the economic effects of wildfires in Canada. It discusses an important cost often excludes in published reports of natural disasters. Second, the paper presents an heterogeneous effect of the wildfire by showing that older individuals and women are particularly vulnerable to natural disasters.

There are some limitations to our analysis. First, we don't have proper data on individuals' health status which would allow us to clearly identify the health effect of the 2011 Slave Lake wildfire. Given the connectivity between individual productivity and their health status, it could highlight some channels that explaining our results. Second, our data does not provide information on wages or hours worked which limits our ability to analyze the labour intensive margins.

2.6 Appendix

2.6.1 Effect of the Slave Lake wildfire on individuals' incomes using alternative matching weights

Table 2-13: Estimated effect of the Slave Lake wildfire on affected individuals' incomes using alternative matching weights

Variables	Total income	Employment income	Self-employment income	Government transfer	Investment income
Treatment	-4,110**	-3,546**	-146.7	556.6***	-155.1*
	(1,877)	(1,551)	(276.2)	(201.0)	(81.21)
Mean dependent variable, pre-event	41,216	38,651	287	1,726	132.3
Observations			24,747		

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011.

2.6.2 Effect of the Slave Lake wildfire on individuals' incomes including the year 2011

In the section we rerun (2.1) while including the year 2011. We now find that the event reduces affected individuals total income by more than $3,400 on average which represents less than $100 difference compared to our main finding.

Table 2-14: Estimated effect of the Slave Lake wildfire on affected individuals' incomes including 2011

Variables	Total income	Employment income	Self-employment income	Government transfer	Investment income
Treatment	-3,421**	-3,032**	-73.7	372.1**	-145.5*
	(1,410)	(1,439)	(242.2)	(235.3)	(84.1)
Mean dependent variable, pre-event	41,425	38,331	307	1,963	142
Observations			35,310		

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level.

2.6.3 Effect of the Slave Lake wildfire on individuals' incomes using two way cluster

In this section, we rerun (2.1) to analyze the effect of the event on individuals' incomes using two ways cluster at the individuals and postal code level. The difference in observations between this result and Table 2-5 is explained by missing postal code information for some individuals over time. We find a similar result as in Table 2-5 even though the magnitude are different because of the change in observations. The drop in employment income due to the event is now significant at 10% level instead of 5% level as in the main result.

Table 2-15: Estimated effect of the Slave Lake wildfire on affected individuals' incomes using two way cluster

Variables	Total income	Employment income	Self-employment income	Government transfer	Investment income
Treatment	-3,315*	-3,064*	-67.8	413.4	-164.4*
	(1,871)	(1,788)	(214.7)	(260.3)	(97.3)
Mean dependent variable, pre-event	41,425	38,331	307	1,963	142
Observations			32,230		

Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the individual and the six digit postal code level. These results do not include the year 2011.

Chapter 3

The impact of voluntary energy conservation programs on environmental and economic performance

3.1 Introduction

Many countries have adopted voluntary programs to address environmental problems, such as toxic releases, water consumption, air pollution, and energy consumption. Borck & Coglianese (2009) report that the United States' Environmental Protection Agency has launched more than 100 voluntary programs, and such programs have also been created by state governments, non-governmental organizations, and industry associations, as well as by governments throughout Europe, Asia, and other continents.[1] Voluntary programs aim to improve environmental outcomes without coercive measures through encouragement, marketing, information provision, and support. The widespread adoption of voluntary environmental programs is a function of their consensual character as well as lack of compulsory requirements. The latter is important as it allows industry to avoid costly production changes that may be associated with conventional or market-based regulations. However, while the consensual character of voluntary programs has increased their appeal, there is conflicting evidence related to the effectiveness of such programs at achieving environmental goals (Borck & Coglianese, 2009; Darnall & Sides, 2008; Prakash & Potoski, 2006). In this paper, we investigate the effectiveness of a long standing and important voluntary energy conservation program in Canada focused on large energy-using firms.[2] The program is run by Natural Resources Canada (NRCAN), and supports participants in improving energy efficiency by providing information and resources to participating firms.[3] By comparing the energy intensity of participating firms before and after joining the program, we find no evidence that participation in the program affects energy intensity. Our results suggest that voluntary programs may not be adequate substitutes for mandatory regulations for improving industry environmental performance.

The Canadian Industry Program for Energy Conservation (CIPEC), operated by Natural Resources Canada, targets all large energy-using firms in Canada. The majority of large energy users targeted by the program (70-80%) are in the manufacturing sectors, and these firms are the focus of our analysis. This program offers various resources and opportunities

[1]Prominent examples of voluntary environmental programs include the US Environmental Protection Agency's 33/50 Program, launched in 1991, which encourages companies to voluntarily reduce their emissions of 17 toxic chemicals; the 2010/2015 PFOA Stewardship Program launched in 2006 which targets eight major companies to voluntarily reduce their emissions of per- and polyfluoroalkyl substances; and the European Union's Eco-Management and Audit Scheme (EMAS), launched in 1993, that aims at reducing industry energy consumption.

[2]Despite the focus on large energy-using firms, all firms, interested to join the program, are admitted.

[3]In this study, we capture firms' energy efficiency through the measures of total energy, electricity, and natural gas intensities.

to participants that are aimed at helping participating firms improve energy efficiency. For example, participating firms obtain access to energy management workshops and seminars, and are provided with access to energy-saving tools as well as technical information. CIPEC also offers financial support to eligible participants to undertake energy audits as well as to adopt energy management systems.[4] Finally, the program provides a platform (website and annual reports) where participants' energy saving commitments are recorded and made publicly available and where energy efficiency achievements are promoted. The CIPEC program also grants awards to participants that succeed in cutting energy efficiency and publicly promote recipients of these awards.

There is an extensive literature analyzing the adoption and the effectiveness of voluntary energy programs (DeCanio & Watkins, 1998; Howarth et al., 2000; Lyon & Maxwell, 2003; Price, 2005; Fleckinger & Glachant, 2011; Backlund et al., 2012; Cornelis, 2019). Analyzing the effectiveness of the Green Lights and Energy Star Office Products programs, launched in 1990 by the United States Environmental Protection Agency, Howarth et al. (2000) find that the Green Lights program has increased investments in cost-saving lightning systems while the Energy Star Office Products has improved the energy efficiency for suppliers of computers and electronic equipment. This study highlights a market failure that firms failed to exploit in absence on the program (Howarth et al., 2000) In addition of helping in the adoption of energy-efficient lighting systems in the industrial sector, the success of the Green Lights program is also explained by the characteristics of participant firms joining the program (DeCanio & Watkins, 1998). Using the Disclosure data and implementing a probit analysis, DeCanio & Watkins (1998) find that participant to the Green Lights program are likely to be big firms, to have a higher growth rate and a good performance as measure by price over earnings ratio. In a meta analysis, Cornelis (2019) analyze voluntary energy agreements in Europe in order to determine whether these programs can improve energy efficiency in industry. Considering three aspects including the context in which voluntary agreements are concluded, the design of the voluntary agreements, and the results of some long-running voluntary agreements, Cornelis (2019) finds that a voluntary program can be effective if it is ambitious enough and imposes energy commitments at the level of participant firms instead of targeting the industry sector as a whole with a general goal. In the case of the CIPEC program, the environmental goals are somewhat unclear despite the various supports provided by CIPEC to participant firms including cost-shared assistance to perform ISO 50001, industry network opportunity, and recognition through Energy Star Program. For Kotchen (2020), voluntary and information based approaches (VIBAs) can be seen as a

[4]The actual amount of financial support received by firms and the list of firms receiving financial support is confidential and was not available for this project.

solution to potential market failures such as incomplete and asymmetric information. VIBAs can be successful if they provide improved provision of information that promotes efficiency through some adjustments in product, capital, and labour markets. For an excellent review of the voluntary energy programs, please see Price (2005); Cornelis (2019).

Our study estimates the effect of the CIPEC program on manufacturing firm energy intensity and economic performance over the period 2004-2012. We conduct our analysis using firm-level data from Canada's Annual Survey of Manufacturing and Logging linked with the General Index of Financial Information, which allow us to observe firm-level energy consumption, output, and to calculate measures of productivity. Using this data, we conduct the empirical analysis in three steps.

First, we analyze the factors that explain firm participation in this program. We run a cross comparison analysis to identify firm characteristics associated with the program participation. The results suggest that participation is associated with firms with multiple establishments, exporting firms, firms that generate their own energy, firms with higher levels of energy consumption, greater total employment as well as higher levels of total production. We also find that CIPEC participation is concentrated in certain provinces as well as certain industry sectors. Our results on participation are in line with the literature, which suggests that larger firms with higher energy consumption or toxic emissions have higher propensity to participate in voluntary environmental programs (Arora & Cason, 1996; DeCanio & Watkins, 1998).

Second, we estimate the effect of the program on manufacturing firm energy intensity and economic performance as captured by total factor productivity and total output. We use information that we gather on program adoption for all firms in our sample as well as date of program adoption. We use coarsened exact matching (CEM) as proposed by (Iacus et al., 2011, 2012) to generate a sample of non-participants comparable to program participants. We then use a difference-in-difference (DID) approach with the matching weights, derived from CEM, to analyze the program effectiveness. Similar to Kube et al. (2019), our analysis relies on the assumption that the matched non-participants are comparable to the participants after conditioning on firm, year-by-province, and year-by-industry fixed effects. We find that the program has no effect on the energy intensity of participating firms on average. We also find no effect on electricity and natural gas intensities.[5] We use a similar approach to estimate whether the program has any impact on economic outcomes, including total output and total factor productivity, and find that the program does not significantly affect these economic outcomes.

[5] Electricity and natural gas consumption respectively represent 60 and 30% of manufacturing total energy consumption over the period 2004-2012.

We complement the DID analysis with an event study analysis. The estimated results suggest that participants and non-participants energy and economic outcomes trend similarly prior to adoption of the program, suggesting that non-participant outcomes may offer a good counterfactual for participants. The event study results show that the program does not significantly affect participants energy intensity or economic performance in the short, medium, or long-run.

Third, we provide additional insight into the potential effects of the program by analyzing the effect of the program on energy intensities for firms with different characteristics. We estimate firms' energy intensities by size and labour intensity. We find that small firms experience an increase in energy intensity after joining the CIPEC program, while the reverse is true for larger firms. Our results also show that the program is associated with an increase in energy intensity for labour intensive firms, whereas capital intensive firms reduce energy intensity after joining the CIPEC program.

Finally, we conduct a robustness check in which we restrict our sample to single establishments firms. This allows us to minimize any spillover effect related to the use of multi-establishments firms. We still find no statistically significant effect of the program on firm energy intensity.

Our study builds on a body of ongoing work that explores the effectiveness of voluntary environmental programs. Early studies focused on chemical releases and toxic emissions in the United States and find mixed results. Khanna & Damon (1999); Gamper-Rabindran (2006); Vidovic & Khanna (2007) study the U.S EPA's 33/50 program that aims to reduce toxic releases and pollution emissions from industrial plants. These studies use an essentially cross-sectional approach, and rely on the predicted probability of participation for each firm, to instrument firm participation. These studies find conflicting results. Gamper-Rabindran (2006); Vidovic & Khanna (2007) finds no pollution abatement due to the program while Khanna & Damon (1999) find a 28% decrease in firms' toxic release. Arimura et al. (2008) study the effect of ISO 14001 (a voluntary environmental management system) adoption on Japanese firms natural resource use, solid waste generation, and wastewater effluent. Using cross-sectional survey data, Arimura et al. (2008) instrument firm participation in the program using variables that are presumed to affect the program adoption but not directly affect firms' environmental performance. The results show that ISO14001 reduces Japanese firms natural resource use and solid waste generation.

Recent studies of voluntary environmental programs tend to leverage panel data to compare toxic releases, energy consumption, or emissions before and after a firm joins the voluntary program. In some cases, these comparisons are supplemented with a matching technique in order to draw a sample of non-participants that resembles the participants (Frondel et al., 2018; Kube et al., 2019; Clay et al., 2021). Implementing a DID estimation with matching weights, Clay et al. (2021) study the effect of Leadership in Energy and Environmental Design (LEED) on US federal building energy savings. They find no significant effect of this program on participants energy efficiency. In a study close to the present one, Kube et al. (2019) study the effect of a German voluntary program that aims to reduce firms' carbon dioxide emission intensity and energy intensity. Kube et al. (2019) compare carbon dioxide and energy intensity of participating firms using a DID approach supplemented with CEM. They find that the program slightly decreases firm emission intensity and energy intensity.

The remainder of this paper is organized as follows. Section 3.2 explains the origins and functionality of CIPEC program. Section 3.3 describes the data. Section 3.4 discusses the estimation strategy while section 3.5 describes the results. in section 6, we present the robustness checks. And finally section 3.7 concludes and discusses implications for policy.

3.2 The Canadian Industry Program for Energy Conservation

CIPEC started in 1975 in Canada in response to the global oil crisis of the 1970s. The program was the result of discussions between the Government of Canada and senior energy industry executives about plans to reduce the dependency of Canadian firms on oil. It later expanded to non-oil industries across Canada. Since the start, CIPEC has been designed to be an efficient voluntary partnership with the objective of reducing industry energy consumption and therefore enhancing their economic performance. It helps firms cut costs and become energy efficient through networking and share of on best energy efficiency practices, tools and savings opportunities.

The program is organized into three main branches including CIPEC executive board members, CIPEC task force council members, and CIPEC sector task forces. The CIPEC executive board, composed of senior executives from leading companies in energy efficiency, share experience about ways to reduce energy costs and make production operation more energy efficient. The CIPEC task force council meets regularly in order to share ideas and make recommendations about ways to reduce energy costs and greenhouse gas emissions. Finally, the CIPEC sector task forces are responsible for creating achievable goals and developing actions plans in order to improve industry energy efficiency in 21 sectors.[6] The task

[6] These sectors include aluminum, brewery, cement, chemicals, construction, dairy, electrical and electronics, electricity generation, fertilizer, food and beverage, forest products, foundry, general manufacturing, lime, mining, oil sands, petroleum products, plastics, steel, transportation equipment manufacturing, upstream oil and gas. The 21 sectors in CIPEC do not always align with the definition of sectors in North America Industry Code Sector (NAICS).

forces are formed by more than 50 trade associations and many companies that work jointly to identify needs and best practices for energy efficiency.[7]

CIPEC, which is a part of Natural Resources Canada, offers incentives to its members to undertake energy audits and other energy efficiency improvements.[8] CIPEC members can also benefit from extra sources of funding from NRCAN including a fund for industrial facility energy management system adoption, to a maximum of $40,000.[9]

CIPEC members are also eligible for other financial assistance such as process integration and computational fluid dynamics studies which target firms using a large amount of energy. This cost-sharing subsidies are in line with Segerson & Miceli (1998)'s study about the decision of firms participation into a voluntary program. Firms public image also constitutes an important factor in the decision to enter into a voluntary program as found in Arora & Cason (1995). CIPEC program also offers a public recognition to its members through different programs including the Energy Star for industry certification and CIPEC annual reports which present energy efficiency success stories, profiles innovators and innovations, and announces new programs and incentives for industry.[10]

To join the CIPEC program, firms have to send a letter to NRCAN expressing their willingness to enroll in the program and become energy efficient. The registration is quick, easy, and free. There is no need to show proof of your energy use in recent years. Participant firms commit to participate in CIPEC network activities, share energy management best practices, and improve their energy efficiency. The CIPEC program does not impose any specific goal in term of energy efficiency.[11]

[7]It is possible that information on energy efficiency practices generated by the CIPEC program could spill over from CIPEC participants to non-participants, for example through trade association networks. In this case, it would make the the program stronger and effective but at the same time, it would undermine our evaluation of the program.

[8]More than 730 cost-sharing projects were financed through the Industral Energy Audit Incentive Program.

[9]The eligible costs include salaries of internal employees for work specific to the energy management information systems (EMIS), professional, scientific, and contracting services related to the EMIS, fees for data collection, benchmarking, and analysis services, purchase of instrumentation software and metering equipment, and fees associated with training on the EMIS.https://www.nrcan.gc.ca/energy-efficiency/energy-efficiency-industry/financial-assistance-energy-efficiency-projects/20413

[10]One of the programs is called 'The Dollars to $ense Energy Management workshop series'. It provides adaptive training to workers in the participant companies. https://www.nrcan.gc.ca/energy/efficiency/industry/training-awareness/5461

[11]https://www.nrcan.gc.ca/energy-efficiency/energy-efficiency-industry/canadian-industry-program-energy/become-cipec-leader/20382

3.3 Data and methodology

In this section, we first explain how we determine which firms join the CIPEC program and in which year. We then outline the manufacturing and tax data used to investigate the effectiveness of the CIPEC program. We briefly explain how we compute the total factor productivity using the combined business-tax data. Finally, we discuss the summary statistics.

3.3.1 Participants to CIPEC program

Every year, NRCAN publishes the list of CIPEC participants for the previous year, which includes all former and new participants. This list includes the legal name of each participant and the industry in which it operates.[12] Using these information, we build a complete list of CIPEC participants over the period 2004 to 2012 that includes the year each participant joined the program. In addition to each participant's name, we also gather additional information including business number, postal code, city, and province of operation. These information are used to link CIPEC data to the confidential business data based on the Annual Survey of Manufacturing and Logging (ASML).[13] Using the information provided, Statistics Canada analysts successfully merge 70% of enterprises in the CIPEC data to the confidential business data.[14]

The identification of program participants is complicated somewhat by the fact that registration with CIPEC can be done by either a single establishment firm, by a multiple establishment firm where one or more establishments register with CIPEC, and by a multiple establishment firm where the firm itself registers with CIPEC. Given the complexity about multi-establishments firms participation to CIPEC program and the need to account for spillover, we conduct this study at the firm level as in Kube et al. (2019). The analysis at the firm level is also supported by the availability of capital stock information at the firm level as explained below in Section 3.3.3. Specifically, this means that in the case of a multi-establishments firm, even if only one of the many establishments participates in CIPEC, all

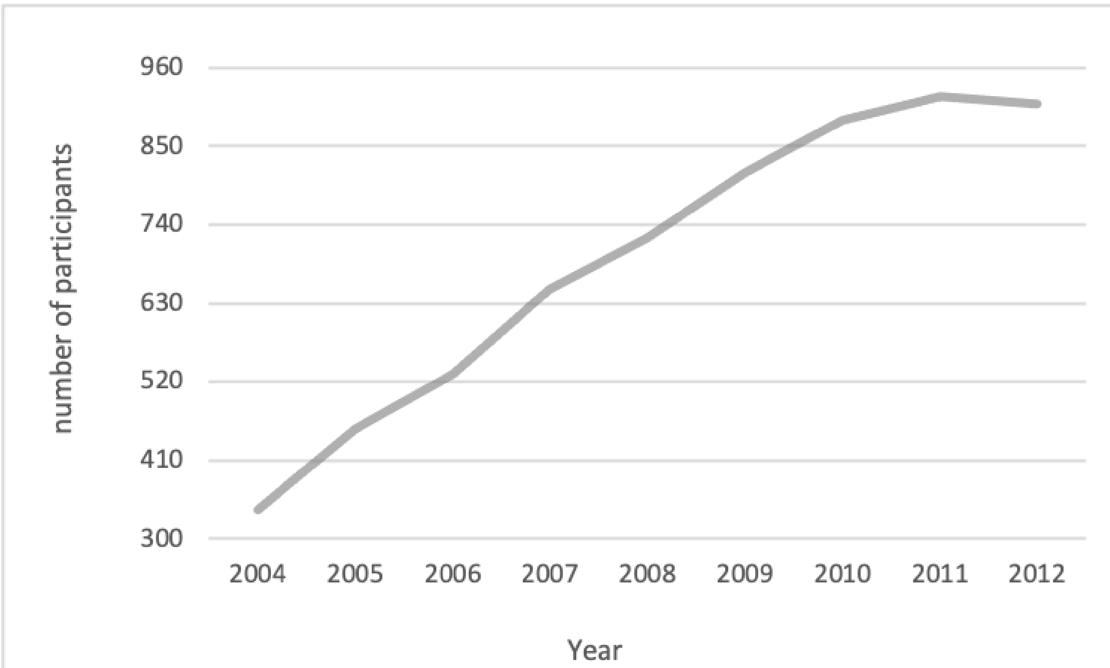
[12] More information on NRCAN publication can be found through the following link: https://www.nrcan.gc.ca/energy-efficiency/energy-efficiency-industry/canadian-industry-program-energy-conservation-cipec/20341

[13] The linkage between our external data and the confidential data is done by Statistics Canada analysts for confidentiality reasons.

[14] The list we provided to Statistics Canada includes manufacturing sectors and other industry sectors. Firms self-declared their industry when joining the program which might be different from the industry classification they operate in under Statistics Canada business registry. The 70% matching rate may indicates that almost all the firms in the manufacturing sector are successfully matched to the ASML data. A 70% matching rate between external data and Statistics Canada business data represents a high matching rate according to Statistics Canada analysts based on previous experience about record linkage.

other establishments of the firm will also be considered participants.[15] As in Kube et al. (2019), doing so allows us to account for any spillover effects across establishments.

Figure 3-1 presents the number of firms that participate in CIPEC during our sample period.[16] This figure shows that the program experienced steady growth over this period. In the empirical section of the paper, we both explore the variables that help to explain participation in CIPEC as well as use the gradual roll-out of the program to understand the impact of the program on firm-level outcomes.



This figure presents firms' registration in CIPEC program from 2004-2012 using the unmatched sample. The program started with almost 340 members and reach out a maximum of almost 919 members in 2011. 570 members joined since 2004.

Figure 3-1: Participants in the CIPEC program over the period 2004-2012

3.3.2 Annual Survey of Manufacturing

We use the longitudinal file collected annually by Statistics Canada on the operation of manufacturing establishments in Canada. It is a survey called Annual Survey of Manufacturing and Logging (ASML), and covers the universe of manufacturing establishments in Canada and provides information on total energy consumption and its components, total production,

[15] A firm can have many establishments operating in different sectors and different provinces. An establishment is a firm if it does not have any parent firm.

[16] During our discussions with the team at NRCAN in charge of CIPEC, we learned that firms entering into this program do not leave it unless they exit from the market. We only observe exit firm if a given firm leave the market. We cannot tell whether a firm actively participates or not in the program.

total employment and its components, total export, and other variables over the period 2004 to 2012.[17]

The ASML provides information on the industry in which each establishment operates as well as some geographical information including province and census-subdivision (CSD).[18] Importantly, ASML data contain a unique firm identifier which allows us to follow each firm over time. The majority manufacturing firms operates in Ontario and Quebec, accounting for almost 65% of the total sample.[19]

ASM does not collect information on manufacturing capital stock, which is important in estimating firm total factor productivity (TFP). To overcome this issue, ASML data have been merged to firms' annual financial statement called General Index of Financial Information (GIFI) which provides information on capital assets.

3.3.3 General Index of Financial Information

The GIFI is an extensive compilation of firms' financial statement items collected by Canada Revenue Agency (CRA). Since 2000, all corporations are required to prepare their financial statement information using the GIFI codes which allows information to be comparable across firms and over the years. The GIFI provides detailed information about the assets and liabilities of Canadian companies, including capital leases, accumulated amortization, and tangible capital assets.

For tax purpose, the CRA uses the term firm for both single and multiple business number (BN) firms. A single BN firm is equivalent to an establishment in the ASM while a multiple BNs firm would be a group of establishments operating under one ownership that produces

[17] Statistics Canada collects confidential data on manufacturing activities across Canada. This dataset contains the universe of establishments from 2000-2012. However, due to changes in the data collection, we restrict our sample to the period 2004-2012. From 2000 to 2003, Statistics Canada sent out a questionnaire to all establishments in Canada. Starting in 2004, ASML was redesigned to reduce respondent burden on very small establishments. In 2004, Statistics Canada decided to drop the bottom 10% of plants of each industry by geographical area from the survey. As a consequence, we observe a spike in the death or exit of firms in 2004 which in principle in not the case. In 2007, Statistics Canada realized that in some geographical areas the bottom 10% include both small, medium, and large establishments and decided to use Canada Revenue Agency information (administrative data) to fill that gap. Given the complexity of the business register, they were not successful at retracing back all the missing establishments. We keep the period 2004-2012 for our analysis as in Najjar & Cherniwchan (2021); Kabore & Rivers (2020); Yamazaki (2017). For more information on ASML data, see: http://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getInstanceList&Id=504733

[18] A CSD is a general term for municipalities or areas treated as municipal equivalents for statistical purposes. More information on CSDs can be found at https://www.statcan.gc.ca/eng/statistical-programs/document/1105_D16_T9_V1

[19] This result is in line with the table 36-10-0222-01 produced by Statistics Canada where Ontario and Quebec respectively represented 37.3% and 19.4% of Canada GDP in 2012.

one financial statement for all its establishments.[20] As mentioned above, this is one of the reasons we conduct this analysis at the firm level, since it allows us to avoid splitting the capital stock among multiple establishments' firm arbitrarily. The GIFI data is merged to the business data at the firm and year level.

3.3.4 Total factor productivity

We estimate the firm total factor productivity (TFP) using Ackerberg–Caves–Frazer (ACF) method (Ackerberg et al., 2015). This method has the advantage to account for both reverse causality compared to Cobb-Douglas TFP estimation. A key challenge associated with the production function estimation comes from the fact that inputs and output are simultaneously chosen by the firms Marschak & Andrews (1944). This simultaneity problem results in inputs being correlated with unobserved productivity, leading to inconsistency of the production function estimates using least squares. To overcome this issue, Olley & Pakes (1996); Levinsohn & Petrin (2003) suggest a control function approach to address this simultaneity problem. This consists to use a proxy variable such as firm-level investment or intermediate input, which is strictly increasing in the unobserved productivity, conditioned on the state variable such as capital input.

However, ACF find a functional dependence problem in the first stage of the LP procedure that regresses output on labor input and the nonparametric function of other inputs. This functional dependence may result in a fundamental non identification problem. They then propose inverting the input demand function that is conditional on state variables, including labor input as well, and provide extensive simulation evidence to support their procedure. We use the ACF method to estimate firm productivity in each industry 3-digit level. This complies with the literature that shows that firms within the same industry share similar characteristics, knowledge bases and therefore tend to pursue the same types of innovation strategies (Malerba & Orsenigo, 1996; Breschi et al., 2000).

3.3.5 Summary statistics

We restrict our sample to firms with total annual energy consumption of at least \$100,000 and a total annual production of least \$1,000,000.[21] This leads us to drop 25 CIPEC participants and 24,000 non-participants from our sample (as we show subsequently, CIPEC participants

[20] In order to reduce the financial statement burden, CRA allows multiple BNs firm to fill one financial statement which sum up all its establishments' financial information.

[21] CIPEC targets large firms with large energy consumption. The data restriction allows us to remove very small firms overrepresented in the control group.

are on average much larger than non-participants). We define the industry of each firm as the industry classification in the first year in which they appear in our data.

Energy intensity is defined as total energy consumption in dollars divided by total output in dollars. Electricity intensity and natural gas intensity are defined in a similar manner. We define a categorical variable to capture firm size as follows: small firms are those with total employees less than 50, medium firms are those with total employees between 50 and 249, and large firms are those with total employees greater or equal to 250.

Our final unbalanced matched sample has more than 7,000 firms where CIPEC participants represents almost 7% of firms. In total, we observe 38,345 firm-year observations. In Table 3-1, we find that, on average, CIPEC participants have higher energy consumption, total employment, total productivity, and total production compared to non-participants. It also shows that 5% of CIPEC participants generate their own energy while the proportion decreases to 1% for non-participants. A large number of participants are large firms (32%) compared to non-participants (6%).

Table 3-1: Summary Statistics for participants and non-participants in CIPEC program over the period 2004-2012.

Variables	All		Participants		Non-participants	
	Mean	Sd	Mean	Sd	Mean	Sd
Total energy ($, in million)	0.68	(2.49)	2.07	(5.74)	0.53	(1.78)
Energy intensity						
$ of energy expenditure	0.03	(0.03)	0.03	(0.03)	0.03	(0.03)
per $ of output						
Electricity intensity						
$ of electricity expenditure	0.02	(0.02)	0.02	(0.02)	0.02	(0.02)
per $ of output						
Natural gas intensity						
$ of natural gas expenditure	0.01	(0.02)	0.01	(0.02)	0.01	(0.02)
per $ of output						
Generating own energy	0.01	(0.1)	0.05	(0.21)	0.01	(0.08)
Multi-establishments firms	0.16	(0.37)	0.39	(0.49)	0.13	(0.34)
Total production ($, in million)	31.2	(137)	98.7	(400)	24.2	(59.4)
Total employment						
(full-time	117.14	(323.19)	297.26	(864.12)	98.3	(183.16)
equivalent workers)						
Capital stock ($, in million)	28.2	(262)	107	(531)	19.9	(214)
Total productivity						
(million, units of output	0.70	(1.15)	0.84	(1.45)	0.68	(1.11)
per unit of input)						
Exporter	0.75	(0.43)	0.84	(0.37)	0.74	(0.44)
Small firms	0.41	(0.49)	0.15	(0.35)	0.43	(0.50)
Medium firms	0.50	(0.50)	0.53	(0.50)	0.50	(0.50)
Large firms	0.09	(0.29)	0.32	(0.47)	0.07	(0.25)
Observations	38,345		3,631		34,714	
Firms	7,280		495		6,785	

Notes: The unit of observation is firm-year. All the moneraty values are in current dollar. This sample represents firms with output greater or equal $1 million CAD and total energy consumption greater or equal than $100,000 CAD. All monetary units are in current CAD.

3.4 Empirical Approach

In this section, we first analyze the characteristics of firms participating to CIPEC program. Using these information, we discuss the matching strategy. Finally, we describe the empirical strategy used to estimate the effect of the program on firm-level outcomes.

3.4.1 Reason for participation

We start by analyzing the type of firms that participate in this program and the reason they expect a net positive benefit from participation. We use the restricted unmatched sample in order to implement this analysis. Previous papers found that firms participate in voluntary programs for two main reasons including internal firm motivation and regulatory incentives (Neugebauer, 2012; Frondel et al., 2004) Other important characteristics contributing to firms' decision to enter voluntary program, are the firm size (reflecting capacity to participate) and the firm financial characteristics as mentioned in (Gamper-Rabindran, 2006; Bracke et al., 2008). We use a least squares estimation to determine the observables firm characteristics explaining CIPEC adoption. This is a cross-sectional analysis where we compare a firm to other firms on the likelihood to adopt CIPEC program.[22]

$$CIPEC_{it} = \alpha + X_{it}\beta_1 + \epsilon_{it} \tag{3.1}$$

where $CIPEC_{it}$ is a binary variable indicating firm i's participation status at time t. X_{it} is a set of covariates including total energy consumption, total output, total employment, capital stock, total productivity, indicator for multi-establishment firm, indicator for firm generating own energy, exporter status, province of operation, and industry sectors.[23] The use of these variables is explained by the difference in mean between participants and non-participants as shown in Table 3-1 as well as past research on the determinants of participation in voluntary programs (Anton et al., 2004; Richter & Schiersch, 2017). We use the inverse hyperbolic sine transformation (IHS) on all continuous variables, because it accommodates the presence of zeroes.[24]

[22] In this specification, we look at the contemporaneous relationship given that participation to the program is free, quick, and easy. However, it is worth analyzing the program adoption with lagged variables which I intend to do in future work.

[23] Due to low number of observations in some industry sectors, we cannot present the information at the industry level.

[24] Bellemare & Wichman (2020) showed that IHS transformation better accounts for 0 or negative values than logarithm transformation. While we use the IHS transformation throughout the analysis, our results are virtually unchanged when we instead use a log transformation.

Table 3-2: Correlates of firm participation in CIPEC program

Variables	Treatment
ihs (total energy)	0.0195***
	(0.00160)
ihs (total output)	0.0127***
	(0.00216)
ihs (capital stock)	-0.000255***
	(7.48e-05)
ihs (total employment)	0.00111
	(0.00235)
ihs (total productivity)	0.000222
	(0.000792)
Exporter	0.00173
	(0.00211)
Generating own energy	0.0153***
	(0.00525)
Multi-establishments firms	0.0106***
	(0.00326)
Newfoundland and Labrador	0.00371
	(0.0166)
Prince Edward Island	0.0218
	(0.0241)
Nova Scotia	0.0251**
	(0.0108)
New Brunswick	0.0316***
	(0.0108)
Quebec	-0.00122
	(0.00343)
Manitoba	-0.0201**
	(0.00873)
Saskatchewan	-0.00443
	(0.0105)
Alberta	-0.0217***
	(0.00514)
British Columbia	-0.0116**
	(0.00469)
Observations	48,258
Firms	9,034

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3-2 shows firm characteristics that contribute to explain program adoption using the unmatched sample. We find that energy consumption, total output, capital stock, multi-establishments firms, generating own energy, provinces and industry of operation, affect firms likelihood to join the program. A one log-point increase of energy consumption or total output leads to respectively a 2 and 1.2% increase in the likelihood of CIPEC adoption. We find no significant evidence that firm productivity affects the program adoption.[25] Generating its own energy or being a multi-establishments firm increases participation in the program by respectively 9 and 1.1 percentage point. We find a weak evidence that firms with higher total employment are less likely to participate in this program. Compared to Ontario, firms in Nova Scotia and New-Brunswick are more likely to adopt this program while firms in Manitoba, Alberta, and British Columbia are less likely to participate in this program.

3.4.2 Estimation effects of CIPEC program in firms' energy and economic outcomes

We identify the effect of CIPEC by comparing a firm that joins CIPEC with other firms that are similar and don't join the program. We therefore run Equations (3.2) and (3.3) using the matching weights.[26]

$$y_{it} = \beta_2 CIPEC_{it} + \gamma_i + \psi_{dt} + \zeta_{pt} + \epsilon_{it} \tag{3.2}$$

Where y_{it} represents the outcomes of firm i at time t. For this analysis we consider the energy outcomes including total energy, energy intensity, electricity intensity, natural gas intensity, total output and total factor productivity.[27] $CIPEC_{it}$ is a dummy variable that takes the value 1 for all years after a firm i joins the program at time t and 0 otherwise. γ_i is the firm fixed effect which captures the average outcome for each firm. ζ_{pt} is a province-by-

[25]It could be that productive firms are maximizing their production while being energy-efficient. In this case, there is no incentive for these firms to join the voluntary program since there is no room for energy improvements. One can imagine that for firms operating below an energy-efficient curve, CIPEC program, through the information provision and other supports, can help improve their energy use while maximizing their production.

[26]In the appendix, we also analyze the effect of CIPEC program on firms' outcomes without matching weights using equations (3.2) and (3.3).

[27]A rational firm will join a voluntary program if the potential benefit of joining exceeds the potential cost. The benefits of participation include strengthened customer loyalty and enhanced firm image, and productivity improvement through process innovation and the stimulation of staff morale (Hui et al., 2001; Nishitani, 2011). For Nishitani (2011), environmental pro-active firms mostly focus on how much the program will benefit them than how much it would cost them. This highlights the fact that voluntary agreement might be able to simultaneously improve both environmental performance and business benefits. It is then worth asking whether energy conservation program affect firms' activities because additional investments are required in order to achieve the objective of the energy program.

year fixed effect. It accounts for annual shocks common to firms of a given province such as economic policy and energy prices. ψ_{dt} is the three digit industry sector-by-year fixed effect and it controls for annual shocks common to each industrial sector, such as input and output prices and technology change. Finally, ϵ_{it} is the error term. The error term may be spatially correlated if there are common unobserved shocks that vary over space and may be serially correlated within a given firm over time. We two-way cluster the error terms at the firm and province-year level to address potential spatial and serial correlation in the error terms.

We also supplement the DID estimation by running an event study analysis as in Equation (3.3). The event-study describes the effect of the program on outcomes in the short, medium, and long-term. It also allows the comparison of pretrend between the participants and non-participants.

$$y_{it} = \sum_{j<=-5, j\neq -1}^{8} \theta_j CIPEC_{it}^{j} + \gamma_i + \psi_{dt} + \zeta_{pt} + \epsilon_{it} \tag{3.3}$$

$CIPEC_{it}^{j}$ is a set of indicators denoting whether a firm i is a CIPEC participant at time $t = j$. Firms enter into this program at different years, so we treat the first year of entering as year 0. We then create lag and lead terms for years before and after joining the program. In our specification, we omit the period $j = -1$ from the regression as that year corresponds to the year before each participant joins the program.

3.5 Results

This section describes our main results. We first start by describing the matching technique used to build a sample of non-participants comparable to the participants. Second, we present the matching-DID and matching-event study results. Third, we explore some heterogeneous effects of CIPEC program by considering firms' size and labour intensity. Finally, we run a robustness analysis to check our main finding.

3.5.1 Matching covariates

In order to account for the difference in mean (Table 3-1) and the factors explaining the program adoption (Table 3-2), we implement a matching strategy using the CEM approach as proposed by (Iacus et al., 2011, 2012). This consists of building a sample of non-participants, using the pre-participation information, that are similar to the participants on observable characteristics. We start by selecting a limited number of covariates to match on, which from our analysis in Section 3.4.1 is believed to affect affect firms' participation to the program. CEM method divides each variable into bins where each observation in the group of participants gets a weight of one and each observation in the group of non-participants get varying weights as explained further below.[28] These weights are then used in the regression analysis. Despite the name Coarsened Exact Matching, CEM is a hybrid between matching and reweighting methods (Black et al., 2020).

Table 3-1 shows that participants firms and non-participants are different in mean while Table 3-2 highlights some characteristics that significantly explain the CIPEC adoption. Therefore, a simple comparison of participants and non-participants will bias the estimated results. Before estimating the effectiveness of the program, we implement a matching strategy that aims to construct a sample of non-participants that resembles the participants on several dimensions ("significant covariates") using the CEM approach as proposed by Iacus et al. (2011, 2012).[29] First, we select the significant covariates explaining the program adoption, as the matching dimensions. We find that total output, total energy, generating own energy, multi-establishment firms, province and industry of operation significantly explain participation into the program. For continuous variables, such as total output and total energy, we define four bins where the size of each bin is $150 million for total output and $50 million for energy consumption. CEM method divides each variable into bins where each observation in the group of participants gets a weight of one and each observation in the group of non-participants get varying weights get varying weights as explained further below. These weights are then used in the regression analysis. Despite the name Coarsened Exact Matching, CEM is a hybrid between matching and reweighting methods (Iacus et al., 2011, 2012). Second, for each participant firm and each dimension, we assign the value of the period $Ti-1$ for each $T >= Ti$ where T represents the time and Ti the entry time to the program.[30] Third, we run the CEM technique which match non-participants to participants based on the specified dimensions for each year over the period 2004-2012. The matching result (Table 3-3) shows that more than 26.8% of observations in the non-participants group cannot be matched while 17.1% of observations in the participants group cannot be

[28] CEM is found to yield strong balance in covariates and lower root mean square error than existing matching techniques (Iacus et al., 2011, 2012).

[29] The matching procedure drops all participant firms with no pre-participation information. We therefore lose 340 firms as shown in Figure 3-1.

[30] The procedure prevents us to match on firms post-participation outcomes or characteristics.

matched.[31][32]

Table 3-3: Matching observations among the group of participants and non-participants

	Observations in non-participants group	Observations in participants group
All	47,886	4,407
Matched	35,023	3,649
Unmatched	12,863	758

3.5.2 Main results

Table 3-4 presents the effect of the program on firm outcomes using (3.2) and the matching weights. The results show that the program does not significantly affect firms electricity intensity and natural gas intensity. Likewise, total energy intensity is unaffected by the program. At a 5% significance level, the estimated confidence interval for firm energy intensity is between -0.15 and 0.32% which indicates that there is zero effect of the program on firms' energy intensity. Given that this program aims at improving firms energy intensity, our results suggest no impact of the program on manufacturing firm energy intensity.[33]

It is therefore not surprising that we find no significant effect of this program on firms total energy consumption with an estimate coefficient between -6.3 and 4% at 5% significant level. We also find that this program has no significant effect on firms' TFP with an estimated coefficient between -7.7 and 3.4% at 5% significance level. As expected, firms total output

[31] In presence of small sample, Black et al. (2020) find that CEM may substantially reduce observations which in turn may affect the average treatment effect.

[32] As explained in (Iacus et al., 2012), after coarsening, the CEM algorithm creates a set of strata where units that have at least one treated and one control unit are retained and the other units are drop from the sample. Therefore, to each matched unit i in a given stratum s, CEM assigns weights as follows:

$$w_i = \begin{cases} 1, i \in T^s \\ \frac{m_C}{m_T}\frac{m_{T^s}}{m_{C^s}}, i \in C^s \end{cases}$$

Where T^s is the number of treated units in the stratum and C^s the number of control units in the stratum. m_T and m_s respectively represent the number of matched and control units in the sample. The unmatched units are assigned a weight (w_i) of zero. The use of weights in the regression analysis facilitates the estimation of the average treatment effect on the treated in a weighted least squares regression program. For more information, see https://docs.google.com/document/d/1xQwyLt_6EXdNpA685LjmhjO2Oy5pZDZYwe2qeNoI5dE/edit

[33] CIPEC is the major energy conservation program at the federal level. We are not aware of another energy program at the federal level. The province of Alberta, for example, has its program called Sector-Specific Industrial Energy Efficiency Grant Program for emissions-intensive and trade-exposed facilities. However, the public available information does not allow us to identify participant firms to this program. In our estimation, we control for the province-year fixed effect which would pick-up any province specific program. Similarly, any federal industry program would be picked up by the industry-year fixed effects.

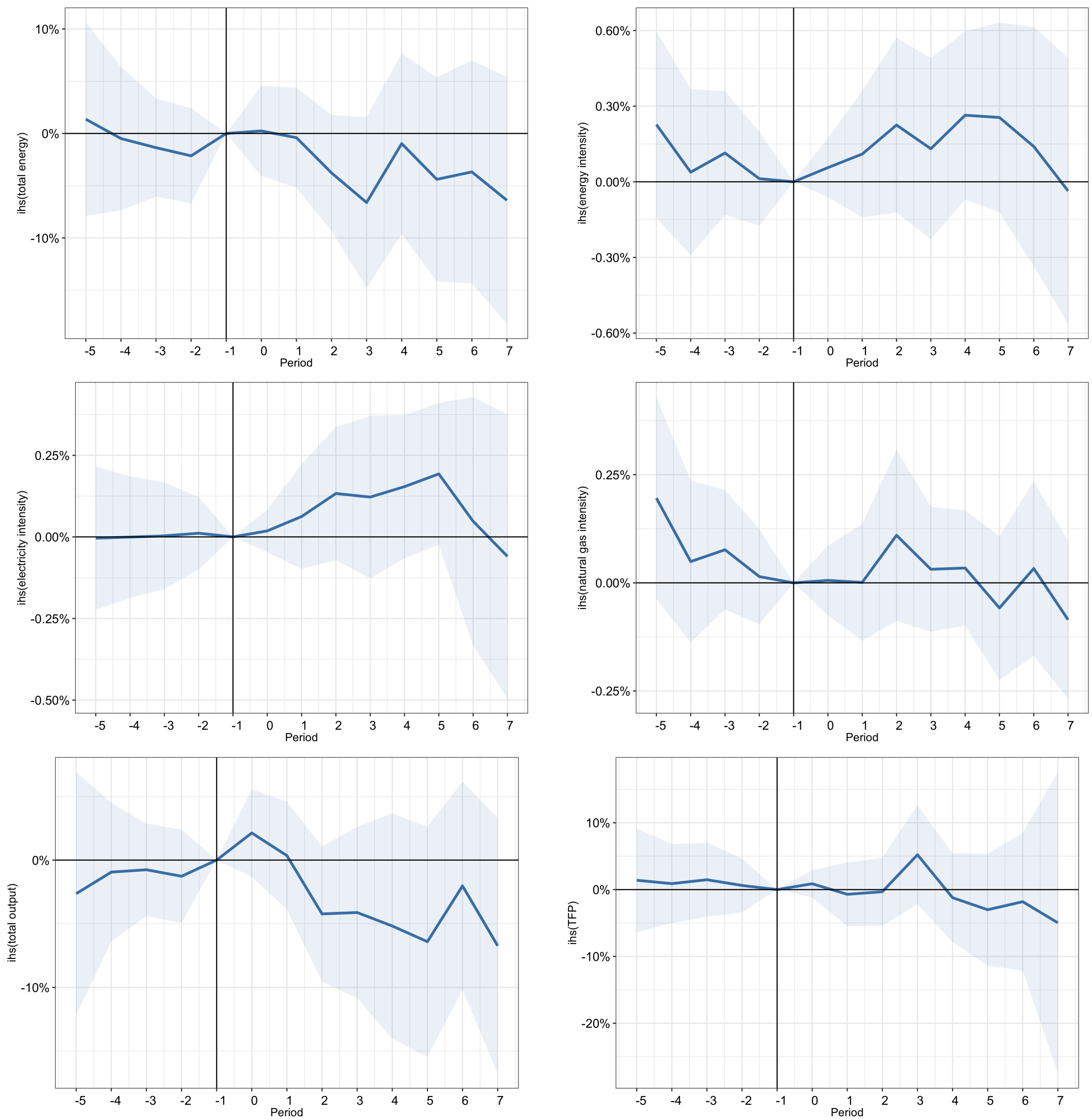
is unaffected by this program at 5% significance level.

Table 3-4: Effect of CIPEC on firms' outcomes using matching weights

Variables	Total energy (x 100)	Energy intensity (x 100)	Electricity intensity (x 100)	Natural gas intensity (x 100)	Total output (x 100)	Total productivity (x 100)
CIPEC	-1.19	0.088	0.078	-0.013	0.204	-2.15
	(2.63)	(0.120)	(0.068)	(0.073)	(2.38)	(2.85)
Observations	38,345	38,345	38,345	38,345	38,345	36,707

Notes: Each regression includes firm, province-year, and industry-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and province-year levels. The difference in samples between Tables 3-3 and 3-4 is explained by the DID analysis which drops singletons from the analysis.

We now expand the result of Table 3-4 over time using (3.3). Figure 3-8 presents the effect of the program on firms' outcomes over the period 2004-2012. We find no statistically significant pretrend for all the variables of interest which indicates that the treated and the matched control group are likely comparable on both the observable and unobservable factors. In the short-term (i.e., the first two years after the joining the program), the results show no significant effect of the program on total energy intensity, electricity intensity, and natural gas intensity. As a result, total energy is also unaffected by the program in the short-term. We do not find a significant evidence that firms economic activity, as represented by TFP and total output, is affected in the short term. In the medium (second and third year after joining the program), we find that the program has no significant effect on energy intensity, electricity intensity and natural gas intensity, This relates to the result suggesting a negative but not significant effect of the program on firm total energy consumption. Similarly, we find no significant effect of the program on firms TFP and total output. In the long-term (fourth year and more in the program), we also find that electricity intensity and natural gas intensity remain unaffected by the program. Therefore, the program has a negative but not significant effect on firm total energy. The participants firms economic activity is also unaffected by the program. We find almost a null effect of the program on firms TFP. Given this finding, we also find that the program has no significant effect on firm total output.



Notes: Each regression includes firm, province-year, and industry-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and province-year levels. The vertical line represents the year $(t-1)$ before the participants firms join the program. We also plot the upper and lower bound associated to each coefficient at the 5% significant level.

Figure 3-8: Effect of CIPEC on firms outcomes over time using matching weights

3.5.3 Labour intensity

In this section, we analyze the effect of CIPEC program on firms energy consumption by differentiating between labour versus capital intensive firms. There is some evidence that capital and energy are substitutes in the industry sectors and so we might expect distinct responses to CIPEC by capital-intensive firms relative to labour-intensive firms (Koetse et al., 2008; Costantini et al., 2019). We use two measures of labour intensity to split the sample into capital-intensive vs. labour-intensive firms: the first measure is labour expense over total output and the second measure is total employment over total sales. A firm is considered labour intensive when its share is above the median labor share in a given industry sector.[34] We then run Equation (3.4) below to analyze the heterogeneous effect of CIPEC program.

$$y_{it} = \beta_1 CIPEC_{it} + \beta_1 CIPEC_{it} \times \textit{labour intensive}_i + \gamma_i + \psi_{dt} + \zeta_{pt} + \epsilon_{it} \tag{3.4}$$

where *labour intensive*$_i$ is dummy variable taking the value of 1 when a firm i is labour intensive and 0 otherwise. Y represents the firm total energy, electricity and natural gas intensities.

Table 3-5 presents the effect of CIPEC program on firms' energy intensity and its components. The estimated results suggest that the program has no significant effect on capital intensive firm electricity and natural gas intensities. Therefore, the total energy intensity of capital intensive firm is unaffected. However, we find some significant evidence of an increase in electricity intensity for labour intensive firms which in return affects the energy intensity. This means that for labour intensive firms, the quantity of electricity required per unit output increases by almost 0.42% following the program adoption.

[34] We consider all years in the definition of labour intensity because it is unclear how to account pre-participation period in labour intensity definition.

Table 3-5: Effect of CIPEC on firms' energy intensity

Variables	Energy intensity (x100)	Electricity intensity (x100)	Natural gas intensity (x100)	Energy intensity (x100)	Electricity intensity (x100)	Natural gas intensity (x100)
CIPEC * capital intensity 1	-0.006	-0.0244	-0.0131	-	-	-
	(0.148)	(0.0807)	(0.0870)	-	-	-
CIPEC * labour intensity 1	0.276	0.284**	-0.0121	-	-	-
	(0.196)	(0.123)	(0.109)	-	-	-
CIPEC * capital intensity 2	-	-	-	-0.0142	-0.001	-0.0474
	-	-	-	(0.131)	(0.0737)	(0.0796)
CIPEC * labour intensity 2	-	-	-	0.516**	0.418***	0.126
	-	-	-	(0.215)	(0.137)	(0.114)
Observations	38,345	38,345	38,345	38,329	38,329	38,329

Notes: Each regression includes firm, province-year, and industry-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and province-year levels.

3.5.4 Establishments size

This section studies the effect of the program on firms energy consumption accounting for firms' size. A. Fishman & Rob (1999) find that larger firms are likely to spend more in research and development while being competitive in a given market. Our aim is to test the hypothesis that large firms have enough resources for adaptive energy investments compared to small or medium firms. This follows Arora & Cason (1995) finding showing that firms' size largely explain their decision to enter in a voluntary program. We use the following equation:

$$y_{it} = \sum_{size=1}^{3} \beta_{size} CIPEC_{it} \times size_i + \gamma_i + \psi_{dt} + \zeta_{pt} + \epsilon_{it} \tag{3.5}$$

We $size$ is a dummy variable representing each firm i's size. $size = 1$, $size = 3$, and $size = 3$ respectively represent small, medium, and large firm.

Table 3-6 presents the effects of the program on energy, electricity and natural gas intensities by firms' size. We find weak evidence that the program increases small firm electricity intensity by 0.25%. This results in an increase of small firms' total energy intensity by 0.46% on average at a 10% significance level. The magnitude of the estimated effect is relatively small and it is imprecisely estimated. We find no statistically significant evidence that medium firms are affected by this program. Our estimated results also suggest a decrease in large firms natural gas intensity by 0.12% on average at the 5% significance level. It seems that the magnitude is not large enough to significantly affect firms' total energy intensity.

Table 3-6: Effect of CIPEC on firms' energy intensity by size

Variables	Energy intensity (x100)	Electricity intensity (x100)	Natural gas intensity (x100)
CIPEC * small	0.462*	0.253*	0.184
	(0.258)	(0.151)	(0.154)
CIPEC * medium	0.117	0.112	-0.005
	(0.148)	(0.078)	(0.092)
CIPEC * large	-0.152	-0.073	-0.123**
	(0.096)	(0.063)	(0.051)
Observations		38,345	

Notes: Each regression includes firm, industry-year, and province-year fixed effects. All the dependent variables are transformed using the IHS transformation.. We use a two-way cluster for the standard errors at the firms and province-year levels.

3.6 Robustness Checks

3.6.1 Single establishment firms

In this section, we analyze the effect of the program on single establishment firms' energy intensity and its components. We generate the matching weight using the sample of single establishment firms based on the following covariates: total energy consumption, total output, total employment, exporter status, producing own energy, province of operation, and the industry sectors before the participation in this program.[35]. We then rerun (3.2).

[35]We use the same bins for continuous covariates as in Section 3.5.1

Table 3-7: Effect of CIPEC on single establishment firms' energy using matching weights

Variables	Energy intensity (x100)	Electricity intensity (x100)	Natural gas intensity (x100)
CIPEC	0.107	0.0088	0.0854
	(0.142)	(0.0645)	(0.0930)
Observations		32,148	

Notes: Each regression includes firm, industry-year, and province-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and province-year levels.

Table 3-7 shows the effect of the program on single establishment firms. We find a null and no significant effect of the program on electricity and natural gas intensities. Overall, firms' total energy intensity is not affected by the program. These results are almost identical to our main results in Table 3-4.

3.6.2 Alternative matching weight

Second, we implement a different matching strategy where the matching covariates do not includes the continuous dependent variables including total energy, total output, and total employment. The new matching covariates are all binary variables and include exporter status, producing own energy, province of operation, and the industry sectors before the participation in this program. We then rerun (3.2) using the new matching weight.

Table 3-8: Effect of CIPEC on firms' energy intensity using alternative matching weight

Variables	Energy intensity (x100)	Electricity intensity (x100)	Natural gas intensity (x100)
CIPEC	-0.005	0.047	-0.022
	(0.112)	(0.054)	(0.066)
Observations		43,398	

Notes: Each regression includes firm, industry-year, and province-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and province-year levels.

Table 3-8 shows the effect of the program on firms' energy intensity and its components using different matching weight than in the main result. The results are similar to our main finding as shown in Table 3-4. The program has a zero and not significant effect on both energy intensity, electricity intensity, and natural gas intensity.

3.7 Summary and concluding remarks

This paper analyzes the effect of CIPEC, a long standing voluntary energy conservation program, on firms' energy intensity and their economic performance. As in similar papers (Kube et al., 2019; Clay et al., 2021), we implement a matching strategy, using various covariates, in order to build a sample of non-participants that is similar to the participants. Our results show that the program has no significant effect on firms' energy intensity. Both electricity and natural gas intensities are unaffected by the program. Similarly, we find that firm productivity and total output are unresponsive to this program. We also find that the program has no significant effect in the short, medium, or long term on firms' energy intensities nor their economic performance. Our result is robust to the use of alternative estimations including the sample of single establishment firms and the use of alternative covariates to generate the matching weight.

The CIPEC program is both a voluntary and information-based program. The purpose of this study is analyzed the effectiveness this program as a whole without any distinction between the voluntary and the information-based aspects of the program. The set up of this program does not allow us to distinguish between the voluntary and the information-based aspects of the this program.

Although we find no effect on firms outcomes, this study sheds a light on some characteristics that explains firms' participation to this program including producing its own energy, being a multi-establishment firm, operating in some provinces or industries, energy consumption, and total output.

The null and non-significant effect of this program on firms energy and economic outcomes can be explained by different factors. First, it might be that participants to the program are already energy efficient firms which does not leave room for additional improvements. In Table 3-1, we find that CIPEC participants have higher productivity than non-participants. Given that, we might also expect the participants to be more efficient in which case we have a ceiling effect. Second, the managers who took the decision to join CIPEC may no longer be in the same position or firm. The new managers who took over the position or firm may have other views/objectives regarding energy efficiency.

One of the objectives of voluntary energy efficiency programs, for both industry and consumers, is to fill the gap of imperfect information which may in turn induce consumers and industry to undertake profitable investments in energy efficiency (Allcott & Greenstone, 2012). In the presence of behavioural failures that lead to to underinvestment in energy efficiency, energy efficiency programs could improve welfare at low or negative cost (Gillingham et al., 2009). Gillingham et al. (2009) find that the effectiveness of an energy efficiency program depends on the extent of existing market failures and the ability of the program to address the problem. For both firms and consumers, the results of energy efficiency outreach depend on various parameters including the extent of the existing market problem, the characteristics of consumers/firms, and the accuracy of the policy at addressing the market failure.

3.8 Appendix

3.8.1 Effect of CIPEC program on firms' energy consumption and economic activity using unmatched sample

Table 3-9 presents the effect of CIPEC program on firms' energy and economic outcomes using Equation (3.2). We find a statistically significant decrease in total energy by more than 5%. However, we do not find any statistically significant effect of the program on firms total energy, electricity, and natural gas intensities. We also find that the program has a negative and statistically significant effect on firms' total output despite having no significant effect on TFP. It seems that the decrease in energy consumption is at the expense of firms' total output.

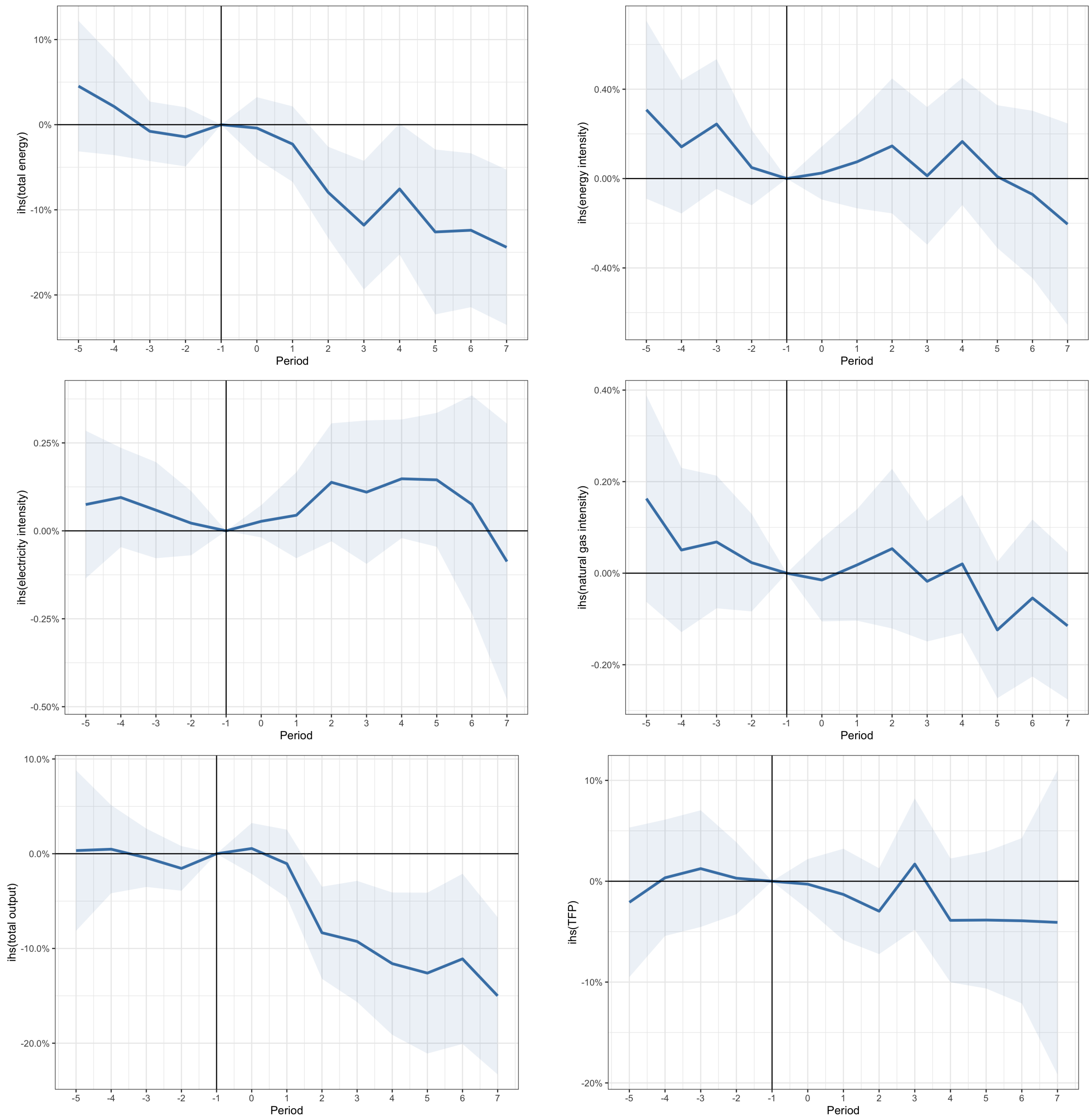
Table 3-9: Effect of CIPEC on firms energy and economic outcomes using unmatched sample

Variables	Total energy x100)	Energy intensity (x100)	Electricity intensity x100)	Natural gas intensity x100)	Total output x100)	Total productivity x100)
CIPEC	-5.25**	-0.0324	0.0452	-0.0354	-4.22**	-1.46
	(2.43)	(0.107)	(0.0461)	(0.0655)	(2.10)	(1.85)
Observations	52,283	52,283	52,283	52,283	52,283	49,831

Notes: Each regression includes firm, province-year, and industry-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and province-year levels.

We expand the results of Table 3-9 over time to analyze the short, medium, and long-term effects of the program. Figure 3-15 shows that the program significantly decreases total energy consumption in the medium and long-term while having no short-term effect.

Despite the decrease in total energy, we find no effect of the program on firms' total energy, electricity, and natural gas intensities in the short, medium and long-term. Similarly, we find that the program has a negative significant effect on firms' total output in the medium and long-term, with no effect in the short-term. We find no significant evidence that firms TFP is affected over time. It seems that the decrease in output is a result of the decrease in total energy consumption.



Notes: Each regression includes firm, province-year, and industry-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and province-year levels. The vertical line represents the year $(t-1)$ before the participants firms join the program. We also plot the upper and lower bound attached to each coefficient at the 5% significant level.

Figure 3-15: Effect of CIPEC on firms outcomes over time using unmatched sample

These results are likely bias given that firms are self-selecting in this program. The participants are may not be comparable to the non-participants as shown in Table 3-1.

3.8.2 Effect of CIPEC program on firms' energy consumption on the matched sample using various cluster

We now test the stability of our standard errors by estimating (3.2) using two type of cluster. First, we estimate (3.2) using two ways cluster at the firm and industry-year level. Table 3-10 shows a similar result as in Table 3-4. The program has zero and no statistically significant effect on firms energy intensity and its components.

Table 3-10: Effect of CIPEC on firms' energy using firm and industry-year cluster

Variables	Energy intensity (x100)	Electricity intensity (x100)	Natural gas intensity (x100)
CIPEC	0.0879	0.0783	-0.0128
	(0.122)	(0.0745)	(0.0683)
Observations		38,345	

Notes: Each regression includes firm, province-year, and industry-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and industry-year levels.

Second, we analyze the effect of the program on firms energy intensity using (3.2) and clustering the standard errors at the firm and year level. Similar to Table 3-4, Table 3-11 shows a zero and no statistically significant effect of the program on firms energy intensities.

Table 3-11: Effect of CIPEC on firms' energy using firm and year cluster

Variables	Energy intensity (x100)	Electricity intensity (x100)	Natural gas intensity (x100)
CIPEC	0.0879	0.0783	-0.0128
	(0.126)	(0.0808)	(0.0677)
Observations		38,345	

Notes: Each regression includes firm, province-year, and industry-year fixed effects. All the dependent variables are transformed using the IHS transformation. We use a two-way cluster for the standard errors at the firms and year levels.

References

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, *83*(6), 2411–2451.

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies*, *33*(3), 1331–1366.

Agarwal, S., Chomsisengphet, S., Meier, S., & Zou, X. (2020). In the mood to consume: Effect of sunshine on credit card spending. *Journal of Banking & Finance*, *121*, 105960.

Allcott, H., & Greenstone, M. (2012). Is there an energy efficiency gap? *Journal of Economic perspectives*, *26*(1), 3–28.

Anton, W. R. Q., Deltas, G., & Khanna, M. (2004). Incentives for environmental self-regulation and implications for environmental performance. *Journal of Environmental Economics and Management*, *48*(1), 632–654.

Arimura, T. H., Hibiki, A., & Katayama, H. (2008). Is a voluntary approach an effective environmental policy instrument?: A case for environmental management systems. *Journal of Environmental Economics and Management*, *55*(3), 281–295.

Arora, S., & Cason, T. N. (1995). An experiment in voluntary environmental regulation: Participation in EPA′ s 33/50 program. *Journal of Environmental Economics and Management*, *28*(3), 271–286.

Arora, S., & Cason, T. N. (1996). Why do firms volunteer to exceed environmental regulations? understanding participation in EPA's 33/50 program. *Land Economics*, 413–432.

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, *32*(4), 33–52.

Backlund, S., Thollander, P., Palm, J., & Ottosson, M. (2012). Extending the energy efficiency gap. *Energy Policy*, *51*, 392–396.

Behrer, A. P., & Park, J. (2017). Will we adapt? Temperature, labor and adaptation to climate change. *Harvard Project on Climate Agreements Working Paper*, 16–81.

Belasen, A. R., & Polachek, S. W. (2008). How hurricanes affect wages and employment in local labor markets. *American Economic Review*, *98*(2), 49–53.

Belasen, A. R., & Polachek, S. W. (2009). How disasters affect local labor markets the effects of hurricanes in Florida. *Journal of Human Resources*, *44*(1), 251–276.

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, *82*(1), 50–61.

Billor, N., Hadi, A. S., & Velleman, P. F. (2000). BACON: Blocked adaptive computationally efficient outlier nominators. *Computational Statistics & Data Analysis*, *34*(3), 279–298.

Black, B. S., Lalkiya, P., & Lerner, J. Y. (2020). The trouble with Coarsened Exact Matching. *Northwestern Law & Econ Research Paper Forthcoming*.

Borck, J. C., & Coglianese, C. (2009). Voluntary Environmental Programs: Assessing their effectiveness. *Annual Review of Environment and Resources*, *34*(1), 305-324. doi: 10.1146/annurev.environ.032908.091450

Bracke, R., Verbeke, T., & Dejonckheere, V. (2008). What determines the decision to implement EMAS? A European firm level study. *Environmental and Resource Economics*, *41*(4), 499–518.

Breschi, S., Malerba, F., & Orsenigo, L. (2000). Technological regimes and Schumpeterian patterns of innovation. *The Economic Journal*, *110*(463), 388–410.

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–40.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235.

Busse, M. R., Pope, D. G., Pope, J. C., & Silva-Risso, J. (2015). The psychological effect of weather on car purchases. *The Quarterly Journal of Economics*, *130*(1), 371–414.

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, *353*(6304), 1112–1127.

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, *95*(5), 1549–1561.

Chen, X., & Yang, L. (2019). Temperature and industrial output: Firm-level evidence from China. *Journal of Environmental Economics and Management*, *95*, 257–274.

Clay, K., Severnini, E. R., & Sun, X. (2021). *Does LEED certification save energy? Evidence from federal buildings* (Tech. Rep. No. 28612). National Bureau of Economic Research.

Coffman, M., & Noy, I. (2012). Hurricane Iniki: Measuring the long-term economic impact of a natural disaster using synthetic control. *Environment and Development Economics*, *17*(2), 187–205.

Conlin, M., O'Donoghue, T., & Vogelsang, T. J. (2007). Projection bias in catalog orders. *American Economic Review*, *97*(4), 1217–1249.

Cook, N., & Heyes, A. (2020). Brain freeze: Outdoor cold and indoor cognitive performance. *Journal of Environmental Economics and Management*, *101*, 102318.

Cornelis, E. (2019). History and prospect of voluntary agreements on industrial energy efficiency in europe. *Energy Policy*, *132*, 567–582.

Costantini, V., Crespi, F., & Paglialunga, E. (2019). Capital–energy substitutability in manufacturing sectors: Methodological and policy implications. *Eurasian Business Review*, *9*(2), 157–182.

Darnall, N., & Sides, S. (2008). Assessing the performance of voluntary environmental programs: Does certification matter? *Policy Studies Journal*, *36*(1), 95–117.

DeCanio, S. J., & Watkins, W. E. (1998). Investment in energy efficiency: do the characteristics of firms matter? *Review of Economics and Statistics*, *80*(1), 95–107.

Dell, M., Jones, B. F., & Olken, B. A. (2009). Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review*, *99*(2), 198–204.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95.

Deryugina, T., & Hsiang, S. (2017). *The marginal product of climate* (Tech. Rep. No. 24072). National Bureau of Economic Research.

Deryugina, T., Kawano, L., & Levitt, S. (2018). The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, *10*(2), 202–33.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, *97*(1), 354–385.

Deschênes, O., & Moretti, E. (2009). Extreme weather events, mortality, and migration. *The Review of Economics and Statistics*, *91*(4), 659–681.

Ederington, J., Levinson, A., & Minier, J. (2005). Footloose and pollution-free. *Review of Economics and Statistics*, *87*(1), 92–99.

Field, C. B., Barros, V., Stocker, T. F., & Dahe, Q. (2012). *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Fishman, A., & Rob, R. (1999). The size of firms and R&D investment. *International Economic Review*, *40*(4), 915–931.

Fishman, R., Carrillo, P., & Russ, J. (2019). Long-term impacts of exposure to high temperatures on human capital and economic productivity. *Journal of Environmental Economics and Management*, *93*, 221–238.

Fleckinger, P., & Glachant, M. (2011). Negotiating a voluntary agreement when firms self-regulate. *Journal of Environmental Economics and Management*, *62*(1), 41–52.

Fowlie, M. L., Reguant, M., & Ryan, S. (2016). Measuring leakage risk. *Report for the California Air Resources Board*.

Frondel, M., Horbach, J., Rennings, K., & Requate, T. (2004). *Environmental policy tools and firm-level management practices: empirical evidence for Germany* (Tech. Rep.). Economics Working Paper.

Frondel, M., Krätschell, K., & Zwick, L. (2018). Environmental management systems: Does certification pay? *Economic Analysis and Policy*, *59*, 14–24.

Galloway, S., & Maughan, R. J. (1997). Effects of ambient temperature on the capacity to perform prolonged cycle exercise in man. *Medicine and Science in Sports and Exercise*, *29*(9), 1240–1249.

Gamper-Rabindran, S. (2006). Did the EPA's voluntary industrial toxics program reduce emissions? A GIS analysis of distributional impacts and by-media analysis of substitution. *Journal of Environmental Economics and Management*, *52*(1), 391–410.

Gillingham, K., Newell, R. G., & Palmer, K. (2009). Energy efficiency economics and policy. *Annual Review Resource Economics*, *1*(1), 597–620.

González-Alonso, J., Teller, C., Andersen, S. L., Jensen, F. B., Hyldig, T., & Nielsen, B. (1999). Influence of body temperature on the development of fatigue during prolonged exercise in the heat. *Journal of Applied Physiology*, *86*(3), 1032–1039.

Graff Zivin, J., Hsiang, S. M., & Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, *5*(1), 77–105.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, *32*(1), 1–26.

Groen, J. A., Kutzbach, M. J., & Polivka, A. E. (2020). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, *38*(3), 653–685.

Groen, J. A., & Polivka, A. E. (2008). The effect of Hurricane Katrina on the labor market outcomes of evacuees. *American Economic Review*, *98*(2), 43–48.

Hancock, P. A., Ross, J. M., & Szalma, J. L. (2007). A meta-analysis of performance response under thermal stressors. *Human Factors*, *49*(5), 851–877.

Heal, G., & Park, J. (2016). Reflections-temperature stress and the direct impact of climate change: A review of an emerging literature. *Review of Environmental Economics and Policy*, *10*(2), 347–362.

Howarth, R. B., Haddad, B. M., & Paton, B. (2000). The economics of energy efficiency: Insights from voluntary participation programs. *Energy Policy*, *28*(6-7), 477–486.

Hsiang, S. M., & Jina, A. S. (2014). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones* (Tech. Rep. No. 20352). National Bureau of Economic Research.

Hui, I., Chan, A. H., & Pun, K. (2001). A study of the environmental management system implementation practices. *Journal of Cleaner Production*, *9*(3), 269–276.

Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, *106*(493), 345–361.

Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened Exact Matching. *Political analysis*, *20*(1), 1–24.

Kabore, P., & Rivers, N. (2020). Manufacturing output and extreme temperature: Evidence from Canada [Working Papers]. (2006E). Retrieved from https://ideas.repec.org/p/ott/wpaper/2006e.html

Khanna, M., & Damon, L. A. (1999). EPA's voluntary 33/50 program: Impact on toxic releases and economic performance of firms. *Journal of Environmental Economics and Management*, *37*(1), 1–25.

Koetse, M. J., De Groot, H. L., & Florax, R. J. (2008). Capital-energy substitution and shifts in factor demand: A meta-analysis. *Energy Economics*, *30*(5), 2236–2251.

Kolstad, C. D., & Moore, F. C. (2020). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*, *14*(1), 1–24.

Kotchen, M. J. (2020). Voluntary-and information-based approaches to environmental management: A public economics perspective. *Review of Environmental Economics and Policy*.

KPMG, L. (2012). *esser Slave Lake Regional Urban Interface Wildfire – Lessons Learned.* Municipal Affairs.

Kube, R., von Graevenitz, K., Löschel, A., & Massier, P. (2019). Do voluntary environmental programs reduce emissions? EMAS in the German manufacturing sector. *Energy Economics*, 104558.

Lemoine, D. (2018). *Estimating the consequences of climate change from variation in weather* (Tech. Rep. No. 25008). National Bureau of Economic Research.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, *70*(2), 317–341.

Li, C., Luo, X., Zhang, C., & Wang, X. (2017). Sunny, rainy, and cloudy with a chance of mobile promotion effectiveness. *Marketing Science*, *36*(5), 762–779.

Lyon, T. P., & Maxwell, J. W. (2003). Self-regulation, taxation and public voluntary environmental agreements. *Journal of Public Economics*, *87*(7-8), 1453–1486.

MacKinnon, J. G., Nielsen, M. Ø., & Webb, M. D. (2019). Wild bootstrap and asymptotic inference with multiway clustering. *Journal of Business & Economic Statistics*, 1–15.

Mackworth, N. H. (1946). Effects of heat on wireless operators. *British Journal of Industrial Medicine*, *3*(3), 143–158.

Malerba, F., & Orsenigo, L. (1996). Schumpeterian patterns of innovation are technology-specific. *Research Policy*, *25*(3), 451–478.

Marschak, J., & Andrews, W. H. (1944). Random simultaneous equations and the theory of production. *Econometrica, Journal of the Econometric Society*, 143–205.

McIntosh, M. F. (2008). Measuring the labor market impacts of Hurricane Katrina migration: Evidence from houston, texas. *American Economic Review*, *98*(2), 54–57.

Mu, J. E., & Chen, Y. (2016). Impacts of large natural disasters on regional income. *Natural Hazards*, *83*(3), 1485–1503.

Najjar, N., & Cherniwchan, J. (2018). Environmental regulations and the clean-up of manufacturing: Plant-level evidence from Canada. *University of Alberta School of Business Research Paper*(2018-701).

Najjar, N., & Cherniwchan, J. (2021). Environmental regulations and the cleanup of manufacturing: Plant-level evidence. *Review of Economics and Statistics*, *103*(3), 476–491.

Neugebauer, F. (2012). EMAS and ISO 14001 in the German industry–complements or substitutes? *Journal of Cleaner Production*, *37*, 249–256.

Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, *108*, 102445.

Nishitani, K. (2011). An empirical analysis of the effects on firms' economic performance of implementing environmental management systems. *Environmental and Resource Economics*, *48*(4), 569–586.

Olley, G. S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, *64*(6), 1263.

Park, J. (2017). Hot temperature and high stakes exams: Evidence from New York City public schools. *URL: https://scholar. harvard. edu/files/jisungpark/files/papernycaejep. pdf*.

Prakash, A., & Potoski, M. (2006). *The voluntary environmentalists: Green clubs, ISO 14001, and voluntary environmental regulations*. Cambridge University Press.

Price, L. (2005). Voluntary agreements for energy efficiency or GHG emissions reduction in industry: An assessment of programs around the world.

Richter, P. M., & Schiersch, A. (2017). CO2 emission intensity and exporting: Evidence from firm-level data. *European Economic Review*, *98*, 373–391.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594–15598.

Segerson, K., & Miceli, T. J. (1998). Voluntary environmental agreements: Good or bad news for environmental protection? *Journal of Environmental Economics and Management*, *36*(2), 109–130.

Seppanen, O., Fisk, W. J., & Lei, Q. (2006). *Effect of temperature on task performance in office environment* (Tech. Rep.). Berkeley, Calif.: Lawrence Berkeley National Laboratory.

Shi, J., & Skuterud, M. (2015). Gone fishing! Reported sickness absenteeism and the weather. *Economic Inquiry*, *53*(1), 388–405.

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of political Economy*, *113*(1), 1–17.

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from us coastal counties. *Review of Economics and Statistics*, *93*(2), 575–589.

Tran, B. R., & Wilson, D. J. (2020). The local economic impact of natural disasters..

Vidovic, M., & Khanna, N. (2007). Can voluntary pollution prevention programs fulfill their promises? Further evidence from the EPA's 33/50 program. *Journal of Environmental Economics and Management*, *53*(2), 180–195.

Weber, S. (2010). Bacon: An effective way to detect outliers in multivariate data using Stata (and Mata). *The Stata Journal*, *10*(3), 331–338.

Xiao, Y. (2011). Local economic impacts of natural disasters. *Journal of Regional Science*, *51*(4), 804–820.

Yamazaki, A. (2017). Jobs and climate policy: Evidence from British Columbia's revenue-neutral carbon tax. *Journal of Environmental Economics and Management*, *83*, 197–216.

Zhang, P., Deschênes, O., Meng, K., & Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, *88*, 1–17.