NBER WORKING PAPER SERIES

WILDFIRE, SMOKE AND MENTAL HEALTH IN CANADA

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Working Paper 33912
http://www.nber.org/papers/w33912

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2025

We thank Holly Musto, Jerry (Fang) Li, and Vicki Scott for facilitating access to the hospital data and seminar participants at Princeton, as well as attendees at the May 2024 Coase conference and the June 2024 ASHE conference for helpful comments, and the SSHRC-IDG grant #430-2019-733 and the NOMIS Foundation for supporting this research. Any errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. I1, Q54

ABSTRACT

This study examines the relationship between wildfires and mental health-related hospitalizations in Canada from 2006 to 2018. Most previous estimates of the mental health costs of wildfire have focused on the impacts of exposure to $PM_{2.5}$. We break new ground by highlighting other pathways for wildfires to affect mental health, including evacuation orders, direct local costs of fires, and climate anxiety, which is proxied using wildfire-related Twitter activity. We find that all these mechanisms affect mental health-related hospitalizations, with especially large impacts on hospitalizations for anxiety and substance abuse. Conditional on air quality, wildfire events that draw national attention worsen the mental health of susceptible people, even when they live far away. Elderly people and those with pre-existing health conditions that make them more vulnerable, are more strongly affected. The results indicate that climate anxiety stoked by wildfire events may account for much of the overall mental health cost. Accounting for these additional mechanisms does little to diminish the estimated effect of $PM_{2.5}$ from wildfire smoke, however, suggesting that the additional factors have effects on mental health that are in addition to those of $PM_{2.5}$.

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Disastrous wildfires have become increasingly common and are now occurring twice as often as they did 20 years ago (Cunningham, Williamson, and Bowman 2024). Canadian wildfires are particularly remarkable for their frequency and scale. Figure 1 shows all North American fires over 500 hectares in 2006-2018, which together account for 97.5% of the total burned area. The figure shows that Canada accounted for the bulk of fire activity on the continent. Moreover, many fires in remote areas burned out of control for long periods. Byrne et al. (2024) estimates that the amount of carbon released during the worst Canadian fire seasons is equivalent to that emitted by all carbon-releasing activity in Russia or Japan in a typical year.

Smoke from wildfires is known to travel long distances and to negatively impact physical health, damaging the respiratory and cardiovascular systems and increasing mortality (Jayachandran 2009; Gould et al. 2024). Wildfire exposure may also take a toll on mental health. One important pathway is through air pollution from wildfire smoke. Air pollution induces inflammation in both the body and the brain (Costa et al. 2019), and brain inflammation has been linked to depression (Anisman and Hayley 2012; Miller and Raison 2016) and anxiety (Salim, Chugh, and Asghar 2012). This mechanism primarily affects individuals downwind of fires, where smoke exposure is highest.

However, wildfires could affect mental health through at least three additional channels. First, fires displace people, and the fear and uncertainty associated with evacuation can leave lasting psychological scars. Second, wildfires disrupt daily life and impair livelihoods—harms likely to be concentrated within a relatively small radius of a fire and potentially affecting people both upwind and downwind. Third, even for those far away, alarming news about severe wildfires may trigger a form of anxiety known as "ecoanxiety" (American Psychological Association 2017).

Symptoms of ecoanxiety range from mild stress to depression, anxiety, PTSD, and substance abuse. These harms should depend on the amount of public attention generated by a fire.

This study examines the relationship between wildfires and mental health-related hospitalizations in Canada from 2006 to 2018. Hospitalization records are linked with geospatial data on all U.S. and Canadian wildfires larger than 500 hectares, sourced from the Canadian Wildland Fire Information System (CWFIS) and the U.S. Monitoring Trends in Burn Severity program (MTBS). To investigate underlying mechanisms, we incorporate data on evacuation orders, wildfire-related Twitter activity, and particulate matter ($PM_{2.5}$) concentrations.

We make three contributions to the existing literature. First, we consider all three of the potential channels outlined above: Direct experience of the wildfire; exposure to wildfire smoke; and increases in eco-anxiety. Second, we explore the sensitivity of the estimated effects of air pollution to the inclusion of the additional mechanisms. Third, we focus on administrative data on hospitalizations with a primary diagnosis of a mental health disorder from the Canadian Hospital Mental Health Database for 2006–2018. Mental health hospitalizations are considerably more frequent than suicides, which have been the focus of some of the recent literature (Molitor, Mullins, and White 2023; Zhang et al. 2024) and allow us to specify the types of mental illness that are most affected by exposure to wildfires. The use of administrative data also helps us to avoid issues due to selective responses to survey data about mental health (Agyapong et al. 2020; Chen, Oliva and Zhang 2024). It is not be possible to conduct a similar study using U.S. data as there is no comparable source of national U.S. hospitalization data that includes geographic identifiers or the day of hospitalization.[1]

[1] U.S. administrative data on hospitalizations nationwide is available from the Agency for Healthcare Research and Quality but includes indicators only for one of four Census regions. Data with zip-code level data is available, but only for selected states and years. These data also only include the month of hospitalization rather than the day.

We find substantial effects of fires on hospitalizations for mental health. While smoke from upwind fires has an important and statistically significant effect, it is not the only mechanism affecting mental health: Evacuations and a proxy for climate anxiety also have a substantial impact. The increases are driven largely by hospitalizations for anxiety and substance abuse, consistent with an important role for climate anxiety. The estimates are robust to a wide range of changes in the way variables are defined and measured and changes in specification. Given that hospitalizations for mental health are rare relative to outpatient treatment, the estimates suggest that wildfire takes a substantial toll on mental health, and that only part of this effect is due to air pollution. Given the increasing frequency and severity of wildfires, the consequences for mental health deserve greater attention.

The rest of this paper is organized as follows. Section 2 provides background on the previous literature. Section 3 describes the novel data set that we assembled for this project. Methods are discussed in Section 4. Results appear in Section 5 and Section 6 offers a discussion and conclusion.

2. Background

A large economics literature shows that there are causal effects of air pollution on outcomes including productivity (Graff Zivin and Neidell 2012; Borgschulte, Molitor, and Zou 2024); cognitive tasks (Archsmith, Heyes, and Saberian 2018; Chang et al. 2019; Chew, Huang, and Li 2021); exam scores (Ebenstein et al. 2016; Gilraine and Zheng 2024); sleeplessness (Heyes and Zhu 2019); crime (Burkhardt et al. 2019; Herrnstadt et al 2021; Lu et al 2018), and workplace injuries (Cabral and Dillender 2024). Moreover, people value cleaner air (e.g. Smith and Deyak 1975; Chay and Greenstone 2005; Bayer, Keohane, and Timmins, 2009).

A parallel correlational literature shows that hospitalizations and Emergency Department visits for mental illness increase on high pollution days (Song et al., 2018; Lee et al. 2019; Newbury et al. 2021; Qui et al. 2024; Strahilevitz, Strahilevitz and Miller 1979; Szyszkowicz et al. 2020; Wang et al 2018). For example, Newbury et al. (2021) study 13,000 people in London who were being treated for mental health disorders and find that those exposed to higher levels of pollution have higher probabilities of being admitted to hospital. There are also studies showing an association between pollution and increases in depression and anxiety (Kioumourtzoglou et al. 2017; Power et al. 2015; Shin, Park, and Choi 2018; Pun, Manjorides, Suh 2017; Petrowski et al. 2021; Zijlema et al., 2016); reduced self-reported happiness (Zhang et al. 2017, Zheng et al. 2019); and increases in dementia (Moulton and Yang 2012; Chen et al 2017) and neurological disorders (Bandyopadhyay 2016).

Recently, economists have begun to explore the causal relationship between air pollution and mental health. Graff Zivin and Neidell (2018) and Bishop, Ketcham, Kuminoff (2023) study variations in long-term air pollution exposure induced by environmental regulation and find that higher exposure increases dementia. Using survey data, Chen, Oliva and Zhang (2024) look at inversions in China and find increases in reports of depressive symptoms, while Zhang et al. (2024) find that Chinese inversions increase suicides. Molitor, Mullins, and White (2023) relate monthly county-level U.S. suicide rates to exposure to wildfire smoke. They find that in rural areas smoke exposure increased suicide rates by approximately 2% while there was no effect in urban areas.

There are very few studies focusing on the other pathways included in our study. To, Eboreime, and Agyapong (2021) provide a scoping review of literature about the mental health effects of wildfires focusing on those who are directly impacted. For example, Agyapong et al. (2020) sent questionnaires to teachers evacuated during the devastating Fort McMurray fire in

2016 and found high rates of post-traumatic stress disorder (PTSD) the 14% who responded.[2] Their paper is typical in focusing on a single dramatic wildfire event, and in using evacuations as a proxy for identifying those directly affected. We will also focus on evacuation as a measure of the direct impacts of fires. In addition, we will include indicators for exposure to fires within 100km (close fires). Using administrative records for mental health hospitalizations avoids potential difficulties with survey non-response and offers a much larger sample than most previous studies of this "direct harms" pathway.

As discussed above, wildfires could affect mental health by stoking climate anxiety. Using clinical screening tests, Uppalapati et al. (2023) and Ballew et al. (2024) find that 7% of U.S. adults experience psychological distress due to climate change, and 3% have severe depression or anxiety. Burke et al. (2022) use Twitter data to track sentiment around wildfires, suggesting a possible way to track climate anxiety. In this paper, we use the number of tweets about wildfires that are posted from 500km or more away from the centroid of a census division on a particular day as a measure of the extent to which fire activity may be provoking generalized climate anxiety in that census division. This distance cutoff was chosen to minimize the possibility of conflating climate anxiety with the direct harms from wildfires—conditional on smoke exposure, tweets originating this far away arguably reflect only the impact of climate anxiety.

In summary, the previous literature suggests that there may be a causal relationship between wildfires and mental health. This relationship reflects three possible mechanisms: Direct experience of the wildfire which we proxy using evacuations and the presence of fires within 100km; exposure to wildfire smoke which we measure as predicted increases in PM2.5 from fires more than 100km away; and increases in eco-anxiety, proxied using tweets about wildfire coming

[2] 197 out of 1,446 eligible respondents returned the on-line questionnaires, indicating how difficult it can be to obtain survey responses during a disaster.

from more than 500km away. We use data on wildfires in Canada and the U.S. linked to mental health hospitalization data from Canada to explore these mechanisms. We find evidence consistent with all three mechanisms and show that the results are robust to using other distances and many other changes in specification.

3. Data

This study combines data on hospital admissions for mental health with information on wildfires, evacuations, particulate matter, and Twitter activity related to wildfires to create data at the level of the day and the Canadian census division. The census division represents the finest geographic unit for which reliable annual population data can be obtained in Canada, enabling the construction of accurate and consistent hospitalization rates per 100,000. This section describes the data sources and the creation of the data set in some detail.

Mental health admissions come from the Hospital Mental Health Database (HMHDB), collected by Canadian Institution for Health Information (CIHI) for 2006 to 2018.[3] The HMHDB includes residential location, diagnosis, admission date, and discharge date for each hospital admission. The dependent variable in most of our models is a 3-day hospital admission rate for any mental health condition and for five broad categories of mental health disorders classified using the 10th International Classification of Disease (ICD-10-CA).[4] The five categories of disorders are: anxiety, mood, substance-related, adjustment disorders, and all other.[5] Each record

[3]For further information see https://www.cihi.ca/en/hospital-mental-health-database-metadata-hmhdb. The HMHDB is extracted from Discharge Abstract Database (DAD). Less than 0.2% of the data comes from the Hospital Mental Health Survey (HMHS) and this data is excluded from our analysis. We also exclude visits that are planned or follow-ups in order to capture mental health emergencies.

[4] For more information see: https://www150.statcan.gc.ca/n1/pub/82-003-x/2018006/article/54971/tbl/tblb-eng.htm

[5] Anxiety includes codes F40 - F42, F430, F431, F438, F439, F930 - F932 and include post-traumatic stress disorder, mood disorders such as depression include codes F30 - F33, F39, F340, F341, F348, F349, F380, F381, F388, substance use codes such as drug overdoses, include F10 - F19, F55. The by far the largest subcategories of hospitalizations for other disorders are for dementia and schizophrenia.

is categorized using the primary diagnosis (MRD_x_*primary*). The focus on 3-day hospitalizations follows Deryugina et al. (2019) and allows some time for delayed effects of exposure and pollution transport. We show below that the results are robust to using 1-day to 10-day hospitalization rates. Admission rates are calculated using annual population estimates in the relevant census division, and the 3-day rate includes admissions on the day of the fire and the two days following.[6]

Canadian wildfire data was obtained from the Canadian Wildland Fire Information System (CWFIS),[7] maintained by Natural Resources Canada. These data provide information about wildfire location, size, and intensity. Because smoke from the U.S. can affect Canadians, data about U.S. fires was taken from the Monitoring Trends in Burn Severity (MTBS) program,[8] a joint initiative of the U.S. Forest Service and the U.S. Geological Survey. This dataset offers detailed information on the latitude and longitude of fire locations, as well as their start and end dates.

The direct harm inflicted by wildfires is proxied using information about wildfire evacuations from the Canadian Wildland Fire Evacuation Database (CWFEDB) which is managed by the Canadian Forest Service of Natural Resources Canada. The underlying data are not publicly accessible, as they include information considered sensitive such as the exact evacuee numbers and detailed notes on each evacuation. However, the NRC gave us grouped information about the size of each evacuation. The frequency of evacuations is highly variable but increased from 36 in 2006 to 102 in 2018 along with a rise in the total number of evacuees from 3,519 to 32,165.

Figure 2 shows the location of evacuations by size. The figure also shows the boundaries of Canadian census divisions. One can see, for example, that the highly populated areas along the U.S. border have census divisions with smaller areas than the sparsely populated northern regions.

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[6] Annual population data comes from Statistics Canada. Data is publicly available at https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=171001390.
[7] Data can be obtained from: https://cwfis.cfs.nrcan.gc.ca/datamart.
[8] Data was retrieved from: https://www.mtbs.gov/direct-download.

Appendix Figure A1 shows the distributions of evacuation lengths and frequencies from January 2006 to December 2018. Most evacuations are relatively short: Roughly three quarters last 25 days or less.

Data about ambient air pollution comes primarily from air quality monitors maintained by Environment Canada's National Air Pollution Surveillance System (NAPS).[9] Following previous studies of wildfire smoke, we use $PM_{2.5}$ as the primary measure of air pollution, but data on O_3 and CO are included as controls in some specifications. Appendix Figure A2 shows the spatial distribution of $PM_{2.5}$ monitoring stations across Canada. There are 318 $PM_{2.5}$ stations of which 215 were active over the whole study period while 103 were added in 2010 or later. Appendix Figure A3 shows that the time series trends in $PM_{2.5}$ are quite similar whether only continuously active monitors or all monitors are used. In order to include as many days as possible for each monitor, missing values are interpolated using data from the nearest monitoring station with non-missing data as long as that station is within 20km of the index station.[10] Census division-level measures are then calculated by taking the mean of all available pollution readings on a given day across all monitors located within 50km of each census division's centroid.

The average daily concentration of PM2.5 was 6.54 $\mu g/m^3$ with a standard deviation of 6.24 over the sample period. However, $PM_{2.5}$ spikes in areas affected by wildfire smoke. Figure 3 shows daily $PM_{2.5}$ in the city of Winnipeg. One can clearly see a spike in particulates in mid-August 2018 in the upper panel, when they reached almost 80 $\mu g/m^3$. The lower panel of the figure shows satellite imagery of fire hotspots and the trajectory of smoke on August 18, 2018.

[9] NAPS was established in 1972 to provide long-term air quality data at a uniform standard across Canada. The data can be found at: https://open.canada.ca/data/en/dataset/1b36a356-defd-4813-acea-47bc3abd859b.
[10] Pollution data was cleaned using the Ambient Air Monitoring and Quality Assurance/Quality Control guidelines found at https://ccme.ca/en/res/ambientairmonitoringandqa-qcguidelines_ensecure.pdf. These guidelines recommend replacing -999 values with missing values and negative numbers with zero, among other measures. Monitor readings are aggregated to the daily level by averaging across hourly observations.

The figure shows that smoke from fires in the Canadian Rockies blew more than 1,000 km to reach Winnipeg, causing the spike in $PM_{2.5}$.

Some specifications use AI-generated $PM_{2.5}$ measures from the model proposed in Paul et al. (2022). This measure of Canadian particulate matter is calculated with a random forest model using data on smoke plumes from remote sensing, satellite estimates of meteorological parameters, measures of fire radiative power, and aerosol optical depth. An advantage of this measure is that it exists for all days and census divisions, but we do not use it as our main measure because it is only available from 2010-2018.

It is important to properly control for weather because weather conditions could have a direct, independent, impact on mental health (see Cianconi et al. 2020) and weather also affects the transport of smoke from fires. Data on Canadian weather conditions was retrieved from hourly historical data from Environment Canada.[11] U.S. data comes from the US Local Climatological Data (LCD).[12] All models control for air temperature, dew point (humidity), air pressure, wind speed, wind direction, sky cover, and precipitation. Cloud cover data comes from the daily reanalysis data of the North American Regional Reanalysis (NARR).[13] NARR incorporates raw data from land-based weather stations, aircraft, satellites, and other meteorological datasets.

[11] Canadian weather data can be accessed here: https://climate.weather.gc.ca/historical_data/search_historic_data_e.html.
[12] The National Oceanic and Atmospheric Administration LCD data comes mostly from airports and is available at: https://www.ncei.noaa.gov/metadata/geoportal/rest/metadata/item/gov.noaa.ncdc:C00684/html
[13] The NARR data is provided by the National Oceanic and Atmospheric Administration. See https://www.esrl.noaa.gov/psd and see https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-regional-reanalysis-narr for more information and the NARR dataset itself.

Wind direction is the geographic direction *from* which the wind blows.[14] We convert this measure to arc degrees[15] and then construct a daily measure using an arctangent function. Daily wind direction values at each weather monitoring station are computed by taking the average across all available measures for each station. Missing observations are imputed using linear interpolation for each monitor. Stations are assigned to each census division using the closest station to each census division centroid and then converting hourly measures to the division-day level.

To get a sense of whether wildfires cause climate anxiety, we examined all daily geo-located tweets and retweets that included the hashtag "#wildfire" in Canada between 2006 and 2018.[16] These data come from *TrackMyHashtag.com*, a social media analytics tool that primarily focuses on tracking and analyzing hashtags on social media platforms. Geo-located tweets are available from users who have agreed to share their location data. These data can be generated through GPS coordinates (latitude and longitude). We distinguish between tweets that were posted inside and outside a 500km radius of each census division's centroid. The maintained assumption is that areas more than 500km away from a fire are not directly affected other than through effects on air quality. Hence, conditional on air quality, a higher volume of tweets about a wildfire may be an indicator of climate anxiety induced by news about fires.

Figure 4 shows the daily number of tweets about wildfires from areas more than 500km away from the census division centroid. The figure shows that spikes in faraway tweets align with

[14] The wind direction measure represents the average direction during a two-minute observation period and is measured 10 meters above the ground. It is expressed as tenths of a degree. 90 degrees means an east wind and 360 degrees means a wind blowing from the geographic North Pole. See https://climate.weather.gc.ca/glossary_e.html.
[15] This implies that a full rotation of a circle is 360 degrees or 2π radians where one degree is equivalent to $\pi/180$ radians.
[16] We also experimented with using Google Trends data. One problem with Google Trends is that the underlying information about the number of Google searches is not available. Everything is normalized so that the maximum number of searches is equal to 100.

significant wildfire events such as the Fort McMurray fire in May 2016, which was the costliest disaster in Canadian history. These spikes suggest that social media activity increases during large wildfires, reflecting heightened public concern which might in turn cause individuals to experience climate anxiety.

These data sources are merged using the residential census division and admission date of each hospital record. Distances are calculated from residential census division centroids. To minimize measurement error in assigning air pollution to individuals, records were dropped if there were no pollution monitoring stations within 30 km of a residential census division centroid. Wildfire locations are coded using the initial latitude and longitude of each fire.

Table 1 presents summary statistics for the main estimation sample, which consists of 301,619 division-day observations. The 3-day total mental illness hospital admission rate in the sample is 361.1 per 100,000[17] with a standard deviation of 350. Mood and substance-related disorders are Canada's leading causes of mental health related hospital admissions. The average census division experiences 8.59 fires greater than 500ha within 2000km, and the average such fire lasts 11.78 days. Relatively few (0.77) of these fires are within 100 km, however.[18] The average evacuation in our sample lasted 3.76 days, and there are 829.54 tweets about wildfires that originate from over 500km away.

[17] The same-day mental illness hospitalization in Canada is 672.15 per 100,000 population. The mean in our final dataset is lower for two reasons. First, Nunavut, Northwest Territories and Yukon are excluded as there are no psychiatric hospitals in those areas and patients must travel to Alberta, Saskatchewan, or Manitoba. Mental illness rates are three times higher in areas where more Indigenous people live (e.g., Nunavut, Northwest Territories and Yukon). Due to confidentiality of the data, we could not identify those areas in our records and therefore these three provinces are excluded from this study. Second, 30% of the total Hospital Mental Health Data Base is excluded as there were no monitoring stations within 30 km. See Figure A4 for a description of variation in mental health hospitalization rates and census divisions that are excluded from this study. These tend to be sparsely populated areas.

[18] Figure A5 shows the distribution of fire sizes and distances from fires.

Following Rangel and Vogl (2018) we define upwind fires as those located within a cone defined by a 30-degree central angle from the dominant daily wind direction in each division. Downwind locations are similarly defined. This is a relatively strict definition that excludes fires that are not clearly upwind or downwind (those to the side of the census division centroid). Hence, we also explore the robustness of the estimates to using wider angles to define upwind and downwind fires. Using the 30-degree definition, only 17.54 fire days per census division are definitely upwind, while 22.65 fire days are definitely downwind, and the other fire days are not counted as either upwind or downwind. The robustness of the estimates is further tested by varying both the exclusion zone size for close fires (from 100km to 200km) and the 2,000 km cut-off for considering $PM_{2.5}$ from distant fires (considering 1000km and 3000km).

Panels B and C of Table 1 examine mean mental health hospitalizations for the census divisions with the highest and lowest quartiles of pollution (Panel B) and fire days (Panel C). Panel B shows that the highest pollution census divisions have $PM_{2.5}$ levels that are more than three times higher than in the lowest pollution census divisions, and mental health hospitalizations are more than twice as high in all categories. Panel C indicates that census divisions with many fire days also have a little less than twice as many mental health hospitalizations compared to the census divisions with the least fire days. However, because these figures reflect exposure to we all fires within 2000km, the difference between high and low exposure census divisions is much less stark than for $PM_{2.5}$.

4. Empirical Strategy

A first step is to explore the relationship between wildfires at different distances and mental health hospitalizations. This exploratory data analysis provides a motivation for some of the choices made in later regressions. The relationship between hospitalizations and distance is modeled as follows:

$$y_{cdmy} = \beta_0 + \beta_1 \boldsymbol{fire}_{cdmy} + \beta_2 W_{cdmy} + \varphi_c + \lambda_{pm} + \theta_{my} + \epsilon_{cdmy}, \quad (1)$$

where the dependent variable y_{cdmy} is the mental health hospitalization rate in census division c, on day d, in month m, and year y. The vector $\boldsymbol{fire}_{cdmy}$ includes a series of indicators for the number of fires in a particular distance bin. The bins are 0-99km, 100-199km, 200-299km, 300-399km, 400-499km, and 500-2000km. The vector W_{cdmy} includes daily measures of temperature, precipitation, humidity, cloud cover, wind speed and air pressure,[19] j_c is a vector of census division fixed effects that account for fixed characteristics of census divisions such as urbanicity, l_{pm} is a vector of province-by-month fixed effects that accounts for seasonal variation in hospitalizations at the province level, q_{my} is a vector of month-by-year fixed effects that account for Canada-wide temporal patterns in hospitalization, and ϵ_{cdmy} is an error term that is clustered at the census division level to allow for correlations in unobserved census division level determinants of hospitalization. The primary parameter of interest is β_1, which captures the impact of the daily number of fires at different distances.

A version of equation (1) is also estimated separating out upwind and downwind fires in the same distance categories. As shown below, these investigations suggest that even downwind fires less than 100km away affect mental health hospitalizations, suggesting that the fires are having direct effects other than through pollution. Downwind fires more than 100km do not appear to increase mental health hospitalizations. However, upwind fires as far as 500km are associated with increased mental health hospitalizations, while those further than 500km away do not. These

[19] Daily temperatures are categorized into ten bins, ranging from below -20 degrees Celsius to above 20 degrees Celsius, with eight intermediate bins each spanning 5 degrees Celsius. For daily precipitation and sky cover, four indicators are generated for each quartile of these variables.

results suggest that conditional on air quality, tweets from areas more than 500km away may be a useful proxy for measuring climate anxiety.

Using the estimates from these models as a guide, we then replace $fire_{cdmy}$ in (1) with four measures defined for each division *c*, on day *d*, of month *m,* and year *y*: 1) $fire^{100}_{cdmy}$ which is the number of fires within 100km of a census division centroid; 2) $evacuation_{cdmy}$, an indicator equal to 1 if there is an evacuation order in place; 3) $PM2.5_{cdmy}$, the $PM_{2.5}$ concentration; and 4) $tweets^{>500}_{cdmy}$, the number of tweets about wildfire posted from 500km or more away from the centroid of census division *c* on day *d*. Including these variables yields the following estimating equation:

$$y_{cdmy} = \alpha_0 + \alpha_1 fire^{100}_{cdmy} + \alpha_2 evacuations_{cdmy} + \alpha_3 PM2.5_{cdmy} + \alpha_4\, tweets^{>500}_{cdmy} + \alpha_5 W_{cdmy} + \varphi_c + \lambda_{pm} + \theta_{my} + \epsilon_{cdmy}, \qquad (2)$$

where the other variables are as previously defined. Estimating this equation allows us to investigate the direct effects of wildfires through evacuations and local economic effects, the impact due to increases in air pollution, and the impact due to climate anxiety.

A potential problem with the estimation of equation (2) is that local $PM2.5_{cdmy}$ reflects not only air pollution from fires, but pollution from other sources such as industry, transportation, and home heating. Hence, actual $PM2.5_{cdmy}$ in a census division will be affected by pollution from upwind fires but is a potentially very noisy measure of fire activity. Moreover, areas that are highly polluted in the absence of fires may have other characteristics that are correlated with residents' mental health. For example, wealthier people might be both less likely to be hospitalized for mental illness (due to lower stress and greater access to alternative forms of care), and more likely to live in urban centers and be exposed to PM2.5. Both considerations would lead ordinary least squares to underestimate the mental health impacts of pollution from fires. Therefore, following Barwick et al. (2018); Chen et al. (2021); Deryugina et al. (2019); Schlenker and Walker, (2016); and Ward (2015), $PM2.5_{cdmy}$ is instrumented using a measure of predicted exposure to particulates from distant upwind wildfires.

The definition of upwind and downwind fires is illustrated in Figure 5. The main instrumental variable approach aims to estimate how smoke from upwind fires between 100km and 2000km away influences $PM_{2.5}$ levels. Data on fires less than 100km away are excluded since these fires could have direct effects on local residents as we showed above. The post-selection double Lasso method (Belloni, Chernozhukov, and Hansen, 2014) was used to select the most relevant characteristic of distant fires as a potential instrument. This method involves estimating separate Lasso regressions for $PM_{2.5}$ and for hospitalizations. Each model included fire characteristics as well as interactions between these characteristics and weather factors at the fire and census division locations. We then identified the variable that was most predictive of both pollution and hospitalizations using the 80% of the data from the most recent years as the training sample and the remaining 20% of the data as the test sample.[20] Figure A6 shows the top predictors (excluding fixed effects). This process identified the following variable as a potential IV:

$$IV_{cdmy} = \sum_{c' \neq c} \frac{upwindfire_{c'dmy} \times size_{c'dmy}}{D^2_{c'c}}, \qquad (3)$$

where the indicator c' is the census division of the wildfire and the other subscripts are as specified above. The variable $upwindfire_{c'dmy}$ is an indicator that takes the value one if there is an active wildfire located in upwind location *c'* and zero otherwise; $size_{c'dmy}$ is the size of the fire in hectares;

[20] Unlike random splits (used in traditional cross-validation), this time-based method respects the temporal ordering of the data and is therefore especially useful when dealing with time-dependent relationships.

and $D_{cc'}$ is the distance between the fire location c' and the census division c centroid. Hence, the first stage model is:

$$PM2.5_{cdmy} = \gamma_0 + \gamma_1 IV_{cdmy} + \gamma_3 evacuations_{cdmy} + \gamma_4 fire_{cdmy}^{100} + \gamma_5 tweets_{cdmy}^{>500} + W_{cdmy}\, \gamma_{46} + \varphi_c + \lambda_{pm} + \theta_{my} + \epsilon_{cdmy}. \quad (4)$$

The parameter of interest in equation (4) is γ_1 which captures the effect of the instrument on the concentration of $PM_{2.5}$.

As a robustness check, we also predicted $PM_{2.5}$ using Extreme Gradient Boosting[21] using a similar set of fire and location characteristics.[22] Figure A7 shows that XGBoost predicts observed $PM_{2.5}$ values well, providing a visual validation of the model's accuracy. Cross-validation was conducted in the same time-based manner as in the Lasso procedure.

Because a novel feature of our work involves measuring the direct effects of evacuations and the use of tweets as a potential measure of climate anxiety, models that focus specifically on those two mechanisms are also estimated. Event study models of evacuations take the following form:

$$y_{cwy} = \rho_0 + \sum_{k=-5}^{10} \delta_k . 1\,(k = week\ to\ evacuation)_{cwy} + \delta_{-6} . 1(k \leq -6) + \delta_{11} . 1\,(k \geq 12) + \varphi_c + \lambda_{pw} + \theta_{wy} + \epsilon_{cwy}\,, \quad (5)$$

[21] Extreme Gradient Boosting is a machine learning algorithm designed for efficient and accurate predictions (by Chen and Guestrin 2016). It is particularly useful for handling large datasets with complex relationships between variables. XGBoost builds predictions step-by-step, with each new tree correcting the errors in previous trees. XGBoost can be capture nonlinear and interactive effects. Kleinberg et al. (2018) demonstrate the usefulness of XGBoost in improving predictions of economic outcomes, such as judicial decisions.

[22] To train the XGBoost model, a comprehensive set of controls and fixed effects are included as specified in Equation (2), along with detailed fire characteristics such as distance to each census division, size, temperature, humidity, and wind speed at the fire location, the daily total number of fires, and counts of upwind and downwind fires within 100, 200, 300, 400, and 500 km radii of the census division centroid.

where y_{cwy} is the mental illness hospital admission rate in census division *c* in week *w* and year y. *1(k=week to evacuation)*$_{cwk}$ are event time dummies that equal 1 if week *w* is *k* weeks away from the evacuation in division *c*. The δ_k (*for* $k=-5$ *to* $k=10$) trace the week-by-week effect of evacuation exposure on the mental illness admission rates. The indicator δ_{-6} is the average effect for all weeks ≥ 6 before the evacuation (the pooled baseline period), while δ_{11} is the average effect for all weeks ≥ 11 after the evacuation (the long-run effect). The vector φ_c represents census division fixed effects, λ_{pw} represents province-by-week fixed effects which control for seasonal patterns at the regional level, and θ_{wy} indicates week-by-year fixed effects which control for common national-level time shocks. The error terms are clustered at the census division level.

To explore the relationship between mental health hospitalizations and evacuations at a more granular geographic level, the event study design is complemented with a set of models estimated at the *city level*.[23] These models exploit both the timing of mental health hospitalizations relative to the evacuation event and the distance between each city and the evacuation area. Specifically, mutually exclusive indicators are defined for discrete time windows after an evacuation (0–4 weeks, 5–9 weeks, and 10 or more weeks away) interacted with geographic distance bands (50 km to 99km, 100 to 199km, 200 to 499km and 500 or more km away). The model allows for separate estimation of evacuation effects for each time–distance pair and is specified as:

$$y_{cdmy} = \eta_0 + \sum_d \sum_\tau \beta_{\tau d} \,.\, 1\,[TimeBin_t = \tau \wedge Distance_c = d] + \gamma_c + \lambda_{pm} + \theta_{my} + \eta_1 W_{cdmy} + \epsilon_{cdmy}\,, \qquad (6)$$

[23] City-level population data are only available at five-year intervals (i.e., census years). As a result, the city-level models presented in Figure 2 rely on fixed population estimates from census years**,** which may introduce some measurement error into the hospitalization rate calculations. Accordingly, the city-level results should be interpreted as complementary to the census division-level event study, offering insights into localized effects that might be masked in more aggregated models.

where y_{ct} is the three-day hospitalization rate per 100,000 in city c, on day d, in month m, and year y. The coefficient $\beta_{\tau d}$ captures the effect of an evacuation observed τ days later in cities at distance d. The model includes city fixed effects γ_c, province by month λ_{pm} and month by year q_{my}, and a vector of controls, including weather and air quality variables W_{cdmy}. Standard errors are clustered at the city level. This framework enables us to ask whether residents further from the evacuation zone respond differently compared to those in the directly affected areas.

A model of the effects of tweets takes the form:

$$y_{cdmy} = \beta_0 + \beta_1 tweets_{cdmy} + \beta_2 W_{cdmy} + \varphi_c + \lambda_{pm} + \theta_{my} + \epsilon_{cdmy}\,, \quad (7)$$

where the key independent variable, $tweets_{cdmy}$, measures the daily count of tweets containing the hashtag #wildfire, constructed separately for tweets originating within 500 kilometers and outside 500 kilometers of each census division's centroid with an active fire. Including both variables helps to further explore the relationship between social media activity related to relatively close local fires and Twitter activity that reflects only very distant fires, our proxy measure for climate anxiety provoked by wildfires.

5. Results

This section first presents estimates of the effects of fires on mental health hospitalizations, and then explores the three mechanisms discussed above, air pollution, direct effects proxied by evacuations and close fires, and effects through climate anxiety as proxied by tweets about wildfire. These models are followed by models which include all three channels.

a) Mental health hospitalizations and fires by distance bands

Table 2 reports estimates from model (1) which shows the estimated effect of the number of fires in bands of different radii on the number of mental health hospitalizations in each census division. The total increase in hospitalizations is 0.789 per 100,000, which is driven largely by hospitalizations for anxiety and substance use disorders. For these two disorders, each additional fire within 100km is estimated to increase the number of mental health hospitalizations per 100,000 by 0.898 and 0.745 per three-day period, respectively. There are also statistically significant effects on hospitalizations for mood disorders and adjustment disorders, but the magnitudes are much smaller.

Fires between 100 and 200km are estimated to have significant effects on mental health hospitalizations, especially for anxiety and substance use disorders, although the magnitudes are smaller than for the closest fires. However, in the next distance band of 200 to 300km, only hospitalizations for substance use disorders rise significantly and there are no statistically significant effects observed for fires at distances over 400km.

The models in Table 2 do not distinguish between upwind and downwind fires. If the effects on mental health hospitalizations are driven mainly by air pollution, then one would expect upwind fires to have larger effects than downwind effects. Table 3 shows estimates from models that distinguish between fires that are clearly upwind, and those that are clearly downwind, ignoring fires that are not in the 30-degree cones shown in Figure 5. Table 3 shows that upwind fires have clearly larger effects on mental health hospitalizations, consistent with an important role for air pollution. Moreover, upwind fires between 400 and 500km away have statistically significant effects on hospitalizations for anxiety and substance use disorders. However, downwind fires within 100km also have significant effects on mental health hospitalizations, especially for anxiety, but also for substance use disorders and adjustment disorders. One interpretation of these results is that local fires (those at distances less than 100km) may affect mental health outcomes through additional channels besides air pollution.

b) Pollution from fires and mental health hospitalizations

Table 4 explores the air pollution channel for fires to affect mental health. Panel A shows the estimated effects of $PM_{2.5}$ on mental health hospitalizations from ordinary least squares (OLS) regressions. As discussed above, these estimates may be biased by omitted variables if, for example, people with access to better outpatient mental health services are both more likely to be exposed to $PM_{2.5}$ and less likely to be hospitalized with mental health conditions.

One solution to this problem is to instrument $PM_{2.5}$ using the instrument defined in equation (3) above. Panel B shows the estimated reduced form parameters, which show that the instrument is a significant predictor of all the types of mental health hospitalizations that we examine. The IV estimates in Panel C indicate that there are significant effects of $PM_{2.5}$ on mental health hospitalization for all categories except mood disorders. Moreover, the estimated effects are considerably larger than those estimated by OLS. Table 1 showed that the difference in $PM_{2.5}$ between the highest and lowest quartile of census divisions was roughly 10 units. An increase in $PM_{2.5}$ of this magnitude from fires is estimated to increase hospitalizations due to anxiety and substance use disorders by 1.41 and 1.92 per 100,000 respectively. There is also an increase of 4.37 in hospitalizations due to adjustment disorders and an increase of 3.02 hospitalizations per 100,000 for other disorders. Panel D shows that using predicted $PM_{2.5}$ from models using XGboost rather than traditional two-stage-least squares produces very similar estimates of the effects of air pollution from fires on mental health hospitalizations.

c) Effects of evacuations

Most of the previous literature about the effects of wildfires on mental health emphasizes inflammation due to air pollution. However, as we have emphasized, there are other potential pathways. Being evacuated is a traumatic event that affects thousands of people per year, and which could have negative impacts on mental health. Figure 6 shows estimates from event study models of the effects of evacuation based on equation (5). These estimates are at the week and census division level. They indicate that a mandatory evacuation order increases hospitalizations for anxiety and substance use disorders by about two and five hospitalizations respectively, starting immediately and persisting for more than ten weeks afterwards. There are no pretrends in the six weeks leading up to the evacuations. There are more fleeting increases in hospitalizations for mood disorders and adjustment disorders in the week after the event. It appears that the elevation in mood disorders quickly returns to normal, while the increase in adjustment disorders persists for some weeks (though increases after the first two weeks are imprecisely estimated).

Figure 7 provides a more detailed exploration of the effects of evacuations by distance from the evacuation site and timing. This figure is estimated at the city level, a finer level of geography than the census division so that we can directly pinpoint effects on the city that is evacuated. They use the 3-day average of mental health hospitalizations as in most of our other specifications. The estimates show that the effects on mental health hospitalizations are concentrated in the affected city and in a 50 to 100km band around the evacuated city. Presumably populated areas in this band might also be at risk of evacuation. In terms of timing, the first set of estimates in each sub-figure shows the overall "post" effect at all weeks, while the remaining sets of estimates show estimated effects at weeks 1-4, 5-9, and 10 plus.

The estimates indicate that being evacuated increases mental health hospitalizations for anxiety by about 5 per 100,000 in the weeks immediately following the evacuation. The effect falls to about 3 per 100,000 after 4 weeks but remains elevated in the evacuated city even after 10 weeks. Hospitalizations for substance abuse also rise by about 5 hospitalizations per 100,000 in the affected city in the weeks immediately after the evacuation, and do not begin to moderate until after 10 weeks. As in Figure 6, the estimates suggest that there are smaller effects on hospitalizations for mood disorders and adjustment disorders. The former moderate after four weeks, while the estimated effect on hospitalizations for adjustment disorders remain elevated in the affected city.

d) Effects of climate anxiety as measured by tweets about wildfire

Tables 2 and 3 suggested that fires more than 500km away have little influence on mental health hospitalizations. However, fires that generate social media attention could stoke climate anxiety even when they are far away. Table 5 presents regression estimates of the relationship between tweets originating less than 500km away from a census division centroid and those originating 500-2000km away.

Both measures are significantly correlated with mental health hospitalizations. Since Table 3 suggested that tweets from areas within 500km of a fire might reflect direct fire effects, in what follows we mainly focus on tweets from areas further away. However, both measures have similar estimated effects on total mental health hospitalizations, with the largest impact being on hospitalizations for anxiety. For example, at the mean of 2.81 tweets per day about wildfire originating from 500-2000km away, an additional tweet about wildfire is estimated to increase hospitalizations for anxiety by 0.0167. There are also smaller effects on hospitalizations for substance use disorder, mood disorders, and adjustment disorders, but the major impact, consistent with the climate anxiety story, is on anxiety.

d) Towards a more complete model of the impact of wildfires on mental health hospitalizations

Table 6 shows estimates of equation (2), with $PM_{2.5}$ instrumented as described above. In addition to measures of evacuations and tweets originating more than 500km away, this model also includes the number of fires within 100km since Table 3 suggested that even downwind fires within this radius have effects on mental health hospitalizations. Fires within 100km also have large effects on local $PM_{2.5}$, as shown in Appendix Figure A8, which may be captured by these indicators.

Consistent with Figures 6 and 7, Table 6 indicates that evacuations have large effects on mental health hospitalizations. The largest impacts are on anxiety and substance abuse disorders, but there are also statistically significant impacts on mood and adjustment disorders. The number of fires within 100km (usually 1 or fewer per census division, as shown in Table 1) also has this pattern of effects. The estimated effects of $PM_{2.5}$ are slightly smaller than in Table 4, but not significantly so. The similarity in the estimates provides some validation of the instrumental variables strategy since it suggests that adding additional fire-related determinants of mental health hospitalizations does not change the IV estimates of the effects of $PM_{2.5}$. Wildfire-related tweets originating more than 500km away have statistically significant effects, suggesting that social media attention to distant fires can raise hospitalizations due to anxiety and substance abuse, with smaller effects on hospitalizations for mood and adjustment disorders.

In summary, an evacuation is associated with 1.78 additional hospitalizations per 100,000 and a fire within 100km leads to 0.26 additional hospitalizations per 100,000. An additional unit of $PM_{2.5}$ leads to 0.08 additional total mental health hospitalizations per 100,000, and every additional tweet including the hashtag #wildfires and originating from more than 500km away increases hospitalizations by 0.003 per 100,000.

Consistent with the estimates presented earlier, evacuations, fires within 100km, and tweets about wildfire, all have the largest impacts on hospitalizations for anxiety and substance use disorders. In contrast, $PM_{2.5}$ has the largest impact on adjustment disorders, and on the "other" mental health category, suggesting that it may operate through a different mechanism. Appendix Table A2 breaks the other category into its largest components (dementia and other neurocognitive disorders, schizophrenia, ADHD and other neurodevelopmental disorders, and a residual). While none of the estimates are precisely estimated, the largest coefficient on $PM_{2.5}$ is for dementia, consistent with previous work suggesting an impact of $PM_{2.5}$ on that outcome (Bishop, Ketcham, Kuminoff 2023; Graff Zivin and Neidell 2018).

The last column of Table 6 shows the impact of fires on pre-planned mental health admissions. These admissions can be viewed as a placebo test since fires should not increase pre-planned mental health admissions, though they could possibly decrease them (e.g. someone who was supposed to be admitted but is evacuated, might not show up for their pre-planned admission). Reassuringly, we find no significant impact of wildfires on pre-planned mental health admissions.

Up to this point, we have been considering the effect of fires on whether a hospitalization occurs (the extensive margin) but not the effect on the length of a hospitalization (the intensive margin). If wildfires increase the number of hospitalizations, then it also seems reasonable that they might increase the duration of hospital stays by worsening the overall distribution of mental health. Table 7 examines the effect on length of stay, in days. The estimates suggest that evacuations increase the average length of stay by almost a third relative to the mean. PM2.5 has a much smaller impact, as do tweets when entered alone, though not when entered in conjunction with the other measures of wildfire activity.

e) Heterogeneous effects

Table 8 examines the impact of wildfire by the presence or absence of secondary respiratory or cardiovascular conditions. The table shows that people with these conditions exhibit larger responses to all the wildfire measures, although people without these conditions continue to show elevated levels of hospitalizations for anxiety and to have more hospitalizations for substance use disorder when there are evacuations or fires within 100km. The effects of $PM_{2.5}$ are larger and more consistently statistically significant for individuals with respiratory and cardiovascular conditions, as are the estimated effects of tweets about wildfire. These estimates suggest that the mental health toll is higher for people whose physical condition makes them especially vulnerable.

Consistent with this interpretation, Table A3, which breaks out the effects by age, shows that the elderly have the largest responses to fires within 100km and to tweets, the proxy for climate anxiety.[24] Individuals younger than 20 have smaller responses to $PM_{2.5}$, which might be consistent with lower baseline levels of inflammation. Table A4 shows estimates separately by gender. The estimated effects are consistently larger for males than for females, even though females have higher underlying rates of mental health hospitalizations.

f) Robustness

Table 9 explores the robustness of the findings by replacing contemporaneous values of the independent variables measuring wildfire activity with values from 100 days before or 100

[24] Arguably, elderly people were less likely to be active on Twitter, but we are interpreting tweets as a measure of general media attention to a fire. For example, many people were tweeting about the Fort McMurray fire, but there was also wide coverage from television, radio, and newspapers that an elderly person could have seen.

days after the index date. These measures of temporally distant fire activity are not statistically significant, suggesting that it is contemporaneous fire activity that matters.

Timing issues are further explored in Appendix Figure A9. The main estimates shown above are based on a 3-day measure that includes the index day and the two days following to allow for slight delays in the effect of fires on hospitalizations. Appendix Figure A9 shows that the point estimates would be somewhat larger if we used a 5-day measure (the index day and the four days following) but would begin to attenuate if we included more days. Hence, the use of the 3-day measure can be viewed as conservative.

The estimates discussed above are robust to many additional changes in specification. Table A5 shows estimates from models that use a cone of 60 degrees to determine which fires are upwind and included in the construction of the instrument for $PM_{2.5}$. The estimates are similar to those reported above. Similarly, Table A6 shows the impact of changing the buffer zone around the census division centroid for the purposes of constructing the instrument. Panel A shows the effect of including upwind fires between 200 and 2000km (and changing the definition of a close fire to one within 200km), while Panel B shows the effect of including upwind fires between 100 and 3000km. The estimates are slightly smaller than those in Table 6 but show the same patterns of sign and statistical significance.

Table A7 shows estimates using the Paul et al. (2022) AI-generated measure of $PM_{2.5}$ (called CanOSSEM). As discussed above, this measure is only available from 2010-2018. Hence, Panel A repeats the IV model from Table 6 using only 2010-2018. The estimates are similar to those in Table 6. Panel B shows a reduced form specification using the CanOSSEM measure instead of $PM_{2.5}$. Again, the estimates are like those discussed above.

While $PM_{2.5}$ is often used to measure air pollution in studies of the effects of wildfire, wildfires may also generate other pollutants. Hence, Appendix Table A8 shows estimates adding measures of ozone and carbon monoxide (CO), where these values are instrumented using one and two-day leads of the instrument.[25] Panel A shows that we do not find any statistically significant effect of ozone, nor does including it affect the other estimates. There are many fewer CO monitors, so that including CO greatly reduces the available sample size. However, the estimates are similar to those discussed above except that the effect of fires within 100km becomes statistically insignificant due to larger standard errors.

Since weather has effects on mental health, Table A9 shows estimates excluding days with rain or cloud cover, which might be gloomy. Panel A of Appendix Table A9 includes only 3-day periods without rain, while Panel B includes only days with 10% cloud cover or less. While the sample size is greatly reduced, the qualitative pattern of findings is again quite like that shown in Table 6.

Another potential problem with the baseline estimates is that the dependent variable is a rate, calculated using the number of hospitalizations divided by the population size. In small census divisions, small changes in either hospitalizations or population counts could cause outliers in the rates. Appendix Table A10 shows the results of either excluding observations with the highest and the lowest estimated rates (Panel A) or eliminating outliers by setting them to the 10^{th} percentile if they are less than the 10^{th} percentile, or to the 90^{th} percentile if they are over the 90^{th} percentile (Panel B). The estimates using hospitalization levels are slightly larger but closely mirror those

[25] Using one- and two-day leads of the instrument as additional instruments is valid instruments if these future values are not influenced by current local health. Moreover, these leads are likely to be correlated with near-term changes in ambient ozone and CO concentrations due to lagged atmospheric transport, satisfying the relevance criterion. The first-stage F-statistic of 62.15 confirms the strength of the instruments and reduces concerns about weak identification.

based on hospitalization rates in Table 6, suggesting that the results are not driven by places with outlier hospitalization rates.

Table A11 shows models estimated separately for wildfires that occurred on weekends and those that occurred on weekdays. The estimates are uniformly bigger for weekdays than for weekends, suggesting that people suffer more from disruption to their activities during the work week and are more resilient in the face of disruptions to weekend plans.

Appendix Table A12 investigates clustering by census division and year, census division and date, or pollution stations and years. Since there are relatively few pollution stations, the third way of clustering results in the largest standard errors, but the signs and significance levels of the effects remains very similar. We have also estimated models experimenting with alternative sets of fixed effects including regressions with division-by-month and month-by year fixed effects and regressions with division-by-year, month, and province effects. Appendix Table A13 shows that including census division interacted with time adds a lot of fixed effects to the models and attenuates the estimates slightly, but the patterns are like those discussed above in terms of signs and statistical significance.

6. Discussion and Conclusions

We have shown that exposure to evacuations, other costs directly associated with being close to wildfires, and a proxy for climate anxiety all have effects on mental health in addition to the effects that occur through increased exposure to $PM_{2.5}$ from upwind fires. All four channels lead to statistically significant increases in mental health-related hospitalizations (Table 6) and in the length of mental health hospitalizations (Table 7). A key advantage of using hospital data is that it includes diagnostic information, which allows us to ask which diagnoses are most affected. We consistently find that the largest effects are on hospitalizations for anxiety and substance abuse.

Table 10 quantifies the costs of wildfires due to increases in mental health hospitalizations by combining the regression-based effect sizes from Tables 6 and 7 with the frequency of exposure in each CD and an estimate of the average cost of each day of mental health hospitalization. The estimates suggest that wildfire-related mental health hospitalizations cost approximately $39.4 million annually in the 119 census divisions we examine, which account for 70.8% of the Canadian population. However, given that hospitalization is an extreme mental health outcome and that these estimates exclude outpatient care, prescription use, long-term consequences of mental health disorders, and indirect costs like lost earnings or caregiving, the true burden of wildfire on mental health is likely substantially higher.

Turning to the individual cost components, we find that mental health hospitalizations due to wildfire-driven evacuations cost approximately $8.6 million per year, while upwind $PM_{2.5}$ exposure contributes an additional $7.5 million. Direct costs of close fires, defined as those less than 100km away, are relatively small at approximately $0.2 million, reflecting the fact that there are relatively such few events. The largest component of the estimated overall cost is due to climate anxiety, as captured via Twitter activity, which accounts for $23.2 million in additional mental health hospitalization costs.

While most previous estimates of the mental health costs of wildfire have focused on the impacts of exposure to $PM_{2.5}$, our analysis breaks new ground by highlighting other pathways for wildfires to affect mental health, such as through the trauma of evacuations. Moreover, we show that wildfire events that draw national attention worsen the mental health of susceptible people, even when they live far away. People with pre-existing health conditions that make them vulnerable and the elderly are especially affected. Indeed, the “indirect” costs of climate anxiety stoked by wildfire events may account for much of the mental health cost. Accounting for these additional mechanisms does little to diminish the estimated effect of $PM_{2.5}$ from wildfire smoke, however, suggesting that these additional mechanisms have effects on mental health that are in addition to those of $PM_{2.5}$.

References

Agyapong, Vincent I. O. and Ritchie, Amanda and Brown, Matthew R. G. and Noble, Shannon and Mankowsi, Monica and Denga, Edward and Nwaka, Bernard and Akinjise, Idowu and Corbett, Sandra E. and Moosavi, Shahram and Chue, Pierre and Li, Xin-Min and Silverstone, Peter H. and Greenshaw, Andrew J. "Long-term mental health effects of a devastating wildfire are amplified by socio-demographic and clinical antecedents in elementary and high school staff." *Frontiers in Psychiatry* 11, no. 448 (2020): 1-11.

American Psychological Association. *Mental health and our changing climate: Impacts, implications, and guidance* (2017). https://www.apa.org/news/press/releases/2017/03/mental-health-climate.pdf.

Anisman, Hymie, and Shawn Hayley. "Inflammatory factors contribute to depression and its comorbid conditions." *Science Signaling* 5, no. 244 (2012): pe45.

Archsmith, James, Anthony Heyes, and Soodeh Saberian. "Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation." *Journal of the Association of Environmental and Resource Economists* 5, no. 4 (2018): 827-863.

Ballew, Matthew T., Sri Saahitya Uppalapati, Teresa Myers, Jennifer Carman, Eryn Campbell, Seth A. Rosenthal, John E. Kotcher, Anthony Leiserowitz, and Edward Maibach. "Climate change psychological distress is associated with increased collective climate action in the US." *npj Climate Action* 3, no. 1 (2024): 88-102.

Bandyopadhyay, Amitava. "Neurological disorders from ambient (urban) air pollution emphasizing UFPM and PM 2.5." *Current Pollution Reports* 2 (2016): 203-211.

Barwick, Panle Jia, Shanjun Li, Deyu Rao, and Nahim Bin Zahur. "The healthcare cost of air pollution: Evidence from the World's largest payment network." *Review of Economics and Statistics* (2024): 1-52.

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins. "Migration and hedonic valuation: The case of air quality." *Journal of Environmental Economics and Management* 58, no. 1 (2009): 1-14.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. "Inference on treatment effects after selection among high-dimensional controls." *Review of Economic Studies* 81, no. 2 (2014): 608-650.

Bishop, Kelly C., Jonathan D. Ketcham, and Nicolai V. Kuminoff. "Hazed and confused: The effect of air pollution on dementia." *Review of Economic Studies* 90, no. 5 (2023): 2188-2214.

Borgschulte, Mark, David Molitor, and Eric Yongchen Zou. "Air pollution and the labor market: Evidence from wildfire smoke." *Review of Economics and Statistics* 106, no. 6 (2024): 1558-1575.

Burke, Marshall, Sam Heft-Neal, Jessica Li, Anne Driscoll, Patrick Baylis, Matthieu Stigler, Joakim A. Weill et al. "Exposures and behavioural responses to wildfire smoke." *Nature Human Behaviour* 6, no. 10 (2022): 1351-1361.

Burkhardt, Jesse, Jude Bayham, Ander Wilson, Ellison Carter, Jesse D. Berman, Katelyn O'Dell, Bonne Ford, Emily V. Fischer, and Jeffrey R. Pierce. "The effect of pollution on crime: Evidence from data on particulate matter and ozone." *Journal of Environmental Economics and Management* 98 (2019): 102-267.

Byrne, Brendan, Junjie Liu, Kevin W. Bowman, Madeleine Pascolini-Campbell, Abhishek Chatterjee, Sudhanshu Pandey, Kazuyuki Miyazaki et al. "Carbon emissions from the 2023 Canadian wildfires." *Nature* 633, no. 8031 (2024): 835-839.

Cabral, Marika, and Marcus Dillender. *Air pollution, wildfire smoke, and worker health*. National Bureau of Economic Research, No. Working paper w32232 (2024).

Chang, Tom Y., Joshua Graff Zivin, Tal Gross, and Matthew Neidell. "The effect of pollution on worker productivity: Evidence from call center workers in China." *American Economic Journal: Applied Economics* 11, no. 1 (2019): 151-172.

Chay, Kenneth Y., and Michael Greenstone. "Does air quality matter? Evidence from the housing market." *Journal of political Economy* 113, no. 2 (2005): 376-424.

Chen, Shuai, Paulina Oliva, and Peng Zhang. "Air pollution and mental health: Evidence from China." *AEA Papers and Proceedings*, 114, (2024): 423-4282014.

Chen, Shuai, Yuyu Chen, Ziteng Lei, and Jie-Sheng Tan-Soo. "Chasing clean air: Pollution-induced travels in China." *Journal of the Association of Environmental and Resource Economists* 8, no. 1 (2021): 59-89.

Chen, Hong, Jeffrey C. Kwong, Ray Copes, Perry Hystad, Aaron van Donkelaar, Karen Tu, Jeffrey R. Brook et al. "Exposure to ambient air pollution and the incidence of Dementia: A population-based cohort study." *Environment International* 108 (2017): 271-277.

Chen, Tianqi, and Carlos Guestrin. "Xgboost: A scalable tree boosting system." *Proceedings of the 22nd ACM SIGKD International Conference on Knowledge Discovery and Data Mining*, (2016): 785-794.

Chew, Soo Hong, Wei Huang, and Xun Li. "Does haze cloud decision making? A natural laboratory experiment." *Journal of Economic Behavior & Organization* 182 (2021): 132-161.

Cianconi, Paolo, Sophia Betrò, and Luigi Janiri. "The impact of climate change on mental health: A systematic descriptive review." *Frontiers in Psychiatry* 11 (2020): 190-206.

Costa, Lucio G., Toby B. Cole, Khoi Dao, Yu-Chi Chang, Jacki Coburn, and Jacqueline Garrick. "Neurotoxicity of air pollution: Role of neuroinflammation." *Advances in Neurotoxicology*, vol. 3 (2019): 195-221.

Cunningham, Calum X., Grant J. Williamson, and David MJS Bowman. "Increasing frequency and intensity of the most extreme wildfires on Earth." *Nature Ecology & Evolution* 8, no. 8 (2024): 1420-1425.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif. "The mortality and medical costs of air pollution: Evidence from changes in wind direction." *American Economic Review* 109, no. 12 (2019): 4178-4219.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth. "The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution." *American Economic Journal: Applied Economics* 8, no. 4 (2016): 36-65.

Gilraine, Michael, and Angela Zheng. *Air pollution and student performance in the US*. National Bureau of Economic Research Working paper w30061 (2022).

Gould, Carlos F., Sam Heft-Neal, Mary Johnson, Juan Aguilera, Marshall Burke, and Kari Nadeau. "Health effects of wildfire smoke exposure." *Annual Review of Medicine* 75, no. 1 (2024): 277-292.

Graff Zivin, Joshua, Matthew Neidell. “Air pollution's hidden impacts,” *Science*. 359 (2018): 39–40.

Graff Zivin, Joshua, and Matthew Neidell. "The impact of pollution on worker productivity." *American Economic Review* 102, no. 7 (2012): 3652-3673.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian. "Air pollution and criminal activity: Microgeographic evidence from Chicago." *American Economic Journal: Applied Economics* 13, no. 4 (2021): 70-100.

Heyes, Anthony, and Mingying Zhu. "Air pollution as a cause of sleeplessness: Social media evidence from a panel of Chinese cities." *Journal of Environmental Economics and Management* 98 (2019): 102-247.

Jayachandran, Seema. "Air quality and early-life mortality: Evidence from Indonesia’s wildfires." *Journal of Human Resources* 44, no. 4 (2009): 916-954.

Kioumourtzoglou, Marianthi-Anna, Melinda C. Power, Jaime E. Hart, Olivia I. Okereke, Brent A. Coull, Francine Laden, and Marc G. Weisskopf. "The association between air pollution and onset of depression among middle-aged and older women." *American Journal of Epidemiology* 185, no. 9 (2017): 801-809.

Kleinberg, Jon, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan. "Human decisions and machine predictions." *The Quarterly Journal of Economics* 133, no. 1 (2018): 237-293.

Lee, Suji, Whanhee Lee, Dahye Kim, Ejin Kim, Woojae Myung, Sun-Young Kim, and Ho Kim. "Short-term PM2.5 exposure and emergency hospital admissions for mental disease." *Environmental Research* 171 (2019): 313-320.

Lu, Jackson G., Julia J. Lee, Francesca Gino, and Adam D. Galinsky. "Polluted morality: Air pollution predicts criminal activity and unethical behavior." *Psychological Science* 29, no. 3 (2018): 340-355.

Miller, Andrew H., and Charles L. Raison. "The role of inflammation in depression: from evolutionary imperative to modern treatment target." *Nature Reviews Immunology* 16, no. 1 (2016): 22-34.

Molitor, David, Jamie T. Mullins, and Corey White. "Air pollution and suicide in rural and urban America: Evidence from wildfire smoke." *Proceedings of the National Academy of Sciences* 120, no. 38 (2023): e2221621120.

Moulton, Paula Valencia, and Wei Yang. "Air pollution, oxidative stress, and Alzheimer′ s disease." *Journal of Environmental and Public Health* 2012, no. 1 (2012): 472751.

Newbury, Joanne B., Robert Stewart, Helen L. Fisher, Sean Beevers, David Dajnak, Matthew Broadbent, Megan Pritchard et al. "Association between air pollution exposure and mental health service use among individuals with first presentations of psychotic and mood disorders: Retrospective cohort study." *The British Journal of Psychiatry* 219, no. 6 (2021): 678-685.

Paul, Naman, Jiayun Yao, Kathleen E. McLean, David M. Stieb, and Sarah B. Henderson. "The Canadian Optimized Statistical Smoke Exposure Model (CanOSSEM): A machine learning approach to estimate national daily fine particulate matter (PM2.5) exposure." *Science of The Total Environment* 850 (2022): 157956.

Petrowski, Katja, Stefan Bührer, Bernhard Strauß, Oliver Decker, and Elmar Brähler. "Examining air pollution (PM10), mental health and well-being in a representative German sample." *Scientific Reports* 11, no. 1 (2021): 18436.

Power, Melinda C., Marianthi-Anna Kioumourtzoglou, Jaime E. Hart, Olivia I. Okereke, Francine Laden, and Marc G. Weisskopf. "The relation between past exposure to fine particulate air pollution and prevalent anxiety: Observational cohort study." *British Medical Journal* 350 (2015).

Pun, Vivian C., Justin Manjourides, and Helen Suh. "Association of ambient air pollution with depressive and anxiety symptoms in older adults: results from the NSHAP study." *Environmental Health Perspectives* 125, no. 3 (2017): 342-348.

Qui, Minghao, Jessica Li, Carlos F. Gould, Renzhi Jing, Makoto Kelp, Marissa Childs, Mathew Kiang, Sam Heft-Neal, Noah Diffenbaugh, and Marshall Burke. *Mortality burden from wildfire smoke under climate change*. National Bureau of Economic Research Working paper w32307 (2024).

Rangel, Marcos A., and Tom S. Vogl. "Agricultural fires and health at birth." *Review of Economics and Statistics* 101, no. 4 (2019): 616-630.

Salim, Samina, Gaurav Chugh, and Mohammad Asghar. "Inflammation in Anxiety." *Advances in Protein Chemistry and Structural Biology* 88 (2012): 1-25.

Schlenker, Wolfram, and W. Reed Walker. "Airports, air pollution, and contemporaneous health." *The Review of Economic Studies* 83, no. 2 (2016): 768-809.

Shin, Jinyoung, Jin Young Park, and Jaekyung Choi. "Long-term exposure to ambient air pollutants and mental health status: A nationwide population-based cross-sectional study." *PloS One* 13, no. 4 (2018): e0195607.

Smith, V. Kerry, and Timothy A. Deyak. "Measuring the impact of air pollution on property values." *Journal of Regional Science* 15, no. 3 (1975): 277-288.

Song, Jie, Liheng Zheng, Mengxue Lu, Lihui Gui, et al. "Acute effects of ambient particulate matter pollution on hospital admissions for mental and behavioral disorders: A time-series study in Shijiazhuang, China," *Science of the Total Environment* 636 (2018): 205-211.

Strahilevitz, Meir, Aharona Strahilevitz, and John E. Miller. "Air pollutants and the admission rate of psychiatric patients." *The American Journal of Psychiatry* 136, no. 2 (1979): 205-207.

Szyszkowicz, Mieczysław, Roger Zemek, Ian Colman, William Gardner, Termeh Kousha, and Marc Smith-Doiron. "Air pollution and emergency department visits for mental disorders among youth." *International Journal of Environmental Research and Public Health* 17, no. 12 (2020): 4190.

To, Patricia, Ejemai Eboreime, and Vincent IO Agyapong. "The impact of wildfires on mental health: A scoping review." *Behavioral Sciences* 11, no. 9 (2021): 126-151.

Uppalapati, S., Ballew, M., Campbell, E., Kotcher, J., Rosenthal, S., Leiserowitz, A., & Maibach, E. *The prevalence of climate change psychological distress among American adults*. Yale University and George Mason University. New Haven, CT: Yale Program on Climate Change Communication (2023).

Wang, Xiaoying, Wangcheng Wang, Shilin Jiao, Jing Yuan, Chunping Hu, and Lin Wang. "The effects of air pollution on daily cardiovascular diseases hospital admissions in Wuhan from 2013 to 2015." *Atmospheric Environment* 182 (2018): 307-312.

Ward, Courtney J. "It's an ill wind: The effect of fine particulate air pollution on respiratory hospitalizations." *Canadian Journal of Economics/Revue canadienne d'économique* 48, no. 5 (2015): 1694-1732.

Zhang, Peng, Tamma Carleton, Liguo Lin, and Maigeng Zhou. "Estimating the role of air quality improvements in the decline of suicide rates in China." *Nature Sustainability* 7, no. 3 (2024): 260-269.

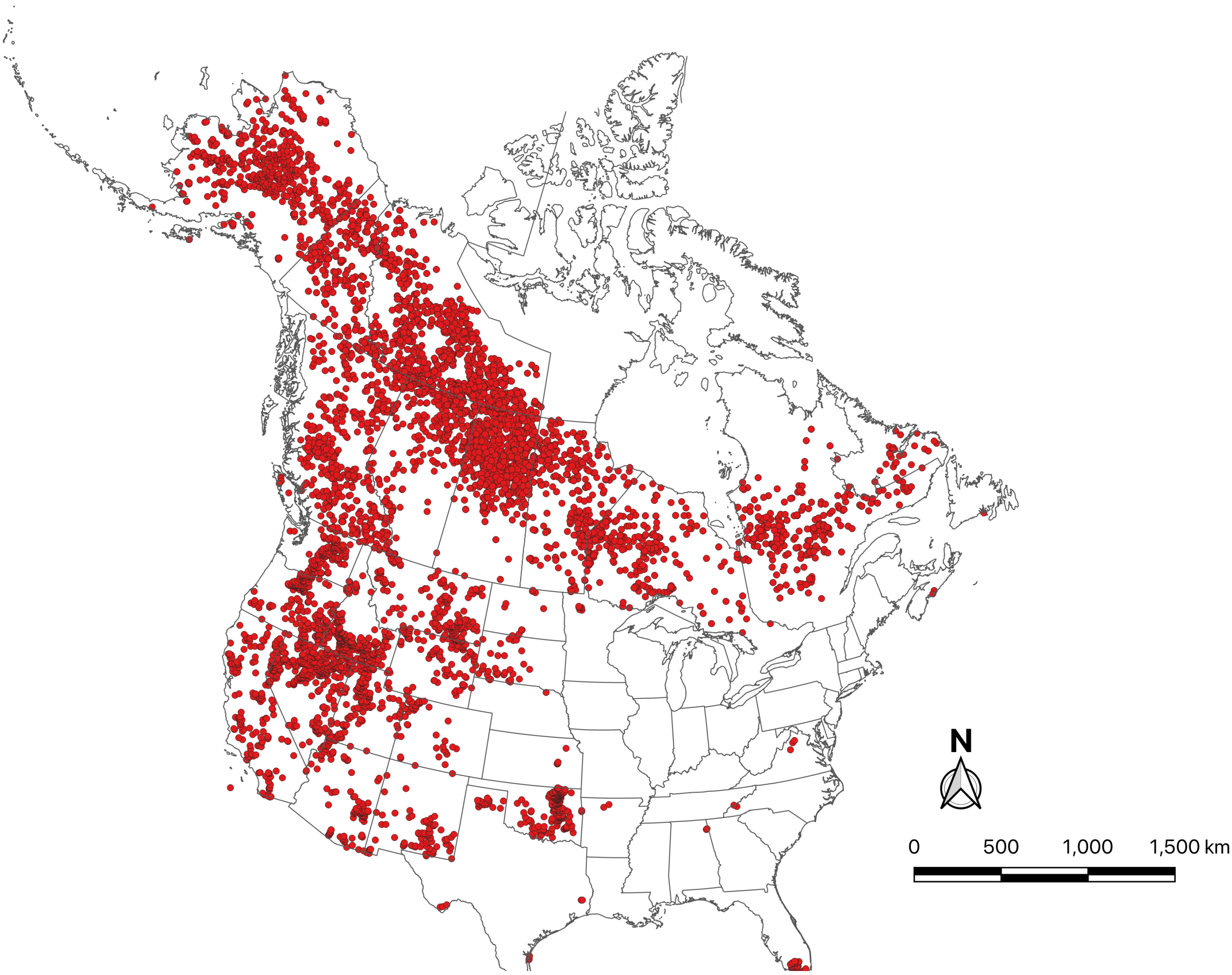
Zhang, Xin, Xiaobo Zhang, and Xi Chen. "Happiness in the air: How does a dirty sky affect mental health and subjective well-being?" *Journal of Environmental Economics and Management* 85 (2017): 81-94.

Zheng, Siqi, Jianghao Wang, Cong Sun, Xiaonan Zhang, and Matthew E. Kahn. "Air pollution lowers Chinese urbanites' expressed happiness on social media." *Nature Human Behaviour* 3, no. 3 (2019): 237-243.

Zijlema, Wilma L., Kathrin Wolf, Rebecca Emeny, Karl-Heinz Ladwig, Annette Peters, Håvard Kongsgård, Kristian Hveem et al. "The association of air pollution and depressed mood in 70,928 individuals from four European cohorts." *International Journal of Hygiene and Environmental Health* 219, no. 2 (2016): 212-219.

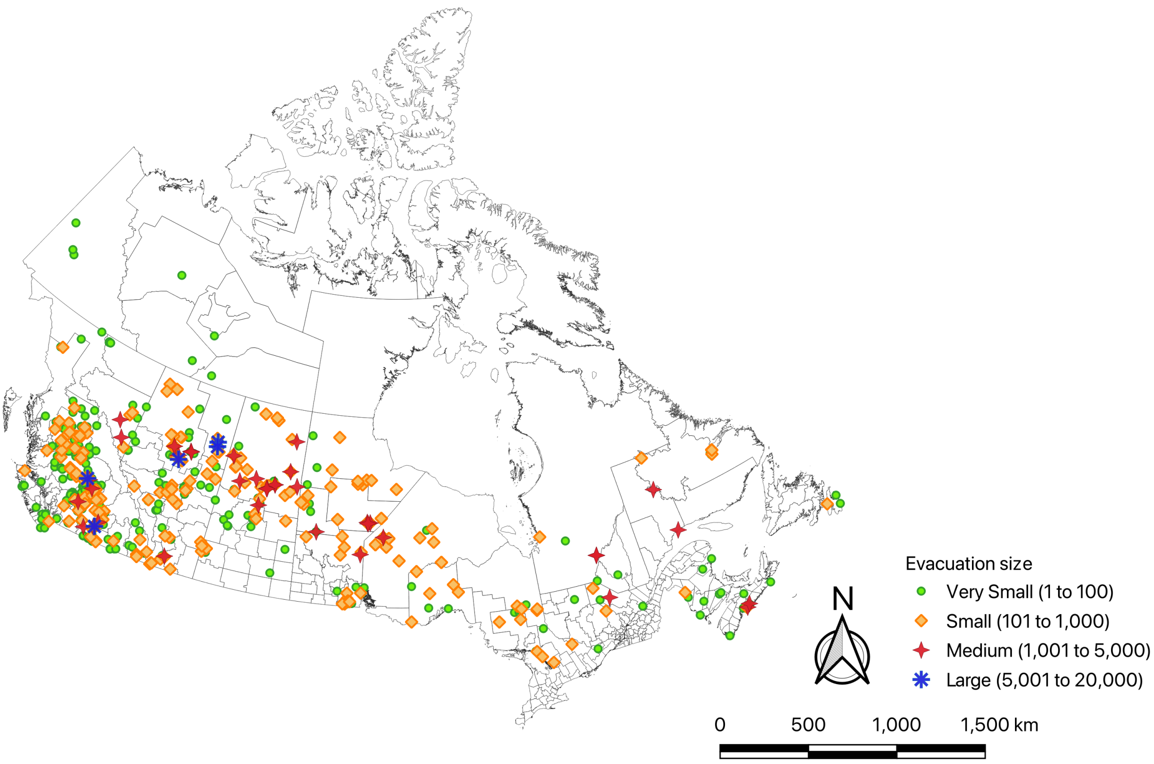
Figures

Figure 1: U.S. and Canadian fires larger than 500 hectares, 2006-2018



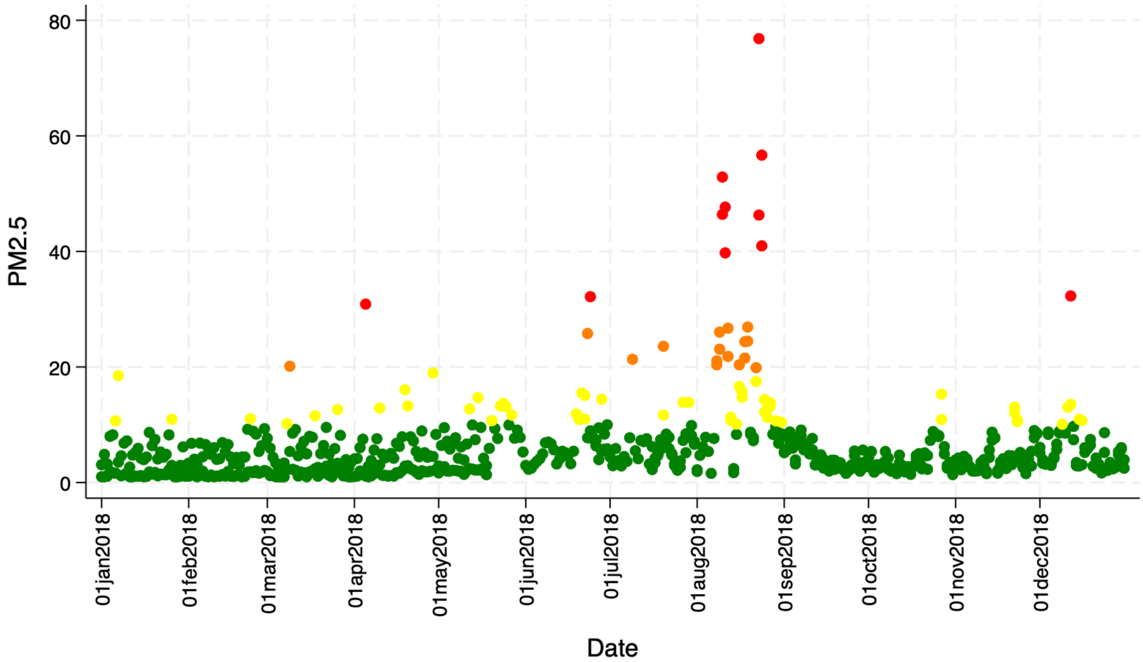
Notes: The map illustrates the locations of fires larger than 500ha from January 2006 to December 2018.

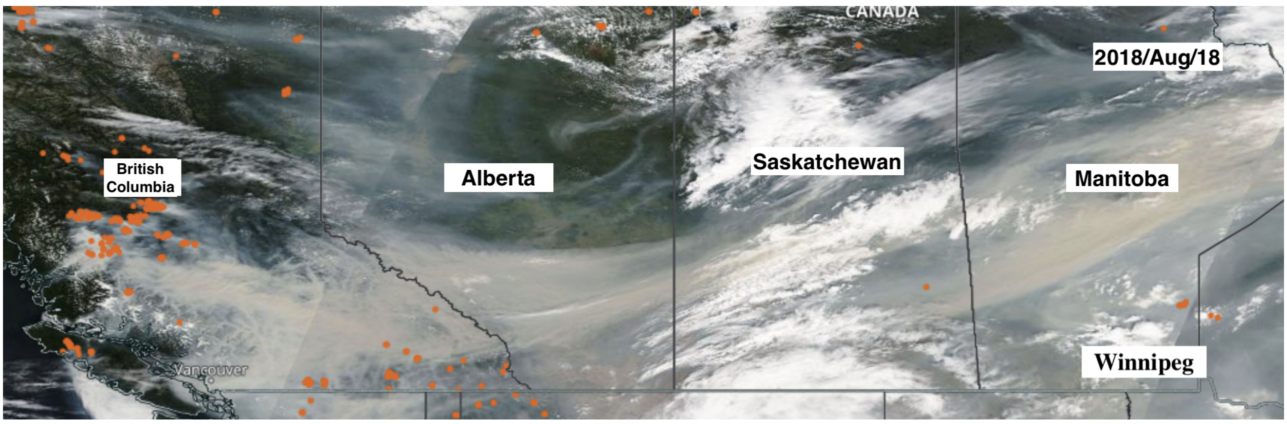
Figure 2: Evacuation orders by size, 2006–2018



Notes: The map displays the location and size of evacuation orders issued from January 2006 to December 2018. The size categories were provided by Natural Resources Canada (NRC).

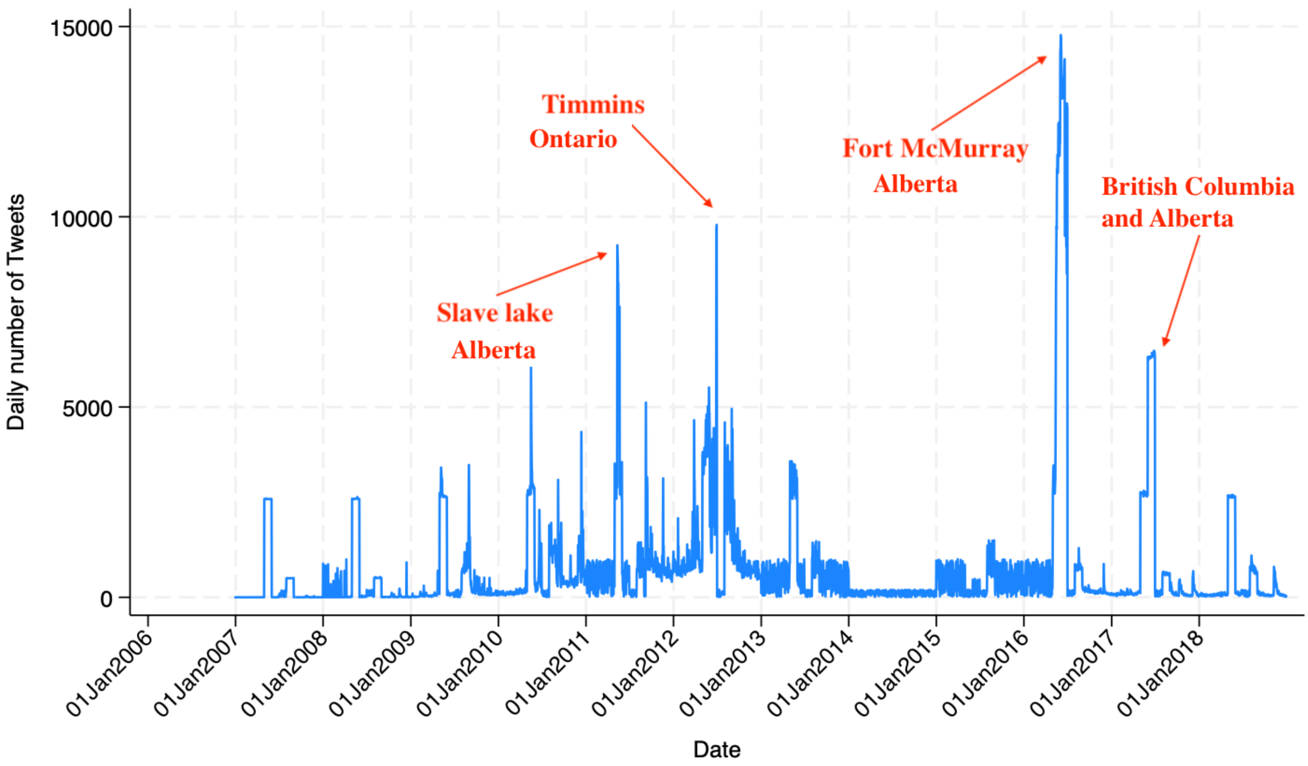
Figure 3: Daily $PM_{2.5}$ in Winnipeg and aerial views of smoke on most affected days in 2018





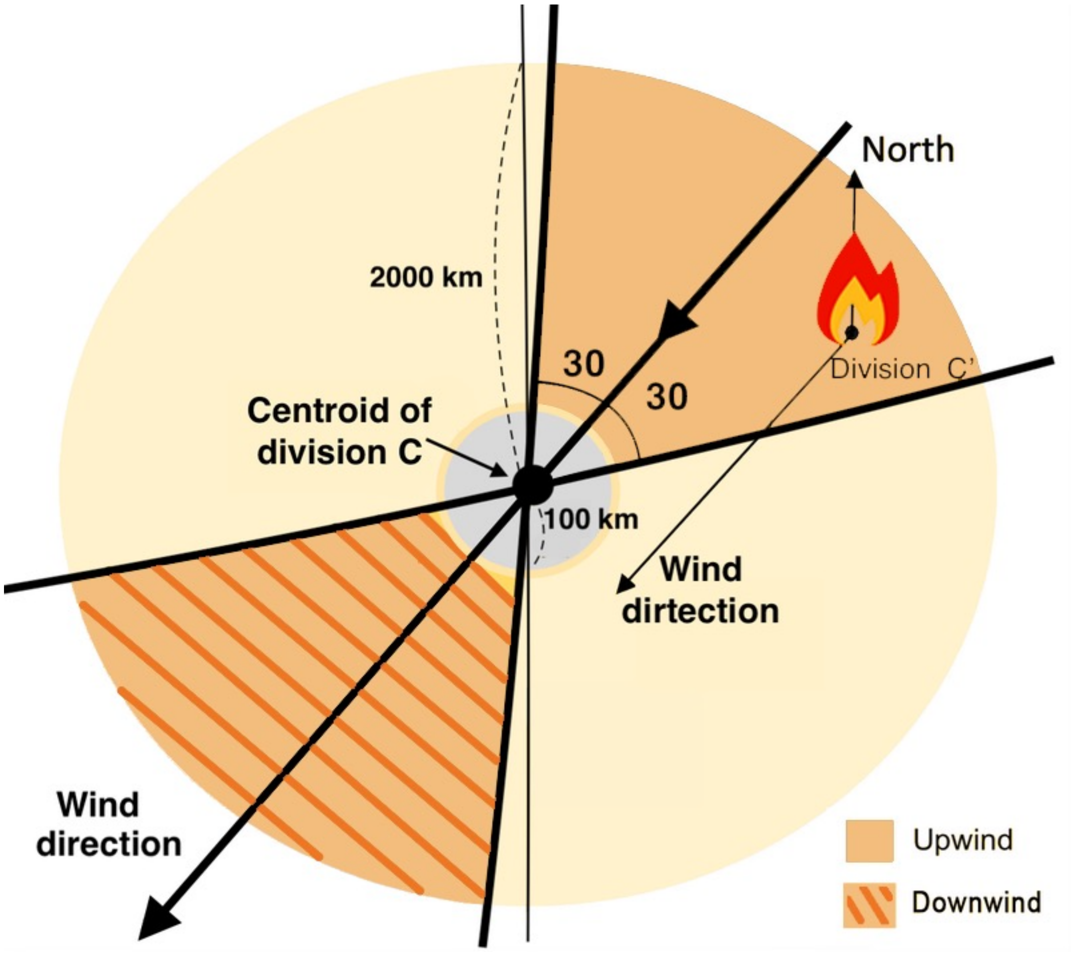
Notes: The upper panel shows daily $PM_{2.5}$ concentrations in Winnipeg for 2018 with data color-coded by the 2018 air quality standard. The lower panel displays visible satellite imagery of smoke and satellite fire hotspot detection across Canada from NASA Worldview for $PM_{2.5}$ on August 18th, 2018.

Figure 4: Daily number of tweets including hashtag #wildfire



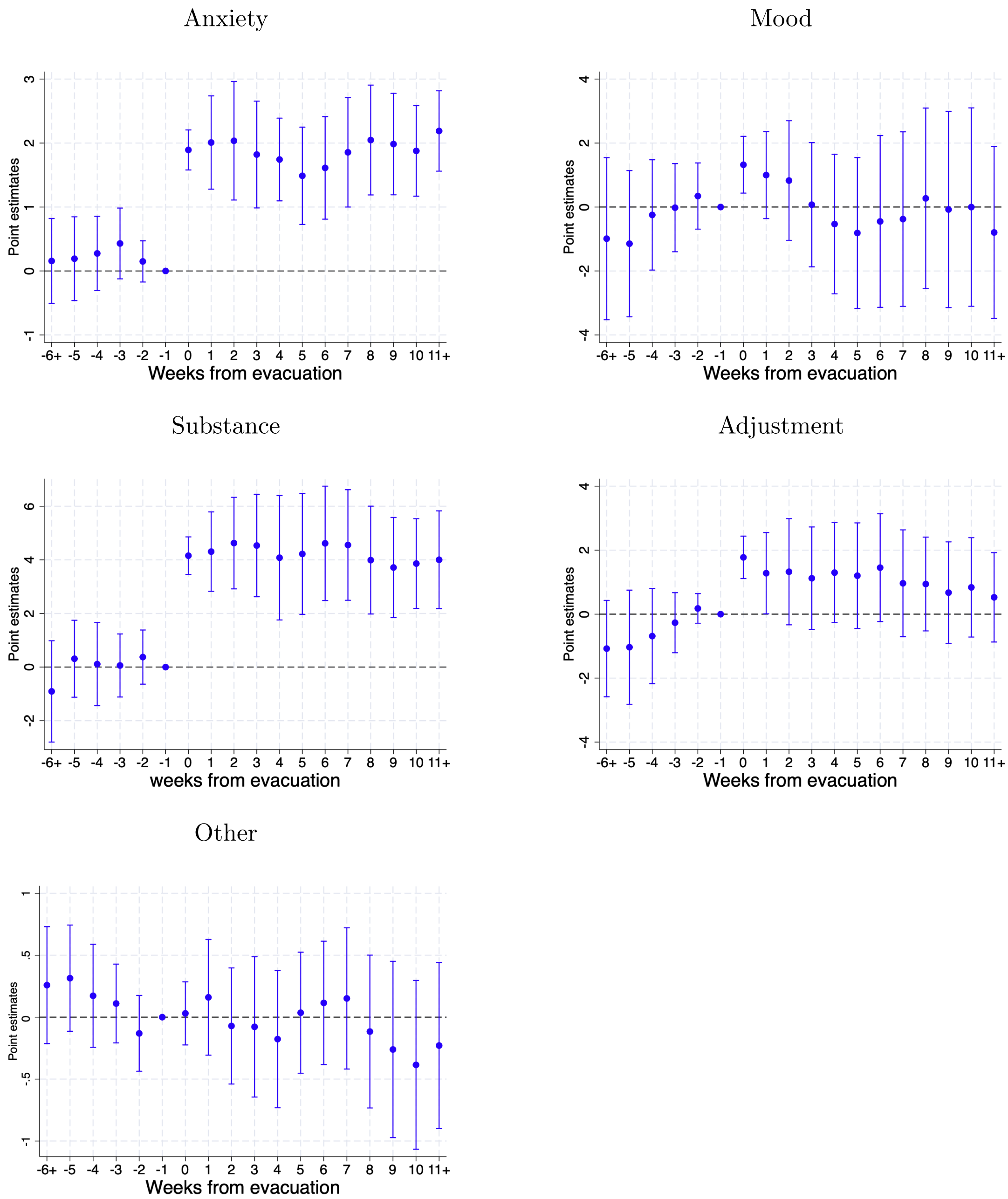
Notes: This figure shows the daily count of tweets that included hashtag #wildfire and are posted from Canada but more than 500 km away from the census division of active wildfires from January 2006 to December 2018.

Figure 5: Definition of upwind and downwind fires



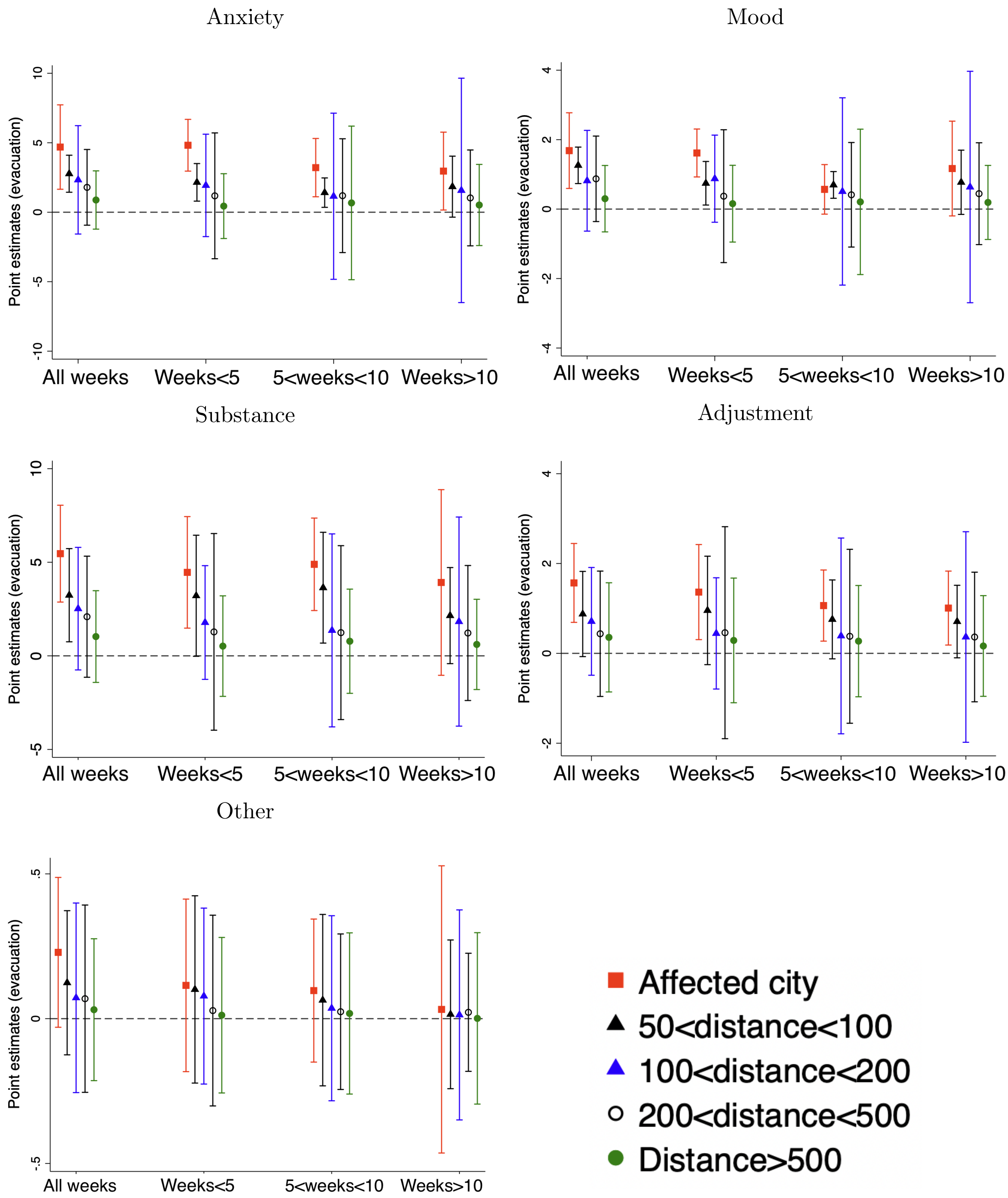
Notes: This figure shows upwind and downwind fires within 2000 km from the centroid of a census division. Fires within 100 km of each census division are excluded. Fires within 100 km are excluded, as they may affect mental illness hospitalizations through evacuations and other direct mechanisms.

Figure 6: Direct effect of evacuations: Event study



Notes: These graphs display the average effect of evacuation orders over the 10 weeks following issuance in the affected census division, using event study regressions that include division, week-by-year and province-by-week fixed effects. The dependent variable is the weekly admission rate per 100,000 for each type of hospitalization. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. Whiskers represent the 95% confidence intervals based on robust standard errors clustered by census division.

Figure 7: Effect of evacuations by duration and distance



Notes: These graphs illustrate the point estimates of evacuation indicators across different distances and durations of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in *city* c's centroid. The dependent variable is the three-day hospital admission rate for mental illness per 100,000 population for anxiety, substance, mood, adjustment, and other mental health disorders. All regressions include division, month-by-year, and province-by-month fixed effects, as well as flexible controls for temperature, dew point, precipitation, cloud cover, and wind speed. Whiskers represent the 95% confidence intervals based on robust standard errors clustered by division.

1 Tables

Table 1: Summary statistics

	Division-year		Division-date	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A				
Number of census divisions	119			
Days	4,748			
Three-day admission rates (per 100,000):				
Total	361.11	350.05	3.41	3.52
Anxiety	46.03	89.30	0.45	2.11
Mood	88.52	121.19	0.83	2.36
Substance-related	76.31	88.17	0.72	3.84
Adjustment	9.41	8.11	0.09	2.30
Other	140.84	289.14	1.31	3.17
Days with active fires larger than 500ha and within 2000 km				
Upwind	17.54	28.86	0.05	2.04
Downwind	22.65	32.48	0.09	3.89
Total	101.12	33.52	0.34	3.87
Within 100 km	0.77	0.65	0.001	0.05
100-200 km	3.10	2.45	0.01	2.31
200-300 km	8.57	5.99	0.02	0.42
300-400 km	11.80	8.08	0.03	0.61
400-500 km	22.39	14.55	0.07	1.02
+500 km	54.37	25.05	0.21	1.86
Fires larger than 500ha and within 2000 km				
Total number	8.59	9.25	0.04	0.66
Duration (days)	11.78	39.16	0.06	2.76
Size (ha)	1564.36	2312.59	-	-
Evacuations				
Days	3.76	34.31	0.02	7.42
Tweets with hashtag #wildfire				
Total	1266.13	114.56	3.78	28.12
Originating within 500 km of a fire	436.61	111.12	0.97	7.84
Originating over 500 km from a fire	829.54	218.21	2.81	15.39
Panel B: Comparison of hospitalizations by pollution quartile	Low		High	
	Mean	Std. Dev	Mean	Std. Dev.
Number of census division	30	30	-	-
$PM_{2.5}$ ($\mu g/m^3$)	4.09	13.34	0.78	9.28
Three-day admission rates (per 100,000): Division-date level				
Total	2.51	1.99	5.62	3.24
Anxiety	0.32	2.09	0.72	2.21
Mood	0.61	1.34	1.37	2.56
Substance-related	0.53	3.47	1.90	4.63
Adjustment	0.06	1.08	0.14	2.58
Other	0.97	1.69	2.17	3.42
Panel C: Comparison of hospitalizations by fire quartile	Low		High	
	Mean	Std. Dev.	Mean	Std. Dev.
Number of census division	30	30	-	-
Days with active fires	74.71	23.77	89.93	39.64
Three-day admission rates (per 100,000): Division-date level				
Total	2.83	1.81	4.89	5.22
Anxiety	0.36	1.71	0.63	4.03
Mood	0.69	1.85	1.19	3.42
Substance-related	0.59	3.19	1.03	7.12
Adjustment	0.07	0.98	0.12	1.21
Other	1.09	1.18	1.88	3.29

Note: The period is 2006–2018. The unit of observation in Panel A is census division-year. The five most significant subcategories under 'Other' in terms of the annual mean of the three-day admission rate per census division are: Schizophrenia (47.18), dementia (33.15), neurodevelopmental disorders (8.80), bipolar (1.86), and obsessive-compulsive (0.94).

Table 2: Effects of fires at different distances on mental illness hospitalizations

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
Fires within 100 km	0.898**	0.185*	0.745***	0.045*	0.529	0.789**
	(0.314)	(0.091)	(0.179)	(0.019)	(0.298)	(0.274)
Fires between 100 to 200 km	0.617**	0.137*	0.518***	0.033*	0.370	0.421**
	(0.217)	(0.069)	(0.128)	(0.015)	(0.211)	(0.152)
Fires between 200 to 300 km	0.375	0.081	0.361*	0.022	0.213	0.238
	(0.225)	(0.064)	(0.175)	(0.013)	(0.182)	(0.148)
Fires between 300 to 400 km	0.278	0.055	0.239	0.015	0.171	0.190
	(0.236)	(0.035)	(0.181)	(0.017)	(0.194)	(0.149)
Fires between 400 to 500 km	0.226	0.033	0.141	0.013	0.076	0.157
	(0.257)	(0.034)	(0.091)	(0.021)	(0.097)	(0.178)
Fires between 500 to 2000 km	0.111	0.016	0.066	0.008	0.035	0.080
	(0.121)	(0.020)	(0.049)	(0.009)	(0.051)	(0.104)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.452	0.447	0.451	0.449	0.448	0.456
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. Each row reports the estimated effect of the total count of fires larger than 500ha within its respective distance category. Each column corresponds to a separate regression. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Standard errors, clustered at the division level, are reported in parentheses. * Significant at the 5% level. ** Significant at the 1% level. *** Significant at the 0.1% level.

Table 3: Effects of upwind/downwind fires at different distances on mental illness hospitalizations

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
Upwind fires within 100 km	1.349***	0.233*	1.007***	0.068***	0.715	1.066**
	(0.403)	(0.098)	(0.209)	(0.018)	(0.399)	(0.403)
Downwind fires within 100 km	0.356*	0.059	0.099*	0.037*	0.044	0.281
	(0.148)	(0.031)	(0.041)	(0.017)	(0.078)	(0.158)
Upwind fires between 100 to 200 km	0.971**	0.176*	0.745***	0.050***	0.531	0.711**
	(0.305)	(0.069)	(0.154)	(0.014)	(0.303)	(0.221)
Downwind fires between 100 to 200 km	0.259	0.044	0.072	0.028	0.034	0.207
	(0.175)	(0.032)	(0.039)	(0.021)	(0.071)	(0.134)
Upwind fires between 200 to 300 km	0.679*	0.118*	0.502***	0.036**	0.355	0.478*
	(0.282)	(0.056)	(0.116)	(0.012)	(0.275)	(0.219)
Downwind fires between 200 to 300 km	0.180	0.032	0.055	0.021	0.024	0.128
	(0.162)	(0.024)	(0.038)	(0.019)	(0.052)	(0.117)
Upwind fires between 300 to 400 km	0.458*	0.061	0.313**	0.020	0.205	0.363*
	(0.201)	(0.036)	(0.121)	(0.011)	(0.181)	(0.148)
Downwind fires between 300 to 400 km	0.109	0.016	0.028	0.012	0.016	0.081
	(0.096)	(0.019)	(0.027)	(0.018)	(0.037)	(0.077)
Upwind fires between 400 to 500 km	0.314*	0.032	0.146**	0.011	0.089	0.238*
	(0.154)	(0.025)	(0.055)	(0.009)	(0.095)	(0.112)
Downwind fires between 400 to 500 km	0.062	0.009	0.015	0.007	0.011	0.047
	(0.063)	(0.017)	(0.016)	(0.015)	(0.024)	(0.046)
Upwind fires between 500 to 2000 km	0.183	0.018	0.061	0.005	0.047	0.137
	(0.142)	(0.069)	(0.011)	(0.032)	(0.045)	(0.148)
Downwind fires between 500 to 2000 km	0.027	0.004	0.006	0.004	0.004	0.021
	(0.033)	(0.008)	(0.007)	(0.007)	(0.013)	(0.025)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.432	0.428	0.436	0.433	0.427	0.434
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. Each row reports the estimated effect of the count of upwind and downwind fires larger than 500ha within 30° north and south of the daily wind direction. Each column corresponds to a separate regression. Each panel reports the daily count of upwind and downwind fires within its respective distance category. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table 4: OLS and IV estimates of effect of $PM_{2.5}$ on mental illness hospitalizations

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
			Panel A. OLS			
$PM_{2.5}$ ($\mu g/m^3$)	0.073***	0.017	0.089***	0.094***	0.079*	0.052***
	(0.008)	(0.010)	(0.011)	(0.012)	(0.031)	(0.006)
R^2	0.541	0.545	0.550	0.546	0.538	0.559
			Panel B. Reduced form			
$\frac{\text{Upwind fires} \times \text{size}}{\text{Distance}^2}$	0.263***	0.087	0.312***	0.691**	0.503**	0.198**
	(0.060)	(0.049)	(0.069)	(0.205)	(0.148)	(0.050)
R^2	0.332	0. 327	0.329	0.337	0.329	0.330
			Panel C. IV			
$PM_{2.5}$ ($\mu g/m^3$)	0.141**	0.043	0.192***	0.437**	0.317*	0.105***
	(0.041)	(0.056)	(0.052)	(0.139)	(0.122)	(0.029)
R^2	0.447	0. 451	0.448	0.449	0.448	0.453
Cragg-Donald F-statistic	56.719					
First-stage R^2	0.702					
			Panel D. XGboost			
Predicted $PM_{2.5}$ ($\mu g/m^3$)	0.149*	0.051	0.175**	0.405**	0.302*	0.113**
using XGBoost	(0.065)	(0.048)	(0.061)	(0.138)	(0.118)	(0.035)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.418	0. 421	0.417	0.420	0.417	0.425
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. Each column reports a separate regression. In Panel A, $PM_{2.5}$ refers to average concentration measured at the census division level. Panel B reports reduced form estimates, replacing $PM_{2.5}$ with an instrument selected via Lasso-based variable selection. Panel C presents IV estimates instrumenting $PM_{2.5}$ with the the same instrument as panel B. Panel D uses predicted $PM_{2.5}$ values from an XGBoost model. All regressions include fixed effects for census division, month-by-year, province-by-month, and day of the week, as well as flexible controls for temperature, dew point, precipitation, and cloud cover. Standard errors clustered by division are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table 5: Climate anxiety

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
	Panel A. Tweets within 500 km					
Tweets within 500 km	0.015**	0.010**	0.019*	0.004***	0.005*	0.011**
	(0.004)	(0.004)	(0.008)	(0.001)	(0.002)	(0.003)
Tweets outside 500 km	0.017***	0.004*	0.007*	0.002*	0.002	0.013**
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.005)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.353	0. 352	0.352	0.353	0.350	0.355
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. Panel A reports the estimated effect of the daily count of tweets containing the hashtag #wildfire within 500 km of the census division's centroid with a mean of 0.97 tweets per day per division. Panel B reports the estimated effect of the daily count of tweets containing the hashtag #wildfire from locations in Canada that are between 500 km and 2000 km from the census division's centroid, with a mean of 2.81 tweets per day per division. Each column corresponds to a separate regression. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table 6: Effects of fire on mental illness hospitalizations through all mechanisms

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total	(7) Pre-planned
Evacuations	2.237***	1.292*	2.178***	1.169**	1.032	1.775***	0.003
	(0.670)	(0.591)	(0.687)	(0.414)	(0.573)	(0.527)	(0.802)
Fires within 100 km	0.337***	0.107*	0.489***	0.026**	0.106	0.261***	0.001
	(0.075)	(0.054)	(0.148)	(0.009)	(0.084)	(0.057)	(0.068)
$PM_{2.5}$ ($\mu g/m^3$)	0.101**	0.005	0.161**	0.399*	0.250	0.079**	0.001
	(0.039)	(0.060)	(0.053)	(0.156)	(0.131)	(0.029)	(0.009)
Tweets outside 500 km	0.042***	0.004***	0.002*	0.004**	0.001*	0.003**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	301,619	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.537	0.533	0.532	0.532	0.534	0.530	0.539
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411	0.024

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Column 7 presents the regression results for scheduled (pre-planned) hospital admissions. The first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in the centroid of census division c. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table 7: Effects on the length of hospital stay (in days)

	(1) Evacuation	(2) Fires within 100 km	(3) $PM_{2.5}$	(4) Tweets	(5) All
Evacuations	2.182^{***}	-	-	-	1.852^{***}
	(0.466)	-	-	-	(0.387)
Fires within 100 km	-	0.037	-	-	0.021
	-	(0.025)	-	-	(0.053)
$PM_{2.5}$ ($\mu g/m^3$)	-	-	0.098^{*}	-	0.076^{*}
	-	-	(0.047)	-	(0.036)
Tweets outside 500 km	-	-	-	0.001^{***}	0.001
	-	-	-	(0.000)	(0.001)
Observations	301,619	301,619	301,619	301,619	301,619
R^2	0.334	0.327	0.321	0.305	0.424
Length of stay (mean)	6.403	6.403	6.403	6.403	6.403

Notes: The dependent variable represents the daily average length of stay for all mental health hospitalizations in each census division. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. The first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$, instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table 8: Effects of fire on mental illness hospitalizations for people with and without secondary respiratory and cardiovascular diagnoses

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
Panel A. Respiratory and cardiovascular						
Evacuations	2.765***	1.603*	2.649**	1.452**	1.280	2.220***
	(0.804)	(0.733)	(0.854)	(0.512)	(0.710)	(0.644)
Fires within 100 km	0.418***	0.133*	0.606***	0.032**	0.131	0.324***
	(0.093)	(0.067)	(0.183)	(0.011)	(0.104)	(0.070)
$PM_{2.5}$ ($\mu g/m^3$)	0.122**	0.006	0.200**	0.487*	0.310	0.098**
	(0.047)	(0.073)	(0.065)	(0.193)	(0.162)	(0.035)
Tweets outside 500 km (per 10)	0.005***	0.002**	0.005**	0.001*	0.001	0.004**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
R^2	0.518	0.526	0.523	0.522	0.518	0.529
Three-day admission rate (mean)	0.194	0.291	0.223	0.033	0.472	1.213
Panel B. No condition						
Evacuations	1.790**	1.034	1.742*	0.935	0.826	1.419**
	(0.653)	(0.701)	(0.685)	(0.502)	(0.604)	(0.453)
Fires within 100 km	0.270**	0.086	0.392**	0.021	0.085	0.209*
	(0.102)	(0.083)	(0.147)	(0.014)	(0.097)	(0.091)
$PM_{2.5}$ ($\mu g/m^3$)	0.081*	0.004	0.129	0.320	0.200	0.063
	(0.040)	(0.078)	(0.072)	(0.182)	(0.163)	(0.052)
Tweets outside 500 km	0.003*	0.001	0.003	0.001	0.001	0.002
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.522	0.521	0.517	0.523	0.520	0.521
Three-day admission rate (mean)	0.051	0.099	0.107	0.012	0.157	0.428

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Panel A reports the effects on individuals with respiratory and/or cardiovascular co-morbidities, while Panel B presents the effects on individuals with no background conditions. In each panel the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table 9: Estimates of the effects of fires 100 days in the past or future

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
			Panel A. +100 days			
Evacuations	0.082	0.052	0.283	0.136	0.131	0.002
	(0.899)	(0.819)	(0.951)	(0.603)	(0.971)	(0.863)
Fires within 100 km	0.058	0.015	0.087	0.004	0.017	0.001
	(0.057)	(0.034)	(0.094)	(0.008)	(0.054)	(0.061)
$PM_{2.5}$ ($\mu g/m^3$)	0.013	0.001	0.018	0.051	0.030	0.001
	(0.055)	(0.499)	(0.075)	(0.220)	(0.201)	(0.007)
Tweets outside 500 km	0.001	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
R^2	0.484	0.486	0.483	0.487	0.483	0.490
			Panel B. -100 days			
Evacuations	0.097	0.197	0.069	0.139	0.149	0.094
	(0.901)	(0.995)	(0.956)	(0.741)	(0.768)	(0.688)
Fires within 100 km	0.053	0.013	.081	0.004	0.012	0.044
	(0.059)	(0.034)	(0.095)	(0.009)	(0.052)	(0.063)
$PM_{2.5}$ ($\mu g/m^3$)	0.015	0.001	0.023	0.056	0.028	0.011
	(0.055)	(0.060)	(0.094)	(0.198)	(0.212)	(0.042)
Tweets outside 500 km	0.001	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.008)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.488	0.485	0.483	0.487	0.482	0.485
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. In Panels A and B, evacuations, nearby fires, PM2.5, and tweet variables using their respective values from 100 days before and after, respectively. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division *c*. Fires within 100 km represents the daily count of fires larger than 500ha occurring within 100 km of census division *c*. $PM_{2.5}$ is instrumented using a Lasso-based variable selection method. Tweets outside 500 km captures the daily count of tweets containing the hashtag #wildfire, posted from locations within Canada but more than 500 km away from census division *c*. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%

Table 10: Annual costs of fire-related mental illness hospitalizations

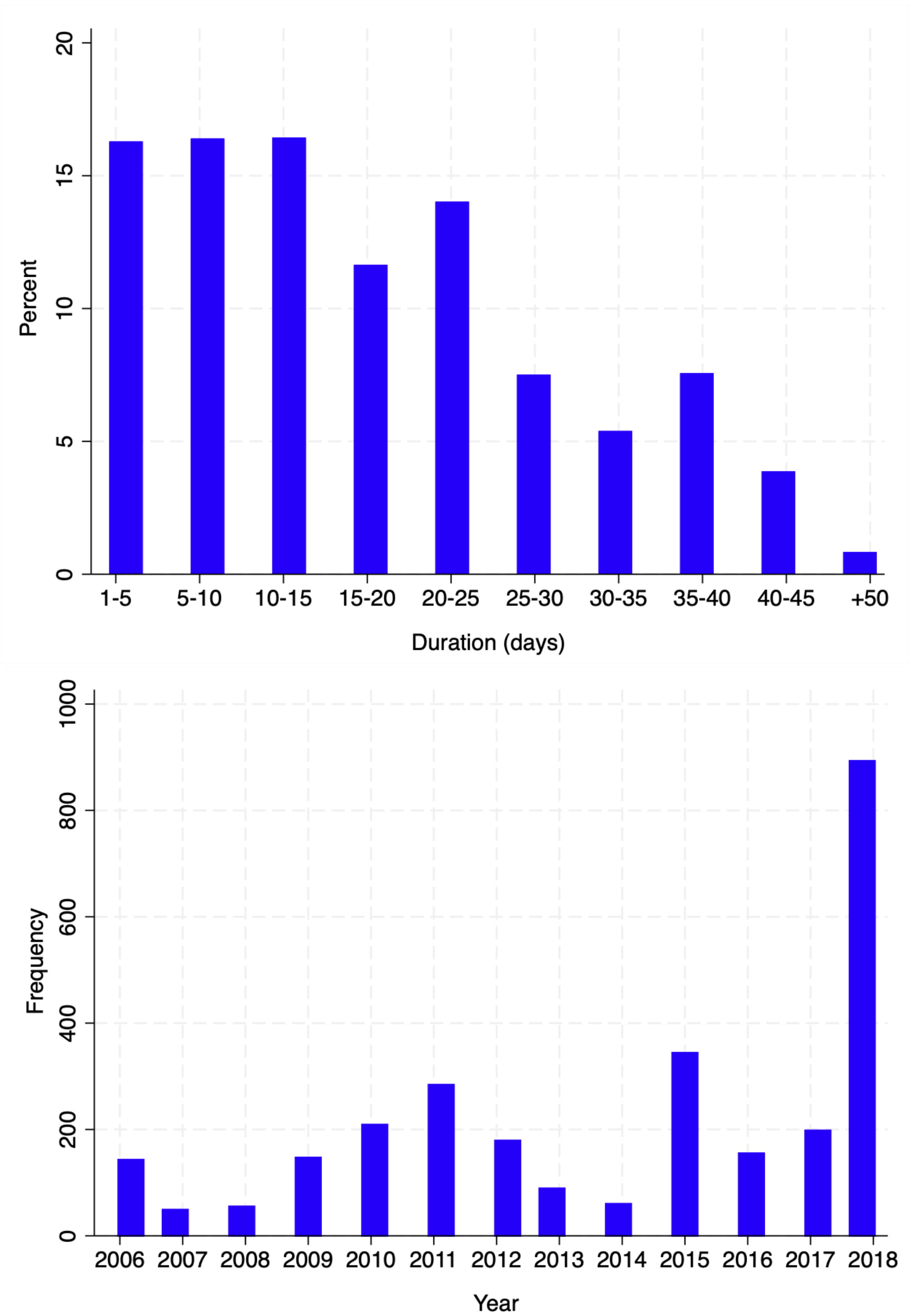
	Evacuation days	**Days with close fires**	**$PM_{2.5}$ from fires>100km[2]**	**Climate anxiety: Tweets from >500km**	**Additional total annual cost from fires**
Annual # events per CD[1]	3.76	0.77	82.44	829.54	
Effect on hospitalizations[3]	1.78	0.26	0.08	0.03	
Effect on length of stay in days[4]	1.852	–	0.076	–	
Total additional hospital days per year given baseline length of stay of 6.40[5]	55.03	1.28	47.95	148.67	
Cost per CD assuming hospitalization costs of $1,310 per day ($)[6]	72,086.03	1,676.80	62,809.18	194,760.32	331,332.33
Cost for 119 sample CDs (million $)	8.58	0.20	7.47	23.18	39.43

Notes: Authors' calculations. [1]From column 1 of Table 1. Entry for $PM_{2.5}$ is point estimate×4.7 (See note 2). [2]Figure A.8 indicates that each fire day generates 4.7 units and there is a mean of 17.54 fire days in Table 1.[3]Estimates from column 6 of Table 6. [4]Estimates from column 5 of Table 7. [5] Includes increased days due to more hospitalizations and longer length of stay. 6.40 is the mean baseline length shown in Table 7. [6]Figures in Source: `https://www.cihi.ca/en/patient-cost-estimator`

A Appendix

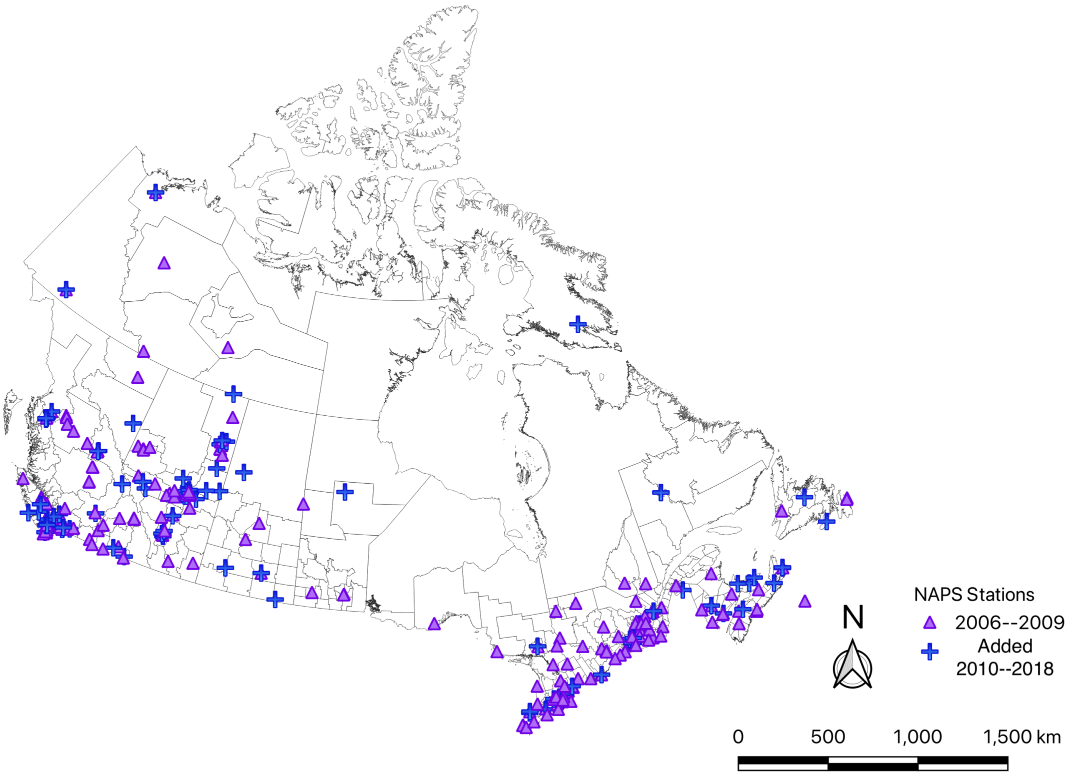
Figures

Figure A.1: Evacuations by year and duration, 2006–2018



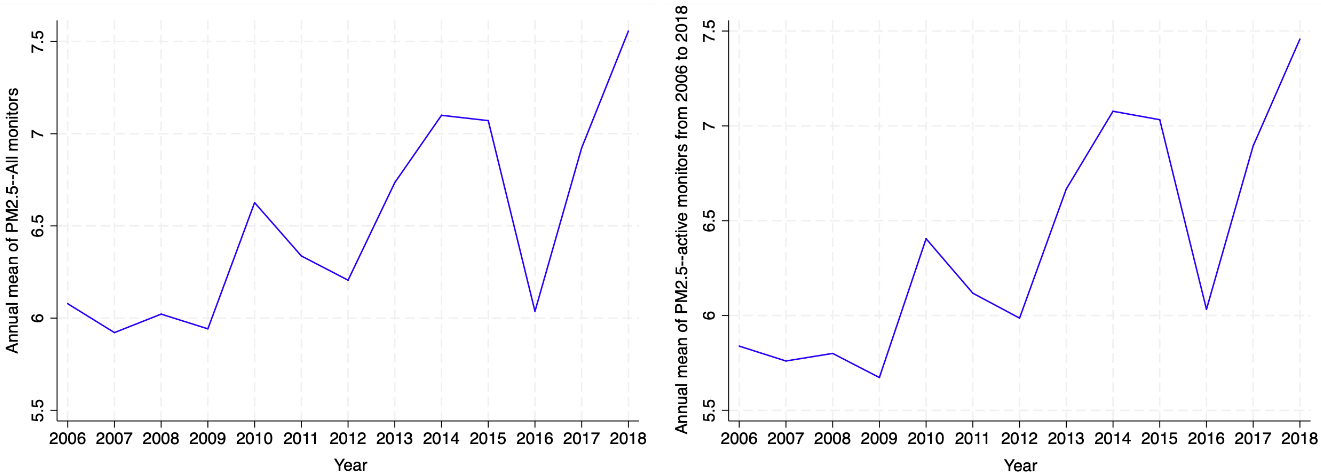
Notes: The upper panel illustrates the distribution of evacuation orders lengths. The lower panel shows the frequency of evacuation days by year from January 2006 to December 2018.

Figure A.2: $PM_{2.5}$ monitoring stations, 2006–2018



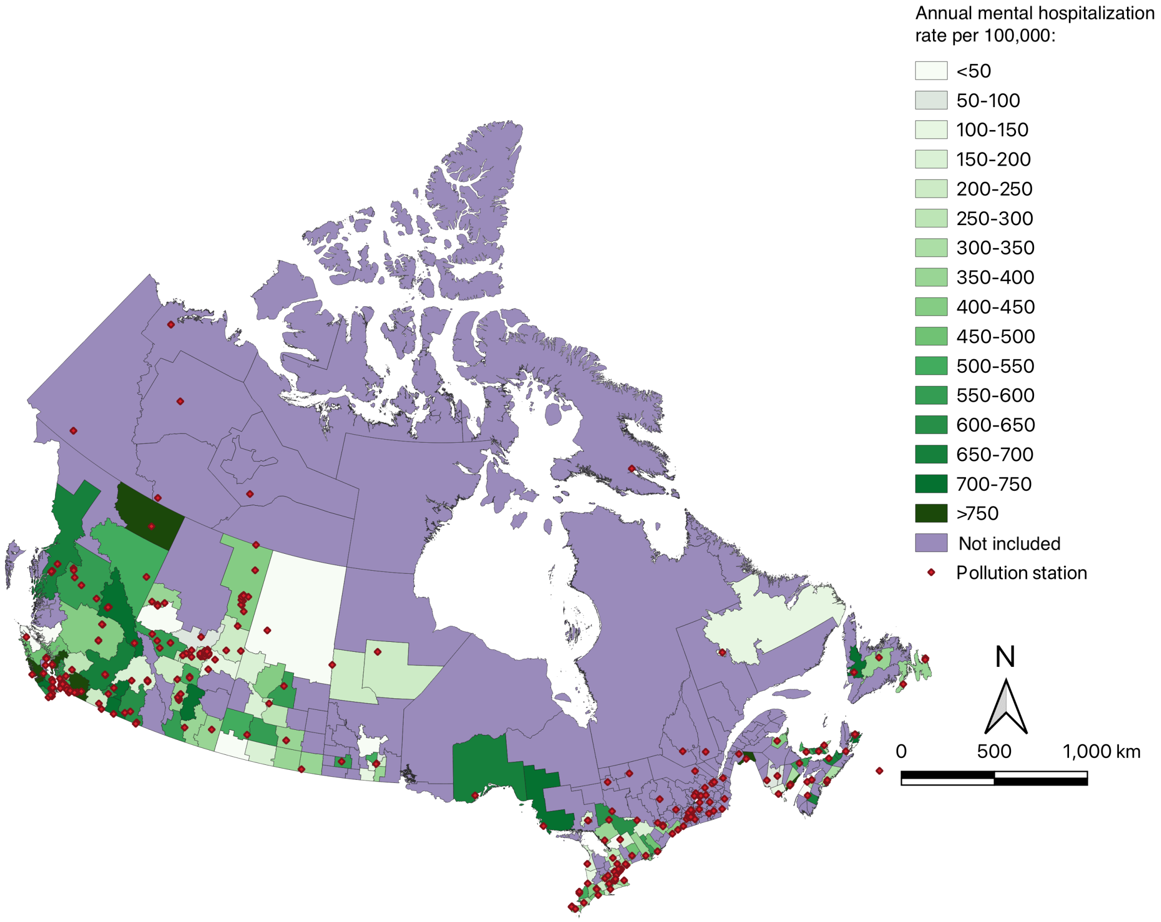
Notes: The map shows locations of NAPS stations from January 2006 to December 2018.

Figure A.3: Trend in $PM_{2.5}$ concentrations, 2006–2018



Notes: The left panel displays annual $PM_{2.5}$ concentration across Canada using all stations. The right panel shows annual $PM_{2.5}$ concentration using stations that were active for the entire period of 2006 to 2018.

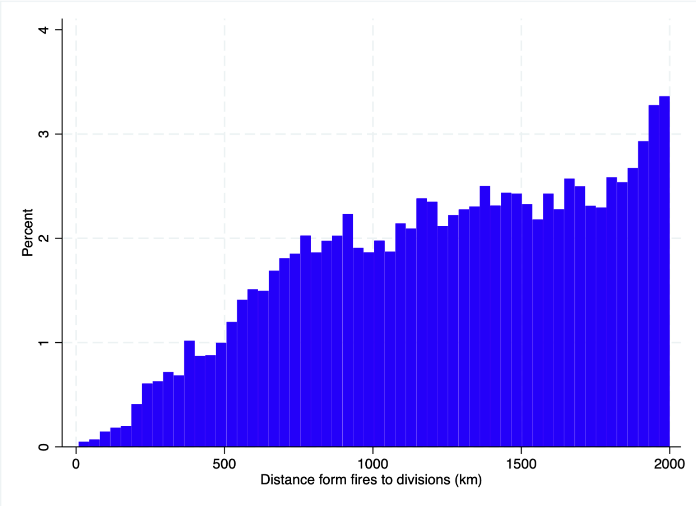
Figure A.4: Geographical variations in mental illness hospitalization rate, 2006–2018



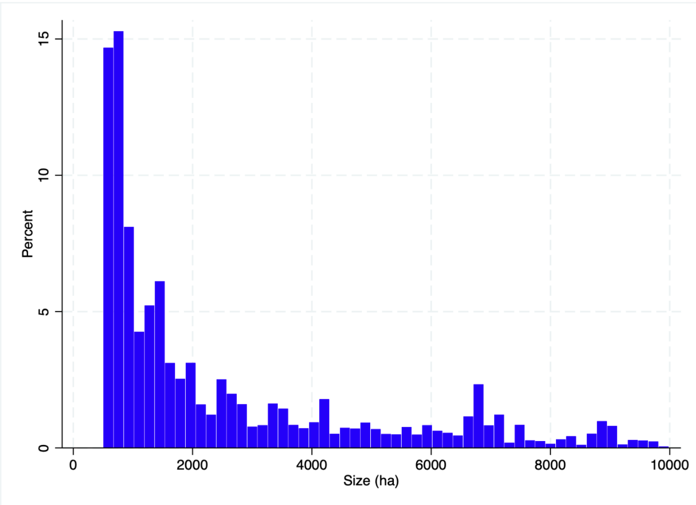
Notes: This map presents annual mean of three-day mental illness hospitalizations per 100,000 population across census divisions that are included in final sample of our analysis.

Figure A.5: Upwind fire distance and size distribution and overall $PM_{2.5}$ prediction

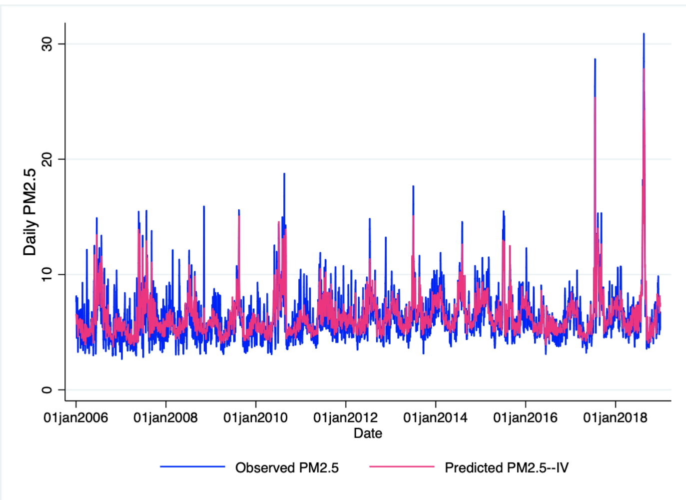
A) Distance distribution



B) Size distribution



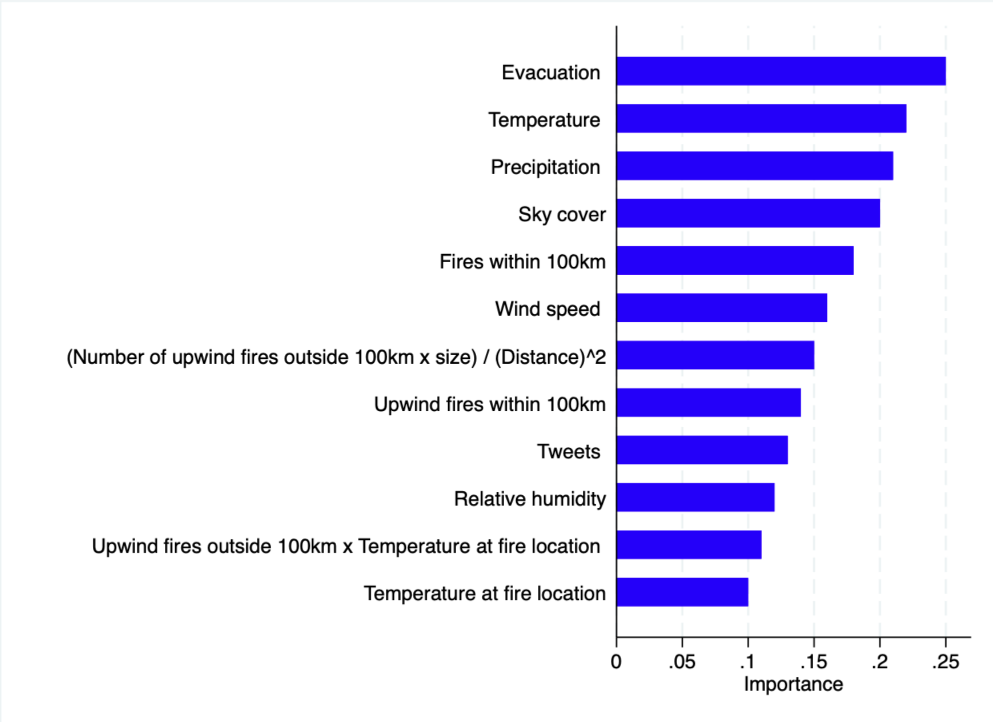
B) Observed vs. predicted $PM_{2.5}$–Canada



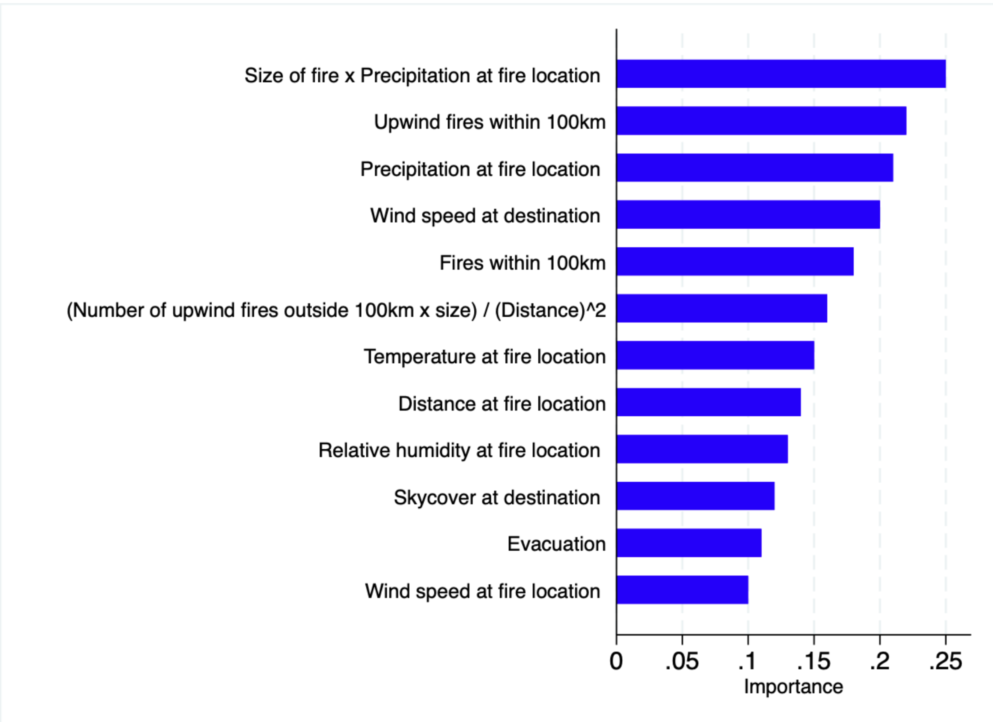
Notes: Panel A illustrates the distribution of distances between fires and the centroid of each census division. Panel B presents the distribution of fire sizes. Panel C displays the $PM_{2.5}$ predictions generated by our instrumental variable model.

Figure A.6: Variable importance from Lasso regressions

A) Mental health

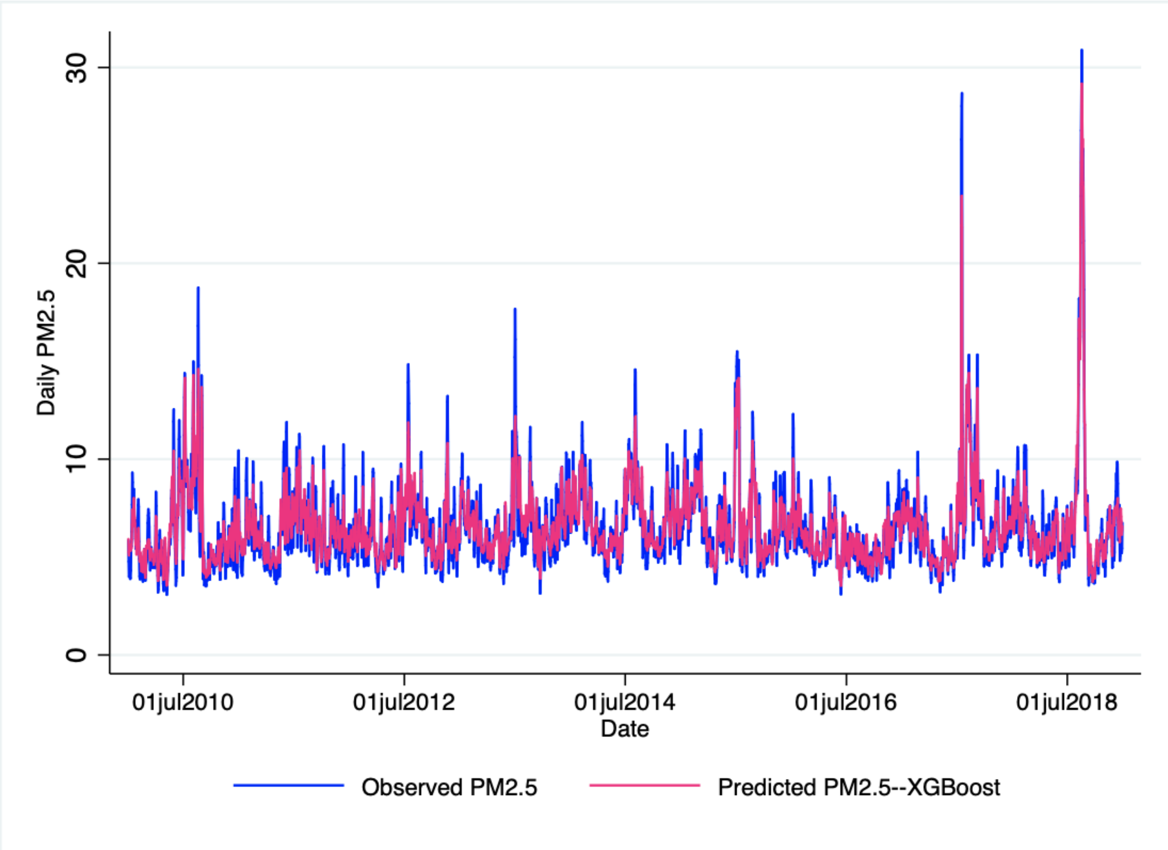


B) $PM_{2.5}$



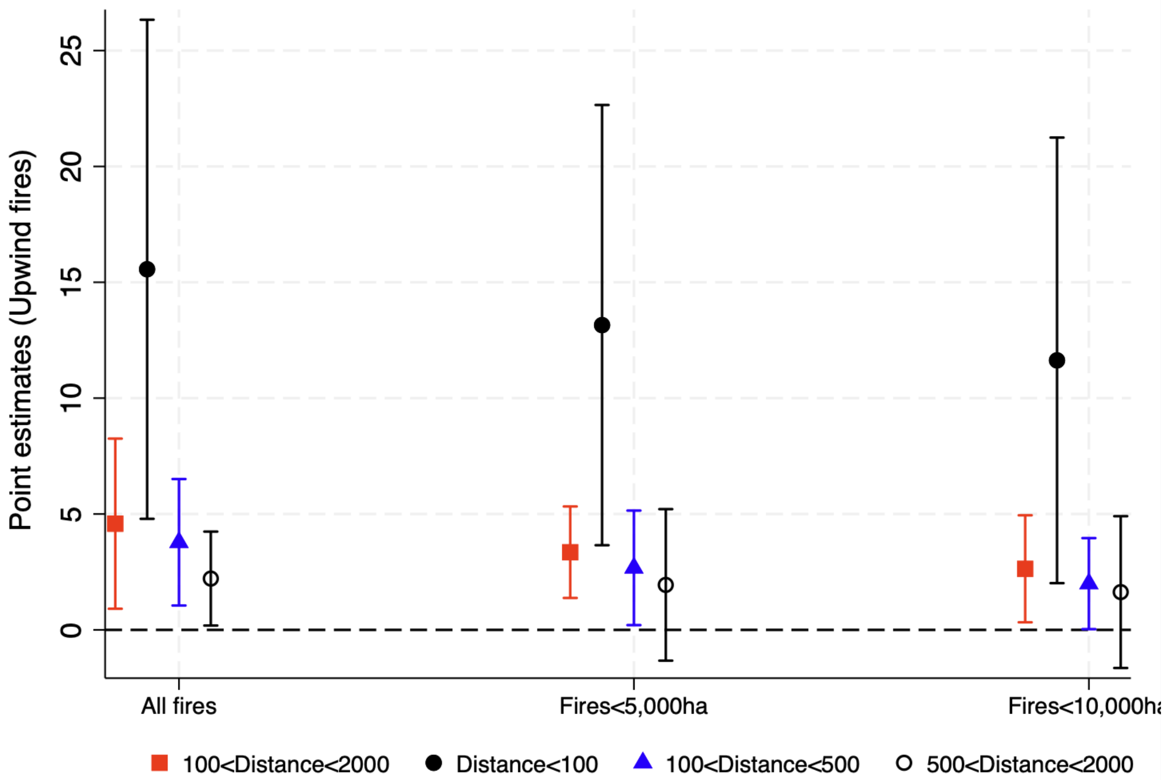
Notes: These plots present variable importance from Lasso regressions used in constructing the instrumental variable (excluding fixed effects). The model includes fixed effects for division, month-by-year, province-by-month, and day-of-week, along with daily $PM_{2.5}$ and flexible controls for temperature, dew point, precipitation, and cloud cover at both the destination and fire location. Additionally, the Lasso regressions accounts for fire size, distance between fires and census divisions, and flexible interactions between fire characteristics and other environmental factors.

Figure A.7: Observed vs. predicted $PM_{2.5}$ using Extreme Gradient Boosting (test sample)



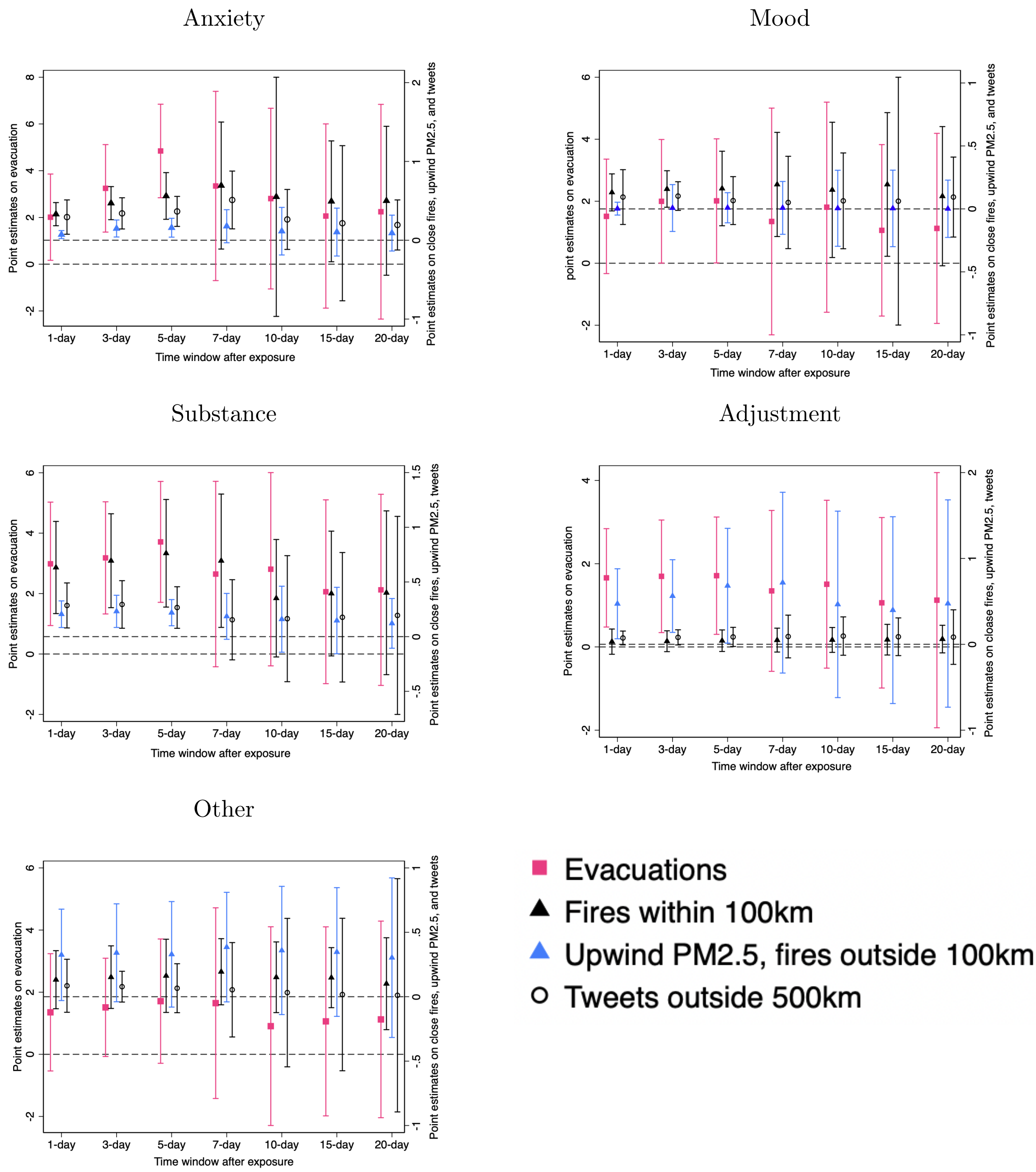
Notes: This graph illustrates the predictive performance of our extreme gradient boosting (XGBoost) algorithm, comparing its predictions on the test sample against observed $PM_{2.5}$ levels from the training data. Training sample comprises the 80% of observations from the most recent years, while the remaining 20% of earlier observations form the test sample.

Figure A.8: Effect of upwind fires on $PM_{2.5}$ by distance and size



Notes: This figure illustrates the effects of upwind fires on $PM_{2.5}$ concentrations across various distance intervals and fire sizes. The outcome variable is the daily $PM_{2.5}$ concentration for each census division. All regressions include fixed effects for division, month-by-year, province-by-month, and day-of-week, as well as flexible controls for temperature, dew point, precipitation, cloud cover, and wind speed. Whiskers represent the 95% confidence intervals, calculated using robust standard errors clustered at the division level.

Figure A.9: Estimated effects using alternative windows following fire days



Notes: These figures present estimates from our preferred specification, varying the time window of the dependent variable from 1 to 20 days. The dependent variable is the mental illness hospital admission rate per 100,000, measured over the number of days indicated on the x-axis for each relevant category. All regressions include fixed effects for division, month-by-year, province-by-month, and day-of-week, along with flexible controls for temperature, dew point, precipitation, cloud cover, and wind speed. Gray whiskers represent the 95% confidence intervals, computed using robust standard errors clustered at the division level.

Tables

Table A.1: Additional summary statistics

	Mean	Std. Dev.
Three-day admission rates (per 100,000): Division-year level		
Other	140.84	289.14
Dementia	33.15	77.13
Schizophrenia	47.18	88.04
Bipolar	1.86	1.03
Neurodevelopmental	8.80	14.19
Obsessive-compulsive	0.94	1.25
Weather at census division centroid		
Temperature (°C)	7.47	11.19
Dew point (°C)	1.93	10.40
Precipitation (mm)	2.49	6.22
Wind speed (km/h)	12.11	6.66
Sky cover (%)	49.73	22.55
Weather at fire location		
Temperature (°C)	9.44	10.99
Dew point (°C)	2.45	9.53
Precipitation (mm)	0.82	9.97
Wind speed (km/h)	11.78	6.84
Pollution		
$PM_{2.5}$ ($\mu g/m^3$)	6.74	9.50
O_3 (ppb)	25.95	9.64
CO (ppb)	0.229	0.118

Note: The period is 2006–2018. The unit of observation is census division-year

Table A.2: Effects of wildfires on mental illness hospitalizations in the 'other' category

	(1) Dementia and other neurocognitive	(2) Schizophrenia	(3) ADHD and other neurodevelopmental	(4) Residuals
Evacuations	0.223	0.024	0.078	0.122
	(0.142)	(0.126)	(0.092)	(0.142)
Fires within 100 km	0.029	0.008	0.002	0.012
	(0.016)	(0.009)	(0.003)	(0.017)
$PM_{2.5}$ ($\mu g/m^3$)	0.011	0.001	0.004	0.008
	(0.007)	(0.068)	(0.027)	(0.012)
Tweets outside 500 km	0.001	0.001	0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	301,619	301,619	301,619	301,619
R^2	0.514	0.512	0.504	0.511
Three-day admission rate (mean)	0.311	0.440	0.821	0.482

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. These four categories account for the majority of hospital admissions classified under "Other" mental ilness conditions. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. The first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.3: Effects of wildfires on mental illness hospitalizations by age

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
			Panel A. 0–20			
Evacuations	1.109*	0.576*	1.154	0.902*	0.167	0.927*
	(0.486)	(0.243)	(0.643)	(0.367)	(0.469)	(0.398)
Fires within 100 km	0.164	0.061	0.008	0.214***	0.098	0.121
	(0.109)	(0.034)	(0.164)	(0.037)	(0.077)	(0.087)
$PM_{2.5}$ ($\mu g/m^3$)	0.046*	0.028	0.027	0.091***	0.004	0.037*
	(0.021)	(0.016)	(0.047)	(0.025)	(0.032)	(0.017)
Tweets outside 500 km	0.000**	0.000	0.000	0.000*	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.483	0.503	0.504	0.497	0.510	0.499
Three-day admission rate (mean)	0.046	0.083	0.072	0.009	0.131	0.341
			Panel B. 21–65			
Evacuations	1.487*	0.934	1.120***	0.495	0.608	1.251*
	(0.631)	(0.487)	(0.293)	(0.300)	(0.436)	(0.491)
Fires within 100 km	0.213	0.067	0.317	0.018	0.068	0.179
	(0.151)	(0.036)	(0.185)	(0.010)	(0.063)	(0.122)
$PM_{2.5}$ ($\mu g/m^3$)	0.195***	0.048	0.127***	0.041	0.038	0.162***
	(0.063)	(0.027)	(0.038)	(0.021)	(0.028)	(0.049)
Tweets outside 500 km	0.001**	0.000	0.001**	0.003**	0.002	0.001**
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
R^2	0.539	0.522	0.509	0.531	0.539	0.526
Three-day admission rate (mean)	0.323	0.582	0.504	0.060	0.918	2.388
			Panel C. +65			
Evacuations	1.082	0.904	1.118*	0.524	0.892	0.871
	(0.672)	(0.512)	(0.518)	(0.319)	(0.474)	(0.551)
Fires within 100 km	0.092	0.154***	0.341	0.024**	0.077	0.079**
	(0.162)	(0.039)	(0.184)	(0.009)	(0.053)	(0.030)
$PM_{2.5}$ ($\mu g/m^3$)	0.152*	0.052	0.099	0.040	0.078	0.133*
	(0.073)	(0.037)	(0.060)	(0.024)	(0.048)	(0.062)
Tweets outside 500 km	0.001**	0.000	0.002**	0.004**	0.002	0.001*
	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.524	0.514	0.523	0.526	0.518	0.531
Three-day admission rate (mean)	0.092	0.166	0.144	0.017	0.262	0.682

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A reports the effects on individuals aged 0 to 20. Panel B presents the effects for those aged 21 to 65. Panel C shows the effects for individuals older than 65. In all panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.4: Effects of wildfires on mental illness hospitalizations by gender

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
	Panel A.Male					
Evacuations	2.518***	1.412**	2.097***	1.184*	0.998	1.956***
	(0.561)	(0.472)	(0.539)	(0.461)	(0.612)	(0.507)
Fires within 100 km	0.348***	0.105*	0.451**	0.024*	0.107	0.304***
	(0.072)	(0.053)	(0.146)	(0.012)	(0.078)	(0.055)
$PM_{2.5}$ ($\mu g/m^3$)	0.227***	0.005	0.164**	0.377**	0.243	0.137***
	(0.036)	(0.036)	(0.062)	(0.134)	(0.136)	(0.030)
Tweets outside 500 km	0.003***	0.001*	0.003*	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.525	0.523	0.516	0.532	0.542	0.519
Three-day admission rate (mean)	0.161	0.333	0.504	0.047	0.787	1.833
	Panel B. Female					
Evacuations	1.725***	0.881*	1.342**	0.654*	0.719	1.401***
	(0.489)	(0.432)	(0.454)	(0.279)	(0.401)	(0.424)
Fires within 100 km	0.265***	0.069*	0.319***	0.017*	0.064	0.197***
	(0.051)	(0.035)	(0.088)	(0.007)	(0.056)	(0.042)
$PM_{2.5}$ ($\mu g/m^3$)	0.138***	0.003	0.103*	0.278**	0.169	0.115***
	(0.030)	(0.052)	(0.042)	(0.103)	(0.089)	(0.025)
Tweets outside 500 km	0.002*	0.001	0.002	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.504	0.510	0.512	0.513	0.516	0.512
Three-day admission rate (mean)	0.300	0.499	0.216	0.038	0.525	1.578

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A reports the estimates for the male subsample. Panel B presents the effects for the female subsample. In both panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.5: Effects of wildfire on mental illness hospitalizations using a 60 degree cone to define upwind fires

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
Evacuations	2.103**	1.085	1.754**	0.892*	0.885	1.670**
	(0.672)	(0.622)	(0.591)	(0.375)	(0.553)	(0.547)
Fires within 100 km	0.309***	0.094***	0.448***	0.024*	0.098	0.246***
	(0.066)	(0.026)	(0.137)	(0.011)	(0.079)	(0.049)
$PM_{2.5}$ ($\mu g/m^3$)	0.095***	0.005	0.146*	0.338***	0.218*	0.117**
	(0.026)	(0.035)	(0.058)	(0.092)	(0.106)	(0.039)
Tweets outside 500 km	0.003*	0.001	0.002*	0.001*	0.001	0.003*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.531	0.525	0.528	0.523	0.535	0.527
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. This table presents estimates based on defining upwind and downwind fires as those occurring within 60° of the prevailing daily wind direction. The first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.6: Robustness to changing the radius defining close fires and distant fires

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
	Panel A. Close fires are < 200km, distant fires are 200-2000km					
Evacuations	1.690***	1.040*	1.745***	0.854*	0.820	1.440***
	(0.494)	(0.523)	(0.537)	(0.346)	(0.454)	(0.396)
Fires within 200 km	0.291***	0.091*	0.430**	0.022*	0.089	0.231**
	(0.060)	(0.046)	(0.133)	(0.011)	(0.073)	(0.074)
$PM_{2.5}$ ($\mu g/m^3$)	0.078*	0.004	0.110*	0.289**	0.165	0.064*
	(0.033)	(0.044)	(0.046)	(0.102)	(0.101)	(0.026)
Tweets outside 500 km	0.003*	0.001*	0.002*	0.001*	0.001	0.002*
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
R^2	0.514	0.513	0.511	0.504	0.526	0.514
	Panel B. Close fires are < 100km, distant fires are 100-3000km					
Evacuations	1.882***	1.173*	1.922***	1.046**	0.890	1.713***
	(0.543)	(0.595)	(0.577)	(0.371)	(0.466)	(0.490)
Fires within 100 km	0.239***	0.080*	0.304**	0.008	0.079	0.203***
	(0.059)	(0.038)	(0.115)	(0.009)	(0.074)	(0.046)
$PM_{2.5}$ ($\mu g/m^3$)	0.087**	0.005	0.142*	0.350**	0.213	0.072**
	(0.033)	(0.030)	(0.058)	(0.132)	(0.120)	(0.027)
Tweets outside 500 km	0.003*	0.003**	0.001	0.002*	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.516	0.527	0.514	0.511	0.512	0.508
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A reports the effects when the buffer is adjusted to exclude fires within 200 km of each census division. Panel B presents the effects when the buffer is expanded to include fires within a range of 100 to 3,000 km. Adjustments to buffers are applied to both fire count and the construction of the instrument variable. In both panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.7: Robustness to using AI-generated (CanOSSEM) $PM_{2.5}$, 2010-2018

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
	Panel A. IV estimates for $PM_{2.5}$ for period 2010 - 2018					
Evacuations	2.122***	1.142*	1.912***	0.971**	0.878	1.512***
	(0.597)	(0.554)	(0.553)	(0.372)	(0.469)	(0.441)
Fires within 100 km	0.290***	0.090	0.443**	0.021	0.095	0.214***
	(0.075)	(0.053)	(0.156)	(0.014)	(0.089)	(0.050)
$PM_{2.5}$ ($\mu g/m^3$)	0.086**	0.322*	0.137***	0.353**	0.204	0.069**
	(0.031)	(0.132)	(0.042)	(0.126)	(0.122)	(0.026)
Tweets outside 500 km	0.004**	0.002*	0.003*	0.001	0.001	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	208,810	208,810	208,810	208,810	208,810	208,810
R^2	0.494	0.491	0.501	0.508	0.497	0.501
	Panel B. Reduced form					
Evacuations	2.524***	1.599*	2.514***	1.280*	1.208	2.274***
	(0.790)	(0.814)	(0.791)	(0.505)	(0.680)	(0.607)
Fires within 100 km	0.395**	0.126*	0.579***	0.029*	0.124	0.312**
	(0.140)	(0.059)	(0.175)	(0.014)	(0.097)	(0.108)
CanOSSEM $PM_{2.5}$ ($\mu g/m^3$)	0.117*	0.245*	0.185***	0.450**	0.278*	0.095**
	(0.046)	(0.123)	(0.058)	(0.154)	(0.139)	(0.034)
Tweets outside 500 km	0.004*	0.001	0.002	0.001	0.001	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	311,402	311,402	311,402	311,402	311,402	311,402
R^2	0.512	0.513	0.518	0.509	0.531	0.529
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A reports estimates using on the same period for which CanOSSEM data are available. Panel B replaces observed PM_2.5 with PM_2.5 estimates generated using the CanOSSEM machine learning algorithm, developed by Paul, N., Yao, J., McLean, K. E., Stieb, D. M., and Henderson, S. B. (2022). In both panels, the first row reports the estimated effect of evacuation orders. Evacuation is a binary indicator equal to one if an evacuation order is issued on date t in the centroid of census division c. The second row reports the estimated effect of the daily count of fires larger than 500 hectares located within 100 km of census division c's centroid. The third row presents the estimated effect of $PM_{2.5}$, which—in Panel A only—is instrumented using a Lasso-based variable selection method. The final row reports the estimated effect of the daily count of tweets containing the hashtag #wildfire, posted from locations within Canada but more than 500 km away from the centroid of the census division. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.8: Robustness to controlling for ozone and carbon monoxide

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
			Panel A. Adding O_3			
Evacuations	2.067***	1.211*	2.013**	1.004*	0.902	1.543**
	(0.565)	(0.601)	(0.689)	(0.402)	(0.640)	(0.490)
Fires within 100 km	0.319*	0.092	0.492*	0.027*	0.103	0.257*
	(0.126)	(0.051)	(0.212)	(0.011)	(0.090)	(0.113)
Tweets outside 500 km	0.003**	0.001	0.001	0.001	0.001	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$PM_{2.5}$ ($\mu g/m^3$)	0.089*	0.004	0.153**	0.313*	0.226	0.073*
	(0.038)	(0.019)	(0.048)	(0.125)	(0.123)	(0.035)
O_3 (ppb)	0.011	0.008	0.105	0.033	0.008	0.009
	(0.024)	(0.050)	(0.085)	(0.061)	(0.016)	(0.018)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.501	0.504	0.499	0.497	0.503	0.511
			Panel B. Adding both O_3 and CO			
Evacuations	1.948**	0.969	1.324*	0.609	0.663	1.723**
	(0.756)	(0.603)	(0.604)	(0.385)	(0.599)	(0.624)
Fires within 100 km	0.297	0.090	0.404	0.025	0.026	0.230
	(0.176)	(0.050)	(0.213)	(0.013)	(0.068)	(0.144)
Tweets outside 500 km	0.003***	0.001	0.002*	0.001	0.001	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
$PM_{2.5}$ ($\mu g/m^3$)	0.104**	0.004	0.127***	0.357***	0.208	0.078*
	(0.039)	(0.041)	(0.034)	(0.063)	(0.151)	(0.033)
O_3 (ppb)	-0.032	0.021	0.039	-0.026	0.012	0.026
	(0.023)	(0.027)	(0.026)	(0.021)	(0.042)	(0.019)
CO (ppb)	0.035	0.024	0.038	0.019	0.007	0.030
	(0.041)	(0.016)	(0.025)	(0.073)	(0.107)	(0.036)
Observations	97,353	97,353	97,353	97,353	97,353	97,353
R^2	0.392	0.381	0.384	0.397	0.396	0.393
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A includes ozone, instrumented using one-day lead of decay function. Panel B includes both ozone and carbon monoxide, instrumented using one and two-day lead of decay function. In Panels B, the sample is restricted to division-days where readings for CO, ozone, and $PM_{2.5}$ are simultaneously available. In both panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.9: Robustness to excluding days with rain and cloud cover

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
			Panel A. No rain			
Evacuations	1.685**	0.881	1.508*	0.793*	0.655	1.350**
	(0.607)	(0.719)	(0.639)	(0.373)	(0.530)	(0.467)
Fires within 100 km	0.258***	0.084	0.299*	0.016	0.075	0.216***
	(0.077)	(0.052)	(0.150)	(0.012)	(0.075)	(0.065)
$PM_{2.5}$ ($\mu g/m^3$)	0.071*	0.004	0.119	0.263	0.178	0.065*
	(0.035)	(0.074)	(0.065)	(0.169)	(0.134)	(0.027)
Tweets outside 500 km	0.003	0.001	0.002	0.001	0.001	0.002
	(0.010)	(0.005)	(0.007)	(0.006)	(0.004)	(0.008)
Observations	171,340	171,340	171,340	171,340	171,340	171,340
R^2	0.404	0.393	0.410	0.419	0.424	0.418
			Panel B. Clear sky: 10% or less cloud cover			
Evacuations	1.552**	0.986*	1.573**	0.842**	0.592	1.261**
	(0.532)	(0.487)	(0.514)	(0.305)	(0.475)	(0.432)
Fires within 100 km	0.231***	0.078*	0.293*	0.018*	0.069	0.192***
	(0.052)	(0.038)	(0.120)	(0.008)	(0.060)	(0.047)
$PM_{2.5}$ ($\mu g/m^3$)	0.068*	0.003	0.122*	0.268*	0.164	0.056**
	(0.029)	(0.008)	(0.061)	(0.109)	(0.105)	(0.021)
Tweets outside 500 km	0.004*	0.001	0.001	0.001	0.001	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	40,813	40,813	40,813	40,813	40,813	40,813
R^2	0.386	0.373	0.352	0.379	0.384	0.377
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A provides estimates for the subsample of days with no rain. Panel B reports estimates for the subsample of days with 10% or less cloud coverage. In both panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.10: Robustness to excluding census divisions with high or low hospitalization rates

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
	Panel A. Excluding the top and bottom 10%					
Evacuations	1.987***	1.185*	2.045***	1.098**	0.978	1.642***
	(0.612)	(0.545)	(0.639)	(0.385)	(0.532)	(0.489)
Fires within 100 km	0.312***	0.098	0.452***	0.024**	0.099	0.245***
	(0.070)	(0.051)	(0.137)	(0.008)	(0.077)	(0.053)
$PM_{2.5}$ ($\mu g/m^3$)	0.096**	0.004	0.150**	0.375*	0.232	0.074**
	(0.037)	(0.056)	(0.049)	(0.147)	(0.123)	(0.027)
Tweets outside 500 km	0.004***	0.001*	0.003**	0.001*	0.001	0.003**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	240,190	240,190	240,190	240,190	240,190	240,190
R^2	0.494	0.491	0.496	0.497	0.501	0.500
	Panel B. Winsorizing the top and bottom 10%					
Evacuations	2.198***	1.275*	2.142**	1.145**	1.015	1.748***
	(0.652)	(0.580)	(0.670)	(0.405)	(0.560)	(0.515)
Fires within 100 km	0.329***	0.104*	0.478***	0.025**	0.103	0.255***
	(0.073)	(0.052)	(0.144)	(0.009)	(0.081)	(0.055)
$PM_{2.5}$ ($\mu g/m^3$)	0.098**	0.004	0.157**	0.390*	0.244	0.077**
	(0.038)	(0.058)	(0.051)	(0.152)	(0.128)	(0.028)
Tweets outside 500 km (per 10)	0.004***	0.001*	0.004**	0.001	0.001	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.510	0.512	0.494	0.513	0.521	0.526
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include fixed effects for division, month-by-year, province-by-month, and day-of-week, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A excludes census divisions in the top (more than 706 per 100,000) and bottom (less than 30 per 100,000) percentiles based on their mental health hospitalization rates. Panel B applies winsorization to the top and bottom 10 percentiles of mental health hospitalization rates across census divisions. In both panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.11: Separate estimates for weekends and weekdays

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
Panel A. Weekdays						
Evacuations	2.005***	1.223*	1.770**	1.054**	0.915	1.875***
	(0.528)	(0.595)	(0.568)	(0.354)	(0.558)	(0.531)
Fires within 100 km	0.285***	0.098*	0.409***	0.022*	0.091	0.235***
	(0.056)	(0.043)	(0.117)	(0.011)	(0.070)	(0.071)
$PM_{2.5}$ ($\mu g/m^3$)	0.078*	0.005	0.127*	0.365**	0.184	0.058**
	(0.033)	(0.027)	(0.055)	(0.138)	(0.113)	(0.019)
Tweets outside 500 km	0.003*	0.001*	0.002*	0.001*	0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	215,445	215,445	215,445	215,445	215,445	215,445
R^2	0.481	0.479	0.491	0.487	0.491	0.493
Panel B. Weekends						
Evacuations	1.282*	0.713	1.375*	0.731*	0.628	0.986*
	(0.556)	(0.495)	(0.579)	(0.325)	(0.514)	(0.456)
Fires within 100 km	0.229*	0.073	0.322***	0.014	0.058	0.162*
	(0.091)	(0.038)	(0.099)	(0.008)	(0.054)	(0.067)
$PM_{2.5}$ ($\mu g/m^3$)	0.054**	0.003	0.078	0.228**	0.130	0.038*
	(0.020)	(0.192)	(0.058)	(0.083)	(0.067)	(0.016)
Tweets outside 500 km	0.002	0.001	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	86,174	86,174	86,174	86,174	86,174	86,174
R^2	0.411	0.413	0.409	0.406	0.412	0.413
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. Panel A provides estimates for the weekday subsample. Panel B reports estimates for the weekend subsample. The first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.12: Robustness to different clustering choices

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
Panel A. Clustered by division and year						
Evacuations	2.237***	1.292*	2.178***	1.169**	1.032*	1.775***
	(0.610)	(0.512)	(0.603)	(0.362)	(0.503)	(0.456)
Fires within 100 km	0.337***	0.107*	0.489***	0.026**	0.106	0.261***
	(0.068)	(0.046)	(0.127)	(0.008)	(0.072)	(0.049)
$PM_{2.5}$ ($\mu g/m^3$)	0.101**	0.005	0.161***	0.399**	0.250*	0.079**
	(0.034)	(0.051)	(0.045)	(0.133)	(0.112)	(0.025)
Tweets outside 500 km	0.004***	0.002**	0.004**	0.001*	0.001	0.003**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Panel B. Clustered by division and date						
Evacuations	2.237***	1.292**	2.178***	1.169***	1.032*	1.775***
	(0.560)	(0.450)	(0.540)	(0.320)	(0.450)	(0.400)
Fires within 100 km	0.337***	0.107**	0.489***	0.026***	0.106	0.261***
	(0.060)	(0.040)	(0.110)	(0.007)	(0.062)	(0.042)
$PM_{2.5}$ ($\mu g/m^3$)	0.101***	0.005	0.161***	0.399***	0.250*	0.079***
	(0.030)	(0.045)	(0.040)	(0.120)	(0.100)	(0.022)
Tweets outside 500 km	0.004***	0.002***	0.004***	0.001***	0.001	0.003***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Panel C. Clustered by pollution station and year						
Evacuations	2.237**	1.292	2.178**	1.169*	1.032	1.775**
	(0.720)	(0.680)	(0.790)	(0.480)	(0.660)	(0.610)
Fires within 100 km	0.337***	0.107	0.489**	0.026**	0.106	0.261***
	(0.090)	(0.062)	(0.170)	(0.010)	(0.095)	(0.070)
$PM_{2.5}$ ($\mu g/m^3$)	0.101*	0.005	0.161*	0.399*	0.250	0.079*
	(0.050)	(0.070)	(0.065)	(0.180)	(0.150)	(0.040)
Tweets outside 500 km	0.004**	0.002	0.004*	0.001	0.001	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.537	0.533	0.532	0.532	0.534	0.539
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include division, month-by-year, province-by-month, and day-of-week fixed effects, along with flexible controls for temperature, dew point, precipitation, and cloud cover. Each column corresponds to a separate regression. In both panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors clustered by division and year in panel A, by division and date in panel B and by pollution station and year in panel C in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.

Table A.13: Robustness to the inclusion of alternative sets of fixed effects

	(1) Anxiety	(2) Mood	(3) Substance	(4) Adjustment	(5) Other	(6) Total
	Panel A. FEs: division-by-month and month-by-year					
Evacuations	1.949**	1.082	1.739**	0.947**	0.746	1.602**
	(0.608)	(0.578)	(0.544)	(0.356)	(0.466)	(0.499)
Fires within 100 km	0.266***	0.093*	0.442***	0.022*	0.086	0.210***
	(0.077)	(0.042)	(0.128)	(0.011)	(0.071)	(0.064)
$PM_{2.5}$ ($\mu g/m^3$)	0.085**	0.004	0.146**	0.322**	0.189	0.069**
	(0.032)	(0.060)	(0.055)	(0.122)	(0.117)	(0.024)
Tweets outside 500 km	0.003**	0.001*	0.002*	0.001*	0.001	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
R^2	0.525	0.521	0.524	0.516	0.528	0.535
	Panel B. FEs: division-by-year, month and province					
Evacuations	1.949**	1.082	1.739**	0.947**	0.746	1.602**
	(0.608)	(0.578)	(0.544)	(0.356)	(0.466)	(0.499)
Fires within 100 km	0.266***	0.093*	0.442***	0.022*	0.086	0.210***
	(0.077)	(0.042)	(0.128)	(0.011)	(0.071)	(0.064)
$PM_{2.5}$ ($\mu g/m^3$)	0.085**	0.004	0.146**	0.322**	0.189	0.069**
	(0.032)	(0.060)	(0.055)	(0.122)	(0.117)	(0.024)
Tweets outside 500 km	0.003**	0.001*	0.002*	0.001*	0.001	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	301,619	301,619	301,619	301,619	301,619	301,619
R^2	0.512	0.528	0.523	0.514	0.516	0.523
Three-day admission rate (mean)	0.461	0.832	0.720	0.085	1.312	3.411

Notes: The dependent variable is the three-day admission rate per 100,000 for each type of hospitalization. All regressions include flexible controls for temperature, dew point, precipitation, and cloud cover, as well as fixed effects specified in each panel. Each column corresponds to a separate regression. In both panels the first row reports the estimated effect of evacuation orders. Evacuation is a dummy variable equal to one if an evacuation order is issued on date t in census division c's centroid. The second row is estimated effect of the daily count of fires larger than 500ha located within 100 km of census division c's centroid. The third row reports the estimated effect of $PM_{2.5}$ which is instrumented using a Lasso-based variable selection method. The last row reports the estimated effect of daily count of tweets containing the hashtag #wildfire posted from locations within Canada but more than 500 km away from census division's centroid. Standard errors, clustered at the division level, are reported in parentheses. * significant at 5% ** significant at 1% *** significant at 0.1%.