Economic Impact of Forest Fires in Alberta

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ECO2843
December 10, 2020

Forest fires cause diffuse and potentially long-lasting health and economic impacts. Studying the impact of forest fires is limited by the measurement and estimation of fire exposure and by the endogeneity between fires and outcomes of interest. We design a simple measure of fire exposure which does not rely on detailed meteorological data. We use lightning as a source of exogeneous variation to instrument total fire exposure and air quality. Our results show a mostly negative economic impact for fires in the current and previous two years. We also see some evidence of a positive short-term impact, possibly driven by efforts to fight fires. We show a successful first stage regression for lightning fires on measures of air quality but fail to establish a link between air quality and outcomes. The reduced form regression of lightning-caused fires directly on outcomes shows a significant impact on income which establishes an approach to instrument other endogenous regressors in future work.

1. Introduction

Forest fires are a serious threat to the health and economies of impacted communities. The immediate impact on first responders and destroyed communities is easy to see, however, the effects of forest fires can extend beyond the direct and immediate effects. These more modest and diffuse effects are harder to measure. There are two major challenges to studying the impact of fires. Firstly, a quantitative measure of fire exposure is required. Pollution from forest fires depends on the size, location, and duration of fires, and can be carried over long distances to affect faraway communities. Secondly, fires are not exogenous to the outcomes that one might study. For example, some fires are caused by economic activity and municipalities may dedicate resources to fire fighting and prevention according to their means.

In this study we develop a simple fire exposure index which captures repeated fire exposure using the size, duration, and proximity of the fires. We use this to study the impact of this fire exposure index on key health and economic outcomes such as income, deaths, and employment. In order to address the endogeneity of fires with these outcomes, we use lightning as a source of exogeneous variation in fire exposure. We use this to instrument the endogenous variables total fire exposure and two measures of air pollution.

We use a comprehensive dataset of forest fires in Alberta to construct a measure of fire exposure for each municipality. This dataset includes the coordinates of the fire, its duration, the area of land burned, and the cause. Our outcomes come from two sources: a cross-section dataset from the 2016 Canadian census and a longitudinal dataset of Albertan municipalities. Outcomes examined are income, migration, employment, average hours worked in a week, deaths, crime, violent crime, and business bankruptcies. Two different measures of air quality are used: the concentration of fine particulate matter with diameter less than 2.5 micrometers (PM2.5) and the percent of days in a year where the air health risk is deemed high according to an index of pollutants.

Forest fires caused by lightning are used as an instrument for total fire exposure and the measures of pollution to estimate their impact on the outcomes. In our main design, we use the fire exposure from lightning fires to instrument total fire exposure and measure its impact on cross sectional measures of income, migration, employment, and hours worked in a week. Our other design uses exposure from lightning fires to instrument the measures of air pollution to measure their impact on repeated measures of death, crime, violent crime, and bankruptcy for a set of municipalities while controlling for municipality fixed effects. We also regress exposure from lightning fires directly on a larger set of municipalities for the same measures and income.

Our results show that income increases as a result of additional fire exposure in the current year but decreases for fire exposure two years prior. In-migration, employment, and hours worked all decrease in the first year, however in-migration increases in the following two years. These results generally show that fires have a negative effect on economic outcomes, both in the short-term and over the following two years. We see some evidence of a positive effect in income in the current year and in-migration in the following year. This could be caused by a known positive economic shock in the near-term driven by efforts to fight fires [1].

We show a successful IV first stage for our measures of air pollution but fail to find statistically significant estimates for the impact on crime, violent crime, death, and business bankruptcies. The regression of lightning fires directly on these outcomes is also insignificant, however, the estimate for the impact on income is negative and of a similar magnitude to the cross-sectional estimation.

This study contributes to a growing literature studying the impact on economic and health outcomes of forest fires. A notable contribution is its attempt to determine the impact of repeated, moderate exposure as opposed to an event-study of acute and severe fire exposure. Building on the work of Nielsen-Pincus et al. (2013), we allow for different effects over the short- and long-term, but focus on the more frequent small scale fires as opposed to the less common mega-fires [1]. Rangel and Vogl (2016) examine the effects of repeated exposure to small and moderate agricultural fires in Brazil, however the scope of their outcomes is limited to infant health [2]. We attempt to bridge the gap between the study of repeated, moderate exposure and that of municipality level economic outcomes.

This study is the first to address the endogeneity of forest fires and health and economic outcomes by using lightning as an instrument. While lightning is becoming an increasingly common instrument for endogenous technology-related variables, such as Internet access in Andersen et al. (2011), to our knowledge this is the first to employ it as an instrument for forest fires [3]. This approach may greatly simplify the data requirements to study and model forest fires. Currently, models used in predicting the impact of smoke from fires depend heavily on satellite data and detailed meteorological data (wind direction and speed, atmospheric pressure etc.) [4]. The proposed framework may allow for an increased understanding of forest fires' impact on communities where detailed data is not available. This study is the first to address the endogeneity of forest fires and health and economic outcomes by using lightning as an instrument. While lightning is becoming an increasingly common instrument for endogenous technology-related variables, such as Internet access in Andersen et al. (2011), to our knowledge this is the first to employ it as an instrument for forest fires [3]. This approach may greatly simplify the data requirements to study and model forest fires. Currently, models used in predicting the impact of smoke from fires depend heavily on satellite data and detailed meteorological data (wind direction and speed, atmospheric pressure etc.) [4]. The proposed framework may allow for an increased understanding of forest fires' impact on communities where detailed data is not available.

2. Background

Forest fires are a devastating natural disaster with serious impacts, both direct and indirect, in the short term and long term on humans, society, and the environment. Due to climate change, they are becoming of even more important concern, as the International Panel on Climate Change has predicted the forest fire season in North America may expand by up to 20-30% [5].While fires can directly affect humans on the front line (such as firefighters), the greatest threat to human health is smoke inhalation, which can impact those far from the fire [6].

The greatest threat smoke poses to human health is the particulate matter (PM) which can be carried over long distances [7]. In Canada, approximately one third of the PM emission are estimated to have originated from forest fires [8]. Of particular concern is the smallest of this PM, PM2.5 (particulate matter with a diameter less than 2.5 micrometers) as it is difficult to filter out even indoors and can settle deep into the lungs [9]. It is well recognized that smoke from fires may cause adverse health effects. Liu et al. (2015) review 61 studies that look at the health effects of wildfire smoke [6]. These studies cover many different locations and health outcomes and find mixed results. The strongest consensus is that wildfire smoke increases respiratory morbidity. Some studies find an increase in cardiovascular morbidity and mortality while others do not. These mixed results however should not be viewed as contradictory, as they study different populations in different environments exposed to different fires. The authors also identify a key issue in this literature as the separation of pollution from forest fires from that of other sources (such as industry and transportation). We attempt to isolate the fire-caused pollution by instrumenting pollution with lightning caused forest fires. Another key issue that is identified by Rangel and Vogl (2016) is that fires (more specifically agricultural fires in Brazil) may positively predict health since they track economic activity [2]. Rangel and Vogl therefore look at the variation between fires located upwind and downwind from populations in order to separate the impact of smoke from that of increased economic activity. While we are not looking at agricultural fires, there is still an endogeneity issue if increased industry or human activity causes forest fires. Our study does not rely on the more sophisticated meteorological data used in this study, creating a simpler methodology.

Forest fires can also impact economic outcomes directly. Boustan et al. (2017) studied severe natural disasters in the US (including forest fires) and found they increased county out-migration by 1.5 percentage points and lower housing prices and rent [10]. They found that while larger disasters had larger effects, smaller forest fires were more impactful than other similarly sized disasters and the impact has been growing over time. Mueller, Loomis, and González-Cabán (2009) looked at the impact of forest fires on house prices [11]. They find that while being in close proximity to a forest fire lowers a house's value, being close to a second fire lowers the value by even more than the first. These two studies put together suggest that repeated exposure to moderately sized fires may make an area less desirable, decreasing the cost of housing and increasing out-migration. Our study looks at a measure of in-migration, which may change in response to fire exposure as areas become more or less desirable.

Nielsen-Pincus, Moseley, and Gebert (2013) also looked at the impact of wildfires in the US on economic outcomes [1]. They found that while the fire was active, and suppression efforts were ongoing, the employment and wages in the affected county increased. However, once the fire was contained, the area experience increased economic volatility, often lowering employment and wages.

Another area of focus in the literature is on the cognitive performance of those exposed to increased pollution levels. Heyes, Neidell, and Saberian (2016) found that the PM2.5 levels in Manhattan were linked to the performance of the S&P 500 [12]. Specifically, when exposed to higher pollution levels, traders exhibited decreased risk tolerance, possibly due to decreased cognitive performance or mood. A study in China by Graff Zivin et al. (2019) looked at the performance of students writing a standardized test in relation to pollution from fires [13]. Increased exposure to upwind agricultural fires decreased testing performance. This suggests that when exposed to high levels of pollution, people may perform worse in academic and business environments.

3. Data

This study employs a dataset of fires in Alberta, a cross sectional measure of outcomes from the 2016 Canadian census, a longitudinal measure of outcomes and air quality, and a longitudinal measure of pollution. Table 8, Table 9, and Table 10 provide a list of the key variables and summary statistics. Using the fires dataset, we construct an index of annual fire exposure for each Albertan municipality.

3.1 Fires

The dataset of fires in Alberta is provided by the Alberta Agriculture and Forestry Service [14]. It contains information on approximately 19,800 fires in Alberta from 2006 to 2018. The information includes the location, size, duration, and cause of fires. The location is measured in latitude and longitude coordinates which we use to calculate distances.

Fire size is the estimated surface area of the fire in hectares. Fires are assigned a class from A to E according to their size. Approximately 50% of fires were class A fires and listed at the minimum size of 0.01 hectares (100 meters squared). These fires were excluded from analysis as their impact is likely minimal and their true size is unlikely to be exactly 0.01 hectares. Approximately 1.5% of fires were larger than 200 hectares (the size of about 200 football fields). These fires were also excluded both for statistical and economic reasons. When included, these fires tended to dominate regressions and have a disproportionate impact. Additionally, we believe fires of this frequency and magnitude are better suited in event-driven analyses such as a difference-in-difference approach.

The duration of fires was calculated as the difference between the estimated start and end of the fire. Approximately two thirds of fires burned for less than a day while the longest lasting 1% burned for several months. Size and duration are correlated so many long-burning fires were excluded by the size cutoff.

Fires are assigned one of 12 general causes which include recreation, railroad, resident, power line industry, and, importantly, lightning. Approximately 35% of fires were labeled as being caused by lightning. One of the 12 fields is "undetermined" and approximately 3% of fires are labeled this way.

We believe the major limitation of this dataset is the measurement accuracy. Precise determination of the location, size, duration, and cause of a fire is likely challenging in practice. It is also possible that some fires, especially small fires, go undetected.

3.2 Canadian Census

We use the 2016 Canadian census for a cross sectional measure of four outcome variables and three control variables [15]. We use this information at the census subdivision level (referred to in this paper as municipality) for the 428 census subdivisions in Alberta. The census is limited by imperfect response rates and missing measurements for certain municipalities. Certain municipalities are sparsely populated and are susceptible to greater data inaccuracy, variance, or rounding errors.

3.3 Longitudinal Data

We also employ longitudinal measurements of outcomes and air quality through Alberta's Open Government Program [16]. These measurements cover between 30 and 425 of Alberta's municipalities for years up to 2018. In addition to the usual risk of inaccurate or imprecise measurement, this dataset is also limited by the imperfect overlap of years and municipalities which is not the same for all variables.

3.4 Pollution Data

We obtain data on PM2.5 (fine particulate matter) from the National Air Pollution Surveillance (NAPS) program [17]. We use hourly measures of PM2.5 for stations located in 30 municipalities in Alberta. These measures are interpolated for missing hourly measurements and averaged over calendar years.

3.5 Fire Exposure Index

Figure 1 shows the approximate size and location of the fires and municipalities in this study. We design a function that takes information on the size, duration, and location of a fire to calculate the value of that fire's impact on a given municipality. The total annual fire exposure is the sum of the impact from all fires within a given year. The fire exposure, *Fire*, for municipality j in year t is given by:

$$Fire_{jt} = \sum_{i \in \{fires\}_t} \frac{a_i b_i}{e^{0.01 d_{ij}}}$$

Where a_i is the area of the fire i in hectares, b_i is the duration in hours, and d_{ij} is the distance in kilometers between municipality j and fire i. The variable i is an index over all fires in year t. The fire exposure from lightning fires is calculated in the same way where i is indexed over only fires caused by lightning. The distance between the municipalities and fires is calculated using the Geopy Python package which takes the latitude and longitude coordinates and calculates straight-line distance using an ellipsoidal approximation of the earth.

The distance d_{ij} is scaled by a factor of 0.01. This governs how quickly the impact drops off by distance and is most likely the key tuning parameter for this functional form. Under the chosen parameters, the impact of a fire is reduced by 40% at 50km, 80% at 160km, 90% at 250km and 98% at 400km. We believe this to be reasonable according to studies that have measured the actual concentration and distance traveled of fire pollutants using meteorological devices [18]. Price et al. (2012) used a similar approach to design scalar functions of fire impact [4].

4. Empirical Strategy

Our main design uses the fire exposure from lightning fires to instrument total fire exposure and measure its impact on cross sectional measures of income, migration, employment, and hours worked in a week. The first stage regresses the fire exposure index (calculated on an annual basis for each municipality) on the fire exposure index restricted to fires caused by lightning:

$$Fire_{year,CSD} = \alpha_1 LightningFire_{year,CSD} + \mu_{year,CSD}$$

Where *Fire* is the calculated fire exposure index in a given year for a given municipality (CSD), *LightningFire* is the calculated fire exposure index restricted to lightning fires, and μ represents the error term. The predicted fire exposure, $\widehat{Fire}$, is then used in the regression of the economic outcomes of the 2016 census. Since the census is collected in early 2016 (and income is reported for 2015), we treat 2015 as the current year impact. We estimate the impact from fires in the previous three years:

$$CensusOutcome_{CSD} = \beta_1 \widehat{Fire}_{2013,CSD} + \beta_2 \widehat{Fire}_{2014,CSD} + \beta_3 \widehat{Fire}_{2015,CSD} + \boldsymbol{X}_{CSD}\gamma + \epsilon_{CSD}$$

Where *CensusOutcome* refers to the income, employment rate, average hours worked per week, or percentage of residents who moved to the municipality in the past five years for a given municipality, $\boldsymbol{X}$ is a vector of controls (from the 2016 census), consisting of the percentage of people aged 15 to 64, the percentage of people with post-secondary education, and the percentage of people who are married, and ϵ represents the error term. β_3 represents the short-term (same year) effect while β_1 and β_2 illustrate the long-term trend.

For our longitudinal data, we use a fixed effects model where annual fire exposure from lightning is used to instrument either monthly PM2.5 concentration or the annual percentage of days with high risk air quality. The first stage regressions for *AirRisk* and *PM2.5* are done in the same way as *Fire*, however *PM2.5* is instrumented at the monthly level:

$$AirRisk_{year,CSD} = \alpha_2 LightningFire_{year,CSD} + \delta_{year,CSD}$$

$$PM2.5_{month,year,} = \alpha_3 LightningFire_{month,year,CS} + \eta_{month,year,CS}$$

The second stage regresses median income, crime, violent crime, death, and business bankruptcies at the municipality level on our two measures of pollution while controlling for municipality fixed effects:

$$PanelOutcome_{year,CSD} = \chi \widehat{Exposure}_{year,CSD} + MunicipalityFE_{CSD} + TimeFE_{year} + \tau_{year,CSD}$$

Where *PanelOutcome* refers to one of the outcomes from our longitudinal data for a given year and municipality, $\widehat{Exposure}$ represents either $\widehat{AirRisk}$ or $\widehat{PM2.5}$, *MuncipalityFE* is the fixed effects at the municipality level, *TimeFE* is the fixed effects at the year level, and τ represents the error term.

We account for spatial correlation since we expect fire exposure to be clustered around nearby municipalities. We employ spatial standard errors as described in Conley (1999) and Colella et al. (2019) [19] [20]. We use a relatively large distance cutoff of 250km to align with the distance drop off in our fire exposure index. Incorporating these standard errors modestly increased the size of the standard error estimates.

As with any instrumental variable approach, the key assumptions are relevance and exclusion. For relevance, fire exposure from lightning should clearly be predictive of total fire exposure and fires are a known cause of PM2.5 and other pollutants that determine our measure of air quality. The exclusion restriction is less trivial. We require our measure of lightning fire exposure to not be related to our outcomes other than through the endogenous variables for which we instrument. If, for example, unusually hot summers or other weather trends cause more (or fewer) lightning fires, while also affecting our outcomes, the exclusion restriction would be violated. Another issue could be the very large forest fires that are excluded from this study. We assume that these large fires do not cause effects like crowding out lightning fires and making them less likely, or alternatively drying out the land and making them more likely. For our regressions with air quality we must assume that fires impact crime, violent crime, deaths, and bankruptcies exclusively through changes in air quality. This relies on a "bad judgement" hypothesis [12] [13] and requires that impacts caused by other vectors like property damage are negligible.

In our data, we assume that the cause of forest fires is not systematically misidentified (between lightning and all other causes). Since "unknown" is listed for several fires, we have no reason to believe arbitrary decisions are being made when the cause is not truly known to be lightning or another cause. There may be a further endogeneity issue with fires if their size and duration are not independently determined. For example, large fires are not allowed to burn indefinitely and may receive more immediate suppression efforts. We assume that for the fires in the scope of this study, those caused by lightning are not systematically affected in a way that correlates with outcomes. We also assume that the data collection, for the census, municipal dataset, and PM2.5 measurements are not systematically impacted by fires. This is of particular importance for the PM2.5 dataset as there are missing values that we were required to interpolate. We assume that this was done in an appropriate manner and that the missing values were not correlated with fire exposure in any way.

Lastly, we assume that our calculated fire exposure index is an appropriate measure. While the functional form and parameters were chosen to line up with existing literature, they are a subjective choice, and another index may yield different results. Furthermore, as the municipality location is treated as a point estimate, it is assigned one measure of fire exposure which does not account for the population distribution or density.

5. Results

Our main results are for outcomes from the cross-sectional census data. We also profile the longitudinal results which, although insignificant, provide a template for future work with a successful first stage but insignificant second stage. We also show the reduced form of lightning fires directly on longitudinal outcomes.

5.1 Census Data

Table 1 shows our main result of a negative impact on income from fire exposure for 2013 which persists though the addition of controls and instrumentation. Additionally, we see a more modest but statistically significant increase in income from fire exposure for 2015. Table 2 shows the other outcomes investigated in the census dataset. These regressions show a mostly negative impact with all but one significant coefficient pointing to negative effects in both the same year and prior years. Besides the positive current year impact in income, the other counterintuitive finding is a significantly positive coefficient for in-migration from fires in 2014.

5.2 Longitudinal Data

We were unable to show significant results using the longitudinal measures of crime, violent crime, death, and business bankruptcy. We were able to instrument air quality as measured by PM2.5 concentration or the percentage of days with high risk air quality warnings (Figure 2 and Figure 3), but we were not able to show a link between air quality and the outcomes (Table 3 and Table 4). Similarly, a regression of fires caused by lightning directly onto these outcomes failed to show a significant relationship for those variables (Table 5). Since the fires dataset covers all municipalities we were able to use the reduced from on income (column 8 in Table 5). Here we see a significant negative impact of lightning fires on current year median income.

For robustness we checked for correlation between the municipality demographic controls and the other regressors (Table 6). The positive coefficient for fire exposure in 2015 is observed only when either the percentage post-secondary graduates or percentage married variables are included. This suggests that the observed link between fire exposure and income may be due at least in part to municipality characteristics that are connected to both fire exposure and income. For example, certain municipalities may be more prone to lightning strikes or lightning fires and this may affect the economic development of that area. The instrument may therefore be unsuccessful in removing all of the endogeneity between fire exposure and outcomes.

6. Discussion

Table 7 summarizes the directionality and level of significance for our results. The results paint a mostly negative picture of the impact of fires: reduced in-migration, employment, and hours worked in the first year, and reduced income and hours worked in the second and third years. The significant increases in income in the first year and in-migration in the second year, as well as the direction of some of the insignificant coefficients, are contrary to the idea of a purely negative shock. To assist in the interpretation of these results, consider the predicted impact of a relatively large fire that burns for 10 hours, covers 100 hectares, and is centered 50 km away from a municipality. This fire would have a fire exposure score of 600 and would represent 35% of the annual exposure for the average municipality. Our results predict that this fire would increase current year income by $13 and decrease earnings in 2 years by $127. It would also decrease in-migration by 0.05%, decrease employment by 1.6%, and decrease weekly hours worked in the next year by 0.06%. The change in employment seems too large to be truly caused by a moderately sized fire. This is perhaps further evidence that the instrument is not addressing all of the endogeneity in the relationship between fires and outcomes. The impact on median income from the reduced form regression of the longitudinal data suggests a similar impact as the other income estimate although in the current year. The impact of a lightning fire of corresponding size is predicted to decrease median annual income by approximately $200.

The mostly negative impact is unsurprising and supported by several studies though the mechanism of respiratory morbidity and perhaps damage to property [6]. Additionally, Nielsen-Pincus et al. (2013) finds positive effects on employment and wage during firefighting efforts and increased economic volatility afterwards [1]. This fits well with our observations for income both in direction and magnitude; a small positive impact in the current year which yields to a larger and negative impact two years later.

This study likely lacked the precision to measure the impact of fires or air pollution on crimes, violent crimes, death, and bankruptcy. The effect is likely minimal and the measures of air quality covered only approximately 30 municipalities over a five year period. The successful first stage and significance of the reduced form regression on median income suggest that this may be a blueprint for future analysis.

An obvious extension of this work would be to apply the fire exposure index and fires dataset to a set of outcomes where the link between fire exposure is stronger. This could be done with more frequent measurements (such as monthly measurements for a greater number of municipalities) or with outcomes more sensitive to the effect of fires (such as health outcomes other than death). For example, a suitable study may be to look at the impact of fires on acute respiratory illness which is likely large and plausibly caused exclusively though air pollution. An ideal experiment would be to apply this simplistic approach in parallel to an approach with detailed meteorological data used in other studies. This could validate our approach and demonstrate its utility in cases where detailed meteorological data is unavailable.

If the potential endogeneity observed in this study is indeed caused by climate effects such as warm dry weather, a more robust study could condition the instrument on variables such as precipitation and temperature. This would also necessitate an upstream measure of lightning and begins to overlap with the more data-intensive studies from which we sought to distinguish this study. The primary challenge to future work is clearly the availability of appropriate data both for outcomes and fires. Additionally, as the approach intentionally avoids using more sophisticated meteorological information, its accuracy and precision is inherently limited.

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Tables

Table 1. Impact of total fire exposure on income. Total fire exposure is instrumented with the exposure from fires caused by lightning. Standard errors incorporate geographic clustering of Alberta municipalities.

	Market Income 2015			
	OLS		**IV**	
	(1)	**(2)**	**(3)**	**(4)**
Fire Exposure 2015	-0.0001 (0.007)	0.021*** (0.004)	0.0003 (0.007)	0.022*** (0.008)
Fire Exposure 2014	0.077 (0.081)	0.015 (0.053)	0.068 (0.082)	0.020 (0.047)
Fire Exposure 2013	-0.241** (0.122)	-0.190** (0.078)	-0.247** (0.125)	-0.216** (0.111)
% Aged 15-64		66,818*** (13,674)		66,597*** (10,820)
% with Post-Secondary Education		79,410*** (11,285)		79,209*** (7,893)
% Married		64,348*** (8,319)		64,351*** (7,974)
Constant	48,710*** (1,432)	-46,181*** (7,866)	48,825*** (1,436)	-46,039*** (8,955)
Observations	297	297	297	297
R^2	0.032	0.611	0.032	0.611
Adjusted R^2	0.022	0.603	0.022	0.603
Residual Std. Error	14,971 (df=293)	9,532 (df=290)	14,971 (df=293)	9,533 (df=290)
F-statistic	3.192** (df=3; 293)	76*** (df=6; 290)		

*p<0.1; **p<0.05; ***p<0.01

Table 2. Impact of total fire exposure on income, in-migration, employment, and hours worked per week. Total fire exposure is instrumented with the exposure from fires caused by lightning. Standard errors incorporate geographic clustering of Alberta municipalities. Columns 2-4 are multiplied by 10^6 for clarity.

	Market Income 2015 (1)	**% In-Migrants Previous 5 Years (2)**	**Employment Rate (3)**	**Hours Worked per Week (4)**
Fire Exposure 2015	0.022***	-0.059***	-14.6***	-1.04
	(0.008)	(0.020)	(5.7)	(1.47)
Fire Exposure 2014	0.020	0.375***	-42.5	-38.80***
	(0.047)	(0.118)	(111.4)	(10.80)
Fire Exposure 2013	-0.216**	0.059	88.7	-24.90
	(0.111)	(0.250)	(87.3)	(25.40)
% Aged 15-64	66,597***	195,962	100,301,200***	14,580,970***
	(10,820)	(192,199)	(16,278,690)	(940,040)
% with Post-Secondary Education	79,209***	-572,537***	24,086,830**	2,267,218
	(7,893)	(127,261)	(11,802,680)	(2,018,673)
% Married	64,351***	45,827	34,309,090***	7,085,288***
	(7,974)	(45,144)	(11,859,100)	(2,131,723)
Constant	-46,039***	97,813	-27,566,830***	28,519,420***
	(8,955)	(124,325)	(7,415,582)	(1,676,701)
Observations	297	394	394	394
R^2	0.611	0.185	0.316	0.287
Adjusted R^2	0.603	0.172	0.304	0.281

*p<0.1; **p<0.05; ***p<0.01

Table 3. Impact of air quality on various outcomes estimated using fixed effects. Air quality is instrumented using the exposure from fires caused by lightning. Air quality is measured as the percentage of days with a high risk air quality warning which is determined by a collection of air pollutants. Variables are measured at the Alberta municipality level annually from 2013 to 2017. The coefficient estimates are multiplied by 10^6 for clarity.

	Crimes (1)	**Violent Crimes (2)**	**Deaths (3)**	**Business Bankruptcies (4)**
% Days High Risk Air Quality	-1,236 (1,397)	-120.8 (161.0)	-18.64 (430.0)	1.47 (6.41)
Observations	86	86	147	102
R^2	0.042	0.000	0.010	0.010
Adjusted R^2	-0.273	-0.328	-0.279	-0.370
F-statistic	0.784	0.562	0.002	0.053

Table 4. Impact of PM2.5 levels on various outcomes estimated using fixed effects. The PM2.5 level is the average concentration of fine particulate matter in the air. Average monthly PM2.5 level is instrumented using the total monthly exposure from fires caused by lightning. Dependent variables are measured at the annual level and scaled down to monthly measurements with standard errors accounting for the group clustering. Variables are measured at the Alberta municipality level annually from 2013 to 2017. The coefficient estimates are multiplied by 10^6 for clarity.

	Crimes (1)	**Violent Crimes (2)**	**Deaths (3)**
PM2.5 level	-0.559 (1.623)	0.119 (0.241)	-0.066 (0.192)
Observations	884	884	1,711
R^2	0.008	0.005	0.001
Adjusted R^2	-0.088	-0.088	-0.061
F-statistic	0.119	0.244	0.117

Table 5. Regression of lightning fires directly on outcomes estimated using OLS and fixed effects (FE). Variables are measured at the Alberta municipality level annually from 2010 to 2017. The coefficient estimates for columns 1-6 are multiplied by 10^6 for clarity.

	Crimes		**Violent Crimes**		**Deaths**		**Median Annual Income**	
	OLS (1)	FE (2)	OLS (3)	FE (4)	OLS (5)	FE (6)	OLS (7)	FE (8)
Lightning Fire Exposure	18.28 (122.48)	14.53 (28.19)	6.23 (15.37)	0.21 (6.91)	-0.32* (0.19)	0.01 (0.19)	-2.77*** (0.40)	-0.726*** (0.159)
Constant	538,848*** (134,173)		69,874*** (16,840)		10,994*** (212)		80,846*** (432)	
Observations	855	855	855	855	2448	2448	3656	3656
R^2	0.000	0.000	0.000	0.000	0.001	0.000	0.013	0.006
Adjusted R^2	-0.001	-0.112	-0.001	-0.112	0.001	-0.165	0.013	-0.089
F-statistic	0.022 (df=1; 853)	0.266 (df=1; 768)	0.164 (df=1; 853)	0.001 (df=1; 768)	2.80 (df=1; 2446)	0.003 (df=1; 2100)	47.93 (df=1; 3654)	20.65 (df=1; 3336)

*p<0.1; **p<0.05; ***p<0.01

Table 6. Investigating potential endogeneity in the estimation of the impact of fire exposure on income. The positive coefficient for fire exposure in 2015 is observed only when either % with post-secondary education or % married variables are included. Similar estimates are observed when % married is introduced in column (3) in place of % with post-secondary education.

	Market Income 2015			
	(1)	**(2)**	**(3)**	**(4)**
Fire Exposure 2015	0.001 (0.007)	0.005 (0.006)	0.019*** (0.005)	0.022*** (0.004)
Fire Exposure 2014	0.084 (0.082)	-0.085 (0.070)	-0.047 (0.059)	0.019 (0.054)
Fire Exposure 2013	-0.263** (0.125)	-0.205* (0.105)	-0.209** (0.088)	-0.216*** (0.080)
% Aged 15-64		164,319*** (14,673)	65,352*** (15,004)	66,597*** (13,685)
% with Post-Secondary Education			123,010*** (10,783)	79,209*** (11,293)
% Married				64,351*** (8,324)
Constant	48,632*** (1,439)	-53,472*** (9,191)	-24,602*** (8,069)	-46,039*** (7,869)
Observations	297	297	297	297
R^2	0.032	0.323	0.531	0.611
Adjusted R^2	0.022	0.314	0.523	0.603
Residual Std. Error	14,971 (df=293	12,539 (df=292)	10,453 (df=291)	9,554 (df=290)

*p<0.1; **p<0.05; ***p<0.01

Table 7. Tabulation of regression results from tables Table 2, Table 3, Table 4, and Table 5. The positive and negative signs represent the sign of the coefficient and stars represent the same levels of significance as the corresponding table. For the census data, Same Year corresponds to the impact from fires in 2015, one year before corresponds to 2014, and two years before to 2013.

	Variable	**Same Year**	**One Year Before**	**Two Years Before**
Census Data	Income	+***	+	-***
	In-Migration	-**	+***	+
	Employment	-***	-	+
	Hours Worked	-	-***	-
Lightning Fire Reduced Form	Income	-***		
	Crime	+		
	Violent Crime	+		
	Deaths	+		
PM2.5	Crime	-		
	Violent Crime	+		
	Death	-		
Air Risk Data	Crime	-		
	Violent Crime	-		
	Death	-		
	Business Bankruptcy	+		

Table 8. Descriptive statistics for fires between 2013 and 2015. Data from the Alberta Agriculture and Forestry Service [14].

Total Fires		1581
Used in this study (excluding very small and large fires)		539
Fires caused by lightning used in this study		268
Total Fire Exposure	Mean CSD exposure	1695
	SD	1684
	IQR (25-75)	1608
Lightning Fire Exposure	Mean CSD exposure	825
	SD	1132
	IQR (25-75)	804

Table 9. Descriptive statistics of census data used in this study. Data from the 2016 Canadian Census [15].

Variable	**Measure**	**Mean**	**SD**	**25^{th} percentile**	**50^{th} percentile**	**75^{th} percentile**
Income	Average annual market earnings	$48,550	$15,134	$41,174	$48,291	$56,638
In-Migration	% of population lived in different CSD 5 years ago	9.7%	10.9%	7.0%	9.8%	13.5%
Unemployment	% unemployed	12.9%	10.9%	6.9%	9.5%	15.6%
Hours Worked	Mean weekly hours worked	40.8	3.3	39.6	41.6	42.8

Table 10. Descriptive statistics on the longitudinal data used in this study covering years 2010-2017. Data from the Alberta Open Government Program [16] and the National Air Pollution Surveillance Program [17].

Variable	Measure	Mean	SD	25th percentile	50th percentile	75th percentile
Crimes	Annual crimes per capita	0.15	0.18	0.06	0.10	0.17
Violent Crimes	Annual violent crimes per capita	0.07	0.43	0.01	0.02	0.03
Deaths	Annual deaths per capita	0.011	0.009	0.004	0.008	0.016
Bankruptcy	Annual business bankruptcies per capita	0.0006	0.0000	0.0001	0.0002	0.0010
PM2.5	Annual average PM2.5 concentration	6.8	2.2	5.1	6.9	8.1
Air Quality	% days with High Risk air quality	0.004	0.005	0.001	0.002	0.004

Table 11. First stage regression for total fire exposure instrumented by fire exposure from lightning fires. Variables are measured at the Alberta municipality level annually from 2013 to 2015.

	Estimate	**SE**	**t-value**	**p-value**
Intercept	579	18	32.2	<0.0001
Lightning Fires	1.25	0.01	103.8	<0.0001
Observations		1,698		
R-squared		0.8638		
F-statistic		10,780		

Table 12. First stage regression for PM2.5 concentration instrumented by fire exposure from lightning fires. Monthly exposure from fires caused by lightning is regressed on average monthly PM2.5 levels. Variables are measured at the Alberta municipality level from 2013 to 2017.

	Estimate	**SE**	**t-value**	**p-value**
Intercept	6.8091	0.1330	51.2	<0.0001
Lightning Fires	0.0039	0.0005	8.1	<0.0001
Observations		2,768		
R-squared		0.023		
F-statistic		65.10		

Table 13. First stage regression for air quality instrumented by fire exposure from lightning fires. Air quality is measured as the percentage of days with a high risk air quality warning which is determined by a collection of air pollutants. Variables are measured at the Alberta municipality level annually from 2013 to 2017.

	Estimate	**SE**	**t-value**	**p-value**
Intercept	2.8×10^{-3}	0.5×10^{-3}	6.3	<0.0001
Lightning Fires	1.7×10^{-6}	0.5×10^{-6}	3.4	0.0008
Observations		165		
R-squared		0.066		
F-statistic		11.61		

Figures

Figure 1. Visualization of Alberta municipalities (red) and fires (blue). The size of points corresponds to the approximate surface area of municipalities and fires. The displayed fires are those in the years covered in this study (2013-2015).

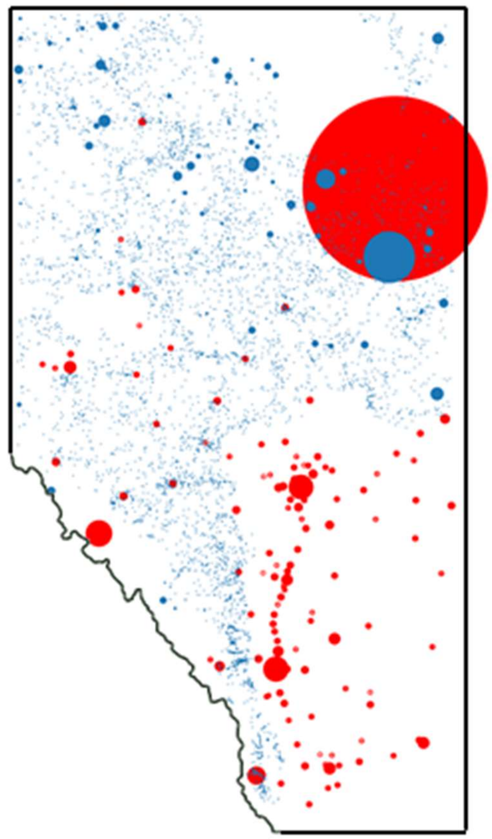
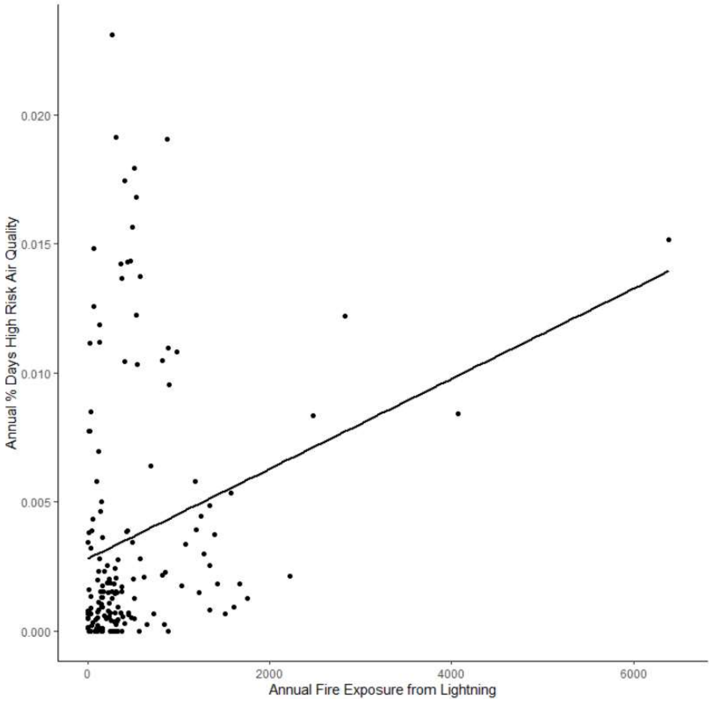
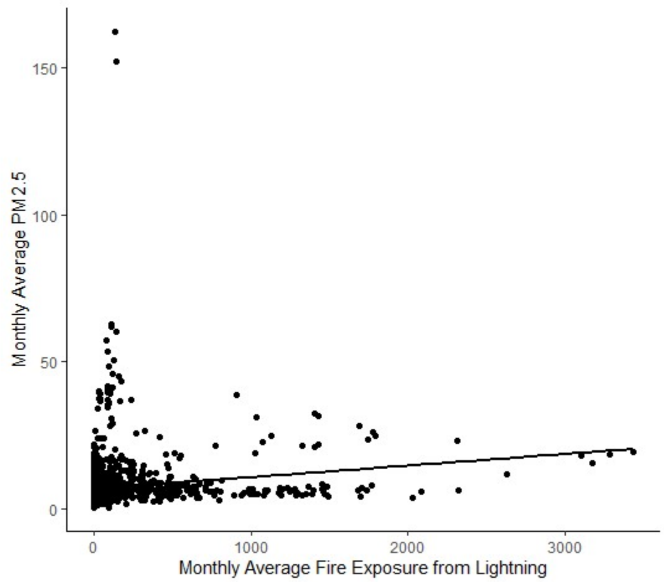


Figure 2. Illustration of the first stage regression for air quality instrumented by fire exposure from lightning fires. Air quality is measured as the percentage of days with a high risk air quality warning which is determined by a collection of air pollutants. Variables are measured at the Alberta municipality level annually from 2013 to 2017.



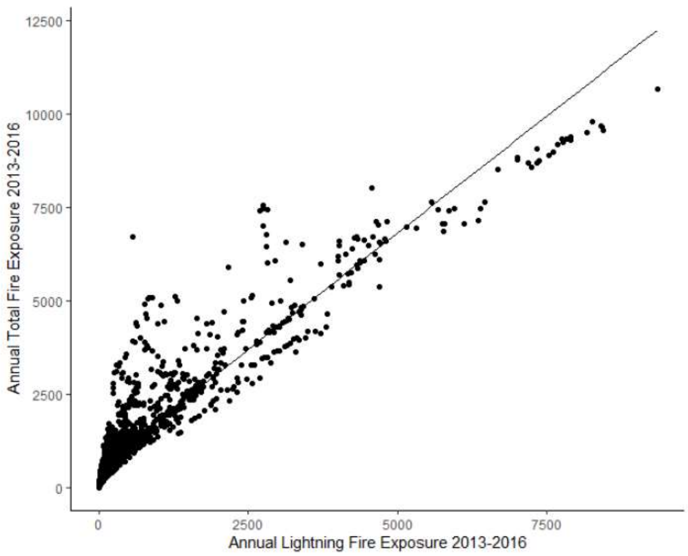
	Estimate	**SE**	**t-value**	**p-value**
Intercept	2.8×10^{-3}	0.5×10^{-3}	6.3	<0.0001
Lightning Fires	1.7×10^{-6}	0.5×10^{-6}	3.4	0.0008
Observations		165		
R-squared		0.066		
F-statistic		11.61 (0.0008)		

Figure 3. Illustration of the first stage regression for PM2.5 concentration instrumented by fire exposure from lightning fires. Monthly exposure from fires caused by lightning is regressed on average monthly PM2.5 levels. Variables are measured at the Alberta municipality level from 2013 to 2017



	Estimate	SE	t-value	p-value
Intercept	6.8091	0.1330	51.2	<0.0001
Lightning Fires	0.0039	0.0005	8.1	<0.0001
Observations		2,768		
R-squared		0.023		
F-statistic		65.10		

Figure 4. Illustration of the first stage regression for total fire exposure instrumented by fire exposure from lightning fires. Both measures of fire exposure are calculated using the fire exposure index in this paper. Variables are measured at the Alberta municipality level annually from 2013 to 2015.



	Estimate	**SE**	**t-value**	**p-value**
Intercept	579	18	32.2	<0.0001
Lightning Fires	1.25	0.01	103.8	<0.0001
Observations		1,698		
R-squared		0.8638		
F-statistic		10,780		