Wildfire Smoke and Labour Market Outcomes: Evidence from Canada

Stanislav Hetalo

Simon Fraser University

8888 University Dr W, Burnaby, BC, Canada, V5A 1S6

Email: shetalo@sfu.ca

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Abstract

Wildfire smoke is known to be an increasing source of air pollution. While general air pollution is documented to have a detrimental effect on health and worker productivity, the impact of wildfire smoke has been less studied. In this paper, I combine a satellite data capturing daily smoke exposure with monthly individual-level work and earnings data across Canada to evaluate the causal impact of wildfire smoke on labour market outcomes. I find that work hours are reduced by almost one hour each week or approximately 2.5 percent for a typical worker in Canada due to population average wildfire smoke exposure. These negative impacts are lasting and persist up to two years into the future. My results highlight the importance of considering the long-term labour market impacts when assessing future air regulations or wildfire prevention investments.

JEL Classification: J21, J22, Q51, Q52, Q53, Q54
Keywords: wildfire smoke, air pollution, labour market, labour supply, hours of work

1 Introduction

Wildfire smoke is becoming a pervasive natural hazard across North America. On Wednesday, June 7, 2023, alone, more than 75 million of people in the eastern U.S. were under high alert air quality warnings due to wildfire smoke plumes from Canada[1]. In addition, wildfires are now a leading contributor to dangerous particulate matter (PM) emissions in Canada and are growing in size and magnitude (Meng et al., 2019). These trends are also projected to intensify both locally and globally in the future (Flannigan et al., 2013; Burke et al., 2023). Given the prevailing and widespread rise in harmful air pollution from forest fire smoke, this study evaluates the impact of wildfire smoke exposure on the Canadian labour market.

Generally, air pollution is known to have a detrimental effect on human health and economic outcomes (Manisalidis et al., 2020). A large literature documents adverse effects on mortality, chronic health conditions, and cognitive functioning (Chay and Greenstone, 2003; Kampa and Castanas, 2008; Brockmeyer and d'Angiulli, 2016; Archsmith et al., 2018). Contaminated air also directly affects workers by decreasing labour supply, reducing productivity, and encouraging costly avoidance behaviour (Richardson et al., 2012; Aragon et al., 2017; Zhang and Mu, 2018). However, our knowledge about the negative impacts of poor air quality on labour market outcomes is predominantly focused on contemporaneous or short-term effects (Dominski et al., 2021) and only one study to date finds longer-term labour market impacts from wildfire smoke exposure (Borgschulte et al., 2022).

In this paper, I evaluate the longer-run impacts of monthly variation in the exposure to wildfire smoke on labour market outcomes for workers in Canada. First, I combine monthly data from the Canadian Labour Force Survey (LFS) with high-resolution satellite smoke images across North America[2] provided by the National Oceanic and Atmospheric Administration (NOAA) from June 2010 through December 2019[3]. Next, I calculate several measures of

[1]The full details are covered here: https://www.cnn.com/2023/06/07/weather/new-york-air-pollution-canada-wildfires-climate-wednesday/index.html

[2]This data tracks smoke plumes transportation and generates the final picture of a day at the end of each day, so the influence of daily winds is "embedded" within this data. In a comparable setting using smoke data, Borgschulte et al. (2022) find that controlling for wind patterns has very little to no impact on estimates.

[3]My analysis period starts in June 2010 since the NOAA's satellite data carrying the intensity of smoke plumes becomes consistently available from this month.

wildfire smoke prevalence and intensity for all 73 economic regions[4] in Canada. Finally, using a two-way fixed effects approach that controls for unobserved differences across economic regions and common time shocks, I estimate the causal effect of variation in smoke exposure on labour market outcomes.

I find that wildfire smoke causes statistically significant declines in labour hours worked lasting up to two years into the future following an exposure shock. Quantitatively, an additional day of smoke plume coverage in an economic region leads to a 0.017 decrease[5] in the number of hours worked, which corresponds to a 0.05 percent reduction. Combining this impact with the average number of smoke days over a two year period, work hours are reduced by almost an hour each week or about 2.5 percent for a typical worker in Canada due to wildfire smoke exposure[6]. I also document important impacts on other labour market outcomes: exposure to smoke increases the probability of moving to part-time work as well as becoming unemployed.

Next, I employ the NOAA's satellite data classification that splits all smoke plumes by density into three categories: low, medium, and high. My findings show that high intensity smoke is unsurprisingly the most harmful one for labour performance, but negative effects are also present for medium- and low-intensity smoke days. I also establish an evidence of a prevailing adverse impact of smoke on individuals in Western Canada - those living in the provinces of BC, AB, MB, or SK. The latter finding is presumably due to the increased number of higher intensity smoke days for affected workers.

Unlike other sources of air pollution, such as industrial emissions, wildfire smoke is presumably exogenous to unobserved determinants of labour market outcomes. Supporting this identification assumption, my results are robust across alternative specifications. In a placebo check, I also do not observe any effect of future smoke on current hours worked. While smoke plumes typically drift hundreds of kilometres, a major wildfire could have a direct impact on a local economy if roads are closed or individuals are helping with prevention or mitigation efforts

[4] I focus on an economic region because this is the most specific geographic identifier in the Canadian Labour Force Survey data used to measure labour market outcomes. I exclude the following three territories due to data limitations: Nunavut, Northwest Territories, and Yukon.

[5] This number is an average of the past year and the past 1 to 2 years lagged effects.

[6] The average number of smoke days an individual experiences over a two-year period is 52.6 days. Given this level of exposure, the cumulative impact expected on current hours worked is approximately 0.9 hours per week which represents a 2.5 percent decrease from the average of 34.8 hours per week.

(Mott et al., 2002). Although this direct impact on a community is short-lived, I address this hypothesis by controlling for the number of wildfires in a region and find that my estimates are not influenced by a localized response near the fire. The average immediate influence of wildfires on a typical worker appears to be statistically and economically negligible. Another potential alternative mechanism to explain the observed effect is a prolonged regional drought affecting both fire activity along with labour market outcomes. In fact, a recent study demonstrates a sizeable adverse effect of drought on a wide array of economic outcomes using Australian data (Fleming-Muñoz et al., 2023). This economic response to drought is also unlikely to influence my estimates since smoke plumes drift hundreds of kilometres from their source. Finally, I do not find that smoke exposure affects worker migration, so it is unlikely that the fluctuations in worker locations alter my results.

This paper contributes to the literature in the following ways. First, the majority of recent studies estimate the short-run impacts of sharp changes to air quality following changes in environmental regulations (Wang et al., 2019; Tan and Mao, 2021). While changes in air quality due to new regulations often provide a natural experiment to identify causal effects, these changes can have other impacts on local labour markets, such as through changing costs associated with production at a factory. Wildfire smoke is more plausibly exogenous to other changes in local labour market opportunities since smoke plumes are known to travel hundreds or even thousands of kilometres away from their origins, generating a series of wide range and geo-diverse shocks (Forster et al., 2001; Stohl et al., 2007).

Second, different sources of emissions feature distinct composition and potency of pollutants (Almetwally et al., 2020). Particulate matters from wildfire smoke is often more harmful than similar PM levels from other sources (Adams et al., 2015; Aguilera et al., 2021). Furthermore, volatile organic compounds from forest fire smoke are documented to have a stronger adverse effect on lung functions than compounds from other sources in the same region (Wegesser et al., 2010; Williams et al., 2013). Moreover, much of the literature focuses on the impacts of a single class of pollutants, such as PM (Chen and Hoek, 2020). Wildfire smoke carries multiple types of other pollutants that are not captured by measures of PM such as ozone, volatile organic compounds (VOCs), and other hazardous air pollutants (HAPs) (O'Dell et al., 2020).

Even if reliable measures of each of these contaminants were available, studies which include multiple pollutants often ignore potential interaction effects between the classes of contaminants (Billionnet et al., 2012; Mauderly, 2014). For example, ozone and nitrogen dioxide can interact with PM and create a synergistic adverse effect on human health (Mauderly and Samet, 2009; Mainka and Żak, 2022). In this paper, I consider wildfire smoke events emitting a diverse combination of pollutants, which allow me to address previous critiques about omitting certain air contaminants and their interaction effects.

Third, another stream of literature evaluates the consequences of wildfires above certain threshold in size and other natural disasters that are rare events (Nielsen-Pincus et al., 2013; Burke et al., 2022; Tran and Wilson, 2022), leaving the majority of smoke shocks and their consequences out of consideration. Importantly, smaller smoke events could potentially have significant longer-run effects on workers' performance due to the repeated exposure. In this study, I combine wildfire smoke readings covering all provinces in Canada with individual-level monthly data tracking labour market outcomes to estimate a causal effect of wildfire smoke on the national labour market.

Finally, a growing literature documents the impact of smoke exposure on health outcomes (Reid et al., 2016; Kim et al., 2017; Miller et al., 2017; Shrestha, 2019) but, to my knowledge, only one study evaluates the effect of forest fire smoke on labour market outcomes at a national level. Borgschulte et al. (2022) find that an extra day of wildfire smoke exposure decreases earnings by approximately 0.01 percent in the United States. My study builds on the previous paper in several dimensions. First, I estimate the dynamic impact of smoke exposure on hours worked and show that effect lasts up to two years after the smoke event, while Borgschulte et al. (2022) focuses on labour market earnings with the impact of smoke fading away within the year of exposure. This difference could be potentially attributed to more generous sick leave policies in Canada compared to the United States. Workers with paid medical leave are likely take more time off than employees with limited or no sick leave support from their employers (DeRigne et al., 2016; Chen et al., 2020). Second, I use comprehensive individual-level data tracking labour market outcomes where Borgschulte et al. (2022) focus on county-level aggregate labour market outcomes. I also incorporate the different levels of smoke intensity which has not previously been considered. The use of individual-level data and smoke density allows me to evaluate heterogeneous responses across different types of workers and varying smoke intensities. Finally, despite the known negative impacts of air pollution caused by wildfires and the increasing prevalence of fire smoke in Canada, no prior study documents the causal impact of smoke on Canadian workers.

My results also advance our understanding of the comprehensive social costs of natural disasters. The current literature on wildfire exposure has primarily concentrated on the direct impact from fires, while leaving the effect of drifting smoke plumes mostly untouched (Finlay et al., 2012; Stephenson et al., 2013; Thomas et al., 2017). I emphasize that wildfire smoke creates a series of far-reaching and spatially abundant hazards affecting the overwhelming majority of the Canadian population, not only those living near forested areas. While smoke exposure varies with a region, a typical worker in my sample faces almost a month of smoke days each year. These events can occasionally cause international issues, since wildfire smoke ignores borders and a sizeable number of Canadian fire smoke events have their origins in the U.S. (Miller et al., 2010). Importantly, this body of literature is still sparse while climate change is expected to exacerbate the intensity of wildfires and the respective smoke plumes producing haze externalities across the globe and in Canada (Wang and Chen, 2016; Haider et al., 2019). My findings are among the first to demonstrate a significant negative impact on national labour market outcomes from drifting wildfire smoke plumes. More generally, this paper extends our current understanding on the potential benefits from pollution abatement policies.

The rest of the paper is structured as follows: Section 2 outlines background information on wildfire smoke and labour market; Section 3 describes data sources; Section 4 explains the empirical strategy employed to identify the causal impact of wildfire smoke exposure; I discuss the primary results, investigate heterogeneous impacts, and test the robustness of my findings in Section 5; and, include concluding remarks in Section 6.

2 Background Information

Wildfire smoke is known to worsen ambient air conditions by transmitting fine particulate matters, while also carrying other harmful chemicals, such as carbon monoxide, nitrogen oxides, ozone, and various volatile organic compounds (O'Dell et al., 2020). These pollutants in general have a harmful effect on human well-being. Importantly, the adverse impact of wood smoke is stronger in comparison with a typical human pollution from burning fossil fuels (Aguilera et al., 2021). In contrast with human-induced air pollution, wildfire smoke is usually associated with significantly larger PM levels which exacerbate the effect, since the dose–response function is typically non-linear for higher levels of PM exposure[7] (Chen et al., 2006). In a review paper, Black et al. (2017) documents that wildfires generate considerably greater amounts of fine and ultrafine particulates which penetrate more deeply into the lung. As a result, these tiny particles are more capable to stay within a human body for much longer, which negatively affects one's health and performance. In addition, the formation of volatile and semi-volatile organic compounds is larger for wildfire smoke, while these fire-borne particles are more potent to induce a higher oxidative stress on lung compared to the urban emissions.

The exposed person inhales contaminated air which lets these pollutants break into lungs, negatively affecting their structure and performance, while simultaneously being transferred to the bloodstream (Maier et al., 2008). It is well-documented in the literature that a general exposure to polluted air significantly increases hospital visits that directly include increases in airborne and mental health diseases, morbidity, mortality, and overall life expectancy (Tham et al., 2009; Reid et al., 2016; Sokolik et al., 2019; Lelieveld et al., 2020). Another stream of literature connects air pollution with behavioural responses such as costly defensive actions. Among the well-established research links are: postponing outdoor activities (Graff Zivin and Neidell, 2009); larger medical investments (Deschenes et al., 2017); increase in spending on preventive products (Liu et al., 2018); and a rise in demand for medical insurance (Chen and Chen, 2020).

Air pollution not only affects human health and behaviour but also productivity. An increasing number of studies in economics demonstrate the negative effect of pollution exposure on hours worked (Hanna and Oliva, 2015; Aragon et al., 2017); number of sick leaves (Ostro, 1983; Holub et al., 2020); and worker productivity across different sectors in the economy (Neidell,

[7]Kochi et al. (2010) emphasizes four additional reasons for the differences between a typical and wildfire smoke PM studies: modelling choice, chemical composition dissimilarity, difference in avoidance behaviour, distinction in hazard perception.

2017). The existing literature further provides suggestive evidence of an adverse impact of changes in air pollution from environmental regulations on employment (Davis et al., 2010; Zhao et al., 2022). There is, however, a complex trade-off between environmental regulations and employment, since air pollution control programs can directly reduce the number of jobs in an affected area (Xue et al., 2019; Ng et al., 2022). In turn, wildfire smoke is geographically pervasive and convincingly external to local labour market trends.

The findings from specifically wildfire smoke exposure are, by and large, consistent with general pollution studies. Using the national U.S. data and a standard value of a statistical life, Miller et al. (2017) demonstrates that mortality cost associated with wildfire smoke is greater than the related morbidity cost for adults. Similarly, the local studies of wildfire smoke events exhibit a similar dominance of mortality opposed to morbidity costs calculated for economically active citizens (Moeltner et al., 2013; Kochi et al., 2016). But the fire smoke is not only harmful for adults, it has also a detrimental impact during prenatal and early life periods (Šrám et al., 2005; Jayachandran, 2009; Holstius et al., 2012; Cândido da Silva et al., 2014; Heft-Neal et al., 2022). Apart from health effects, wildfire smoke also induces avoidance and mitigating behaviour, such as a prolonged use of air purifiers (Mott et al., 2002), staying indoors (Kunzli et al., 2006), missing workdays (Richardson et al., 2012), a reduction in outdoor physical activity (Doubleday et al., 2021), and tourism cancellations (Gellman et al., 2022).

But, what do we actually know about the link between the smoke from fires and labour market outcomes? The effect of wildfires on the labour market is documented to be ambiguous. On the one hand, wildfires can reduce business activity and tourism in the affected area (Jones and McDermott, 2021). While on the other hand, wildfires might temporarily accelerate local economy through the increase in investments on suppression and rebuilding activities (Nielsen-Pincus et al., 2014). Yet, very little is known about the comprehensive impact of wildfire *smoke* on workers at the national level. Only one study evaluates the influence of wildfire smoke on labour market outcomes. Borgschulte et al. (2022) establishes the relationship between the smoke from fires and quarterly labour earnings and constitutes a decline in earnings by approximately 0.01 percent using national U.S. data. Yet, there is no known evidence of the wildfire smoke exposure effect on labour hours worked nationwide. My paper addresses this link as an important piece of information on the way to a benchmark for socially preferable environmental regulations.

3 Data Sources

3.1 Wildfire and Weather Data

The National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS) utilizes satellite image sequences to generate geo-referenced smoke polygons and plume densities covering North America. Smoke expert image analysts conduct data quality checks and transform the smoke detections to produce a digital map of wildfire smoke plumes each day. The resulting data has a few potential limitations. A smoke plume may be obscured by significant cloud cover, which leads to a conservative estimate of my key smoke day measure since some smoke days will not be determined (Brey et al., 2018). Given limitations of observable satellite images, the daily data developed by the NOAA group determines the spatial coordinates of smoke but not the altitude of the smoke plumes. While smoke plumes higher in the air will have less of an impact on communities below, researchers document a strong connection between forest fire smoke plumes and ground-based air pollution measurements (Brey and Fischer, 2016; David et al., 2021; Childs et al., 2022; Burke et al., 2023). In order to examine the full impact of wildfire smoke on labour market outcomes, I overlay the HMS smoke plume data on spatial polygons for Canada's 73 economic regions for the period from June 2010 to December 2019 to obtain daily measures of smoke plume coverage and intensity across Canada. I also use a database recording wildfires from the Canadian National Fire Database so that I can control for potential direct disruptions to labour markets caused by wildfire events.

The weather information is available through the Adjusted and Homogenized Canadian Climate Data (AHCCD), which is provided by Environment and Climate Change Canada. The data captures monthly records of minimum temperature, mean temperature, maximum temperature, and precipitation. For economic regions with multiple weather monitors, I average all available weather records within a region. If an economic region is missing climate data for all stations in a certain month[8], I impute these measures using data from within 40 kilometres[9]

[8]There are 19 such cases within the entire dataset, which is 73 economic regions by 115 months.

[9]The value is chosen as a minimum distance to impute all of those 19 cases.

zone outside of the region's boundaries.

3.2 Labour Data

To capture labour market outcomes, I use individual-level Labour Force Survey (LFS) data from Statistics Canada. The LFS data is released on a monthly basis and is used to calculate local and national labour market statistics, such as unemployment rates. It is a sample survey with a cross-sectional design and a rotating panel sample feature. Specified dwellings remain in the sample for six consecutive months. Furthermore, all dwellings during their first month in the survey represent around one-sixth of the entire sample, the households in their second month in the sample constitute another one-sixth, and so on. The LFS dataset contains detailed information about monthly work patterns including: labour force status, hours worked, hours away from work (and the reason for being away), hourly wage, and occupation type. This data also includes detailed demographic information such as gender, age, marital status, and education level. Since I am looking for the effect of smoke events on a typical Canadian worker, I restrict my sample to include only respondents that are 20 to 65 years old and who are not full-time students. Unless otherwise noted, I consider the employed population only. The individual-level LFS data is supplemented with multiple datasets on demographic and economic characteristics at the economic region level available from Statistics Canada[10].

4 Research Design

4.1 Wildfire Smoke Exposure across Canada

I use regional variation in wildfire smoke activity to estimate the causal effects of changes in air pollution on labour market outcomes. To help illustrate my identification strategy, I provide a brief description of a typical major fire during my analysis period, the Slave Lake wildfire, which began 15 km east town of Slave Lake in northern Alberta on Saturday, May 14^{th}, 2011 and was contained by Tuesday, May 17^{th}, 2011[11]. Figure 1 depicts the evolution of smoke

[10] Monthly data on a population, participation rate, and unemployment rate at the economic region level available here: https://doi.org/10.25318/1410029301-eng. Annual data on migration characteristics accessible at: https://doi.org/10.25318/1710013801-eng.

[11] For more details and a disaster chronology, visit https://www.mdlsr.ca/explore/our-heritage/the-2011-wildfire/disaster-timeline.

plumes from the Slave Lake wildfire starting from a day before the disaster through the day it was fully contained. While this was a large fire, burning approximately 4700 hectares or 47 km^2, the area with poor air quality[12] as a result is several orders of magnitude larger[13]. The impact of other fires is similarly widespread due to wind-drifting smoke plumes. A recent paper using U.S. data shows that the average distance between a fire smoke cloud and the nearest wildfire is more than 600 kilometres (Miller et al., 2017). Overall, there is a stark contrast between wildfire events and the consequential *smoke* threat.

Figure 2 and Figure 3 summarize the annual exposure to wildfire and smoke for each economic region across Canada from 2011 to 2019. While most fires occur in the northern parts of Canada, wind drifting plumes from Canada and the U.S. generate smoke events covering substantial geographical area. In fact, all of the 73 economic regions across Canada experience at least some smoke in my sample[14]. These figures, again, illustrate a clear distinction between a wildfire hazard and the resultant *smoke* risk.

The detailed summary statistics are reported in Table 1. Column 1 represents the full sample of respondents, while columns 2 and 3 include only individuals from economic regions that are above or below median smoke exposure, respectively. The average Canadian worker faces more than 2 smoke days per month. Importantly, the proportion of respondents from Western Canada with above median exposure to smoke is almost twice as large as the same share of Western workers with below median wildfire smoke exposure.

4.2 Empirical Strategy

I aggregate the daily smoke data to construct a sequence of exposure measures that count the number of full coverage[15] smoke days for each individual i in region r and month m or quarter

[12]While all observed smoke plumes in the area are unlikely to be produced by this wildfire only, most of the smoke presumably originates from the specific wildfire, since there was very little smoke a day before and no other big fires during the wildfire burning period.

[13]For a visual reference, in Figure 1, the area burned by this wildfire is about 1 percent of the dark blue circle indicating the origin.

[14]The smallest number of smoke days across all economic regions over the period June 2010 to December 2019 is 31 days for economic region West Coast–Northern Peninsula–Labrador.

[15]Since economic regions are sizeable geographic units, I consider a region as fully covered on a certain day if at least 95 percent of the area is covered with smoke plumes.

q[16] and estimate the following equation:

$$Y_{rmi} = \sum_{q=-12}^{-1} \beta_q \cdot Smoke_{r,m+q} + X_{rmi}\gamma + \alpha_r + \alpha_{my} + \varepsilon_{rmi} \quad (1)$$

The left-hand side variable, Y_{rmi}, represents weekly hours worked (or an alternative labour market outcome). The key regressors of interest capture quarterly lagged measures of smoke exposure, $Smoke_{r,m+q}$, for up to three years preceding month *m*. I control for basic individual demographic characteristics, such as age, sex, education level, and marital status along with controls for average monthly temperature, precipitation and the number of smoke days within the current month[17] in the vector X_{rmi}. My empirical model includes regional fixed effects (α_r) that capture all unobservable time-invariant features specific to an economic region and month-by-year fixed effects (α_{my}) which account for common shocks, such as national economic conditions. Two-way clustered standard errors are calculated which allow for arbitrary correlation within regions over time and within months across all regions. The model is weighted by individual level weights available in the LFS[18].

Figure 4 presents the evolution of past days of wildfire smoke on hours worked using estimates from equation 1. I find that wildfire smoke up to two-years prior to the current month decreases hours worked for Canadian workers in my estimation sample. Given these dynamics, I simplify equation 1 by aggregating lagged smoke days at the year level for the two-years[19] preceding the current month:

$$Y_{rmi} = \sum_{y=-2}^{-1} \beta_y \cdot Smoke_{r,m+y} + X_{rmi}\gamma + \alpha_r + \alpha_{my} + \varepsilon_{rmi} \quad (2)$$

Equation 2 represents the *baseline specification*[20] used to measure the impact of wildfire smoke

[16]Quarter $q = -1$ means the past 3-month period, quarter $q = -2$ means past 4 to 6 month period and so on.

[17]While in the main specification I control for the number of smoke days in the month of a survey, it is essential to recognize that a survey collection period is usually ten days long and has varying dates each month. As a result, I could not credibly assess the immediate impact of exposure in this study. Importantly, all results in this paper are robust to a model without the inclusion of the current month number of smoke days. To analyze a shorter-term impact, a higher frequency data tracking hours at the daily or weekly level would be required.

[18]The LFS Microdata User Guide from Statistics Canada requires the use of weights to derive meaningful nationally representative estimates from the survey.

[19]Year $y = -1$ corresponds to a total number of smoke days in the past 12 months, while $y = -2$ refers to a total number of smoke days in the past 13 to 24 months period.

[20]My key dependent variable is hours worked which is bounded from below by zero. Hence, there might potentially be too many zeroes to be consistent with the ordinary least square specification. If I use tobit model instead, a magnitude of the estimates remains mostly unchanged from the main results.

on labour market outcomes[21].

4.3 Alternative Estimation Designs

Several recent articles point out that using ordinary least squares in difference-in-differences settings with two-way fixed effects (TWFE) can lead to biased coefficient estimates under the existence of heterogeneity in effect over treatment intensity, varying doses, or over time (Chaisemartin and D'Haultfoeuille, 2020; Chaisemartin et al., 2022; Roth et al., 2022). In particular, the coefficient of a treatment variable could be decomposed into a weighted sum of average treatment effects where some weights might be negative. Negative weighting arises from the TWFE estimator using previously treated observations as controls in the later time periods (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Morever, the standard TWFE estimator does not put much weight on treatment doses that are very different from the average dose, thus, this estimator can be an inaccurate representation of the average causal response (Callaway et al., 2021; Słoczyński, 2022). These two core issues pose a threat to the estimation designs in many papers relying on TWFE strategy.

In my setting, extreme exposure events, while rare, may be important in terms of impacts and so these TWFE weights could be influential. To address these possibilities, I perform two additional checks and compare them with the results from my preferred specification. The first analysis constructs the DID$_m$ estimator proposed by Chaisemartin and D'Haultfoeuille (2020) that compares the evolution of outcomes among switchers from one treatment dose d to some other value in two consecutive time periods to the same evolution among control groups whose treatment remains at the same dose d in both periods of time. The second test preserves my preferred specification but excludes regions that alternate between low and high levels of smoke exposure over time to assess the potential influence of negative weights. The results of this exercise are consistent with those from the main specification and presented in the Appendix A.

[21] As discussed in Section 3.2, my primary estimation sample for the number of hours worked outcome is limited to individuals who are employed. To address concerns that my sample of interest is affected by the treatment (wildfire smoke) if it impacts employment on the extensive margin, I also estimated the baseline specification including the full population of LFS respondents.The results remain consistent in magnitude and precision.

5 Results

5.1 Baseline Results

Table 2 presents results from equation 2 with the number of hours worked during a month as the dependent variable. Coefficients on my key measures of lagged smoke exposure from my baseline specification are presented in column 2 – while column 1 reports results excluding individual demographic and weather controls. The inclusion of these controls does not have a substantial influence on the key coefficients suggesting there is little sorting of individuals that is correlated with smoke exposure. Importantly, while the point estimate of two-year lagged coefficient appears to be larger than the one-year lag impact, the difference between those effects is not statistically significant. Therefore, I consider these two coefficients as rather similar in magnitude. Columns 3 and 4 present the results for various specifications that include different sets of fixed effects and the inclusion of a linear time trend, respectively. Finally, column 5 utilizes a rotating sample design of the LFS and represents the estimates from the baseline specification for the subsample of individuals that lived in the same dwelling for the entire six months rotation period. Notably, the estimated effect of lagged exposure remains similar across specifications suggesting that my results are not subject to the specific choice and supporting the exogeneity of the key smoke exposure treatment variable.

Overall, the estimates in column 2 of Table 2 imply that an extra day of smoke exposure within an economic region leads to the decrease of hours worked in a week by 0.013 hours in the next year and 0.020 in the second year following exposure. The average two-year effect of a single smoke day given the typical number of weekly hours worked corresponds to an approximately 0.05 percent decline[22]. Using these findings, I sum the effect up to compute the total loss in weekly working hours[23]. I multiply the estimated reduction in one- and two-year periods after the exposure by the average number of smoke days in a month (2.19) times the number of months in a year. My computations reveal a substantial total decline of approximately 0.9 hours or 2.5 percent in a typical week due to the smoke exposure in a preceding two-year

[22]This number is calculated as the average two-year effect ((0.013 + 0.020)/2) divided by the mean number of hours worked (34.823) and multiplied by 100.

[23]To calculate the total loss, I implicitly assume that the estimated marginal effect of a smoke day is similar to the average in my study.

period.

5.2 Additional Measures

To further understand the impact of smoke exposure on labour market, I test whether the treatment effect differs across varying smoke coverage and intensity. I re-estimate equation 2 with my regressor measuring the number of smoke days disaggregated by coverage in the economic region and/or by the level of smoke intensity. As previously mentioned, the HMS data reports three types of smoke intensity: high, medium, and low. In the baseline specification, I only count days as smoke days when the entire economic region is covered (more than 95 percent). Along with the measures of intensity, I examine the impact of days with medium (50-95 percent) or low (1-50 percent) coverages. Column 2 of Table 3 suggests that results are driven by days with full and medium coverages. This result is unsurprising, since the probability of workers facing an adverse smoke plumes diminishes as coverage in the economic region declines. Column 3 of Table 3 suggests that the densest smoke is naturally the most harmful with the average two-year effect being approximately 60 percent larger than a day of the typical smoke exposure. While heavy smoke events are rare, the magnitude of the impact of low intensity smoke days remains similar to the baseline results presented in Table 2. These results imply that even commonly invisible to human eyes lower-intensity smoke days have lasting impacts on workers.

Table 4 reports the estimated impact of wildfire smoke exposure on alternative measures of labour market outcomes using my baseline specification from equation 2. Columns 1 and 2 in Table 4 report estimated coefficients of smoke exposure days on the probability of becoming a part-time worker or unemployed. Here, smoke exposure increases the likelihood an individual is working part time or unemployed. Notably, I do not find a significant effect of smoke exposure on real wages (column 3) or total hours away from work in the month (column 4), suggesting that the loss in hours worked is not being compensated by higher wages nor more non-working hours. While column 5 provides an insight about the potential mechanisms of the underlying adverse effect and emphasizes that this negative impact could be partially explained by the increase in hours away from work due to an illness.

I also evaluate whether these longer-run smoke impacts are observable at the aggregate level. Table 5 shows that smoke has no observable difference on a total population or participation rate at the economic region level. The table also documents small but meaningful hikes in economic region unemployment rates which is consistent with my previous findings. Hence, the results are primarily aligned at both individual and aggregate levels and they produce a consistent picture where the wildfire smoke exposure has a detrimental impact on general labour market.

5.3 Heterogeneous Effects

In the next step, I investigate how the effect of wildfire smoke exposure differ across various characteristics of workers. To perform this analysis, I constructed several binary indicators. The first two indicate whether respondent's main occupation is mostly outdoor work or not using National Occupational Classification (NOC)[24]. Outdoor workers are primarily defined as those working in agriculture or construction. The next indicator splits age of all respondents into two categories - below and above the mean age[25]. Finally, the last index captures the sex of a survey participant. Then, I explore heterogeneity across occupation type, age, and sex. I estimate a version of equation 2 for each column that includes only a corresponding subsample. This part is also complemented with the results from a similar exercise where a relevant indicator function used instead of a subsample.

The outcomes of this step are presented in Table 6. Overall, I find little evidence of a difference among groups of interest. Columns 1 and 2 emphasize that while outdoor workers experience a larger decline in working hours compared to the other workers, the deviation has no statistical significance. Consequently, columns 3 and 4 demonstrate conventionally comparable estimates between younger and older population just with a slight emphasis towards the former. Lastly, as columns 5 and 6 illustrate, there are no striking disparities in the impact of smoke on labour hours between males and females in the data, even after taking into account the distinction in the mean hours worked.

Next, I assess the differential impact of wildfire smoke across regions. Similarly to a previous table, I created two binary indicators. The first one captures whether the respondent lives in

[24] The results remain similar if I use the North American Industry Classification System (NAICS) instead.
[25] The results for age heterogeneity stay essentially the same when I implement a split with more age categories.

Western Canada, which includes four provinces (BC, AB, SK, MB) or Eastern Canada that incorporates the other six provinces (ON, QC, NL, NB, NS, PE). The second index describes survey participant's location as urban if they live in any major census metropolitan area or rural otherwise. Table 7 constitutes that workers in Western Canada suffer the most from an adverse wildfire smoke effect, while labour hours of employees in Eastern Canada generally seem not to be affected by past smoke exposure as outlined in columns 1 and 2, respectively. These findings are effectively coherent, since a majority of wildfires occur in the western part of North America and, furthermore, most of the fire smoke in Canada settles down in Canadian West. Columns 3 and 4 of Table 7 reveal that a negative impact is present for both urban and rural population, although rural workers experience a slightly larger yet insignificant reduction in hours worked due to wildfire smoke exposure.

5.4 Placebo Checks and Alternative Mechanisms

My key causal identification assumption relies on variation in smoke exposure to be exogenous to unobserved determinants of labour market outcomes once conditioning on my set of controls and fixed effects. To assess this assumption, I estimate the effect of wildfire smoke on outcomes that I think are unlikely to be impacted but are correlated with unobserved determinants of my outcome variable. First, I include a measure of future smoke exposure. If my key regressor is truly exogenous, then I expect no effect of future smoke on current labour market outcomes. As reported in column 1 of Table 8, I find no impact of my measure capturing the number of smoke days in the next year on hours worked. Further, the inclusion of this one-year lead of smoke does not affect my estimates for the key lagged coefficients. The last two columns report no effect of smoke on the distribution of age or the fraction of females within the population, respectively. Hence, my results show no influence of wildfire smoke on outcomes that are unlikely to be affected by the exposure.

Finally, wildfire events could directly impact labour market outcomes by changing the level of economic activity through several potential mechanisms such as closed roads along with hiring of individuals to help with fire suppression (Nielsen-Pincus et al., 2014). To examine the extent to which my estimates might be driven by the direct effect of wildfire incidences, I complement my study with the wildfire data. However, the level of response to a particular wildfire clearly depends on the magnitude of it. To account for this, I classify all fires[26] by size conditional on area burned. I characterize a certain wildfire as big, huge, or mega if the area burned by it is at least 200, 2000 or 40500 hectares, respectively[27]. Then, I calculate a monthly number of fires by size category for each economic region. Next, I estimate the version of baseline specification with the number of fires in a region being an extra control variable where applicable.

Columns 1 through 5 from Table 9 report the results of this analysis. Combined together, the first four columns imply no effect of an extra control no matter how devastating fires are on the magnitude of previously found estimates while an impact of an extra variable in each column is negligible. Column 5 demonstrates that restricting the sample by excluding regions that contain at least a single big wildfire in a region in a month of collecting a survey data has very little effect on the estimated coefficients.

Another possibility is that in the longer-run, people might relocate to less wildfire- or smoke-prone places in order to decrease a dangerous exposure. The last two columns of Table 9 assess migration patterns due to smoke at economic region level. I find no increase in emigrants nor any significant changes in migration between provinces due to wildfire smoke exposure. Overall, the set of findings in Table 9 implies that my main results are not driven by direct economic impacts of wildfires nor by differential migration following fire events.

6 Conclusions

Wildfire smoke is widespread source of noxious pollutants that negatively affect human well-being. This paper provides the first analysis of the causal effect between wildfire smoke exposure and national labour market outcomes in Canada. I combine plausibly exogenous satellite-based smoke plume data across all Canadian provinces together with labour outcome data over almost 10 year period to produce causal estimates. My analysis demonstrates economically and

[26]Since the wildfire data registers every single fire record including small campfires with negligible effects, I restrict my analysis to fires with the area burned of at least 1 hectare.

[27]This categorization comes as follows, with acres being converted into hectares where applicable. Canadian National Fire Database operates with "big" wildfires. National Wildfire Coordination Group provides a classification by size with the largest wildfires being of "Class G", which I refer to as "huge" fires for consistency. While National Interagency Fire Center introduces a "mega" wildfire category.

statistically significant declines in actual hours worked due to the exposure to fire smoke. I also find compelling evidence of increases in part-time workers and unemployed presumably at the expense of full-time employees.

The detailed information on individual and geographic scope of the data enables me to examine important questions related to the intensity of wildfire smoke and distinct responses by demographic characteristics. I document that detrimental impact of an exposure to smoke is amplified for heavy smoke intensity days. My study also reveals which part of Canadian population is most susceptible to wildfire smoke exposure. The adverse effect of smoke plumes is exacerbated among workers from Western Canada, while their fellows in Eastern Canada exhibit virtually no effect.

This paper emphasizes the importance of comprehensive examination of labour market channels and longer-run economic effects of air pollution in environmental policy. While policymakers conventionally focus on morbidity and mortality costs considering reduction in labour productivity as minor, my results illustrate that such policies could not be efficient, since they fail to acknowledge a substantial fraction of social costs. The particular topic requires broader examination to unveil the true cost of ambient air pollution.

My results are also directly relevant to wildfire risk management including prevention, mitigation, suppression, and recovery strategies. The wildfire season of 2023 in Canada has become the record-breaking year to date with the total area burned estimates standing at the extraordinary 18.4 million hectares. This number is more than a double of the previous record and more than five times larger than the average annual area burned in Canada[28]. Even though wildfires are natural phenomena and can not be dismissed, better management decisions could mitigate the potential harm from these events. As previously emphasized, the external effect of wildfire – a smoke plume – is large and pervasive across the majority of geographic units in Canada. The far-reaching smoke shocks call for improvements in wildfire policy to make it more cooperative and powerful. Advanced wildfire strategies should evaluate and take into consideration risks beyond the traditional view of protecting exposed property and land. It is essential to comprehensively assess wind patterns and smoke impact of prescribed fires

[28]For more details on the extreme fire season of 2023 in Canada, please visit: https://earthobservatory.nasa.gov/images/151985/tracking-canadas-extreme-2023-fire-season.

during the prevention and mitigation stages. Studies suggest that even low-intensity prescribed burns could lead to large concentrations of particulate matter in the air (Wain et al., 2008; Haikerwal et al., 2015). Eventually, suppression guidelines should incorporate a broader notion of wildfire risks and benefits. A modern wildfire management should extend considerations on the importance of the amount of smoke produced, its potency, and its ability to affect populated metropolitan areas.

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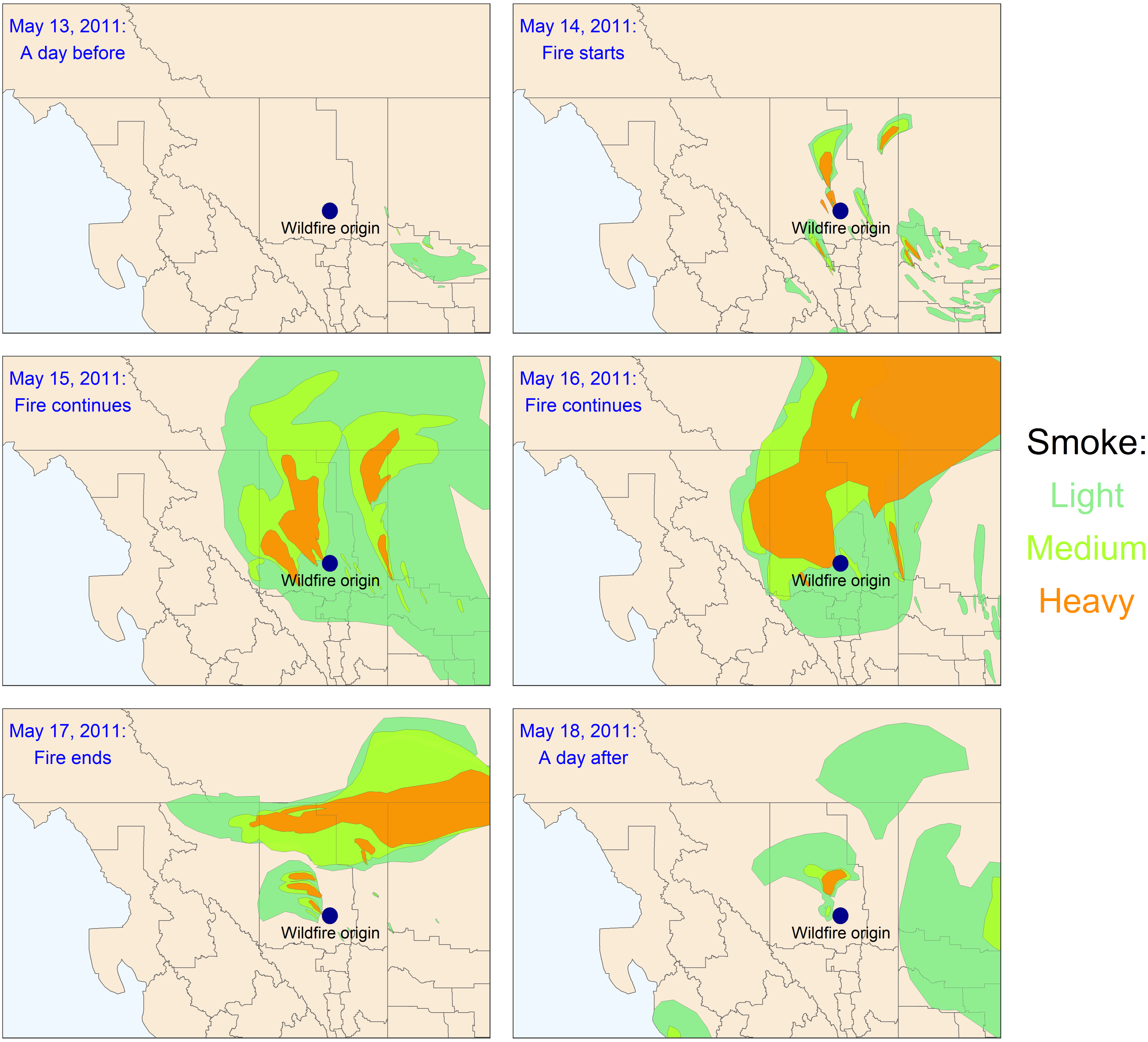
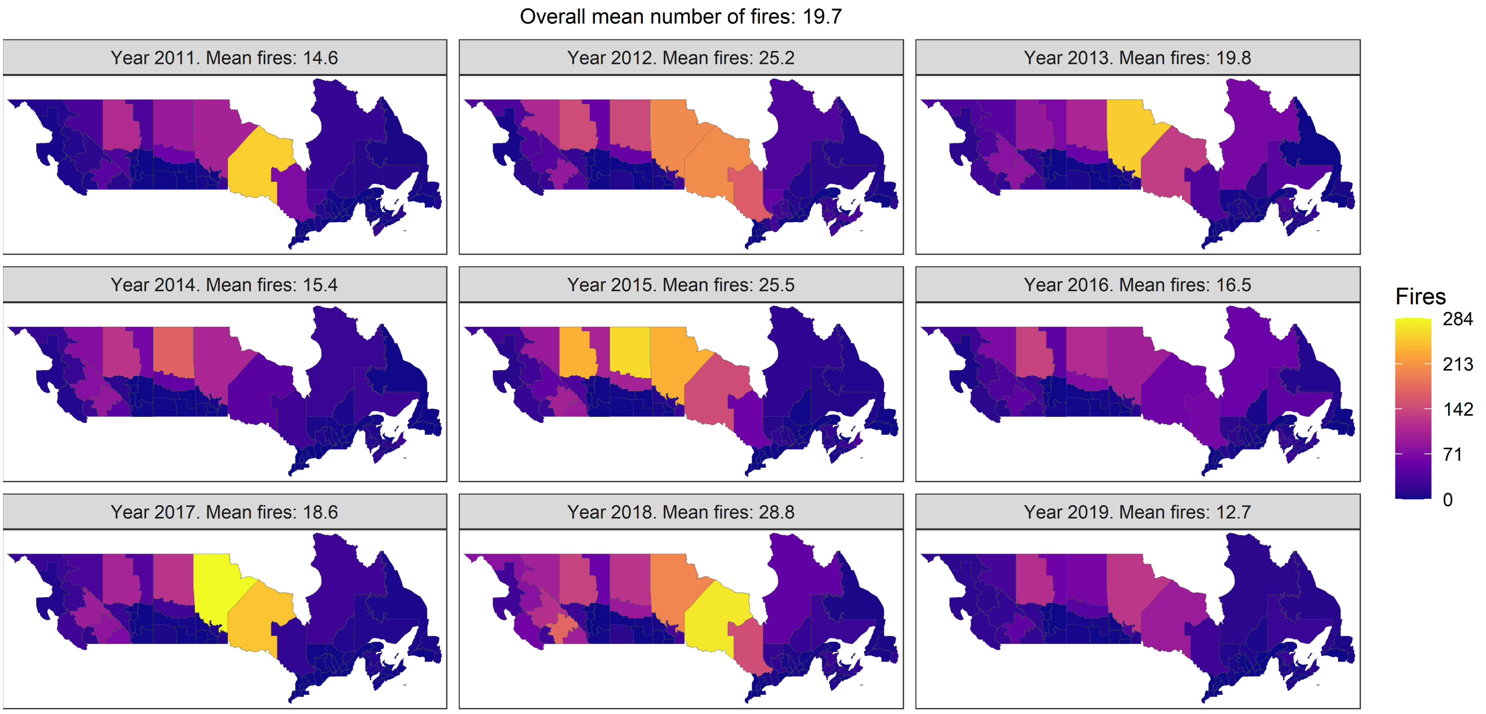
Figure 1: The Slave Lake Wildfire



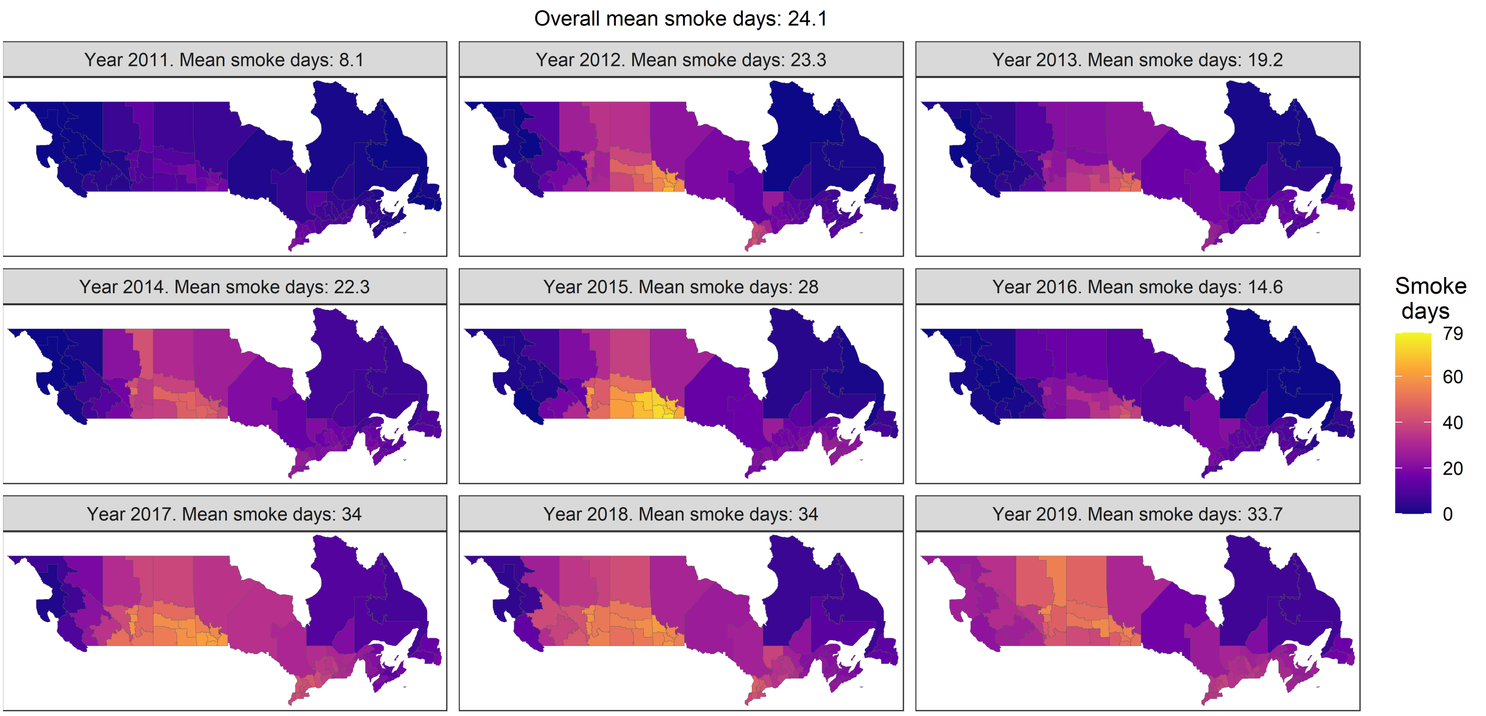
Notes: This figure depicts the evolution of wildfire smoke plumes in the vicinity of Slave Lake fire inception for six consecutive days. The origin of the wildfire is indicated on the map and the area of the corresponding dark blue circle is 100 times larger than the total area burned by this wildfire. Different colors represent up to three distinct smoke intensities available in the HMS data.

Figure 2: Annual Number of Wildfires by Year across Canada



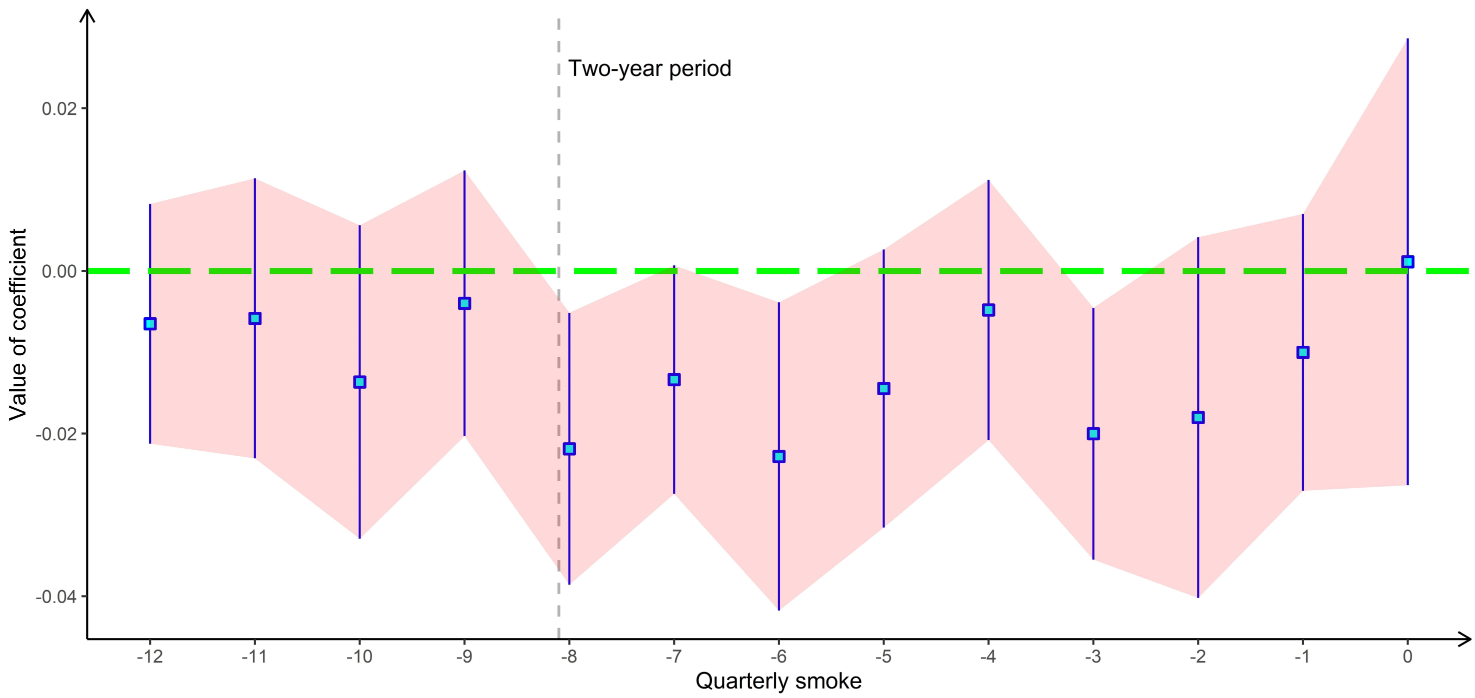
Notes: This figure represents the average annual number of wildfires of size at least 1 hectare by economic regions across Canada over the period 2011-2019. Wildfire records come from Canadian National Fire Database.

Figure 3: Annual Number of Smoke Days by Year across Canada



Notes: This figure shows the average annual number of full coverage smoke days by economic regions across Canada over the period 2011-2019. Smoke records come from Hazard Mapping System.

Figure 4: The Lagged Effect of Wildfire Smoke



Notes: This figure plots the lagged coefficients from a regression of hours worked on the number of smoke days up to 12 quarters prior the LFS data collection month. The dependent variable is actual hours worked in a reference week. The main independent variable is a number of smoke days an economic region is fully covered with a wildfire smoke in the corresponding time period. The regression is weighted by individual weights, contains demographic and weather controls, and includes economic region fixed effects together with month-by-year fixed effects. Standard errors are two-way clustered at the region and month-by-year levels.

Table 1: Summary Statistics

	Mean		
	(1) Full sample	(2) Above median smoke	(3) Below median smoke
Monthly number of smoke days	2.19	2.94	1.29
Monthly temperature	6.11	5.81	6.46
Real hourly earnings (2010 CAD)	23.45	24.28	22.42
Hours worked (weekly)	34.82	35.30	34.22
Proportion of employed	0.75	0.77	0.73
Proportion of males	0.49	0.49	0.49
Proportion of married	0.52	0.55	0.49
Proportion in West	0.39	0.50	0.26
Age	44.23	43.56	45.03
Education: Below college	0.34	0.34	0.33
Education: Post-secondary	0.44	0.42	0.46
Education: University degree	0.23	0.25	0.21
Number of individuals	8,479,926	4,612,578	3,867,348

Notes: Statistics are calculated over individual-level observations. First column corresponds to the full sample, while columns 2 and 3 represent the statistics for respondents from economic regions that are above or below median smoke exposure, respectively.

Table 2: Main Specification

	(1) No individual controls	(2) Baseline specification	(3) ER-month and month-year FE	(4) Linear time trend	(5) LFS panel
Smoke: past year	-0.015**	-0.013**	-0.012***	-0.012	-0.014**
	(0.007)	(0.007)	(0.004)	(0.009)	(0.007)
Smoke: past 1 to 2 years	-0.021***	-0.020***	-0.020***	-0.015*	-0.020***
	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)
Num. Obs.	4,988,940	4,988,940	4,988,940	4,988,940	4,187,613
Mean of dep. var.	34.823	34.823	34.823	34.823	34.751
FE: Region	X	X		X	X
FE: Month-by-Year	X	X	X	X	X
FE: Region-by-Month			X		
Linear Time Trend				X	

Notes: The dependent variable is actual hours worked in a reference week. The main independent variable is a number of smoke days an economic region is fully covered with a wildfire smoke in the corresponding time period. All columns are weighted by individual weights, and include indicated fixed effects. Columns 2 through 5 include controls for demographic and weather variables. Column 4 also contains a monthly time trend. Standard errors are clustered at the region and month-by-year levels. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Varying Coverage and Smoke Intensity

	(1) Baseline specification	(2) Coverage level	(3) Smoke intensity
Smoke: full, past year	-0.013**	-0.011	
	(0.007)	(0.007)	
Smoke: full, past 1 to 2 years	-0.020***	-0.019***	
	(0.006)	(0.007)	
Smoke: heavy, past year			-0.020**
			(0.010)
Smoke: heavy, past 1 to 2 years			-0.037***
			(0.011)
Smoke: medium, past year		-0.009	-0.001
		(0.007)	(0.013)
Smoke: medium, past 1 to 2 years		-0.015*	-0.009
		(0.008)	(0.014)
Smoke: low, past year		0.007	-0.012
		(0.006)	(0.009)
Smoke: low, past 1 to 2 years		0.002	-0.018**
		(0.006)	(0.009)
Num. Obs.	4,988,940	4,988,940	4,988,940
Mean of dep. var.	34.823	34.823	34.823

Notes: Each column is a separate regression. The main independent variable indicates the number of smoke days with varying coverage or intensity in the corresponding period of time. All columns are weighted by individual weights, and include region and month-by-year fixed effects along with demographic and weather controls. Standard errors are two-way clustered at the region and month-by-year levels. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Alternative Labour Outcomes

	(1) Part-time worker (×100)	(2) Unemployed (×100)	(3) Real wage	(4) All hours away	(5) Illness hours away
Smoke: past year	0.021**	0.016*	0.004	0.002	0.000
	(0.009)	(0.009)	(0.004)	(0.003)	(0.003)
Smoke: past 1 to 2 years	0.030**	0.049***	0.002	0.000	-0.006**
	(0.012)	(0.014)	(0.004)	(0.003)	(0.003)
Num. Obs.	4,988,940	6,649,015	4,242,356	787,725	787,725
Mean of dep. var.	13.600	5.100	23.450	10.202	2.127

Notes: Column names represent the dependent variable used. The value of coefficients and mean of dependent variable in columns 1 and 2 are scaled up by 100 for clear representation. All columns are weighted by individual weights, and include region and month-by-year fixed effects along with demographic and weather controls. Standard errors are two-way clustered at the region and month-by-year levels. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Aggregate Labour Characteristics

	(1) Population	(2) Participation rate	(3) Unemployment rate
Smoke: past year	483.364	0.012	0.016
	(642.353)	(0.013)	(0.012)
Smoke: past 1 to 2 years	-649.334	0.011	0.057***
	(917.512)	(0.009)	(0.018)
Num. Obs.	5,274	5,274	5,274
Mean of dep. var.	485,904	64.661	7.129

Notes: Column names represent the dependent variable used. All columns include region and month-by-year fixed effects along with weather controls. Columns 2 and 3 are weighted by economic region population. Standard errors are two-way clustered at the region and month-by-year levels. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneous Effects

	Occupation		*Age*		*Sex*	
	(1) Outdoor	(2) Indoor	(3) Younger	(4) Older	(5) Male	(6) Female
Smoke: past year	-0.021**	-0.012*	-0.013*	-0.014*	-0.012	-0.016**
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Smoke: past 1 to 2 years	-0.034***	-0.016**	-0.024***	-0.015**	-0.021***	-0.020***
	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Num. Obs.	966,873	4,022,067	2,628,835	2,360,105	2,585,381	2,403,559
Mean of dep. var.	39.450	33.712	34.979	34.649	38.496	30.871
Result using indicators	*No significant difference*		*No significant difference*		*No significant difference*	

Notes: Column names represent the subsample of workers used. All columns are weighted by individual weights, and include region and month-by-year fixed effects along with demographic and weather controls. Standard errors are two-way clustered at the region and month-by-year levels. The total number of observations in two columns for each subgroup is the same as in the full sample. Result using indicators line corresponds to an outcome of the analysis using corresponding indicator function instead of a subsample. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Different Regions

	(1) West	(2) East	(3) Urban	(4) Rural
Smoke: past year	-0.013**	-0.008	-0.011	-0.017*
	(0.005)	(0.008)	(0.008)	(0.009)
Smoke: past 1 to 2 years	-0.023***	-0.004	-0.019***	-0.026***
	(0.007)	(0.008)	(0.007)	(0.008)
Num. Obs.	2,012,482	2,976,458	3,597,963	1,390,977
Mean of dep. var.	35.402	34.434	34.469	35.732
Result using indicators	*Effect in West is significantly larger*		*No significant difference*	

Notes: Column names represent the subsample of residents used. All columns are weighted by individual weights, and include region and month-by-year fixed effects along with demographic and weather controls. Standard errors are two-way clustered at the region and month-by-year levels. The total number of observations in the first two and the last two columns is the same as in the full sample. Result using indicators line corresponds to an outcome of the analysis using corresponding indicator function instead of a subsample. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Placebo Checks

	(1) Lead effect	(2) Age	(3) Female (×100)
Smoke: past year	-0.014*	0.002	0.002
	(0.007)	(0.003)	(0.004)
Smoke: past 1 to 2 years	-0.020***	0.003	0.007
	(0.007)	(0.002)	(0.007)
Smoke: lead year	0.000		
	(0.007)		
Num. Obs.	4,350,873	6,649,015	6,649,015
Mean of dep. var.	34.823	44.230	50.690

Notes: Column names represent the type of placebo checks made. The value of coefficients in column 3 is scaled up by 100 for clear representation. All columns are weighted by individual weights, and include region and month-by-year fixed effects along with demographic and weather controls. Standard errors are two-way clustered at the region and month-by-year levels. Significance codes: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 9: Alternative Mechanisms

	Direct Effect of Wildfires					*Migration*	
	(1) All fires	(2) Big fires	(3) Huge fires	(4) Mega fires	(5) Big fires: excluded	(6) Emigrants	(7) Intra-provincial migration
Smoke: past year	-0.013**	-0.013**	-0.013**	-0.014**	-0.015**	-20.841	51.248
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(19.968)	(64.724)
Smoke: past 1 to 2 years	-0.020***	-0.020***	-0.020***	-0.020***	-0.019**	3.115	56.808
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(15.077)	(46.510)
Fires: past year	-0.002	-0.003	0.000	-0.025			
	(0.002)	(0.006)	(0.012)	(0.033)			
Fires: past 1 to 2 years	-0.002	0.000	-0.002	0.152			
	(0.002)	(0.006)	(0.009)	(0.112)			
Num. Obs.	4,988,940	4,988,940	4,988,940	4,988,940	3,487,919	511	511
Mean of dep. var.	34.823	34.823	34.823	34.823	34.687	602.760	0.000

Notes: The fire variable in columns 1 through 5 computes the number of wildfires in a region in the corresponding time period. Column names in columns 1 through 5 represent the type of wildfire counted in the fire variable. Columns 1 through 5 are weighted by individual weights, and include region and month-by-year fixed effects along with demographic and weather controls. Standard errors in columns 1 through 5 are two-way clustered at the region and month-by-year levels. Column names in columns 6 and 7 represent the dependent variable used. Columns 6 and 7 are weighted by economic region population, and include region and year fixed effects. Standard errors in columns 6 and 7 are clustered at the region and year levels. Significance codes: * p < 0.1, ** p < 0.05, *** p < 0.01.

Appendix

A TWFE Robustness Under Heterogeneous Treatment Effect

In this appendix, I address the potential issues associated with OLS estimator in difference-in-differences design as discussed in Section 4.3. As a first robustness check, I compute DID_m estimator as outlined in Chaisemartin and D'Haultfoeuille (2020). This estimator analyses the evolution of dependent variable among two groups: switchers, those that change treatment intensity from one dose d to some other value in two consecutive time periods $t-1$ and t, to the same evolution among control groups whose treatment remains at the same dose d in both periods of time $t-1$ and t. Then the DID_m estimator is equal to the average difference between two groups across all possible pairs of consecutive time periods and across all possible values of treatment doses. To keep computational speed manageable, I augment my specification by collapsing two treatment variables – 1- and 2-year cumulative smoke lags – into a single variable that measures the number of smoke days in the past 24-month period.

As a second sensitivity analysis, I mitigate the potential bias emerging from previously treated geographical units being used as controls by restricting the sample to treated and "clean controls" regions only (Cengiz et al., 2019; Dube et al., 2022). There are several facts about wildfire smoke should be taken into account during this process. First, as highlighted in Section 4.1, the wildfire smoke is ubiquitous in a way there are no economic regions without smoke exposure in Canada. Second, the set of clean controls should be on average a reasonable counterfactual to the treated group each month in my sample. While constructing the perfect subsample is not feasible in my scenario due to pervasive nature of smoke, I propose the strategy that accounts for above-mentioned facts and still provides a useful assessment. I define and keep only two groups in the following way: *"high smoke regions"* that sustain more than two weeks of smoke exposure in the past two years period over the entire sample and serve as a treated group; and *"low smoke regions"* that experience no more than two weeks of fire smoke in the two years period preceding survey month in the sample and function as a (quasi-)clean control group. The restricted sample described above excludes economic regions that alternate between high and low smoke regimes, yet it contains at least one geographic unit from both groups within each Canadian province every month in the sample.

The results of both exercises demonstrated in Table A1. Notably, the magnitude and sign of the effect in columns 2 and 3 remain remarkably robust compared to the main specification presented in column 1. This fact reinforces the use of parsimonious TWFE OLS regression as a preferred specification in the analysis.

Table A1: TWFE Robustness

	(1) TWFE	(2) DID_m	(3) TWFE: restricted sample
Smoke: past 2 years	-0.017*** (0.005)	-0.019** (0.008)	-0.020*** (0.006)
Num. Obs.	4,988,940	4,988,940 (237,415†)	3,623,227
Mean of dep. var.	34.823	34.823	34.901

Notes: Column 1 is the main specification with the collapsed smoke variable. Column names in columns 2 and 3 represent the type of robustness checks made. Columns 1 and 3 are weighted by individual weights, and include region and month-by-year fixed effects along with demographic and weather controls. Standard errors in columns 1 and 3 are two-way clustered at the region and month-by-year levels. Estimation strategy in column 2 includes demographic and weather controls. The standard error in column 2 obtained from two bootstrap replications. The mean of dependent variable in column 2 is calculated for the entire sample. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

† The value in a bracket displays the number of switchers in the sample.