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

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Abstract
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. All residents of Slave Lake, except firefighters and the police force, were forced to evacuate to nearby municipalities for at least one month. In this study, we use longitudinal income tax data from 2004 to 2018, to examine the short, medium, and long-term effect of this wildfire on affected individuals. We find that the wildfire led to a drop in total income of 9.5% on average in the seven years following the wildfire, mainly explained by a decrease in employment income. Effects are concentrated in males, and workers in the forestry and agriculture and oil and gas sectors. Based on a back-of-the envelope calculation, our results suggest that disruptions to the labour market-imposed an aggregate cost of $140 million in the seven years following the disaster, which is equivalent to over 10% of commonly cited economic losses associated with the fire.

Key words: Natural disasters, Wildfires, Income, Individuals, Slave Lake

JEL Classification: D14, H24, Q54, R23

1 Introduction

Destructive natural disasters, such as hurricanes, droughts, and wildfires, are expected to increase in frequency and in intensity due to climate change (Field et al., 2012). Such natural disasters can impose significant costs on individuals. For example, natural disasters can impose direct health costs, can damage and destroy property, and can inhibit economic activity. These costs are relatively easy to measure in an accounting-style analysis, and are often reported following major natural disasters. For example, in their evaluation of the cost of natural disasters, Natural Resources Canada includes disaster preparedness, mitigation, and response, as well as insured and uninsured property losses, business interruptions, and recovery and rebuilding.[1] However, natural disasters can also impose other costs on individuals that are harder to directly measure. For example, they may lead to migration or cause individuals to become separated from the labour market or educational institutions. These indirect and potentially long-lasting impacts are harder to assess but may nevertheless be an important outcome of natural disasters. Understanding such impacts is important, both in order to accurately capture the full magnitude of the costs of natural disasters, as well as to help identify appropriate response strategies.

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.[2] This estimate, however, captures costs related to property damage, contemporaneous damage to health and economic opportunities, and costs associated with disaster suppression and recovery. Importantly this estimate does not include potentially long-run costs associated with changes in economic opportunity.

This paper aims to evaluate the effect of the Slave Lake wildfire on long-run economic outcomes for affected individuals. Our study builds on a body of recent work examining the economic consequences of natural disasters. Many studies analyze the economic costs of natural disasters on affected countries (Cavallo et al., 2013; S. M. Hsiang & Jina, 2014)

[1] https://www.nrcan.gc.ca/climate-change/impacts-adaptations/climate-change-impacts-forests/forest-change-indicators/cost-fire-protection/17783.

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

or sub-national regions (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 a given geographical 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 natural disasters.

To analyze the effects of the 2011 Slave Lake wildfire, we use the Canadian Longitudinal Administrative Databank (LAD), which ensures that we can follow affected individuals before and after the event. We rely on individuals' municipality of residence from their tax declaration to determine both treatment and control groups. The treatment group for this study consists of all people aged 16-64 residing in Slave Lake in 2010, the year prior to the disaster. The control group is constructed in two steps. First, we select municipalities of similar size as Slave Lake (5-10,000 inhabitants) that are between 100-200km away using the 2011 Census. Such municipalities are close enough to serve as good controls but far enough not to be directly impacted by the disaster. Second, we perform a matching strategy to identify individuals in control municipalities that are comparable to those in the treatment group based on the 2010 covariates including total income, employment status, sex, age, marital status, 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. Our results are robust to alternative specifications of the control group.

The empirical analysis begins with an estimation of the causal effect of the Slave Lake wildfire on total income and its main components including employment income, self-employment 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 consider 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. We explore heterogeneity in the impact of the wildfire according to sector of employment, as well as by age and sex, in order to understand vulnerability to climate-related disasters. Finally, we analyze whether the wildfire caused out-migration from Slave Lake.

We find that, in the seven years following the fire, annual total income falls by more than $4,700 as a result of the wildfire, representing almost 9.5% of pre-event average total income. Changes in employment income are responsible for the majority of this drop, and changes in labour market participation appear minor. The total amount of economic activity displaced by the wildfire, among the working-age population in Slave Lake, is estimated at over $140 million over the period 2012-2018.[3] Our estimate suggests that the long-run economic displacement associated with the natural disaster reaches almost 13% of the direct costs of the disaster. We find that long-run costs are concentrated among males, and those employed in sectors directly affected by the wildfire, including agriculture and forestry, and oil and gas.

We find some evidence that the wildfire increased out-migration from Slave Lake. Our estimates suggest that migration out of Slave Lake increased by almost 3 percentage points on average over the period 2012-2018, compared to the matched control group. We do not assess the costs of this migration, but they form part of the overall impacts of the wildfire.

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).[4] Groen et al. (2020) and Deryugina et al. (2018) analyze both short, medium, and long-term effects of hurricanes on 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.

[3] This cost is derived by multiplying the average cost per person per year by the working age population of Slave Lake in 2011 over the period 2012-2018.

[4] Kirchberger (2017); Gignoux & Menéndez (2016) analyze the long-term effects of Indonesian earthquakes on wages. The findings are likely not applicable to developed countries given the difference of institutions and level of development. Indonesia's economy relies heavily on agriculture as opposed to the economies of developed countries.

2 Background: The Slave Lake wildfire

On May 14^{th}, 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 in the region. 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 four 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 the costliest disaster ever in the province of Alberta and led to the largest displacement of individuals.[5]

The wildfire was 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 neighbouring areas due to the 100 km/h wind gusts.

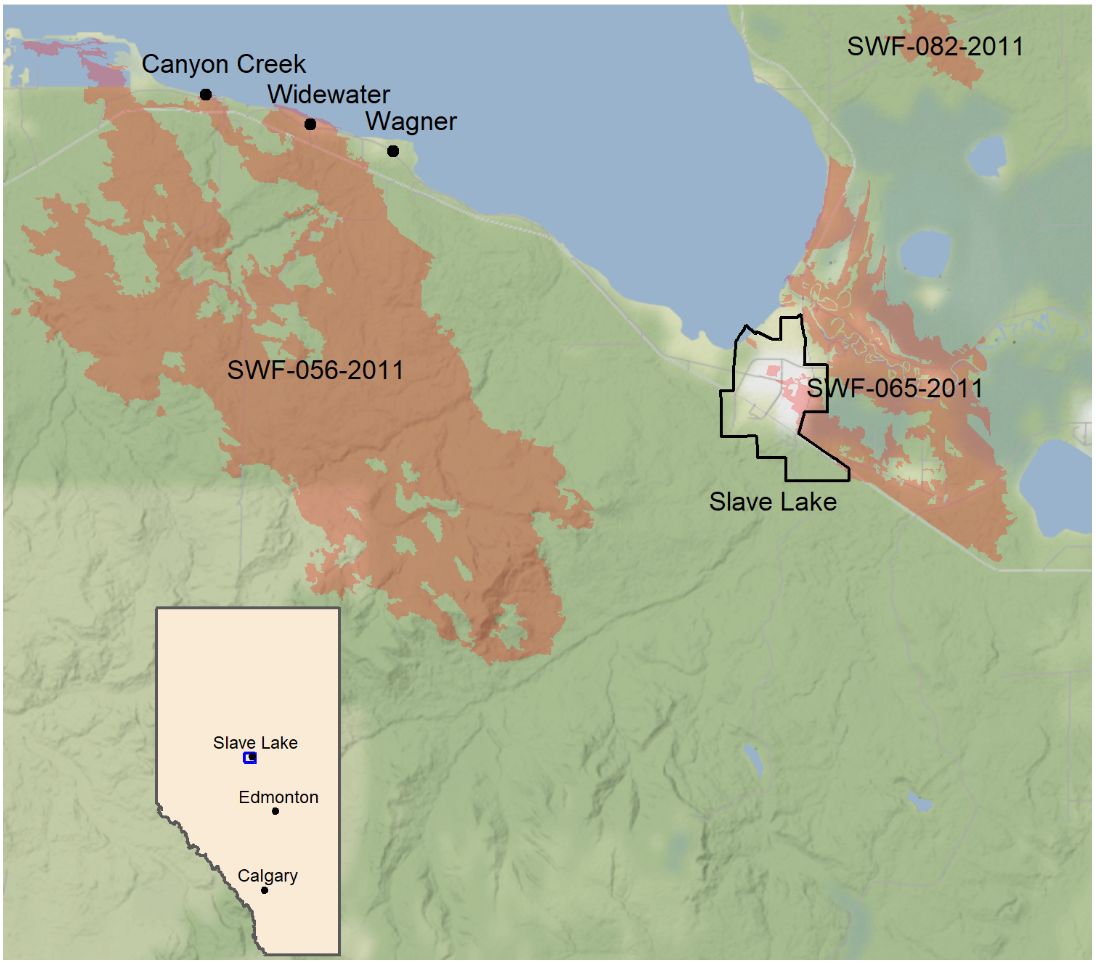
At the time it occurred, the Slave Lake wildfire was the second costliest natural disaster in the history of Canada after the 1998 ice storm. The fire was estimated to inflict a cost of \$1.1 billion including \$400 million in uninsurable losses at that time according to the Insurance Bureau of Canada.[7] The wildfire devastated an estimated area of $47km^2$ as in Figure 1. The fire ravaged almost 40% 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. https://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://www.cbc.ca/news/canada/edmonton/fire-destroys-40-of-slave-lake-1.981352



Three separate wildfires make up the "Flat Top Complex" of wildfires, and are depicted as the brown shaded areas in the figure above. Fire boundaries are 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 major urban area in the region. Fire SWF-056-2011 affected rural areas including Canyon Creek, Widewater, and Wagner. Fire SWF-082-2011 did not cause significant property damage.

Figure 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 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 infrastructure.[9]

The town of Slave Lake, as a regional centre in the region, provides services such as retail, education, health, financial, government, and transportation. Key industries in the affected area are forestry and oil and gas. Oil and gas companies did not suffer direct damage from the fire, however oil production was impacted because the fire threatened 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.

3 Data

This section describes the dataset and variables used in this study, and explains the construction of the treatment and control groups.

3.1 Administrative Tax Database

This study relies on the Longitudinal Administrative Databank (LAD) from Statistics Canada. The LAD is a longitudinal sample of tax filers that started in 1982. The LAD represents a randomly selected 20% sample of all tax filers and their families in the annual T1 family file. Every year, the LAD is augmented with a 20% sample of new tax filers which makes it a representative sample of tax filers in Canada.[11] The LAD provides information on individuals' annual total income which is derived from more than 15 components. For the purpose of this analysis, we focus on the major components of total income including employment and self-employment income and government transfers,

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

which together represent more than 96% of total income. We exclude dividend income from total income because of its high volatility (doing so does not change the qualitative results of our analysis). Government transfers represent income received from the government to supplement market income and to assist those with low or no income.[12] This dataset also has information on individual characteristics including sex, age, number of kids, and marital status. The LAD includes a dummy variable called "low income" that is equal to one if household income is below one-half of the median family income adjusted for family size, following the Statistics Canada definition. Finally, the 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 define the control group.

We consider local labour market outcomes using a number of derived variables. We define individual employment status as follows: an individual is considered "employed" (self-employed) if their employment (self-employment) income in a given year is greater than $0. Similarly, we define a dummy variable that takes the value of 1 for individuals receiving any positive amount of employment insurance and 0 otherwise. In addition to being an important component of government transfers, employment insurance benefits also provide a good proxy for the state of unemployment in a given geographical region.

Migration is one potential response to a natural disaster. Deryugina et al. (2018), for example, find that evacuees from hurricane Katrina migrated to new locations with better economic opportunities, which mitigated the negative economic effect of this disaster. We create a dummy variable that takes the value 1 when an individual's municipality of residence in year t is different from their municipality in 2010 (immediately prior to the Slave Lake wildfire) and 0 otherwise.

3.2 Treatment and control groups

Using the geographical information in our data, we identify individuals exposed to the 2011 Slave Lake wildfire as those with a residence in Slave Lake in 2010. Specifically, we use information from the 2010 tax filing (submitted February-April 2011), which captures where individuals lived on December 31^{st} 2010, and their economic activity for the calendar year 2010. This approach is similar to the one used in Deryugina et al. (2018). Once

[12] Government transfers include Canadian and Quebec Pension Plan benefits, Old Age Security benefits, provincial refundable tax credits, Employment Insurance benefits, family benefits, net federal supplement, social assistance income, Workers' Compensation payments, and GST credits.

the treatment group is identified, the longitudinal nature of the data allows us to follow this group before and after the event.

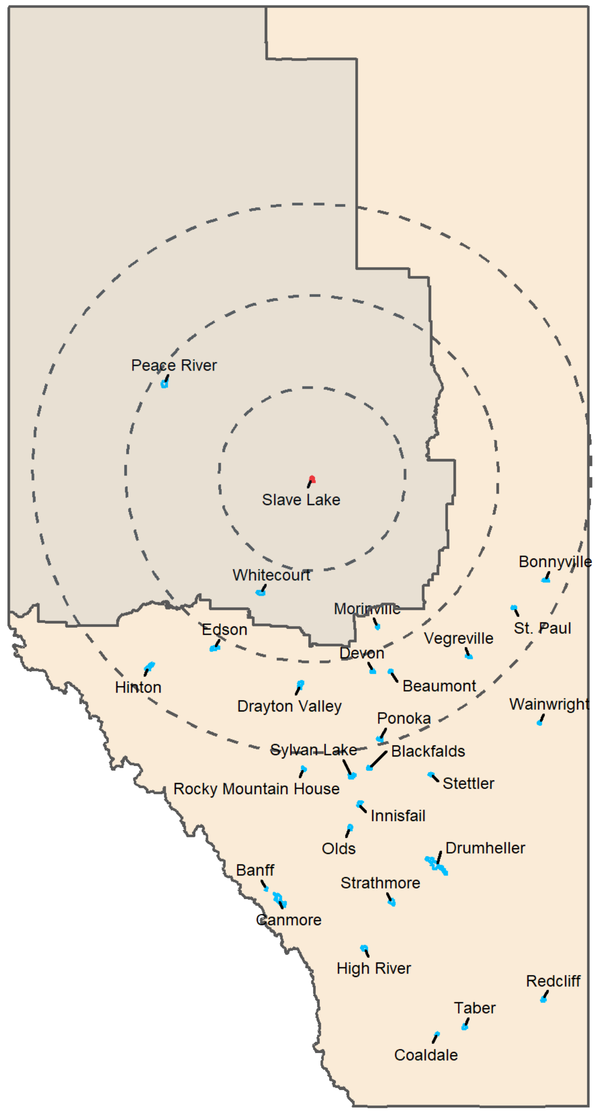
We construct the control group in three steps. We first keep all individuals living in municipalities in Alberta of similar size to Slave Lake (i.e., between 5 to 10 thousand individuals). Second, we restrict our sample to all individuals living in municipalities that are 100-200 km radius away from Slave Lake as in Figure 2.[13] 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.[14] By restricting our control group to individuals living in these area at the time of the disaster, we expect the treatment and the control groups to have similar incomes, labour outcomes, and other characteristics before the event.

Despite the geographical matching, Table 1, described further below, shows differences in incomes and other characteristics between the treatment and the unmatched control group in the pre-treatment period. As a result, in a third step, we match individuals in the treated community (Slave Lake) to individuals in control communities using propensity score weights (PSW). The method is as follows: First, we estimate propensity scores ($p_i(X)$) with a probit regression of treatment on the following 2010 (the year prior to the wildfire) variables: total income (continuous), employment status (employed or not), sex (male or female), marital status (married or unmarried), age (continuous), and sector of employment (a categorical variable with 24 levels, corresponding to 2-digit industries).[15] Second, a weight of one is given to individuals in the treatment group while a weight of $p_i(X)/(1 - p_i(X))$ is provided to individuals in the control group. Propsensity score matching successfully reduces pre-treatment imbalances between the treatment and control group as shown in Table 1.

[13] The retained municipalities are Peace River, Whitecourt, and Morinville.

[14] In the Robustness Section 4.4, we consider alternative approaches to defining the control group.

[15] In section 4.4, we consider all possible combinations of these pre-treatment covariates and show that our results are not sensitive to the choice of matching variables.



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 shaded area in the North-West is the Athabasca-Grand Prairie-Peace River Economic Region, which includes Slave Lake. We use this to define an alternative control group in a robustness excercise.

Figure 2: Location of treatment and control municipalities

For the analysis, we consider the period 2004 to 2018 which represents seven years before and after the 2011 Slave Lake wildfire.[16] 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 over time. We are able to follow individuals if they move to another Canadian province, but not if they move outside of Canada.

3.3 Summary Statistics

Table 1 describes individual characteristics before and after the 2011 Slave Lake wildfire. We observe almost 1,000 treated individuals, and follow these individuals before and after the wildfire. These 1,000 individuals reflect a 20% sample from the working age population of Slave Lake, which is about 4,300 people in 2011 (as per the Census). The table displays information on incomes, employment status, and other characteristics for both treatment, weighted and unweighted control groups. For each variable, we also perform a t-tests, that compares pre-wildfire mean in the treatment group to the weighted and unweighted control groups. We observe large pre-treatment differences in covariates between the treated and unweighted control group. However, we find that the treated group and weighted control group are similar in pre-wildfire mean for most variables.

Over the period 2004-2010, Table 1 shows that 89 and 88% of individuals are employed in respectively the treatment and weighted control group. The proportion of women in treatment and weighted control group are respectively 48 and 47%. The average age in both groups are similar and around 37 years old. Low income earners represent almost 11% of Slave Lake population before the event while they represent 10% in the weighted control group.

[16]The currently available LAD (at the time of analysis) covers the period 1982 to 2018.

Table 1: Summary statistics

Variables	2004-2010 Treatment	Weighted control	Unweighted contol	2011-2018 Treatment	Weighted control	Unweighted conto
			Incomes			
Total income ($)	49,625	48,353	46,428***	61,202	64,007	61,555
	(89,413)	(69,346)	(72,596)	(60,647)	(65,153)	(62,707)
Employment incomes ($)	45,233	43,843	41,686***	53,194	55,548	53,041
	(80,942)	(67,416)	(70,358)	(53,193)	(62,879)	(60,607)
Self-employment income ($)	880	1,090*	1,269***	865	1,247	1,439
	(7,409)	(9,786)	(10,629)	(9,070)	(10,070)	(10,890)
Government transfer ($)	1,820	1,802	1,875	3,467	3,258	3,347
	(4,162)	(4,234)	(4,244)	(6,798)	(6,503)	(6,530)
			Labour characteristics			
Employed	0.89	0.88**	0.86***	0.82	0.82	0.80
	(0.31)	(0.32)	(0.35)	(0.39)	(0.38)	(0.40)
Self-employed	0.08	0.10***	0.11***	0.08	0.11	0.11
	(0.26)	(0.31)	(0.31)	(0.27)	(0.31)	(0.31)
Lower income earners	0.11	0.10*	0.10	0.10	0.09	0.09
	(0.31)	(0.30)	(0.31)	(0.29)	(0.28)	(0.29)
Received employment insurance	0.10	0.10	0.10	0.10	0.09	0.09
	(0.30)	(0.29)	(0.29)	(0.31)	(0.29)	(0.29)
			Other characteristics			
Age	37.55	37.42	37.05***	43.54	43.37	42.98
	(12.49)	(12.35)	(12.33)	(13.22)	(13.10)	(13.05)
Female	0.48	0.47	0.50***	0.48	0.48	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Married/common law	0.63	0.62	0.62	0.68	0.68	0.68
	(0.48)	(0.49)	(0.48)	(0.47)	(0.47)	(0.47)
Migration	0.16	0.17	0.17**	0.23	0.21	0.22
	(0.37)	(0.37)	(0.38)	(0.42)	(0.41)	(0.41)
Individuals	977	4,283	4,294	977	4,283	4,294
Observations	6,182	27,086	27,150	7,396	32,704	32,776

Notes: This table displays the means and standard deviations (in parenthesis) for the main variables over the pre-disaster period (2004-2010) and the post disaster period (2011-2018). The weighted and unweighted control group refer to individuals in similar sized municipalities as Slave lake and within 100-200 km radius. The t-test analysis is performed over the period 2004-2010 and compares the treatment group to the weighted and unweighted control groups. $***$, $**$, and $*$ respectively represent statistical significance at the 1, 5, and 10% levels.

Over the period 2011-2018, Table 1 shows that total income in the treatment group increased on average by $16,600 while it increased by $18,700 on average in the weighted control group - an difference of more than $2,000 relative to the treatment group. The difference appears larger for employment income. These trends are suggestive of an impact of the wildfire on employment incomes in Slave Lake. In contrast, the table does not suggest a difference in overall employment levels over time between the treatment and matched control groups. We explore these trends more formally in Section 4.

Table 2 compares the share of individuals working in different industrial sectors between the treatment group and the weighted and unweighted control group before and after the event. For this analysis, we regroup some 2-digit industries to avoid confidentiality issues due to few observations.[17] Among the individuals identified in "no industry sector" over the period 2004-2010, almost 75% of them are not employed or self-employed. The other 25% of these individuals are either employed or self-employed but their industry sector is unknown or not reported. Considering the t-test results over the period 2004-2010, we do not find a significant difference between the weighted and unweighted group relative to the treatment group. The share of individuals in 'no industry group' goes up from 12 and 13% in 2004-2010, for treated and weighted control group, to 18% in 2011-2018 in both groups. Employment in the agriculture and forestry sector decreases by 50% over the period from 2004-2010 to 2011-2018 for the treatment and weighted control groups.

[17]We combine the following industry sectors: 21 and 23 for oil, mining and utilities sectors, 31-33 for manufacturing sector, 41, 44 and 45 for trade sector, 48-48 for transportation and warehousing sector, 51-53 for finance sector, 54-56 for professional-administrative sector, 61-62 for health and education sector, and 71-72 and 81 for accommodation and service sector. For more information on industry sector classification, see https://www23.statcan.gc.ca/imdb/p3VD.pl?Function=getVD&TVD=1181553

Table 2: Summary statistics: industry

Variables	2004-2010			2011-2018		
	Treatment	Weighted control	Unweighted contol	Treatment	Weighted control	Unweighted contro
No industry	0.12	0.13**	0.14***	0.18	0.18	0.19
	(0.32)	(0.33)	(0.35)	(0.38)	(0.38)	(0.39)
Agriculture and forest	0.02	0.02	0.02	0.01	0.01	0.02
	(0.14)	(0.13)	(0.14)	(0.12)	(0.12)	(0.12)
Mining, oil and utilities	0.11	0.10***	0.07***	0.10	0.09	0.07
	(0.31)	(0.30)	(0.26)	(0.30)	(0.29)	(0.26)
Construction	0.09	0.09	0.09	0.08	0.09	0.09
	(0.28)	(0.29)	(0.28)	(0.28)	(0.29)	(0.29)
Manufacturing	0.08	0.08	0.08	0.07	0.06	0.06
	(0.27)	(0.27)	(0.27)	(0.25)	(0.24)	(0.24)
Whole and retail trade	0.14	0.14	0.14	0.11	0.11	0.11
	(0.35)	(0.35)	(0.35)	(0.32)	(0.31)	(0.31)
Transport and warehousing	0.05	0.05*	0.04	0.06	0.05	0.05
	(0.21)	(0.22)	(0.20)	(0.23)	(0.23)	(0.21)
Information and finance	0.04	0.05***	0.05***	0.04	0.05	0.05
	(0.19)	(0.22)	(0.21)	(0.20)	(0.22)	(0.21)
Professional and administrative	0.08	0.08**	0.07***	0.08	0.09	0.08
	(0.28)	(0.26)	(0.25)	(0.27)	(0.29)	(0.28)
Health and education	0.08	0.07***	0.08	0.09	0.09	0.09
	(0.28)	(0.26)	(0.27)	(0.29)	(0.28)	(0.29)
Accommodation and services	0.12	0.11*	0.10	0.08	0.08	0.08
	(0.32)	(0.31)	(0.31)	(0.27)	(0.27)	(0.27)
Public administration	0.08	0.09**	0.11***	0.09	0.09	0.11
	(0.27)	(0.28)	(0.32)	(0.29)	(0.29)	(0.32)
Individuals	977	4,283	4,294	977	4,283	4,294
Observations	6,182	27,086	27,150	7,396	32,704	32,776

Notes: This table displays the means and standard deviations (in parenthesis) for the main variables over the pre-disaster period (2004-2010) and the post disaster period (2011-2018). The weighted and unweighted control group refer to individuals in similar sized municipalities as Slave lake and within 100-200 km radius. The t-test analysis is performed over the period 2004-2010 and it compares the treatment group to the weighted and unweighted control groups. $***$, $**$, and $*$ respectively represent statistical significance at the 1, 5, and 10%.

4 Empirical Approach

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 as follows:

$$y_{imt} = \theta D_{mt} + \gamma_i + \omega_t + \epsilon_{imt}, \tag{1}$$

where i represents the individual, m the municipality, and t the year. The unit of analysis is the individual. y is the outcome of interest including total income, employment and self-employment incomes, 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. Our coefficient of interest θ captures the causal effect of the event on income over the period 2012-2018. γ_i is the individual fixed effect which controls for time-invariant characteristics 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. 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, like Deryugina et al. (2018); Groen et al. (2020).[18]

In estimating the difference-in-difference regression using Equation (1), we drop the year 2011. 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.[19]

In addition to the difference-in-difference analysis, we run an event-study analysis (Equation (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:

$$y_{imt} = \sum_{k=2004, k\neq 2010}^{2018} \theta_k D_m^k + \gamma_i + \omega_t + \epsilon_{imt} \tag{2}$$

[18] We also rerun (1) using a two-way cluster at the individual and postal code levels. Table 11, in the appendix, shows that standard errors are similar to those in Table 3.

[19] In the appendix, we rerun Equation (1) on individuals' income while keeping the year 2011. We find similar results as in Table 3.

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 in the kth period before and after the disaster compared to the difference in the year before the wildfire (2010).

As with other difference-in-difference analyses, our key identification assumption is the so-called parallel trends assumption. The coefficient θ recovers the causal effect of the wildfire on individual incomes provided the control units are a good counterfactual for the treatment group outcomes conditional on not being treated. As in any other settings, we cannot directly verify the parallel trends assumption, but our context provides several reasons for thinking that it should hold. First, the fire was an unpredictable and exogenous event and is a good example of a "natural experiment." Second, we chose control municipalities that share similar features to the treated municipality, and are in a similar region, so should be exposed to similar unobserved shocks. Third, we use matching based on pre-treatment observables to construct a control group that is similar to the treated group.

4.2 Main results

Using Equation (1), we analyze the average causal effect of the wildfire on incomes, and present the results in Table 3. We find that the wildfire led to a decrease in individual total income by more than \$4,700 on average per year over the post-fire years compared to the matched control group. This represents more than 9.5% of affected pre-event average annual total income. Employment income is the main factor explaining the drop in total income. Slave Lake residents experience a drop in employment income by more than \$4,100 which represents 9.2% of average annual employment income before the event. On average, the event has no statistically significant effect on self-employment income or government transfers. Government transfers include Employment Insurance benefits for qualifying workers and would be automatically triggered in the event of job loss. A null finding might suggest limited impacts on employment, which we explore further below.

Table 3: Estimated average effect of the Slave Lake wildfire on individual incomes

Variables	Total income	Employment income	Self-employment income	Government transfer
Treatment	-4,703**	-4,185**	-209.1	176.4
	(2,157)	(1,746)	(213.4)	(118.3)
Mean dependent variable for treated group, pre-event	49,625	45,233	880	1,820
Observations	68,104			

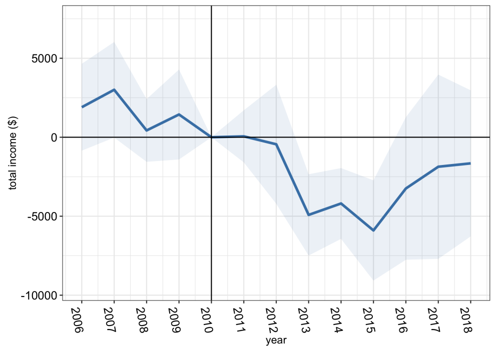
Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. These results do not include the year 2011 (the year the fire occurred).

Table 3 shows the average effects of the wildfire on incomes over the seven years following the event. To understand dynamic effects, we estimate equation (2). Figure 3 presents the causal effect of the wildfire on individuals' incomes over the period 2004-2018. We find no statistically significant pre-trend for most of the variables of interest which indicates that the treated and the weighted control group are likely comparable with respect to both observable and unobservable factors.

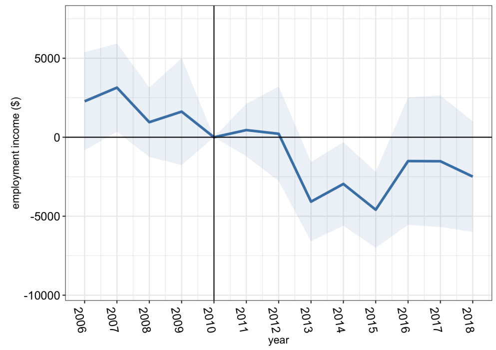
In the short-term (i.e the first two years after the event), we find no effect of the event on employment income. However, the results show a negative but not statistically significant effect on self-employment income and government transfers during this period. Overall, total income is unaffected in the first two years following the fire. One possible reason for the limited short-term impact is that rebuilding and cleanup activity following the wildfire may have stimulated economic activity.

In the medium term (i.e the third and fourth year after the event), we observe a decrease in total income by more than $4,500 on average. This drop is mainly explained by the reduction of employment income by more than $3,500 on average over that period.

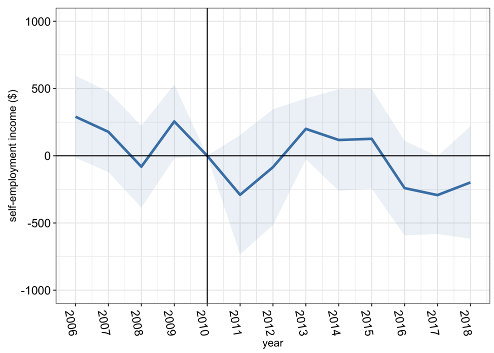
In the long-term (i.e fifth year and more after the event), we still find a decrease in total income by more $3,100 and a decrease in employment income of $2,500. Overall, the results show that the 2011 wildfire in Slave Lake had a negative effect on incomes in the medium and long-term.



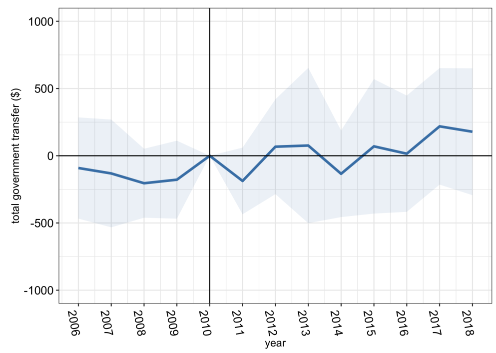
(a) Total income



(b) Employment income



(c) Self-employment income



(d) Total government transfer

Notes: Dark lines and shaded ribbon are point estimates and 95% confidence intervals associated with estimation of Equation (2). Each regression includes individual and year fixed effects. We collapse the years 2004, 2005, and 2006 to year 2006 in order to better highlight the post-trend result. The standard errors are clustered at the 2010 six digit postal code level. The vertical line represents the year before the disaster happened.

Figure 3: Estimated average effect of the Slave Lake wildfire on individual incomes in the short, medium, and long term

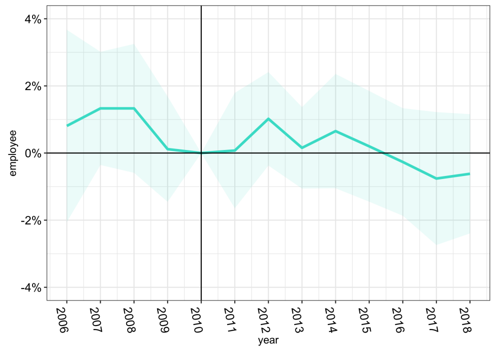
To provide further insight into the factors leading to the reduction in income, we analyze the extensive and intensive margin responses in the labour market. The extensive margin effect, i.e., the movements in and out of the labour market, is estimated by considering changes in employment status, self-employment status, whether an individual receives employment insurance, or is in the low income group, using Equations (1) and (2).

Table 4: Estimated average effect of the Slave Lake wildfire on labour outcomes

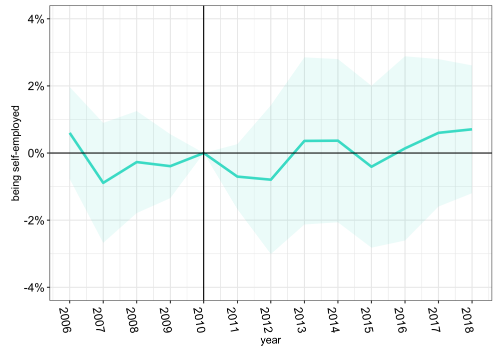
	Employed (x100)	Self-employed (x100)	Received employment insurance (x100)	Being low income (x100)
Treatment	-0.68	0.11	0.38	0.34
	(0.92)	(1.05)	(0.52)	(0.59)
Mean dependent variable for treated group, pre-event	89	8	10	11
Observations			68,104	

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 (the year the fire occurred).

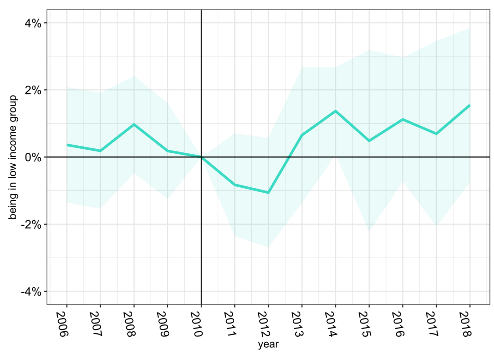
Table 4 presents the average effect of the event on labour market outcomes over the period 2004-2018. We estimate that being exposed to the wildfire reduces the likelihood of being employed by 0.7 percentage points, although our estimate is not precise and we are not able to reject the null hypothesis of zero impact on employment at conventional significant levels. This table also shows that exposure to the wildfire increases the likelihood of being in the low income group by more than 0.3 percentage points, but the coefficient estimate is statistically insignificant. In Figure 5, we find a small increase in the share of individuals that are in the low income group three years and more after the wildfire, although the effect remains insignificant. We find no evidence that this event significantly affects the likelihood of receiving employment insurance or being self-employed. Overall, we find no evidence that the wildfire affected labour market participation.



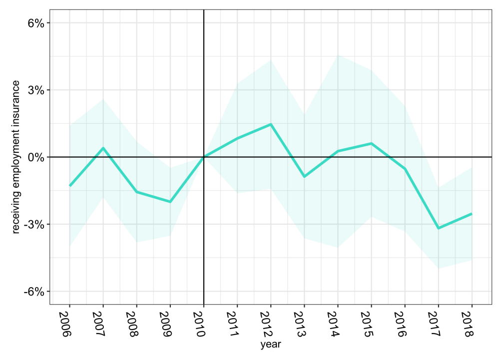
(a) Employed



(b) Self-employed



(c) Low income earner



(d) Received EI

Notes: Each regression includes individual and year fixed effects. We collapse the years 2004, 2005, and 2006 together in order to better highlight the post-trend result. 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 5: Estimated average effect of the Slave Lake wildfire labour outcomes in the short, medium, and long-term

To highlight the intensive margin response, we estimate the effect of the event on employment income conditional on being employed using Equation (1). We restrict our sample to all individuals who are employed in every year (i.e., we examine the impact on income conditional on being employed). We acknowledge that this regression uses a potentially endogenously selected sample (since movement out of the labour force may be different in Slave Lake following the disaster compared to other areas as a result of the fire), but consider this to be a useful estimate of the intensive margin response nonetheless. Further, Table 4 shows that on average the disaster has no significant effect on overall employment rates, so endogenous selection is likely minimal.

Table 5 shows that consistently employed individuals experience a decrease in employment income by more than \$5,800 (representing 11.5% of the average annual employment income) on average as a result of the wildfire. For these individuals, total income falls by more that \$6,800 on average per year, representing 12.5% of the pre-event total annual income. This result suggests that the intensive margin response – i.e., the impact of the disaster on continuously employed individuals – dominates the extensive margin response – i.e., the effect of the disaster on labour market attachment. Unfortunately, the LAD does not provide information on either wages and hours worked, and so while our results show that the wildfire reduces employment incomes, we are unable to determine exactly how these reductions operate through wages or the hours worked.

Table 5: Estimated average intensive margin effect of the Slave Lake wildfire

Variables	Total income	Employment income
Treatment	-6,804***	-5,845***
	(2,455)	(2,224)
Mean dependent variable for treated group, pre-event	54,209	50,787
Observations	56,598	

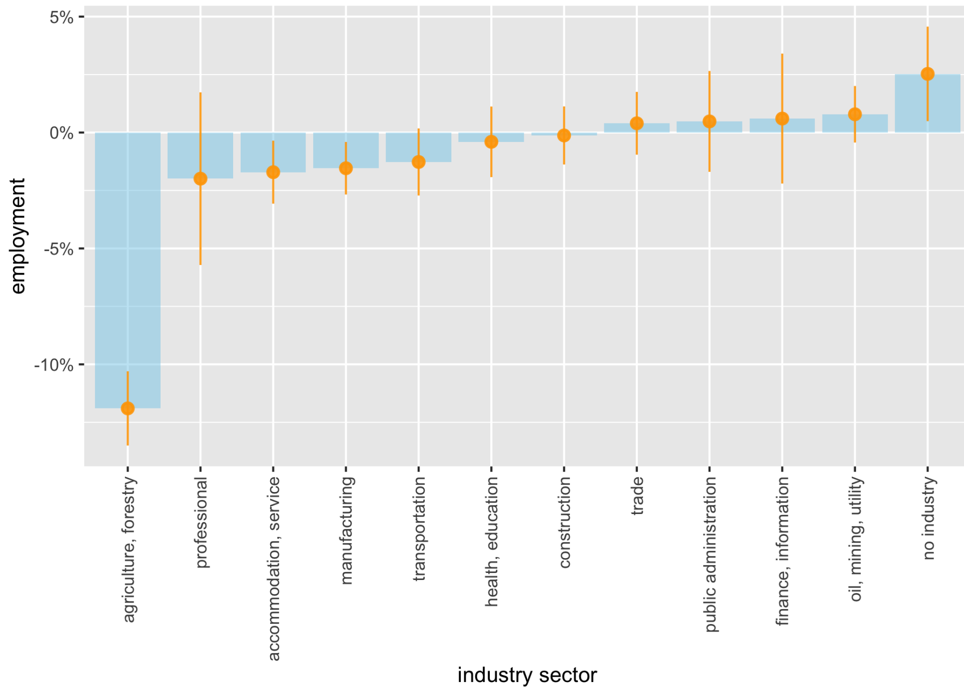
Notes: Each regression includes individual and year fixed effects. The standard errors are in parentheses and are clustered at the 2010 six digit postal code level. In this analysis, we restrict the sample to individuals employed every year over the period 2004-2018. These results do not include the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

To better understand heterogeneity in the impact of the disaster by sector of employment, we inlcude an interaction with pre-wildfire sector in the difference-in-difference model as follows:

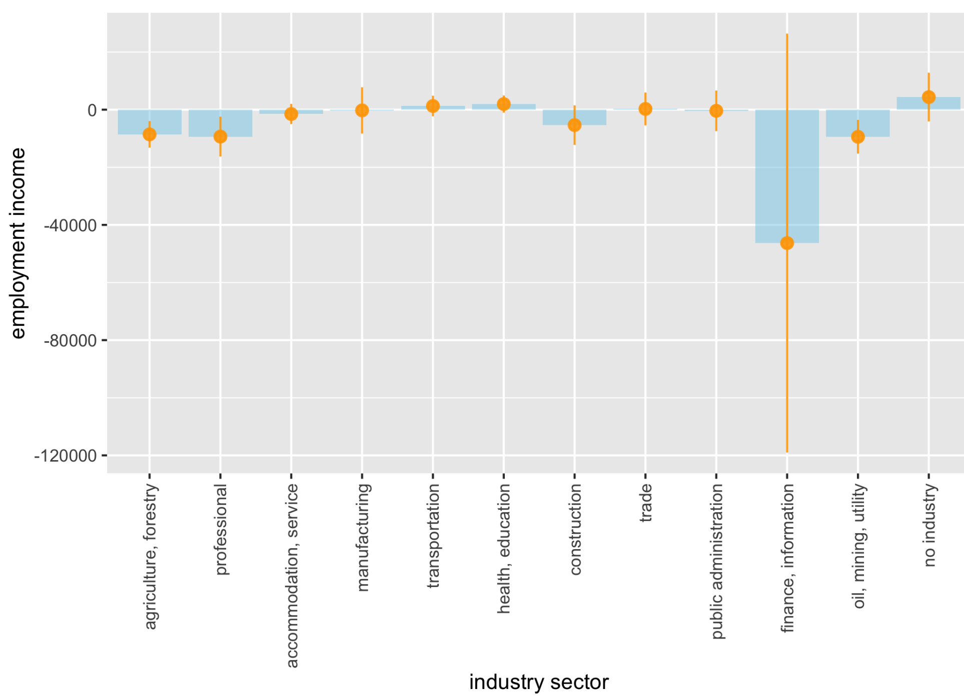
$$y_{imt} = \sum_{d=1}^{11} \theta_d D_{mt} \times industry_d^{2010} + \gamma_i + industry_d^{2010} \times \omega_t + \epsilon_{imt}, \tag{3}$$

where y_{imt} represents either individual's employment status or employment income, $industry_d$ is a dummy variable that takes the value of 1 if an individual is employed in a given sector in 2010 and 0 otherwise.

Results are shown in Figure 7. The share of individuals who worked in forestry-agriculture sector in 2010 experience a 12% decrease and their employment income decrease by \$8,500 as a result of the wildfire, compared to their counterparts in the weighted control group. This decrease is explained by the fact that the fire directly hit this sector by devastating an estimated area of $47km^2$. We also find a decrease in employment income of \$9,400 for workers in oil-utility sector, and \$9,300 for workers in the professional-administrative sector. Despite the drop in employment income, the share of workers in these industry sectors is unaffected. As mentioned in Section 2, the fire disrupted the oil-utility sector activities for at least one month which might have affected employment income. The professional-administrative sector supports other establishments in their day-to-day operations such as providing human capital and managing companies. The disruption of activities in the agriculture-forestry sector and oil-utility sector might indirectly affect individuals working in the professional-administrative sector.



(a) Share of people employed



(b) Employment income

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.

Figure 7: Estimated average effect of the Slave Lake wildfire on share of people employed and employment income by sector conditional of being in a given industry sector in 2010.

4.3 Additional results

4.3.1 Migration

Migration is considered as a way for affected individuals to mitigate the negative effect of natural disasters (Strobl, 2011; Deryugina et al., 2018). We rereun (1) using the defined migration variable as a dependent variable. Results in Table 6 show that migration out of Slave Lake increased by 2.9 percentage points as the result of the wildfire.

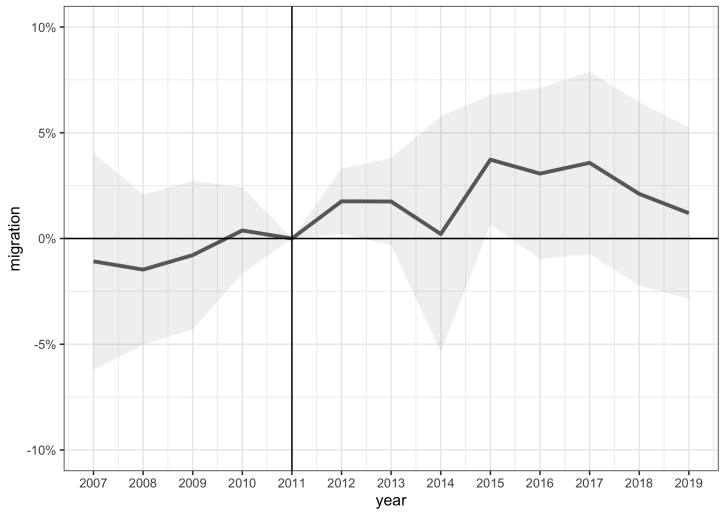
Table 6: Estimated average on migration of the Slave Lake wildfire

Variable	Migration (x 100)
Treatment	2.93**
	(1.32)
Observations	67,851

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

We also estimate (2) using the migration the dependent variable. In Figure 9, we observe an increase in migration for affected individuals from the first year up to the fifth year after the disaster from 1.7 to 3.5 percentage point (no individual years are statistically significant). Overall, this represents an average increase in migration by almost 3 percentage points among the affected individuals compared to the weighted control group. This result is in line with Statistics Canada census profile showing a 1.9% decrease in Slave Lake's population between 2011 and 2016, as compared to an increase by 11.6% in the rest of the province over the same period.[20]

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



Notes: This regression includes individual and year fixed effects. We collapse the years 2004, 2005, and 2006 to year 2006 in order to better highlight the post-trend result. 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 9: Estimated average effect of the Slave Lake wildfire on migration.

4.3.2 Income by age group and sex

Similar to the heterogeneity analysis by industry of employment, we consider heterogeneity by age and sex using the following approach:

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

We define four age groups, based on the ages of individuals at the time of the wildfire: below 25, 25 to 39, 40 to 54, and 55 and over. Table 7 presents the results. We find individuals below 25 and between 40-54 at the time of the disaster experience a decrease in employment income by more than \$4,200 and \$6,100, respectively. We do not find any significant effect of the event on employment rate and self-employment income across the different age groups. Our results suggest a drop in self-employment for affected individuals below 25 years old by 2.9 percentage points.

Table 7: Estimated effect of the Slave Lake wildfire on outcomes by age group

Variables		Employment income	Employed (x 100)	Self-employment income	Self-employed (x 100)
Treatment * below 25		-4,254**	-2.48	-164.3	-3.92***
		(2,133)	(2.08)	(315.3)	(1.40)
Treatment * 25-39		-317.9	0.14	-364.5	1.30
		(1,814)	(1.78)	(278.3)	(1.14)
Treatment * 40-54		-6,166***	-0.81	-83.52	-0.19
		(2,371)	(0.89)	(392.1)	(1.70)
Treatment * above 55		-9,795	-0.72	-267.5	1.87
		(9,665)	(2.91)	(712.1)	(2.01)
Mean dependent variable, pre-event	below 25	19,722	92	229	2
	25-40	37,693	89	492	6
	40-55	53,956	90	1,292	10
	above 55	63,125	85	1,262	8
Observations		68,104			

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' outcomes conditional on sex using (4) where age_i is replaced by $female_i$. Table 8 shows that male employment income falls by more than $6,800 relative to men in the control group. This is consistent with the fact that men are over-represented in the sectors exposed to the disaster. Among the individuals affected by the disaster, 3.7% of women versus 17.6% of men worked in oil-utility sector before the event. Similarly, 1.1% of women versus 2.7% of men worked in agriculture-forestry sector before the event.

Table 8: Estimated effect of the Slave Lake wildfire by sex

Variables		Employment income	Employed (x 100)	Self-employment income	Self-employed (x 100)
Treatment * male		-6,819**	-0.23	86.24	0.70
		(2,969)	(0.94)	(287.7)	(1.07)
Treatment * female		-1,307	-1.15	-536.3***	-0.55
		(1,178)	(1.53)	(198.6)	(1.23)
Mean dependent	male	61,927	93	1,308	8
variable, pre-event	female	26,789	84	408	7
Observations		68,104			

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.

4.4 Robustness Checks

Our regression will recover the causal impact of the wildfire on incomes only if we have identified an appropriate control group. Our choice of control group is based on a three-step process: first, we select control municipalities that are of similar to the treated municipality; second, we select control groups within a similar region as the treated municipality; third, we use matching to select individuals from within the control municipalities that are similar to treated individuals. In this section, we evaluate the robustness of our results to alternative choices for the control group. We conduct our robustness checks by both considering alternative choice of control municipalities, as well as by evaluating alternative approaches to matching individuals from within control municipalities.

Our baseline results draw the control group using a doughnut strategy around the treated municipality – including municipalities at least 100 km away but less than 200km away from Slave Lake (as illustrated in Figure 2). We include only communities with a similar population as Slave Lake, from 5,000 to 10,000 people in 2011, since labour market trends in larger municipalities and more rural areas may be different compared to small towns. In this section, we explore alternative choices for a control group. First, we expand the doughnut to between 100 and 300 km from Slave Lake (illustrated in Figure 2), again focusing on towns of a similar size to Slave Lake (5,000-10,000 population). Second, we use the original doughnut (100 to 200km), but include cities with a 2011 population of 5,000 to 50,000 in the control group. Third, we consider all individuals living in municipalities and cities of any size that are in the Athabasca-Grand Prairie-Peace River Economic Region, which includes Slave Lake (as illustrated in Figure 2). Fourth, we construct the control group using all municipalities in Alberta with have a 2011 population of 5,000-10,000 individuals.

Table 9 presents the effect of Slave Lake wildfire on incomes using Equation (1) with each of the different control groups, as described above. We present results both with and without propensity-score matching of individuals from within the control group to the treated group.

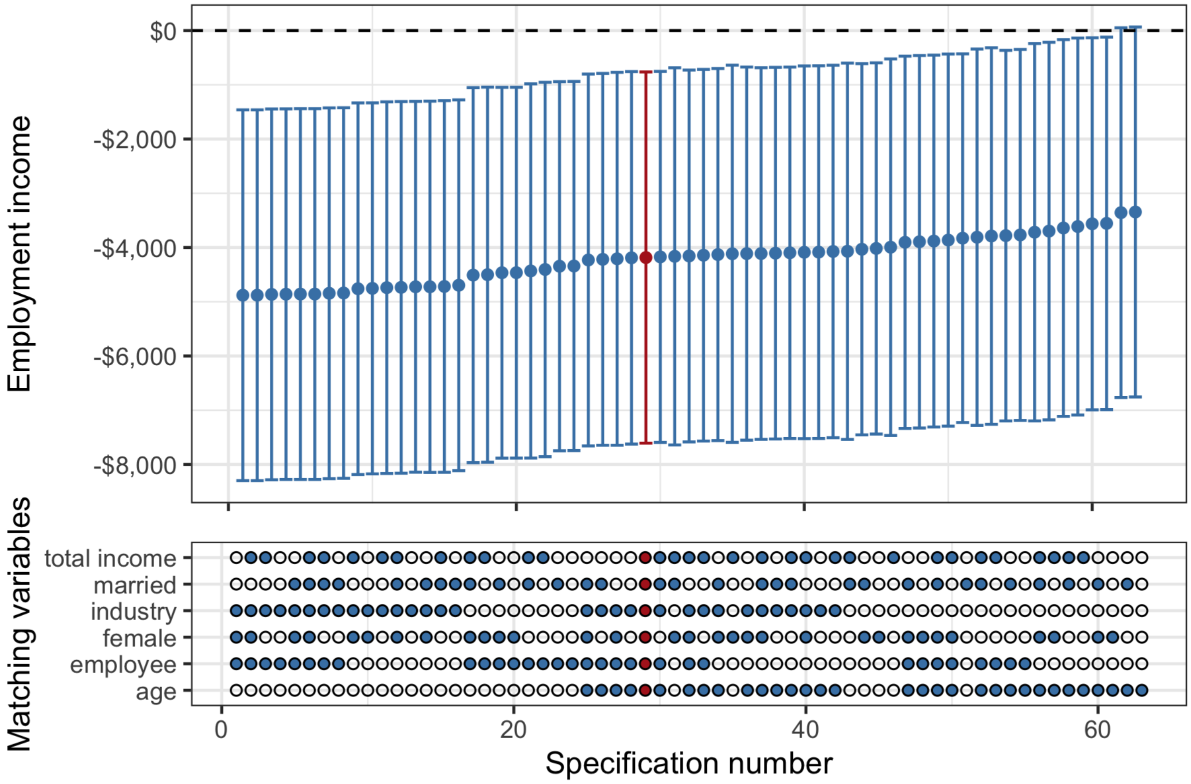
Table 9: Average effect of the Slave Lake wildfire on incomes using various control groups

Variables	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	
	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatche
Total income	-4,703**	-4,117*	-2,611	-2,009	-5,407***	-3,891**	-2,769	-2,082	-2,316	-1,324
	(2,157)	(2,148)	(1,934)	(1,906)	(1,904)	(1,922)	(1,930)	(1,928)	(1,887)	(1,879)
Employment	-4,185**	-3,807**	-1,942	-1,433	-4,652***	-3,085**	-2,829*	-2,357	-1,789	-862.3
income	(1,746)	(1,735)	(1,587)	(1,544)	(1,536)	(1,557)	(1,559)	(1,556)	(1,576)	(1,510)
Employed	-0.68	-1.16	-0.70	-0.81	-0.42	-0.45	-0.74	-1.11	-0.65	-0.62
(x 100)	(0.92)	(0.92)	(0.75)	(0.75)	(0.75)	(0.75)	(0.75)	(0.75)	(0.73)	(0.73)
Self-employ-	-209.1	-220.4	-235.9	-263.1	-317.2*	-328.5*	-42.42	-51.17	-219.7	-251.6
ment income	(213.4)	(218.4)	(182.8)	(184.7)	(182.0)	(184.2)	(186.6)	(189.0)	(179.2)	(180.8)
Self-employed	0.111	0.150	0.425	0.509	0.109	0.171	0.392	0.386	0.326	0.463
(x 100)	(1.05)	(1.05)	(0.910)	(0.910)	(0.909)	(0.910)	(0.908)	(0.906)	(0.902)	(0.901)
Government	176.4	162.1	128.9	37.16	84.71	34.98	168.4*	155.0	101.9	-40.86
transfer	(118.3)	(116.6)	(101.1)	(101.6)	(101.6)	(101.7)	(98.88)	(100.3)	(97.84)	(98.04)
Total observations	68,104	68,229	208,917	209,303	209,347	210,105	271,015	271,708	369,020	371,988

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.

The results in Table 9 show that our main results are upheld when the control group is drawn from a set of communities that are geographically close to Slave Lake (columns (b) and (c)). When we include municipalities that are far away from Slave Lake among the control group, as in columns (b) and (e), the results lose statistical significance, although the results remain directionally the same.

In the second stage of our robustness analysis, we consider the approach to matching individuals in the control communities with individuals in the treated communities. Our matching analysis uses propensity score matching, with propensity scores based on 2010 (pre-wildfire) observations of income, marital status, industry, sex, employment status, and age. In this section, we conduct the matching analysis using different subsets of these matching variables. Given the six potential matching variables, there are $2^6 - 1 = 63$ (we substract one because we do not include the case where no matching variables are used, instead reporting results from the unmatched analysis separately) possible combinations of matching variables. We re-run the main analysis using each of these possible combinations of matching variables. Figure 10 presents the effects of the event on employment income using the corresponding matching weight from the 63 different combinations of matching variables. The results indicate that the choice of matching variables does not have a large impact on the results, and that our choice of matching variables is not an outlier. Overall, no matter which matching variables are selected, we find a similar qualitative impact of the wildfire on employment income.



This regression includes individual and year fixed effects. The standard errors are clustered at the 2010 six digit postal code level. The bars are 95% confidence intervals. The main specification is shown in red, while alterantive specifications are illustrated in blue.

Figure 10: Estimated average effect of the Slave Lake wildfire on affected individuals' employment income.

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 income for a number of years following the disaster. We find that the individuals experience a decrease in their employment income by almost 9.5% on average per year, compared to the 2004-2010 average employment income. We find evidence of an intensive margin effect in which continuously-employed individuals contribute the most to the income drop. We find little evidence of an extensive margin response: employment and self-employment rates are almost unaffected by this event on average. The largest impacts of the wildfire appear to be on workers aged 40 to 54, males, and workers in agriculture, forestry, and oil and gas sectors, which were directly impacted by the fire.

While there have been numerous assessments of health impacts of wildfires, this paper is the first we know of that estimates the economic impact of wildfires on individuals. It finds long-term impacts of the disaster on the labour market earnings of affected individuals. Given the context of increasing intensity and frequency of wildfires, this is an important finding that may be useful in helping to structure disaster response policies.

The costs of wildfires that are typically reported focus on property damage, health costs, as well as direct reduction in economic activity during the fire. In contrast, this paper suggests that wildfires cause on-going labour market disruptions. In our paper, we find a reduction in total income income of 9.5% ($4,703) for seven years following the fire. Given a working age population of 4,260 people in 2011 in Slave Lake, and assuming the impacts persist for seven years, the total reduction in employment income is estimated to be $140 million. This represents almost 13% of the estimated impact of the wildfire on property, health, and direct economic losses, and suggests that on-going labour market disruptions are an important part of the costs of economic disasters that should be considered in assessments of the costs of natural disaster.

This paper also contributes to the broader literature that assesses costs of natural disasters of all kinds, using the same kind of quasi-experimental strategy as employed here. This literature is conflicting, with some analysis finding improvements in economic outcomes following disaster, and others finding the opposite. The current paper is obviously not the last word on the topic, but instead is a contribution to a growing field, and may inform future analysis that seeks to draw broad lessons from context-specific analysis of natural disasters.

There are some limitations to our analysis. First, we don't have 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.

References

Anttila-Hughes, J., & Hsiang, S. (2013). Destruction, disinvestment, and death: Economic and human losses following environmental disaster. *Available at SSRN 2220501*.

Arcaya, M., Raker, E. J., & Waters, M. C. (2020). The social consequences of disasters: Individual and community change. *Annual Review of Sociology*, *46*, 671–691.

Baez, J., De la Fuente, A., & Santos, I. V. (2010). Do natural disasters affect human capital? An assessment based on existing empirical evidence.

Baylis, P., & Boomhower, J. (2019). *Moral hazard, wildfires, and the economic incidence of natural disasters* (Tech. Rep. No. w26550). National Bureau of Economic Research.

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.

Billings, S. B., Gallagher, E., & Ricketts, L. (2019). Let the rich be flooded: The unequal impact of Hurricane Harvey on household debt. *Available at SSRN 3396611*.

Botzen, W. W., Deschênes, O., & Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, *13*(2), 167–188.

Boustan, L. P., Kahn, M. E., Rhode, P. W., & Yanguas, M. L. (2020). The effect of natural disasters on economic activity in US counties: A century of data. *Journal of Urban Economics*, *118*, 103257.

Case, P., Banks, B., Butler, E., & Gosnell, R. (2000). Chapter 7. Assessing potential wildfire effects on people. *Journal of Sustainable Forestry*, *11*(1-2), 159–175.

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

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.

Couch, K. A., & Placzek, D. W. (2010). Earnings losses of displaced workers revisited. *American Economic Review*, *100*(1), 572–89.

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.

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.

Gallagher, J., & Hartley, D. (2017). Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy*, *9*(3), 199–228.

Gignoux, J., & Menéndez, M. (2016). Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia. *Journal of Development Economics*, *118*, 26–44.

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.

Hallstrom, D. G., & Smith, V. K. (2005). Market responses to hurricanes. *Journal of Environmental Economics and Management*, *50*(3), 541–561.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, *15*(3), 199–236.

Hsiang, S., Oliva, P., & Walker, R. (2019). The distribution of environmental damages. *Review of Environmental Economics and Policy*, *13*(1), 83–103.

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. w20352). National Bureau of Economic Research.

Karbownik, K., & Wray, A. (2019). Long-run consequences of exposure to natural disasters. *Journal of Labor Economics*, *37*(3), 949–1007.

Kirchberger, M. (2017). Natural disasters and labor markets. *Journal of Development Economics*, *125*, 40–58.

Kocornik-Mina, A., McDermott, T. K., Michaels, G., & Rauch, F. (2020). Flooded cities. *American Economic Journal: Applied Economics*, *12*(2), 35–66.

KPMG, L. (2012). *Lesser Slave Lake regional urban interface wildfire – Lessons learned* (Tech. Rep.). Municipal Affairs.

Kulig, J. C. (2012). *The Slave Lake fires, May 2011: Lessons learned* (Tech. Rep.). University of Lethbridge.

Markussen, S. (2012). The individual cost of sick leave. *Journal of Population Economics*, *25*(4), 1287–1306.

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.

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..

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

Zahran, S., Shelley, T. O., Peek, L., & Brody, S. D. (2009). Natural disasters and social order: Modeling crime outcomes in Florida. *International Journal of Mass Emergencies and Disasters*, *27*(1), 26–52.

Appendix

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

In the section we rerun (1) while including the year 2011. We find that the event reduces affected individuals employment income by more than \$3,700 on average which represents almost \$400 difference compared to our main finding in Table 3. Overall, the results are similar to our main finding.

Table 10: Estimated effect of the Slave Lake wildfire on affected individuals' incomes including 2011

Variables	Total income	Employment income	Self-employment income	Government transfer
Treatment	-4,227**	-3,763**	-243.0	145.2
	(2,014)	(1,671)	(200.9)	(122.7)
Mean dependent variable, pre-event	49,625	45,233	880	1,820
Observations		73,368		

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.

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

In this section, we rerun (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 3 is explained by missing postal code information for some individuals over time. We find a similar result as in Table 3 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 11: 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
Treatment	-4,751*	-4,218	-220.5	180.0
	(2,494)	(2,642)	(194.4)	(178.9)
Mean dependent variable, pre-event	49,865	45,450	885	1,829
Observations		67,752		

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