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**Abstract**

Wildfires are increasing in frequency and intensity. We study the impact of exposure to wildfires on air pollutants and on human health in Chile, finding substantial impacts on both classes of outcomes. We use data on 15 wildfire seasons (2004-2018) matched with granular (intra-day) records of wind direction and air quality, as well as administrative records of all hospitalizations in the country. By combining the precise location of fires with wind direction at the moment in which fires occur, we estimate causal impacts of exposure to wildfires. We find considerable impacts. Exposure to a large wildfire (250 Ha) is observed to increase $PM_{2.5}$ concentrations by 10% on average in municipalities up to 200km from the epicenter of the wildfire. These effects have appreciable impacts on rates of hospitalization. A one standard deviation increase in exposure to large wildfires is estimated to increase rates of respiratory hospitalizations by 0.75%, while the effect of exposure to the most extreme week of wildfires observed is estimated to increase hospitalizations by as much as a third. Effects are found to be particularly acute for infants, and to grow with the size of the exposure to wildfire (both in terms of duration and area burned).



**JEL classifications:** Q54, I18, R11
**Keywords:** Natural disasters, Wildfires, Air pollution, Human capital, Health



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# 1 Introduction

Climate change is expected to result in an increase in the intensity of disasters associated with natural hazards, such as hurricanes, storms with extreme amounts of rainfall, long-lasting droughts, and heat waves (IPCC, 2022). This will most likely result in increasing adverse effects to human life and economic activity (IPCC, 2022). Indeed, there is already evidence that this has begun (Coronese et al., 2019). Climate change is also expected to accentuate the frequency and size of wildfires as a consequence of increasing soil aridity due to extreme heat and droughts in forest, shrubland and grassland areas (Malevsky-Malevich et al., 2008; Gillett et al., 2004; Pyne, 2019). Moreover, the destructiveness of wildfires is predicted to worsen in the near future as a direct consequence of climate change (Abatzoglou and Williams, 2016; Bowman et al., 2017; Flannigan et al., 2009, 2013).

For Latin America and the Caribbean (LAC), Chapter 12 of the IPCC (2022)'s Sixth Assessment Report predicts that the risk of wildfires will increase in several sub-regions.[1] These wildfires will increasingly result in: i) loss of human lives, infrastructure and physical capital as a consequence of burning by the flames; ii) harm to agricultural and cattle growing economic activity due to deposition of the ashes; as well as iii) adverse effects to health of nearby population due to air pollution from wildfire smoke (Flannigan et al., 2009; Bowman et al., 2017; Cancelo-González and Viqueira, 2018). Indeed, for the case of the United States, for example, it is estimated that wildfires in recent years account for up to 25 percent of total nationwide exposure to fine particular matter ($PM_{2.5}$). This wildfire air pollution affects vast areas of the United States, particularly in the west and mountain regions (Burke et al., 2021).

Given the increasing severity and frequency of natural disasters, it is important fully understand the impacts of exposure to disaster, particularly in areas which are projected to be especially vulnerable to such events. In this paper, we estimate the health impacts of exposure to wildfire in Chile–a highly vulnerable country due to increased fuel aridity of its forests, shrublands and grasslands in vast geographical areas as a consequence of climate-driven extreme heat and long lasting droughts. We combine high-quality data on wildfire with administrative registers of health outcomes over the period of 2004 to 2018 to look at both the static and dynamic effects of wildfire on air pollution and on hospital admissions.[2] In this study, we limit our analysis to the impacts of wildfire on human health, with a focus on how exposure affects the health of individuals residing in the broad geographical areas affected by the air pollution from these

[1] Specifically, in Southern South America (Patagonia), Southwest South America (Chile), Northeast South America (Eastern Brazil), South America Monsoon (Brazilian Amazons), Central America, and Northern South America (Northern Brazil).

[2] We refer to static effects as those health impacts that are manifested almost contemporaneously (in the same week as fire exposure), whereas dynamic effects as those impacts that are manifested in the weeks following the wildfire event.

wildfires, which may propagate substantially beyond the origin of the fire.[3] In ongoing work based on the same empirical design and setting, we will extend our research to consider the broader scope of the costs of wildfires, including educational outcomes, local labor market outcomes, and intergenerational transmission of health impacts.

In order to isolate causal effects of exposure to wildfires, we rely on location- and time-specific fixed effects and model specifications with flexible interactions. Furthermore, this strategy is complemented with high-frequency and granular remotely sensed data on wind direction at the time of the wildfire (Rangel and Vogl, 2019). Using local information on wind directions, we estimate the effect of wildfire exposure on health outcomes focusing on those wildfires that are *upwind* from where people live. This identification strategy relies on the assumption that, all else equal, wind direction at a precise moment in time should not affect health outcomes other than via changes in exposure to the air pollution from the wildfire. Given the geographical location of a wildfire, exposure to the associated air pollution can be considered quasi-random because it depends on the prevailing wind direction. We provide support for these assumptions by noting that i) in similar municipalities with upwind and downwind fires, those with upwind fires have sharp increases in concentrations of air-borne contaminants, while those with downwind fires suffer no such decline in air quality; and ii) in periods prior to wildfires, health outcomes in upwind and downwind areas are similar.

Broadly speaking, our models capture the rapid declines of air quality in municipalities exposed to wildfires, suggesting that appreciable declines in quality are evident even when considering a broad geographic exposure window including individuals living up to 200km from the epicenter of the fire. In terms of health impacts, we find that exposure to the air pollution from large wildfires increases hospitalizations due to respiratory causes and increases all-cause hospitalization among infants. Moreover, we find some evidence that exposure to air pollution from large wildfires has delayed effects on increasing respiratory hospitalizations among the elderly.

These results are in line with estimates from a broader literature in other contexts. Particulate air pollution from wildfire smoke is known to cause significant adverse effects on human health. For example, Frankenberg et al. (2005) and Jayachandran (2009) examine the large widespread fires that took place in Indonesia in 1997. Whereas Frankenberg et al. (2005) find that exposure to the air pollution from those fires had a negative impact on the health of older adults and prime-age women, Jayachandran (2009) finds that prenatal air pollution exposure, due to widespread wildfires over the course of four months, led to a 1.2

[3]An important impact analysis, albeit beyond of the scope of this paper, would be to examine the effects on land cover burned by these wildfires. For example, impacts on high value-added land, such as wineries and fruit plantations for exports, are of considerable interest.

percent decrease in cohort size in Indonesia, representing 15,600 missing children.[4] For the United States, Moeltner et al. (2013) find that large-scale wildfires in California increase $PM_{2.5}$ pollution concentrations in distant metropolitan areas of Nevada (Reno/Sparks), and this has an impact on hospital admissions due to respiratory and cardiovascular causes. Relatedly, Miller et al. (2017) estimate the effect of $PM_{2.5}$ pollution from wildfires on mortality in the Medicare population finding that the annual mortality costs of wildfire air pollution in the United States are just over US$ 6 billion.

In particular, our results cohere with work which uses wind direction to estimate impacts of exposure natural disasters. This identification strategy was first developed by Rangel and Vogl (2019) to examine the causal effects of air pollution from agricultural fires on health outcomes in the State of Sao Paulo, Brazil. The authors employ the differential exposure to air pollution of those fires that are *upwind*–as compared to those that are *downwind*. Rangel and Vogl (2019) find significant effects of air pollution from these agricultural fires on health at birth (birth weight and prematurity), perinatal morbidity (hospital admissions) and perinatal mortality (both stillbirth and death just after birth). Using the same identification strategy He et al. (2020) find significant effects of air pollution from agricultural fires on rural mortality in China, and Morello (2023) find a small effect on hospitalizations due to asthma among the elderly in the Brazilian Amazon.[5] Similarly, Rocha and Sant'Anna (2022) employ exogenous variation in wind direction across municipalities in the Brazilian Amazon, finding that wildfire-related air pollution leads to an increase in hospitalization rates, particularly among children and the elderly.[6] Results from the United States similarly note sensitivity of specific age groups, and in particular older individuals (Deryugina et al., 2019) and younger individuals (Anderson, 2019) when considering wind-driven exposure to air pollution.

In this paper we provide evidence from a new setting, which also covers an extended period of time (15 years), and an entire country (Chile). Apart from the new setting over a longer time period, our results also

[4]More recent studies have found that wildfire air pollution in Indonesia decreases lung capacity (Pakhtigian, 2020), that children are shorter and have lower lung capacity even many years after exposure to these fires (Rosales-Rueda and Triyana, 2019), and that prenatal exposure is associated with lower adult height (Tan-Soo and Pattanayak, 2019). Moreover, Mead et al. (2018) show that more than 60 percent of residents in Malaysia have been exposed to a harmful level of air pollution following episodes of wildfires in Indonesia and other neighboring countries.

[5]Also using this identification strategy, Graff Zivin et al. (2020) find significant effects of agricultural fires on university admission exams in China, and Singh et al. (2022) find significant effects of crop and forest fires on the height-for-age of children less than five years old in India.

[6]Many studies have documented an statistical association between wildfire air pollution and health. For example, Reid et al. (2016) review the epidemiological literature documenting associations between wildfire air pollution and general respiratory outcomes, such as asthma exacerbations and chronic obstructive pulmonary disease. Cascio (2018) updates and expands this review, also documenting statistical associations of wildfire air pollution in the United States with mortality (Zu et al., 2016), preterm birth and low birth weight (Jones and McDermott, 2022), increased cardio-respiratory mortality in Portugal Augusto et al. (2020); Tarín-Carrasco et al. (2021), increased overall mortality in Europe (Kollanus et al., 2017), and increased child mortality in selected low and middle-income countries Xue et al. (2021). For Chile, Ciciretti et al. (2022) find an association between wildfire air pollution in two major cities of Central Chile and emergency care visits due to respiratory problems–specifically, bronchitis, chronic lower respiratory diseases and pneumonia–among children less than one year old and those 1 to 4 years old.

add to the extant literature by examining impacts of exposure to fires of varying intensities. In follow-up work, we will substantially expand outcomes studied to provide a more complete picture of the medium and longer-term costs of wildfires in this setting.

The rest of this paper is structured as follows. We provide some brief background and contextual details in Section 2. In Section 3 we provide information on data sources measuring exposure to fires, pollutants, and health outcomes. Section 4 defines our design and estimation strategy, as well as assumptions required for estimates to be interpreted as causal effects. In Section 5 we present results. We conclude and discuss ongoing extensions of this working paper in Section 6.

## 2 Background and Context

Chile is a geographically diverse country, extending across 38 degrees in latitude, and as such it is exposed to quite variable climatic and environmental conditions. Climate zones vary from desert in the north, to glacial in the south. The country has about 16 million hectares of forest cover, with native forests composing around 85 percent, equivalent to 13 million hectares, and forest plantations accounting for 14 percent, or around 2.3 million hectares. The central region of Chile is significantly exposed to risk of wildfire given both its abundant vegetation and a Mediterranean climate. Historically, these wildfires have been mainly concentrated in the central and south-central regions of Chile, from the Valparaíso to Araucanía districts (Sarricolea et al., 2020).[7] Most of the types of land use and land cover burned in Chile are savannas, croplands, broad leaf and evergreen forests and woody savannas (Sarricolea et al., 2020).

Whereas the majority of wildfires in Chile are started, either directly or indirectly, by human activity (CONAF, 2022), warmer temperatures and droughts make these fires both more frequent and destructive (Westerling et al., 2006). Indeed, the intensity of wildfires in Chile has increased over the last years. For example, in 2017 Chile suffered from a particularly severe wildfire season, when approximately 5,000 square kilometers of forest were burned–for context, this is an area larger than the state of Rhode Island in the United States. This was about 10 times higher than previous yearly averages (CONAF, 2022).

The public and private costs of wildfires are substantial. According to information from Chile's National Forestry Agency (CONAF, for its acronym in Spanish), the direct costs incurred by the state during the 2016-2017 fire season amounted to US$ 362.2 million, which is equivalent to US$ 635.3 per hectare. The classification of these costs includes firefighting (39 percent), housing reconstruction (39 percent) and

[7] This is the most populated region in the country, with 78.9 percent of the population according to census records (INE, 2018).

support to productive sectors (16 percent), among others. Regarding private spending on forest fires reported by the Chilean Timber Corporation (CORMA, for its acronym in Spanish), during the 2017-2018 fire season forestry companies increased their expenditures to almost US$ 80 million, 60 percent more than at the beginning of the 2016 season. The number of people dedicated to fire prevention and combat increased by 700 in the same period, and the amount of resources allocated to prevention tripled that season, reaching US$ 18 million. In addition, according to CORMA's 2013-14, 2014-15, 2015-16 and 2016-17 season reports, the main forestry companies allocated, on average, US$ 50 million to fire prevention and firefighting (González et al., 2020).

Beyond these proximal costs of wildfires, there are considerable additional societal costs which have been documented. The widespread presence of forest fires considerably increases atmospheric pollutants which are known to have severe consequences on people's health, harming cardiovascular and respiratory systems. The objective of this paper is to estimate and quantify the health effects of exposure to these air pollutants. We focus on hospitalizations which reflect severe impacts on overall health.

# 3 Data

We generate a week by municipality level panel covering all wildfires and hospitalizations in the country over the period of 2004-2018. We additionally incorporate registers of population and air quality similarly at the municipality level at high temporal frequency. Chile consists of 346 municipalities[8], and these 346 municipalities are observed over 783 weeks (15 years), resulting in a balanced panel of 270,918 observations. Data on hospitalizations and wildfire are both from administrative registries at the micro-level, while data on air quality are remotely sensed at ground level covering the country at a fine grid level. Below we provide full information on the sources of these data, how they are processed to generate a municipality-level panel, key variables, and provide summary statistics.

## 3.1 Inpatient Hospitalizations

We have collected and systematized administrative records on all inpatient hospitalization records from the Chilean Ministry of Health's Department of Health Statistics and Information (DEIS, for its acronym in Spanish) covering the period of 2004, the first year these data are available, and up to 2018. Inpatient hospitalization data are rich, indicating each cause of hospitalization and its duration. These data cover all

[8] Municipalities in Chile are the third-level administrative district. These municipalities each have their own mayor and administrative bodies, and vary in size (most are about about the size of a zip code area in the United States), with certain large cities containing multiple municipalities, and in rural areas generally covering a whole town.

hospitalizations in the country, whether occurring in the public or the private system.[9] These are recorded at the individual level, with one observation for each hospitalization, with information on the principal cause of hospitalization (using standardized ICD-10 codes), demographics such as age and sex, and information on the length of the stay. The data additionally include information of the municipality in which the individual resides–which need not be the same one as the municipality where the individual is hospitalized–which allows us to link individuals to exposure to wildfire air pollution (see Section 3.3 below).

We examine all hospitalizations and also focus on specific classes of morbidities which are conceivably linked to fires, namely hospitalizations for respiratory causes, hospitalizations for cardiovascular disease, and for burns. These particular causes are generated from ICD-10 codings. We additionally consider age-specific hospitalizations, both for all causes, as well as for the specific causes mentioned above. The total number of hospitalizations occurring in each municipality is aggregated to municipal level totals and is calculated as rates per 100,000 individuals using municipal$\times$age$\times$time population records provided by Chile's National Institute of Statistics.

In Table 1, panel A we provide summary statistics of administrative records covering all hospitalizations at the municipal by week level. These are all cast as rates per 100,000 exposed population. For the entire population, we observe that respiratory cause account for around 10 percent of all hospitalizations–a mean of 21 hospitalization per 100,000 inhabitants in a week, compared to 182 per 100,000 for all cause hospitalizations–closely followed by circulatory causes. Rates of hospitalization are documented for a number of specific age groups–infants to over 65 years old–and rates are observed to vary considerably by age group. Unsurprisingly, rates of hospitalization are around 4 times higher among infants than in the general population, and around 2 times higher in those aged 65 and older. It is worth noting that in a small number of cases, not all cells have defined values of rates. For example, among infants, less than 1 percent of the cells (2,455 of 270,188) have no defined rate of hospitalization, given that there are zero populations in this particular group in a number of very small municipalities.

## 3.2 Wildfires

We access data on all wildfires occurring in Chile between the period of 2004 until 2021 from administrative records maintained by CONAF. These data are collected and systematized by CONAF and have been made available in a comparable way from 1985 onwards. We work with the period of years necessary to match with hospital records discussed previously, and given that these data are available until the end

[9] A full description of these data and quality checks at the micro level are discussed in Clarke et al. (2022).

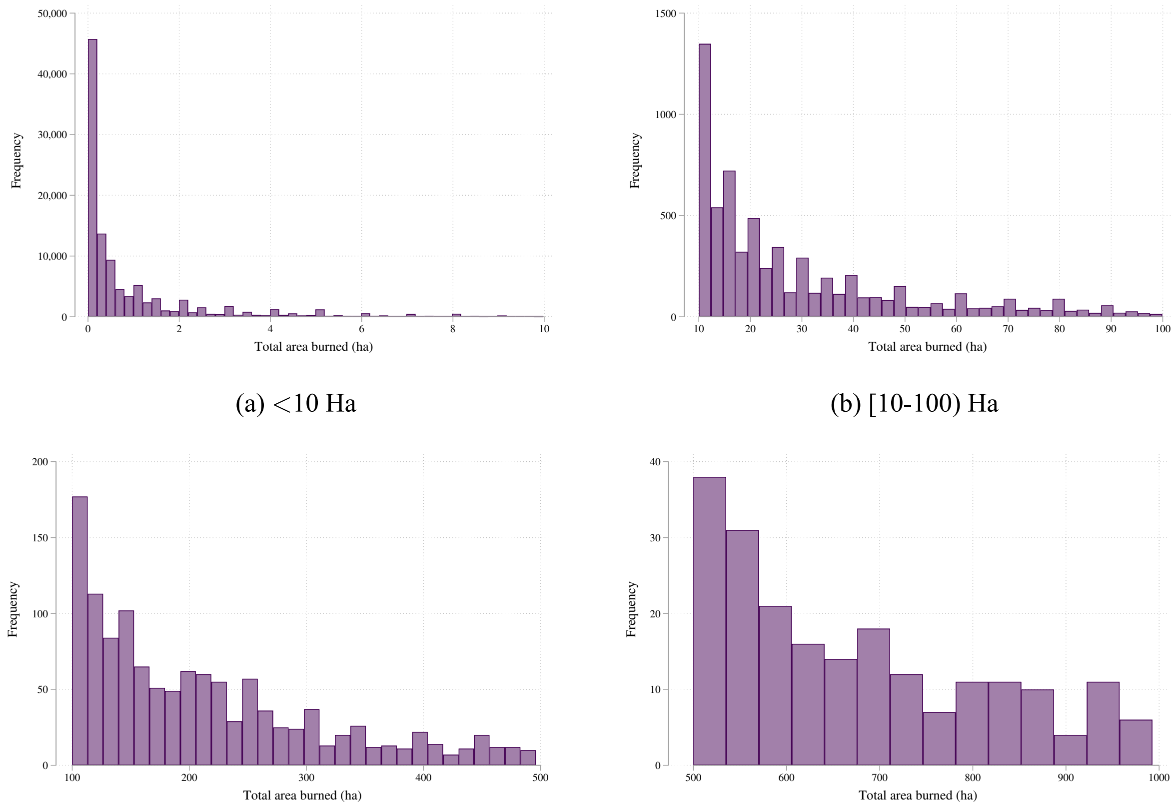
Table 1: Summary Measures of Key Dependent and Independent Variables

| | Obs. | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| **Panel A: Hospitalization Measures** | | | | | |
| All cause hosptilzations (rate per 100,000) | 270,918 | 181.93 | 99.92 | 0 | 4,545.45 |
| Respiratory hospitaliztaions (rate per 100,000) | 270,918 | 21.28 | 23.51 | 0 | 1,515.15 |
| Circulatory hospitaliztaions (rate per 100,000) | 270,918 | 13.62 | 15.40 | 0 | 1,515.15 |
| Burns-related hospitaliztaions (rate per 100,000) | 270,918 | 0.75 | 3.81 | 0 | 1,234.57 |
| All cause hospitalizations (Ages 0-1) | 268,463 | 684.91 | 842.62 | 0 | 100,000 |
| Respiratory hospitalizations (Ages 0-1) | 268,463 | 209.67 | 490.45 | 0 | 100,000 |
| Circulatory hospitalizations (Ages 0-1) | 268,463 | 1.59 | 43.37 | 0 | 12,500 |
| Burns-related hospitalizations (Ages 0-1) | 268,463 | 2.51 | 50.21 | 0 | 15,384.6 |
| All cause hospitalizations (Ages 65 plus) | 270,188 | 403.71 | 374.62 | 0 | 100,000 |
| Respiratory hospitalizations (Ages 65 plus) | 270,188 | 77.93 | 120.02 | 0 | 7,142.86 |
| Circulatory hospitalizations (Ages 65 plus) | 270,188 | 76.03 | 113.79 | 0 | 10,000 |
| Burns-related hospitalizations (Ages 65 plus) | 270,188 | 0.95 | 12.30 | 0 | 2,941.18 |
| Population | 270,918 | 49779.99 | 87836.01 | 66 | 1156302 |
| Year | 270,918 | 2011.01 | 4.32 | 2,004 | 2,018 |
| **Panel B: Exposure to Wildfires and Pollutants** | | | | | |
| $PM_{2.5}$ Concentration | 270,480 | 2.21e-08 | 2.59e-08 | 1.32e-10 | 6.13e-07 |
| Downwind fires $\geq$ 0 Ha | 270,918 | 5.65 | 26.89 | 0 | 1,743 |
| Downwind fires $\geq$ 50 Ha | 270,918 | 0.90 | 3.50 | 0 | 145 |
| Downwind fires $\geq$ 100 Ha | 270,918 | 0.69 | 2.79 | 0 | 106 |
| Downwind fires $\geq$ 150 Ha | 270,918 | 0.57 | 2.48 | 0 | 80 |
| Downwind fires $\geq$ 200 Ha | 270,918 | 0.52 | 2.32 | 0 | 70 |
| Downwind fires $\geq$ 250 Ha | 270,918 | 0.46 | 2.17 | 0 | 64 |
| Downwind fires $\geq$ 500 Ha | 270,918 | 0.31 | 1.73 | 0 | 50 |
| Upwind fires $\geq$ 0 Ha | 270,918 | 4.63 | 26.25 | 0 | 1,601 |
| Upwind fires $\geq$ 50 Ha | 270,918 | 0.72 | 3.10 | 0 | 125 |
| Upwind fires $\geq$ 100 Ha | 270,918 | 0.55 | 2.42 | 0 | 97 |
| Upwind fires $\geq$ 150 Ha | 270,918 | 0.45 | 2.17 | 0 | 95 |
| Upwind fires $\geq$ 200 Ha | 270,918 | 0.40 | 2.03 | 0 | 91 |
| Upwind fires $\geq$ 250 Ha | 270,918 | 0.36 | 1.90 | 0 | 86 |
| Upwind fires $\geq$ 500 Ha | 270,918 | 0.23 | 1.45 | 0 | 63 |

**Notes**: Observations cover municipality by week cells for the 346 municipalities and 783 weeks over the period of 2003-2018. Panel A refers to rates of hospitalizations per 100,000 exposed population and are generated based on consistently applied ICD-10 codings from administrative records. Rates are presented for the full population, as well as two particular age groups (individuals aged 0-1 year and individuals aged $\geq$ 65 years). A small number of missing observations exist for municipal by week cells where the population is zero for a given age, as in these cases population rates are undefined. All measures in Panel B refer to exposures to wildfires of the indicated size at a weekly level, with an exposure referring to a 3-hour period in this municipality in which it was within 200km of a fire of the indicated size. Downwind and upwind refer to the municipality being located downwind ($\pm$ 30 degrees), or upwind ($\pm$ 30 degrees) of the fire.

of 2018, our final sample used in models laid out below consists of fire seasons 2004-2018. These records contain a record of each wildfire, including information on the region, province and municipality in which it occurred, precise geo-reference, the type of land-cover affected, the duration of the wildfire, and the total area burned.

Figure 1: Wildfire Exposures by Magnitude of Fire




(a) <10 Ha

(b) [10-100) Ha

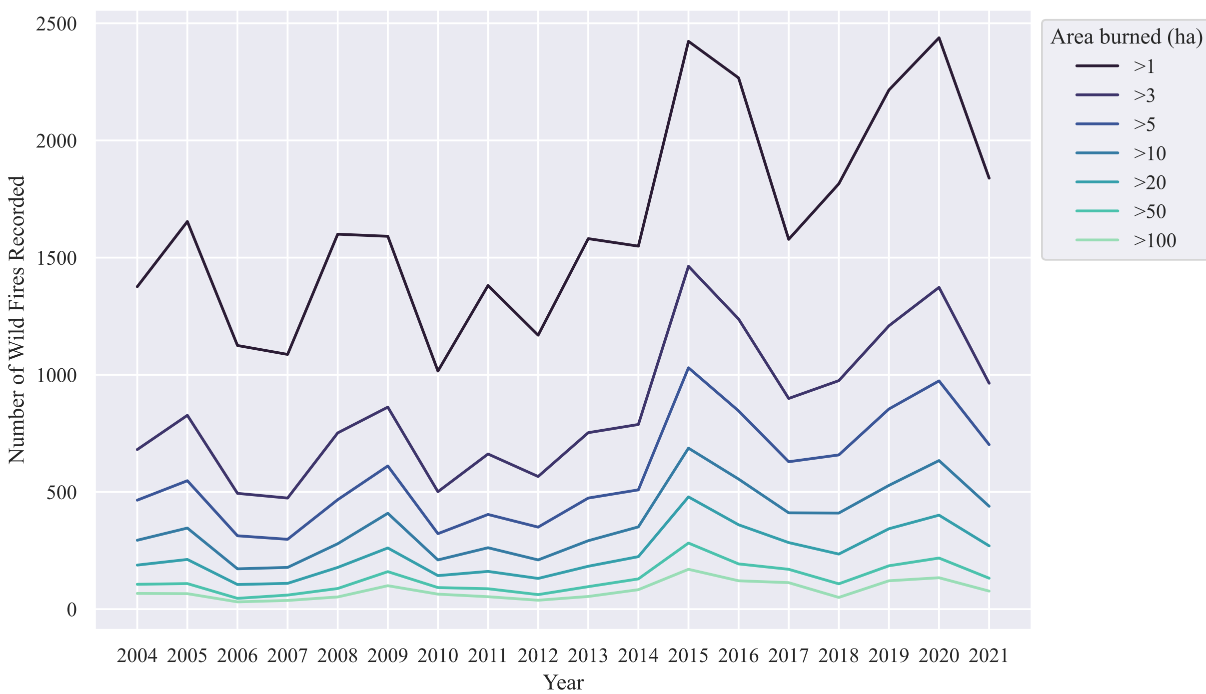
(c) [100-500) Ha

(d) [500-1000) Ha

**Notes:** Histograms describe the number of fires registered across all records maintained by CONAF by the area which they are reported to burn. Given the heavy left-skew of the distribution, these are displayed by area in panel (a)-(d), where panels do not have identically scaled y-axes. These histograms are based on all fires reported at any time during the 2004-2018 fire seasons.

Measures of the total area burned are estimated by CONAF personnel, or in the case of large wildfires, with a magnitude of greater than 200 hectacres (hereafter Ha), these are determined based on satellite images. Measures of total duration of fire are calculated as the time elapsed between the moment when fires were first detected, and the time at which the wildfires were reported to be extinguished. Among all wildfires registered, the majority of wildfires are relatively small (at less than 1 hour and less than 1 Ha burned), though a long tail is observed, with a number of substantially more serious fires. To illustrate this, descriptive histograms of the total area burned, and total duration of recorded fires are displayed in Figure 1, where a small number of outliers have been removed from the plot (fires of $>100$ ha or $> 23$ hours). Appendix Figure A1 documents similar patterns in terms of duration burned. In general, over the period under study we observe some evidence of an increase in exposure to fires, particularly among larger fires. Figure 2 plots the total number of fires reported nationally in each year between 2004-2021, over a range of fire sizes (measured by area burned). If considering all fires of 1Ha or larger, we observe that the number of fires has increased from around 1,500 per year in the early 2000s to around 2000 in the 2020s, and see similar patterns, albeit at much lower magnitudes, for fires of considerably larger sizes. We assess empirically the importance of fires of varying sizes in the Results section of this paper.

Figure 2: Wildfires over Time by Magnitude




**Notes**: The total number of wildfires recorded by CONAF's administrative databases over time is plotted by the total size of the fire. A larger number of fires smaller than 1 hectacre is recorded.

### 3.3 Air Pollution, Wind direction and Meteorological Data

We obtained satellite-level data on fine particulate matter, $PM_{2.5}$, from reanalysis data from the Climate Change Service of the European Centre for Medium-Range Weather Forecasts (ECMWF). In particular, the ECMWF's CAMS global reanalysis (EAC4) provides a dataset at the $0.75° \times 0.75°$latitude-longitude at the earth surface level (more precisely, at atmospheric pressure of 1,000 hPa). This is roughly a $70 \times 70$km grid, every three hours, for the period 2004 to 2018.[10] Summary statistics for this measure are presented in Panel B of Table 1 (measured in $Kg/m^3$), with the variable having been processed to provide a weekly average for each municipality, based on the weekly average of the grid intersecting the municipality. Note that for this measure, there are a small number of observations missing over the entire period, which corresponds to a

[10]For more details, see https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-reanalysis-eac4?tab=overview.

single municipality (Chilean Antarctica).

We obtained satellite-level data on wind direction and velocity, at 10 meters above ground level, from the ERA5-Land reanalysis data of Copernicus' ECMWF. This yields a granular wind direction grid, at the $0.1° \times 0.1°$latitude-longitude–that is, roughly, at a $9 \times 9$ Km grid–every three hours for the period 2004-2018.[11] Using the geo-referenced location of the wildfires, together with data on their duration span, we linked these wildfires to the coordinates of the closest wind-direction data-point to calculate the likely direction of the plume of pollutants, every three hours. This is then overlaid to the bearing from the location of the wildfire to the urban areas near the wildfires. In this way, we identify wildfires that are *upwind* or *downwind* with respect to any given municipality at each period of time (refer to further discussion in Section 3.3 below). Summary statistics of these measures are provided in Panel B of Table 1. These refer to exposure to fires of varying sizes, from all fires ($\geq 0$ Ha) up to very large fires ($\geq 500$ Ha). These measures all refer to the number of 3-hour long periods in a given week when a municipality was exposed to a fire of this size.

Finally, to capture meteorological and climate conditions we use reanalysis data from ERA5's Copernicus Satellite Sentinels provided by ECMWF. This allows us to obtain ground-level data for temperature and precipitation at the $0.1° \times 0.1°$(equivalent to roughly $9\times 9$ Km).

# 4 Methods

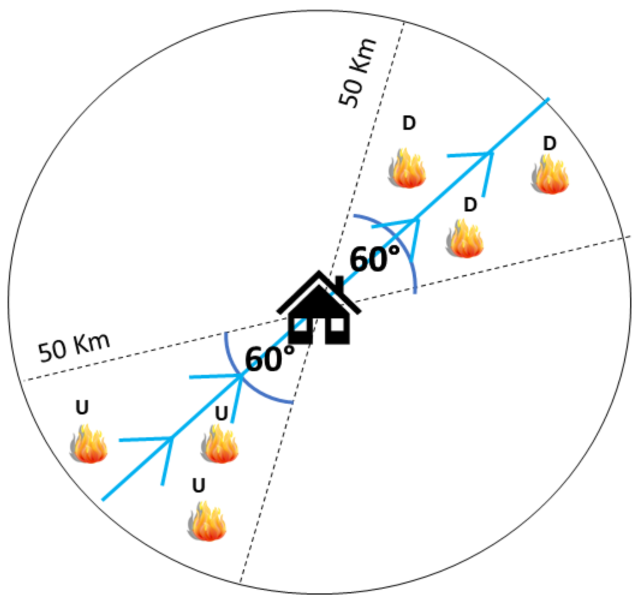
Our design seeks to estimate the causal impact of exposure to wildfires at the population level. Given that exposure to fire is not random–for example, individuals located in more southern, hotter areas of the country, and areas closer to more vegetation are more likely to be exposed to wildfire–we seek to gain causal identification by interescting a fire's location with (exogenous) wind direction. In simple terms, causal identification comes from the fact that while wildfire location may not be as good as random, the wind direction–which is as good as random at any given moment–will cause some municipalities to be exposed to the air pollutants of a wildfire given that the wildfire is *upwind* from these municipalities, while otherwise similar municipalities are not exposed, given that the wildfire is *downwind* from these municipalities. Below, we first lay out details of this design in Section 4.1 before laying out precise empirical specifications in Section 4.3.

[11]Details on this reanalysis data are available on the website of the Copernicus Climate Change Service https://cds.climate.copernicus.eu/cdsapp#!/software/app-era5-explorer?tab=overview.

## 4.1 Wind Direction as a Causal Empirical Design

To ensure that we capture exogenous exposure to wildfire air pollution, we follow the empirical strategy first adopted by Rangel and Vogl (2019) to identify causal effects. This strategy consists of using ground-level wind direction data to identify wildfires that are *upwind* from a given municipality as well as wildfires that are *downwind* from it. In this way, we estimate the effects of exposure to the air pollution from *upwind* wildfires on the health outcomes of the population residing in each municipality, as well as documenting the considerable relevance of upwind exposure as a driver of ambient air pollution.

Figure 3: Exposure to Wildfires Air Pollution



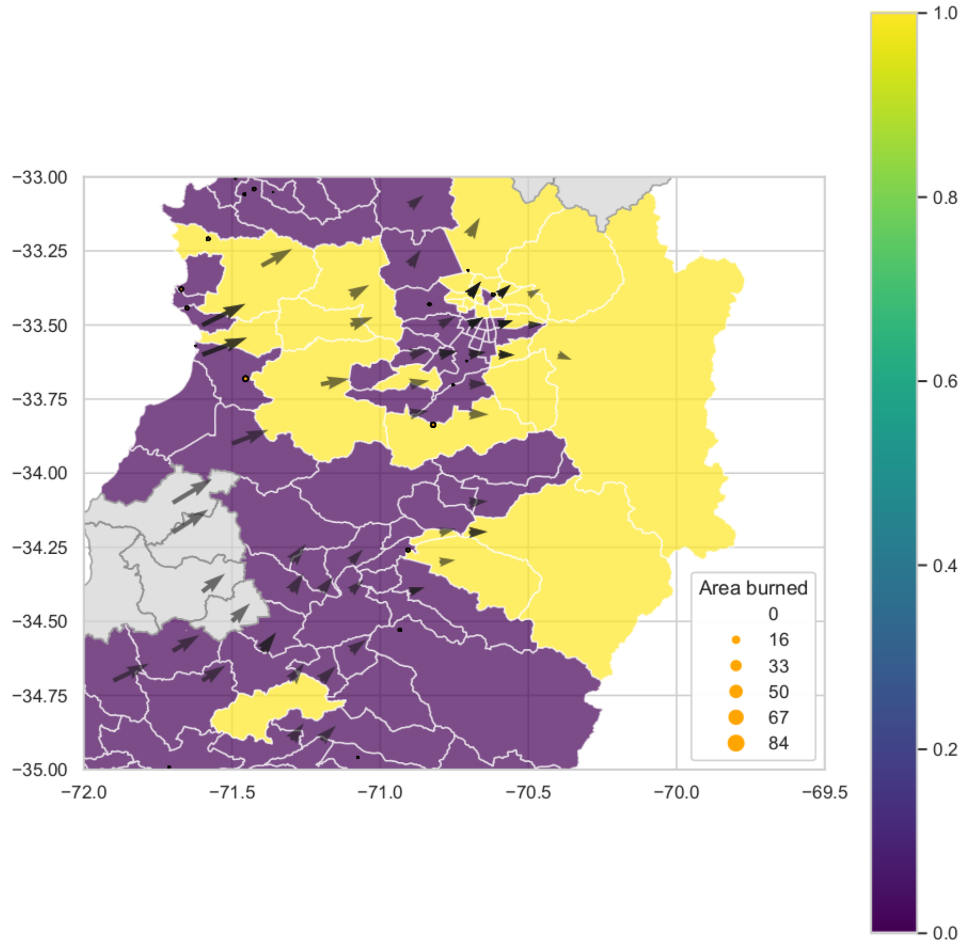

Notes: A schematic representation of exposure to wildfires is presented. Within a distance of 50km from a municipality *upwind* wildfires are denoted **U** and *downwind* wildfires are denoted **D**. The light blue ray represents wind direction, and the 60° yields the pie-area defining *upwind* and *downwind* wildfires.

Figure 3 above illustrates this strategy. In our specification, an *upwind* wildfire for a given municipality (**U**, in the figure) is a fire which falls within the sector of the circle formed where a 60° angle bisects the wind direction, represented as the blue ray in Figure 3.[12] Conversely, a *downwind* wildfire (**D**, in the figure) falls within the sectant formed by a 60° angle bisected by the *opposite* of the wind direction. The logic of this design–and something which we will demonstrate empirically–is that the prevailing wind will take air pollutants from the smoke plume of wildfires which are upwind from a municipality towards the municipality, exposing residents to these air pollutants, while the prevailing wind will take air pollutants from wildfires

[12]The urban centroid refers to the population-weighted geographical central point of the municipality.

downwind from the municipality away from the municipalities, implying that residents are un-exposed.

Figure 4: Exposure Design to (Upwind) Wildfires Air Pollution




Notes: Large orange points represent fires, gray arrows represent wind directions (arrow heads) and velocities (length of arrow). Shaded colors refer to whether municipalites have an upwind wildfire (yellow), downwind wildfire (purple) or not within 50km of a wildfire. This is a representative figure at a particular moment of time, focusing only on the metropolitan region of Santiago. To observe how such patterns evolve over longer periods, refer to the dynamic figure: http://damianclarke.net/resources/fires_and_wind_upwind.gif.

In practice, and for a particular moment of time, this design is laid out in the map presented in figure 4 above. This map displays the metropolitan region of Santiago (Chile's capital), and surrounding regions, with white boundaries representing municipal borders. Wind vectors displayed as arrows document the direction of wind at a particular moment of time, as well as their velocity (indicated by the length of the arrow). The location of fires burning at that is indicated with orange circles. Thus, depending on how wind intersects wildfires, nearby municipalities are exposed (municipalities indicated in yellow) or unexposed (municipalities indicated in purple) to their air pollutants. Municipalities colored in gray are located greater than 50km from the nearest wildfire, and hence these wildfires are classified neither as upwind nor non-

Figure 5: Seasonal Patterns of Presence and Exposure to Wildfires


**Notes:**

upwind. Appendix Figure A2 provides a similar representation we plot for the whole country, additionally noting distances to active fires.

Definitions of exposure to the air pollutants from a wildfire in this way are thus dynamic. As for a given wildfire it may be classified as upwind at a particular moment, but later in time the direction of wind may change, and it will be classified as downwind. For wildfires which burn for a short period of time this may not occur, but for fires with a longer duration, this is likely to occur. For this reason, the definition of upwind or downwind wildfires is dynamic.

To generate these measures we begin with a record of each wildfire and its duration. This is combined with records of wind direction and speed which are available with a frequency of 3 hours. In our dataset we expand each wildfire for the full duration for which it is burning, in blocks of 3 hours, and then this is merged with the wind direction and speed with closest proximity to the fire in that 3-hour block. For example, a wildfire which burns for 48 hours is associated with 16 cells in our dataset, each of which contains the unique wind direction and wind speed at the 3-hour period for the wildfire's location. All municipalities within 50 kilometers of these wildfires are then considered as potentially exposed, and if a municipality has a wildfire within a 60° bearing of the current wind direction (i.e., -30° to +30°), this wildfire is classified as *upwind*. If wildfires are diametrically opposed to the current wind direction, plus or minus 30° (i.e., 150° to 210°), they are classified as *downwind* from the municipality. Any wildfires within a 50 kilometers distance from a municipality, but that are not upwind, are classified as ”non-upwind” wildfires. This consequently results in a municipality panel dataset with a frequency of 3 hours indicating whether a municipality is exposed to one or potentially multiple wildfires, and whether this wildfire(s) is upwind or downwind. This procedure is repeated for all wildfires. Moreover, it is also repeated considering only wildfires burning at least certain minimum surface areas–specifically, at least 50 hectares, 100 hectares, 200 hectares, and so on.

To conduct analysis at a weekly level, laid out further below, we calculate for each municipality the number of 3-hour periods during the week in which it was exposed to an upwind wildfire, and similarly the number of 3-hour periods in which it was exposed to a downwind wildfire. In implementing this strategy, we observe expected seasonal cyclicality in the presence of and exposure to wildfires (Figure 5) throughout the year, where in peak summer months up to 60 percent of the municipalities are exposed to at least one *upwind* wildfire, with up to 70 percent of municipalities being exposed to any type of wildfire.

## 4.2 Further Design Considerations

In this paper we are interested in examining the health effects of exposure to ambient air pollution. To this end, we leave out of our sample those people living within a ”buffer zone” of 5km from the wildfire. We do this under the assumption that those living in such a proximity to a wildfire may experience first-hand the destructive consequences of the flames and direct smoke. Thereby, these people may not be exposed to the ambient air pollution from the wildfire, but instead, to much elevated levels of air pollution as well as other possible health stressors and harms.[13] Moreover, when analyzing our main health outcomes, we identify those individuals that experience health problems that are due to direct exposure to wildfires–such as those experienced by firefighters and/or those who experience respiratory problems due to direct exposure to active wildfires ”on-site.” To this end, our health data allow us to identify the first reason for the symptoms, as assessed by health care professionals according to ICD-10 codes. For those who experience injuries and other consequences due to external causes (ICD-10 codes S00 through T88) our data allow us to identify whether the reason is associated with direct exposure to smoke, fire and flames (ICD-10 codes X00 through X08). Thereby, these ICD-10 codes allow us to group those people into a separate category.

[13] In addition, those in very short proximity to wildfire may change their behavior in such a way that it is not feasible to construct a control group for these individuals.

## 4.3 Empirical Specifications

### 4.3.1 Contemporaneous Effects

We take this design to the data in the following way. To begin, we estimate contemporaneous models which estimate the impact of exposure to upwind and downwind fires on a number of health and environmental outcomes. Specifically, we estimate:

$$y_{mrt} = \alpha + \beta \text{Upwind}_{mt} + \gamma \text{Downwind}_{mt} + \varphi_m + \mu_r \cdot \lambda_t + \boldsymbol{X}'_{mt}\boldsymbol{\Gamma} + \varepsilon_{rmt}, \tag{1}$$

where $y_{mrt}$ refers to outcomes in municipality $m$, in region $r$ and in week $t$. These outcomes are regressed on the number of upwind fires and the number of downwind fires occurring in that particular week. The coefficient of interest $\beta$ captures the marginal effect of exposure to upwind wildfires conditional on any exposure to downwind wildfires; similarly, $\gamma$ captures the marginal effect of exposure to downwind fires conditional on any upwind exposures. We capture any municipality-specific time-invariant factors, such as geographic location, with $\varphi_m$. Importantly, we consistently include region by week fixed effects, here $\mu_r \cdot \lambda_t$.[14] This is key to the design, as it allows us to isolate exposure to marginal upwind or downwind fires when comparing to municipalities within the same region and time period. Finally, in certain specification we include time-varying controls capturing conditions such as temperature and humidity. The term $\varepsilon_{rmt}$ is a stochastic error term, and standard errors are consistently clustered in two ways, by municipality and week. Two-way clustering is appropriate given that we have a large sample in both dimensions suggesting that asymptotic assumptions are likely met (Cameron and Miller, 2015). Clustering by municipality allows for arbitrary correlations of shocks within municipalities across time, while clustering by week allows for arbitrary correlations between shocks over space in a particular moment of time.

Outcomes examined for equation 1 are, firstly, rates of ambient $PM_{2.5}$, and secondly, rates of hospitalization for a range of morbidities and demographic groups. In the case of $PM_{2.5}$, rather than estimate at the weekly level, which is likely to considerably smooth sharp spikes in contaminants closely occurring around wildfires, we estimate specifications at a daily level, where all other details follow equation (1). In the case of models for hospitalization rates, specifications are consistently weighted by municipal population to ensure that results are not driven by municipalities with very small populations where small changes in the number of events can lead to very large changes in rates.

[14] Municipalities are nested within "regions" (or districts). There are 16 "regions" in Chile, which make up the second level of administrative government.

These models provide the reduced-form effect of wildfire exposure on the outcomes considered. Alternatively, one could estimate two-stage models where wildfire exposure is used to instrument pollution, and the instrumented effect of pollution is then used in a second stage regression of hospitalizations on pollutants. Currently, we present reduced-form and first-stage regressions separately, though note that these can be scaled to give the equivalent two-stage least square estimates.

#### 4.3.2 Persistent Effects

Our parameter of interest, $\beta$ and $\gamma$ in equation (1) above, captures the contemporaneous effect of wildfires on outcome $y_{mrt}$. However, in certain cases impacts may persist for more than a single period of time, or not appear instantaneously, and as such we also estimate the dynamic version of equation (1). Specifically, this is:

$$y_{rmt} = \alpha + \sum_{j=-J}^{K} \beta^j \text{Upwind}_{m,t+j} + \sum_{j=-J}^{K} \gamma^j \text{Downwind}_{m,t+j} + \varphi_m + \lambda_t + \boldsymbol{X}'_{mt}\boldsymbol{\gamma} + \varepsilon_{rmt}, \tag{2}$$

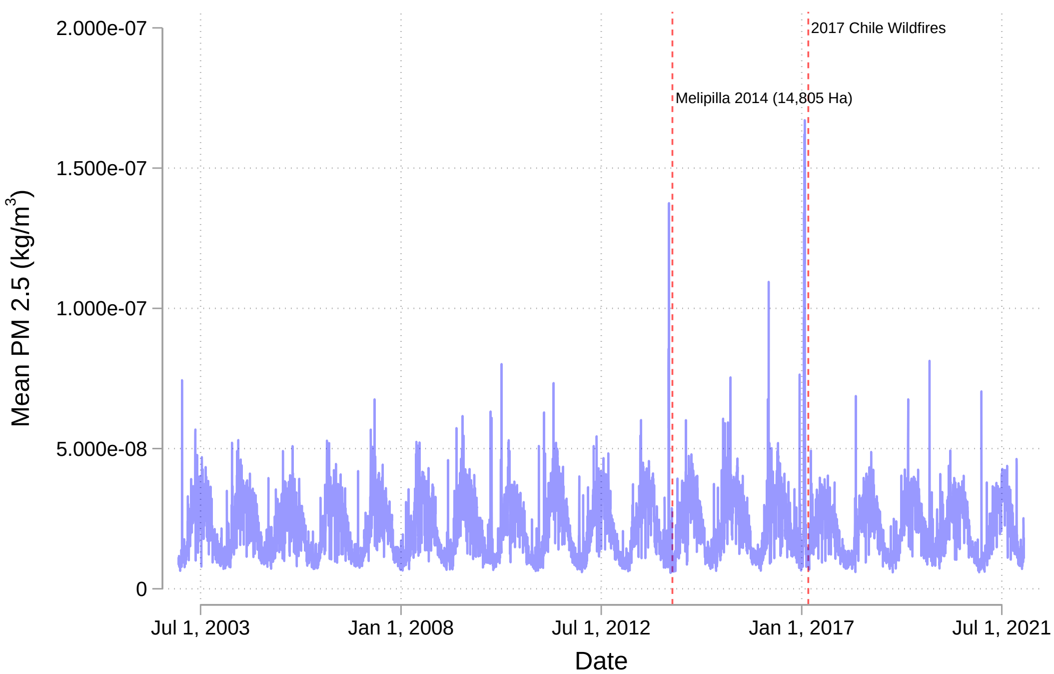
where all details follow those laid out previously in (1). Instead of (only) considering the contemporaneous impact of wildfire air pollution, however, we also consider $J$ lag and $K$ lead effects. The $J$ lags refer to impacts of having been previously exposed to the air pollution from a wildfire. For example, exposure to a wildfire one week previously may be reflected in hospitalization rates if individuals remain hospitalized for an extended period. Likewise, health impacts from exposure may be aggravated over a period of time and possibly result in hospitalization in the following week(s). On the other hand, the $K$ leads can be viewed as a partial test of our identifying assumptions, as there can be no impact of *future* exposure to wildfire on contemporary health outcomes, conditional on current and prior exposures. If our model is correctly specified, those terms associated with the $K$ leads should not be observed to be significantly different from zero. This is a test in the lines of Granger (1969) causality.

## 5 Results

### 5.1 Impacts of Wildfire on $\text{PM}_{2.5}$ Pollution

A first key consideration is whether this design actually captures true exposure to air pollutants. For this reason, we first estimate equation (1) where the outcome consists of $\text{PM}_{2.5}$ concentrations. Descriptively, it appears clear that large wildfires are important drivers of air pollution levels. Figure 6 presents a descriptive plot of mean rates of daily ambient $PM_{2.5}$ in Chile over the period of 2003-2021. While there is clear cyclical variation in line with temporal patterns in which $PM_{2.5}$ concentrations are substantially higher in winter than summer, key sharp spikes are observed during summer months each year. The most notable of these are indicated with red vertical lines (slightly shifted so as not to obscure the spikes), and are observed surrounding large wildfires, or series of megafires. For example, the wildfires of 2017 are associated with mean $PM_{2.5}$ concentrations which are an entire order of magnitude higher than is standard in summer months, and rates of $PM_{2.5}$ concentrations around four times higher than winter peaks.

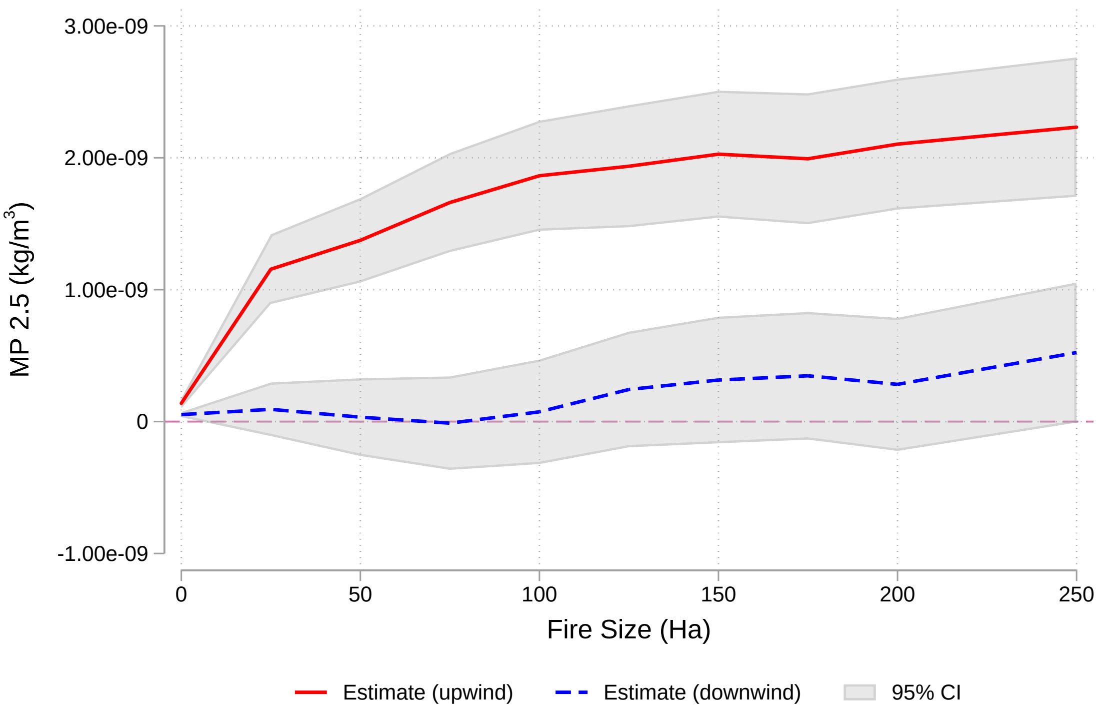
Figure 6: $PM_{2.5}$ Concentrations over Time




**Notes**: Mean daily $PM_{2.5}$ concentration is plotted across the entire country for the period under study. Vertical dashed lines note key fire events. These dashed lines are offset slightly to the right, as otherwise they exactly overlap with large spikes observed in $PM_{2.5}$ concentrations. These events refer to the largest fire of the 2013-2014 fire season, which was a a fire in the locality of Melipilla which began on the 3rd of January 2014, eventually burning over 14,000 hectares, and the 2017 wildfires which affected over 500,000 hectares in the South of the country, with 11 lives lost and thousands of homes destroyed in the fire, and with a peak intensity on January 27-28 of 2017.

We estimate this relationship formally in Figure 7. Here we present a series of parameter estimates and their corresponding 95% CIs for the coefficients $\beta$ (solid red line) and $\gamma$ (dashed blue line) from equation (1). In this case, upwind and downwind effects are estimated based on a range of fires as indicated on the x-axis, namely all fires of 0 Ha or above, all fires of at least 50 Ha or above, up to all fires of at least 250 Ha or above (in increments of 50 Ha). Sets of coefficients on upwind and downwind are estimated in a single model for each fire size plotted in the figure.

Figure 7: Exposure to Wildfires and $PM_{2.5}$




Notes: Each coefficient and confidence interval presents the impact of regression where airborne PM 2.5 concentrations are regressed on the number of wildfires which are *upwind* (red solid line) and *downwind* (blue dashed line) from a given municipality. Observations consist of municipality cells in each 3 hour block occurring from 2002 to 2021 (18,147,000 observations). Each specification includes full municipal and hour×day×month×year fixed effects, and the definition of the independent variable is based on exposure to wildfires of the size indicated on the x-axis or generated. 95% confidence intervals are presented based on standard errors clustered by municipality.

In all specifications, we observe clear impacts of exposure to wildfires on ambient concentrations of $PM_{2.5}$. Moreover, we observe exposure to upwind fires produces large increases in $PM_{2.5}$ concentrations, while exposure to downwind fires produces small increases, which are often not statistically distinguishable from 0. This suggests validation of the exposure design insofar as municipalities which are arguably similar receive remarkably different exposures to air pollutants from wildfires owing to the wind direction at the particular time of the fire. The impact of wildfires is estimated to vary considerably by the size of fires considered. When all fires are considered (estimate at 0 on the x-axis), we see significant but relatively small impacts of the exposure to a single upwind wildfire on $PM_{2.5}$. Point estimates in this case are at around $2\times10^{-10}$kg/m$^3$, which is around 1% of a standard deviation of $PM_{2.5}$ concentrations in the period under study (refer to Table 1). However, impacts increase substantially, as only larger wildfires are considered. For wildfires of 100 Ha or above, an additional exposure is estimated to increase ambient contaminants by around 10% of a standard deviation ($2\times10^{-9}$ kg/m$^3$), with estimated effect sizes observed to grow nearly monotonically as successively larger fires are considered. In the case of downwind exposures, we observe that null effects are observed across the board, though these move to being marginally significant when considering very large fires, consistent with the fact that very larger smoke plumes may impact nearby municipalities even if fires are located downwind.

## 5.2 Impacts on Inpatient Hospitalizations

We now turn to consider the impacts of exposure to wildfires air pollution on health outcomes as measured by inpatient hospitalizations. In Table 2 we present results for equation (1) considering all cause hospitalizations in Panel A, and hospitalizations for respiratory causes only (ICD-10 codes J00-J99) in panel B. Each column considers separate independent variables based on the total number of fires of at least the size indicated in column headers. For example, column 1 uses as dependent variables the number of upwind and downwind fires of at least 50 Ha to which a given municipality is exposed, and similarly in other columns with fires of larger dimensions.

In panel A, while estimated effects of exposure to upwind fires are positive, effects are not statistically distinguishable from zero even in the case of very large fires of 500 Ha and above. Given that all cause hospitalization includes many hospitalizations which cannot conceivably be affected by air pollution exposure (refer to Appendix Table A1 for a description of all top-level ICD-10 classifications). This is not surprising, as effects in affected morbidity classes will be diluted by noise in other non-affected classes. The total effect sizes in this case are relatively moderate. For example, considering (insignificant) effect sizes, a 1 standard deviation increase in exposure to 50 Ha upwind wildfires would increase rates of hospitalization by less than 0.05% ($0.035\times3.1/181.9$), while a similar 1 standard deviation increases in upwind fires of larger sizes are estimated to increase rates of hospitalization by no more than 0.16% (corresponding to fires of 500 Ha or larger; all standard deviation increases refer to values in Table 1).

Turning to effects related to causes more sensitive to wildfires air pollution, panel B estimates impacts of exposition on hospitalizations specifically for respiratory causes. Here we observe that upwind wildfire exposure consistently increases rates of hospitalization, and these effects are statistically distinguishable from zero when considering very large fires. In the case of fires of 500Ha or above, we estimate that an additional upwind wildfire during the week increases rates of hospitalization for respiratory causes by 0.109 per 100,000 residents. When expressed in terms of a 1 standard deviation movement in upwind fires, this effect is equivalent to a 0.75% increase in rates of hospitalization across all ages ($0.109\times1.45/21.284$). While

Table 2: Effects of Wildfire Exposure on Hospitalizations, by Fire Size

| | 50 Ha<br>(1) | 100 Ha<br>(2) | 200 Ha<br>(3) | 500 Ha<br>(4) |
|---|---|---|---|---|
| **Panel A: All Cause Hospitalizations** | | | | |
| Upwind fires during week | 0.035 | 0.094 | 0.046 | 0.201 |
| | (0.100) | (0.127) | (0.129) | (0.177) |
| Downwind fires during week | -0.222 | -0.307 | -0.359 | -0.415 |
| | (0.172) | (0.194) | (0.233) | (0.265) |
| Mean of Dep. Var. | 181.932 | 181.932 | 181.932 | 181.932 |
| Observations | 270,918 | 270,918 | 270,918 | 270,918 |
| R-Squared | 0.77 | 0.77 | 0.77 | 0.77 |
| | 50 Ha<br>(1) | 100 Ha<br>(2) | 200 Ha<br>(3) | 500 Ha<br>(4) |
| **Panel B: Respiratory Hospitalizations** | | | | |
| Upwind fires during week | 0.020 | 0.039 | 0.045 | 0.109** |
| | (0.042) | (0.050) | (0.047) | (0.054) |
| Downwind fires during week | 0.019 | 0.023 | 0.028 | 0.032 |
| | (0.034) | (0.038) | (0.038) | (0.043) |
| Mean of Dep. Var. | 21.284 | 21.284 | 21.284 | 21.284 |
| Observations | 270,918 | 270,918 | 270,918 | 270,918 |
| R-Squared | 0.60 | 0.60 | 0.60 | 0.60 |

**Notes**: Sample consists of municipality by week cells between 2004-2019. All specifications include time (week by year) and area fixed effects (municipality and region by week by year). Column headers indicate exposure to fires greater than specific sizes. All outcomes are cast as rates per 100,000 population considering all ages, with dependent variable means listed in Table footers. All observations are weighted by municipality population. Standard errors clustered by municipality and week are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

these results may not sound very large, consider that the most extreme municipality×week cell exposure was 63 four hour periods during the week (consistent with multiple large wildfires burning all week).[15] For a municipality with such an extreme exposure, the linear marginal effects suggest impacts of up to a 33% increase in hospitalizations (0.109×63/21.284). In general, and in line with results from Figure 7, we observe no impact of exposure to downwind wildfires, which is consistent with the fact that there is no observed impact on pollutants when wildfires are downwind.

These results presented in Table 2 are for individuals of all ages, though extant evidence from both

[15] Upwind and downwind fires refer to the total number of exposures in blocks of 3 hours, and if multiple fires are burning concurrently in a given 3-hour period, this will be captured as multiple exposures in this period. For this reason, certain municipalities have more than 56 exposures in a week, which is the total number of 3-hour blocks in 7 days.

environmental and other literatures makes clear that certain groups of individuals are more vulnerable to health shocks than others (Ogasawara and Yumitori, 2019; UNICEF, 2021; Almond et al., 2018). Results are presented by age in Table 3 considering impacts across age groups. Panel A considers ages which are potentially more exposed (infants and young children, and individuals aged 65 and above), while panel B considers groups which are likely less sensitive (older children and younger adults). Models in Table 3 follow those in Table 2, in the interests of space considering only wildfires of 100 Ha or larger or wildfires of 250 Ha or larger. In this case, in particular for individuals age between 0 and 1, we observe significant effects of exposure to upwind wildfires. For infants, we observe that exposure to a single additional period of upwind exposure increases rates of hospitalization by 1.2-1.4 per 100,000, or around a 0.6% increase in total hospitalizations. As in results noted in Table 2, we observe no impact of exposure to downwind wildfires. Results appear largely concentrated among infants, with no significant results observed for other age-groups, even among older adults. Appendix Figures A3 (upwind exposure) and A4 (downwind exposure) present estimates in a more fine-grained way, considering five-year age groups. Here we observe that while there is evidence of certain effects at specific older age groups (for example an increase in hospitalizations among 61-65 year-olds in A3 panel (b)), these effects are not consistently observed in the same way as those among infants. When considering effects for downwind exposure, we observe that estimates are both smaller, and generally null (Appendix Figure A4).

Finally, in considering static effects corresponding to equation 1, we document effects of upwind exposure by age on specific hospitalization causes in Figure 8. Here we present results for each age group documented in Table 3 however now considering hospitalizations for respiratory causes (panel (b)), hospitalizations for diseases of the circulatory system (panel (c)), and hospitalization for burns-related causes (panel (d)). For comparison, results for all hospitalizations are presented in panel (a). In general, results once again point to main impacts being driven by exposure among infants. There are a small number of other significant effects observed, though these are small (e.g., effects on respiratory hospitalizations among those 16-40 years old).

### 5.3 Dynamic Impacts of Wildfire Exposure on Hospitalizations

In this section we present results for impacts of exposure to wildfires not only in the current period of time (current week) but also in recent periods. In these analyses, we are interested in dynamic effects for two reasons. Firstly, these allow us to capture potentially non-immediate effects, which may emerge either if hospitalizations resulting from wildfire exposure are serious and individuals remain hospitalized for a number

Table 3: Wildfire Exposure and All Cause Hospitalizations by Age

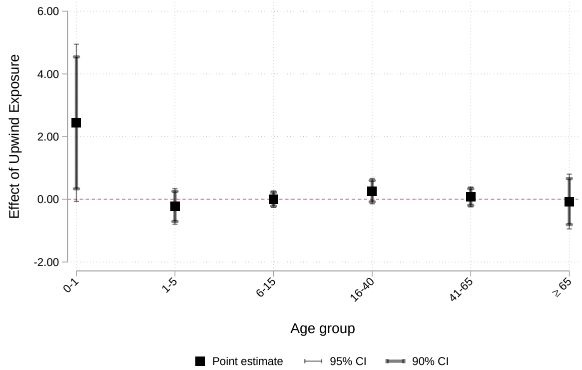
| | Infant (0-1) | | Toddler (1-5) | | Older Adults (65+) | |
|---|---|---|---|---|---|---|
| | 100 Ha | 250 Ha | 100 Ha | 250 Ha | 100 Ha | 250 Ha |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Sensitive Ages** | | | | | | |
| Upwind fires during week | 1.153* | 1.435* | -0.074 | -0.029 | 0.077 | 0.182 |
| | (0.649) | (0.768) | (0.204) | (0.225) | (0.268) | (0.329) |
| Downwind fires during week | -0.119 | -0.357 | -0.125 | -0.225 | 0.113 | 0.002 |
| | (0.723) | (0.831) | (0.285) | (0.361) | (0.304) | (0.388) |
| Mean of Dep. Var. | 443.401 | 443.401 | 121.096 | 121.096 | 356.141 | 356.141 |
| Observations | 286,247 | 286,247 | 286,196 | 286,196 | 288,336 | 288,336 |
| R-Squared | 0.50 | 0.50 | 0.36 | 0.36 | 0.58 | 0.58 |
| | **Children (6-15)** | | **Young Adults (16-40)** | | **Mid age (41-65)** | |
| | 100 Ha | 250 Ha | 100 Ha | 250 Ha | 100 Ha | 250 Ha |
| **Panel B: Less-Sensitive Ages** | | | | | | |
| Upwind fires during week | 0.084 | 0.071 | 0.171 | 0.187 | 0.062 | 0.060 |
| | (0.106) | (0.114) | (0.139) | (0.150) | (0.123) | (0.143) |
| Downwind fires during week | -0.063 | -0.093 | -0.343 | -0.483 | -0.059 | -0.154 |
| | (0.155) | (0.187) | (0.226) | (0.331) | (0.143) | (0.176) |
| Mean of Dep. Var. | 81.480 | 81.480 | 175.579 | 175.579 | 155.707 | 155.707 |
| Observations | 287,814 | 287,814 | 288,910 | 288,910 | 288,910 | 288,910 |
| R-Squared | 0.39 | 0.39 | 0.61 | 0.61 | 0.66 | 0.66 |

**Notes**: Sample consists of municipality by week cells between 2004-2019. All specifications include time (week by year) and space fixed effects (municipality and region by week by year). Column headers indicate exposure to fires greater than specific sizes. All observations are weighted by municipality population. Standard errors clustered by municipality are listed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

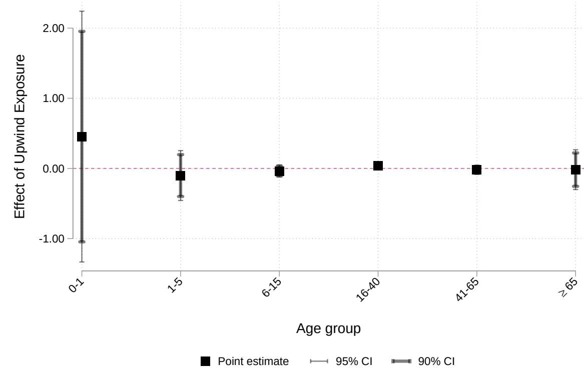
of weeks, or dynamic in nature, with exposure in a given week also resulting in further complications in the immediate future. Secondly, these allow us a partial test of identifying assumptions insofar as no effect should be observed on current hospitalizations given exposure to a wildfire in the future. If we observe such anticipatory effects, we may be concerned that effects estimated up to this point owe to differential trends in outcomes in exposed and non-exposed areas, rather than causal estimates.

Results for equation (2) are presented in Figure 9 below. Here we consider all cause hospitalizations for infants, which in the previous sub-section have been documented to increase considerably based on exposure to wildfires. Here we consider 2 lead terms (pre-exposure periods), the instantaneous effect (denoted as ”Lag

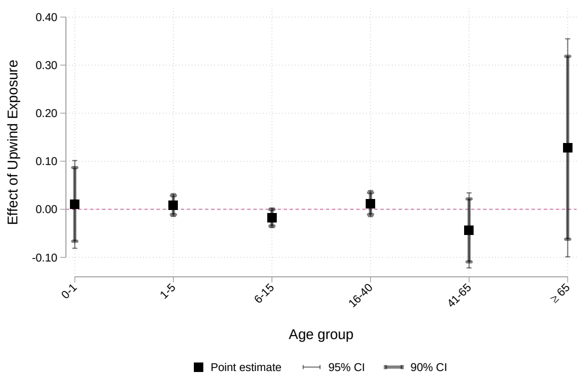
Figure 8: Impacts of Fire Exposure (Upwind) on Age-Specific Hospitalizations, by Cause



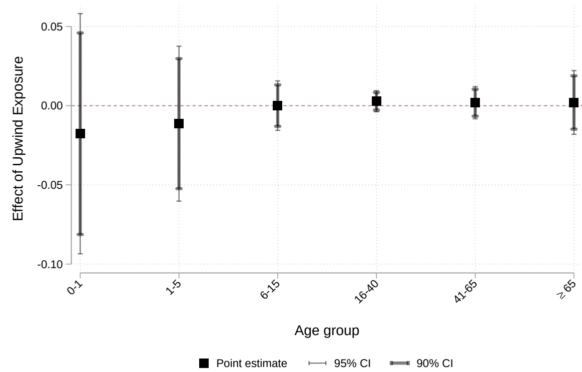

(a) All cause hospitalizations




(b) Respiratory Causes




(c) Circulatory Causes



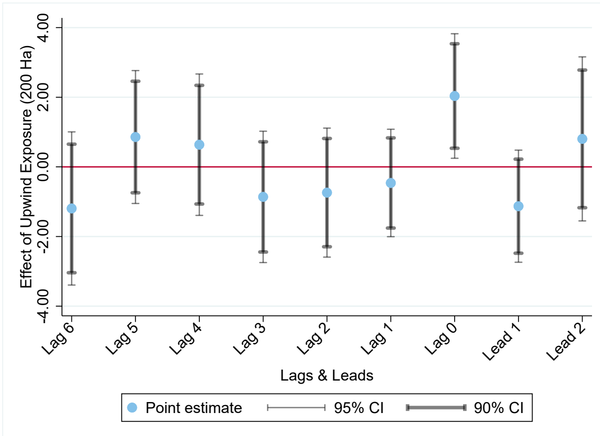

(d) Burns

Notes: Each coefficient and set of confidence intervals is drawn from a separate regression model identical to that presented in Table 2 based on municipality and week cells from 2004–2019. Outcomes are defined as mortality per 100,000 in the age group indicated on the horizontal axis. Each panel is based on dependent variable (upwind fire exposure) to any wildfire of 150 hectares are greater. All other details follow notes to Table 2.

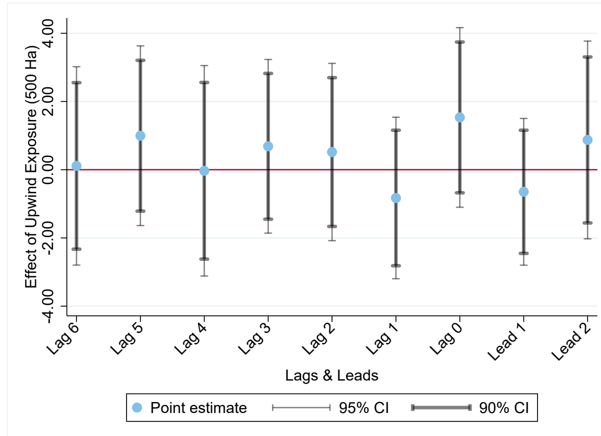
0” in Figure 9), and 6 further lag terms. This allows us to capture impacts of wildfires being realized up to a month and a half after the original exposure. Results are presented for exposure to large fires: fires greater than or equal to 200 Ha in panel (a), and greater than or equal to 500 Ha in panel (b).

Here we observe that exposure to wildfires results in considerable spikes at the time of exposure (”Lag 0”), with little evidence of longer-term impacts. In the case of 200 Ha fires, effects are large and statistically significant, while in the case of 500 Ha fires, results are very similar in magnitude, but with wider confidence intervals. In general, at least up to 6 weeks post-exposure, we do not observe significant impacts. This of course does not rule out the possibility that exposure to wildfire in current periods may have longer-term outcomes. Indeed, results from the wider literature suggest substantial accumulative results may be

Figure 9: Dynamic Impacts of Upwind Wildfires on Infants' Hospitalizations for All Causes




(a) Fires $\geq$ 200 Ha



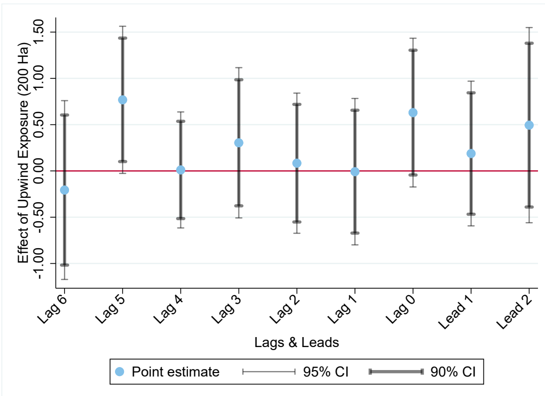

(b) Fires $\geq$ 500 Ha

Notes: Each coefficient and set of confidence intervals is drawn from a regression model akin to that presented in Table 2 based on municipality and week cells from 2004-2019. These estimates are obtained from running a dynamic model, as in equation (2), with 6 lags and 2 leads. All other details follow those provided in notes to Table 2.

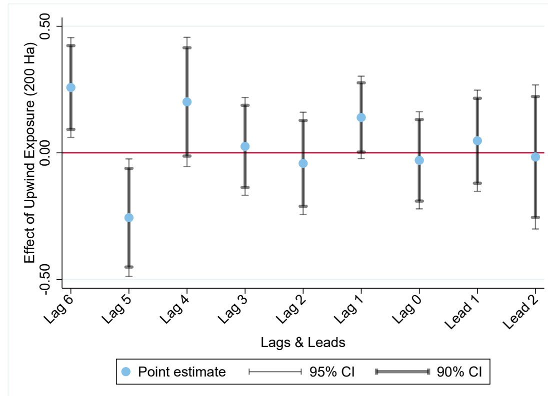
observed throughout life (Fuller et al., 2022; Russ et al., 2021). Rather, these results simply suggest that, in the surroundings of large wildfires, most impacts are observed contemporaneously with no clear evidence of spillovers in hospitalizations in future weeks. In work-in-progress based on linked microdata we are examining how exposure affects future health at an individual level across an individual's life course.

Results for alternative age groups, and for respiratory hospitalizations in particular, are presented in Figure 10. These results estimate identical models to those documented in Figure 9 panel (a), however now considering only respiratory hospitalizations, and for each age group previously considered in Table 3. Similar results, but for larger fires of 500 Ha are provided as Appendix Figure A5. Here once again we consistently observe null effects for pre-exposure periods, providing further support for the upwind exposure design. We observe effects suggestive of increases in hospitalizations at Lag 0 for infants (panel (a)), and older adults (panel (f)), but neither are statistically significant. We observe some evidence of delayed effects for certain groups (for example panel (b) and (f), though effects are considerably smaller than those documented for infants.

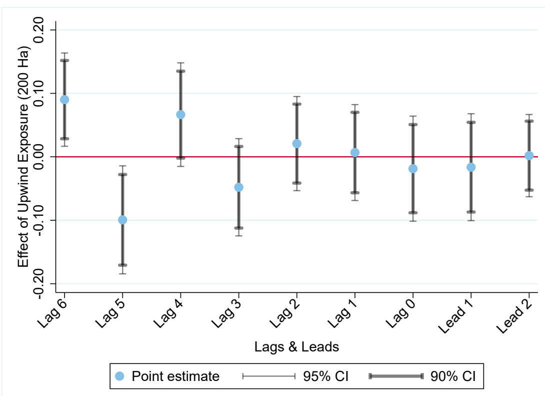
Figure 10: Dynamic Impacts of Upwind Wildfire Exposure on Respiratory Hospitalizations, by Age Group



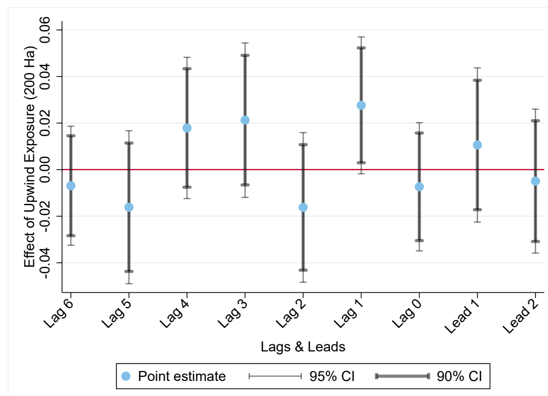

(a) Infants



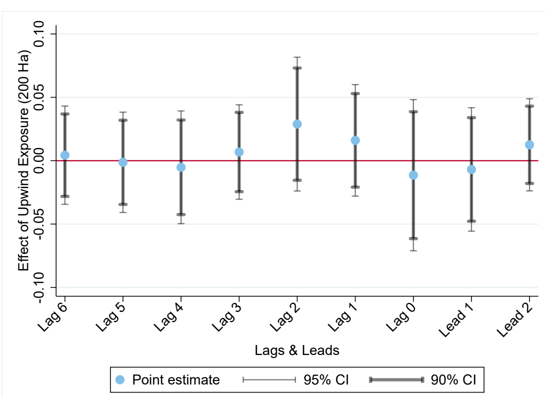

(b) Toddlers



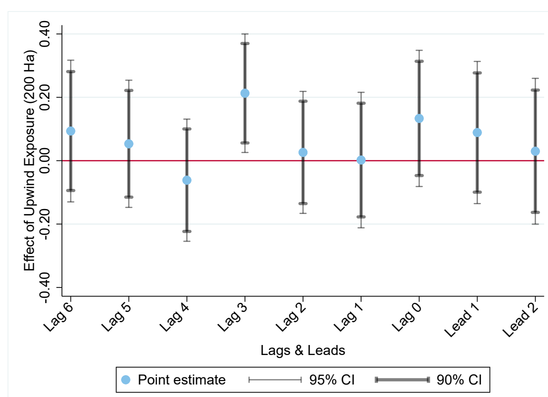

(c) Children




(d) Young Adults




(e) Middle Age




(f) Elderly

Notes: Each coefficient and set of confidence intervals is drawn from a regression model akin to that presented in Table 2 based on municipality and week cells from 2004–2019. These estimates are obtained from running a dynamic model, as in equation (2), with 6 lags and 2 leads. All other details follow those provided in Notes to Table 2.

## 6 Conclusion

In this paper we study the impact of wildfires on air pollution in nearby areas, and on population-level health outcomes measured by rates of inpatient hospitalization. We cross high-quality administrative records of hospitalizations from Chile with rich, fine-grained measures of wildfires, air pollution, and wind direction over 15 wildfire seasons. Leveraging presumably random shifts in air pollution exposure, we set up a causal design by comparing outcomes in municipalities in which fires are upwind (and hence exposed to their air pollutants) and those in which fires are downwind (and hence unexposed).

We document that upwind wildfires result in substantial increases in air pollution. Exposure to an additional 3 hour period of a wildfire within a day increases $PM_{2.5}$ pollution by around 10 percent. Correspondingly, exposure to wildfires air pollution is found to result in increased rates of hospitalizations for respiratory causes among the entire population, and for all causes among infants. In general, infants are observed to be most sensitive to exposure to wildfire, at least when considering the likelihood of hospitalization. These results are concerning given evidence that the impacts of environmental shocks may last many years into the future.

Our results suggest that hospitalizations are most affected when individuals are exposed to larger wildfires, and when exposure occurs for longer periods of time. We observe that increases in hospitalizations are largely contemporaneous, occurring in the week in which wildfires occur, as well as a delayed effect for the elderly. The fact that these results are notable even at the population level suggests that policy responses to wildfires should consider health-system readiness as a key variable.

The impacts of wildfires in this setting are likely to be considerably broader than their impacts on hospitalizations alone. Fortunately, this causal design can be extended to include a range of other outcomes, and microdata is available for a considerably broader class of outcomes, and over a broader time period. We are currently extending this design to cover a substantially longer period (30 years), and additional outcomes. In particular, we are considering the effect of wildfires on health at birth, mortality, inter-generational impacts on health, educational attainment, and labor market outcomes. While the results here suggest that the increasing frequency and intensity of wildfires will imply worsening health of the population affected by their air pollutants and increase costs of health system level, future work considering additional outcomes will allow us to more completely estimate the individual and society-level costs of wildfires.

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Online Appendix – Not for Print

**Wildfires and Human Health: Evidence from 15 Wildfire Seasons in Chile**

Rubí Arrizaga, Damian Clarke, Pedro Cubillos, Cristóbal Ruiz-Tagle

# A Appendix Tables

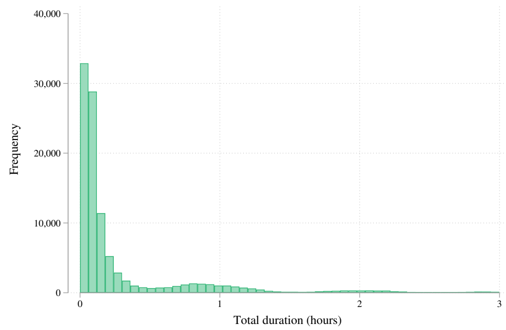
Table A1: Summary of Causes of Hospitalizations by ICD-10-CM Codes Classification

| Cause of Hospitalization | Number of Records. | Percent of Total |
|---|---|---|
| Pregnancy, childbirth and the puerperium | 5,967,795 | 19.3 |
| Diseases of the digestive system | 3,838,183 | 12.4 |
| Diseases of the respiratory system | 3,164,196 | 10.2 |
| Injury, poisoning and certain other consequences of external causes | 2,925,878 | 9.5 |
| Diseases of the genitourinary system | 2,465,906 | 8.0 |
| Diseases of the circulatory system | 2,259,001 | 7.3 |
| Neoplasm | 2,224,070 | 7.2 |
| Diseases of the musculoskeletal system and connective tissue | 1,216,836 | 3.9 |
| Factors influencing health status and contact with health services | 1,102,733 | 3.6 |
| Certain infectious and parasitic diseases | 844,474 | 2.7 |
| Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified | 807,229 | 2.6 |
| Endocrine, nutritional and metabolic diseases | 782,932 | 2.5 |
| Certain conditions originating in the perinatal period | 727,280 | 2.4 |
| Mental, Behavioral and Neurodevelopmental disorders | 554,913 | 1.8 |
| Diseases of the nervous system | 507,943 | 1.6 |
| Diseases of the skin and subcutaneous tissue | 458,588 | 1.5 |
| Diseases of the eye and adnexa | 399,935 | 1.3 |
| Congenital malformations, deformations and chromosomal abnormalities | 381,776 | 1.2 |
| Disease of blood | 179,182 | 0.6 |
| Diseases of the ear and mastoid process | 121,919 | 0.4 |
| Codes for special purposes | 8 | 0.0 |
| Total | 30,930,776 | 100 |

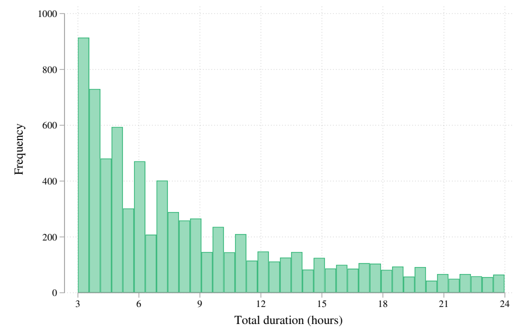
**Notes**: Observations cover all hospitalizations in all municipalities of Chile between years 2001 and 2019, excluding those by external causes of morbidity (ICD-10 V00-Y99).

# B Appendix Figures

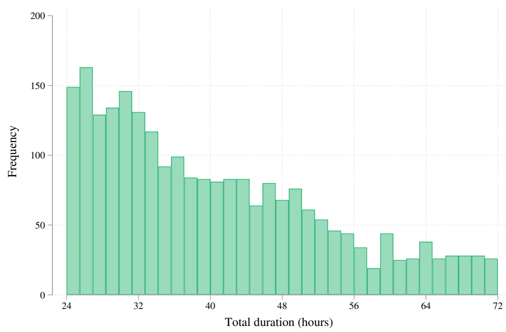
Figure A1: Wildfire Exposures by Duration of Fire



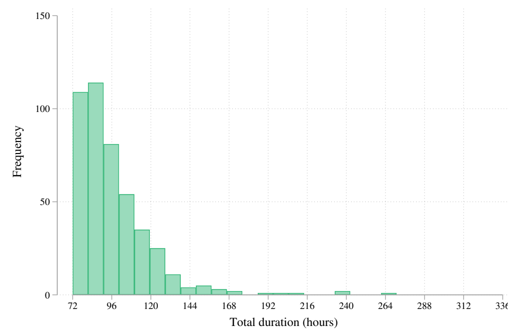

(a) <3 Hours




(b) [3-24) Hours



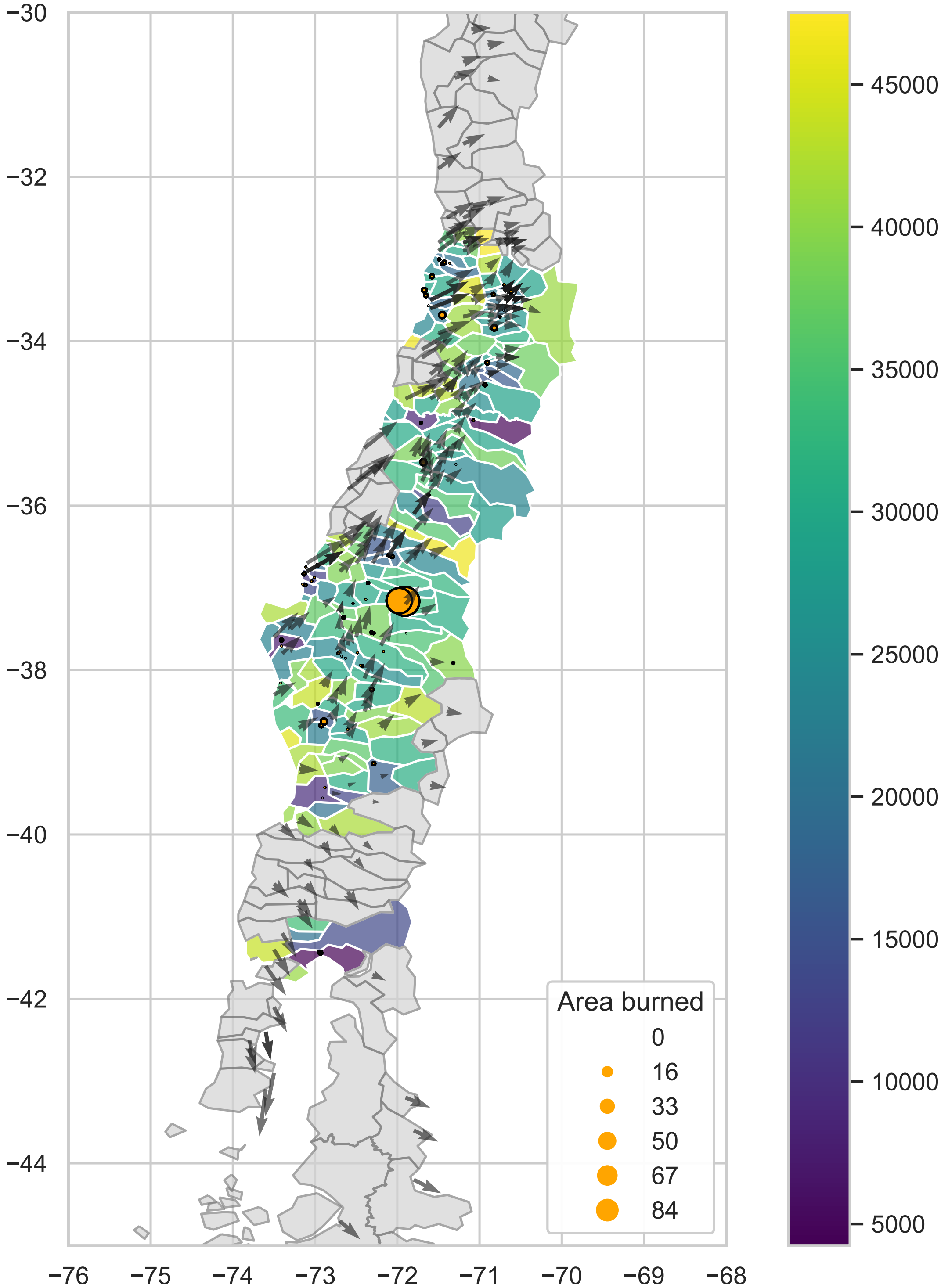

(c) 24-72) Hours




(d) [72-336) Hours

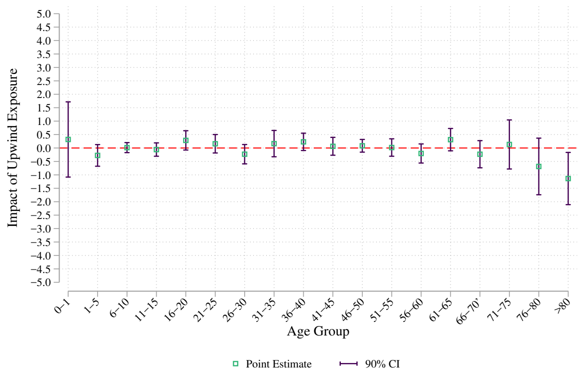
**Notes:** Histograms describe the number of fires registered across all records maintained by CONAF by the duration of the fire. Given the heavy left-skew of the distribution, these are displayed by duration in panels (a)-(d), where panels do not have identically scaled y-axes. These histograms are based on all fires reported at any time during the 2004-2018 fire seasons.

Figure A2: Exposure Design to Wildfires (Distance)

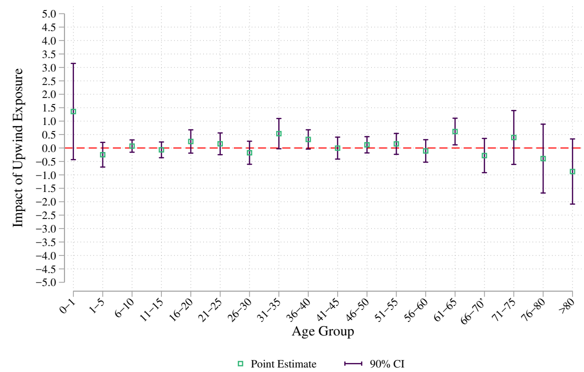



Notes: Large orange points represent fires, and gray arrows represent wind directions (arrow heads) and velocities (length of arrow). Shaded colors refer to the distance, in meters, from each municipality to the nearest wildfire. This is a representative figure at a particular moment of time. To observe how such patterns evolve over longer periods, refer to the dynamic figure: http://damianclarke.net/resources/fires_and_wind_distance.gif.

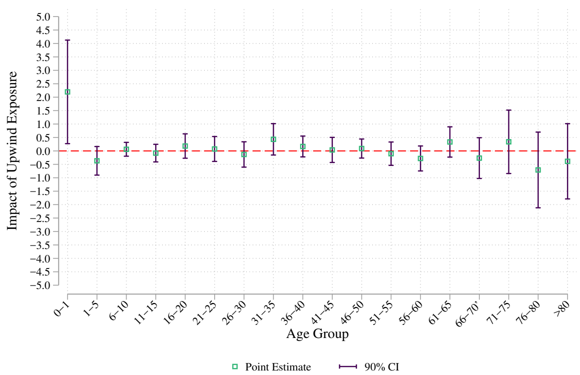
Figure A3: Impacts of Fire Exposure (Upwind) on All Cause Hospitalizations by Age



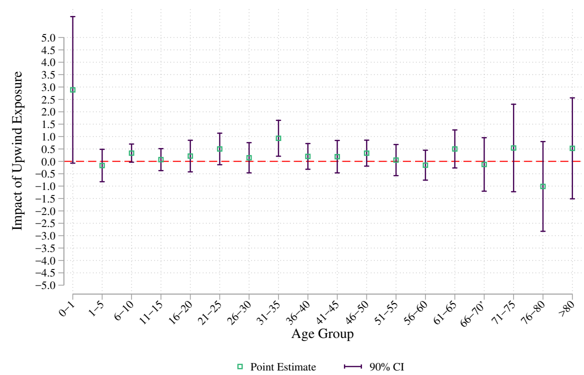

(a) Fires $\geq$ 50 Ha




(b) Fires $\geq$ 100 Ha



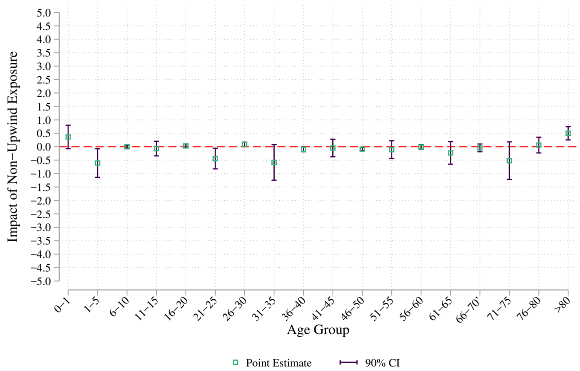

(c) Fires $\geq$ 200 Ha



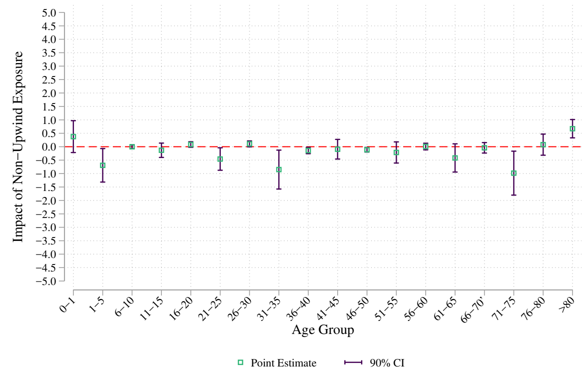

(d) Fires $\geq$ 500 Ha

Notes: Each coefficient and set of confidence intervals is drawn from a separate regression model identical to that presented in Table 2 based on municipality and week cells from 2004–2019. Outcomes are defined as mortality per 100,000 in the age group indicated on the horizontal axis. Each panel is based on dependent variable (upwind fire exposure) to any wildfire of the size indicated in panel captions. All other details follow notes to Table 2.

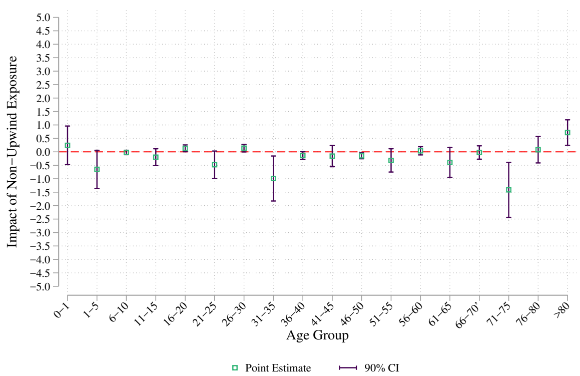
Figure A4: Impacts of Fire Exposure (Non-Upwind) on All Cause Hospitalizations by Age



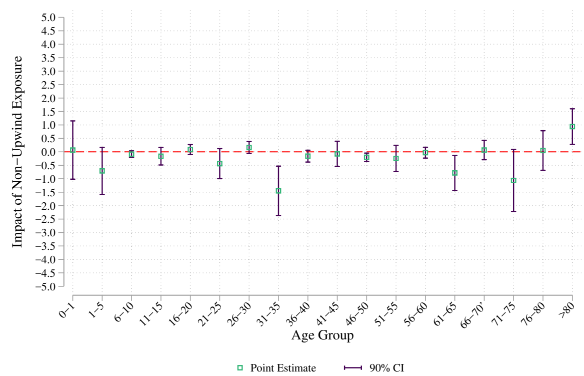

(a) Fires $\geq$ 50 Ha




(b) Fires $\geq$ 100 Ha



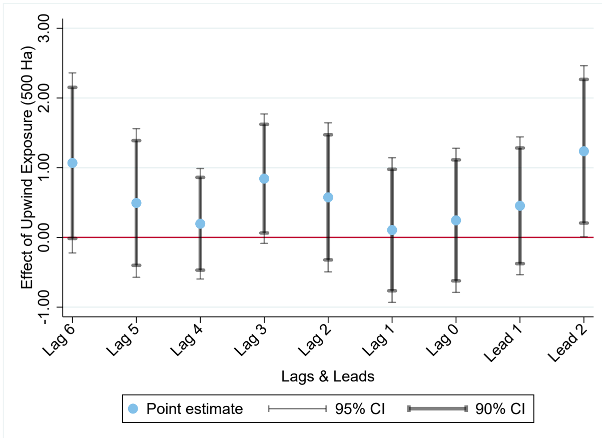

(c) Fires $\geq$ 200 Ha



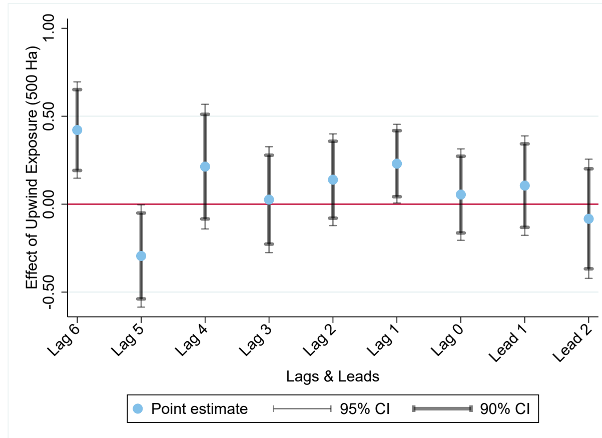

(d) Fires $\geq$ 500 Ha

Notes: Refer to notes to Figure A3. All details are identical in this figure; here, however, exposure refers to non-upwind exposure to fires in the week and municipality cell.

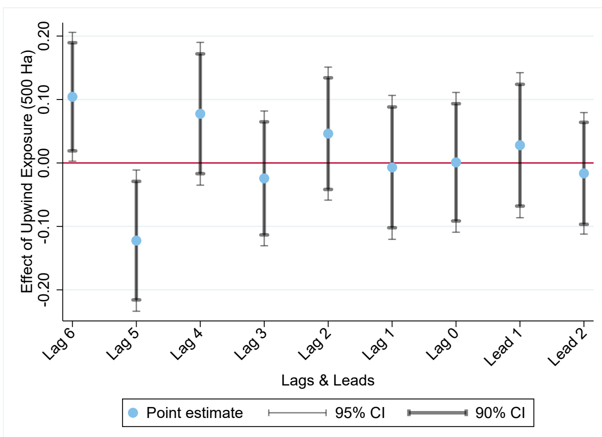
Figure A5: Dynamic Impacts of Upwind Fire Exposure ($\geq$ 500 Ha) on Respiratory Hospitalizations, by Age Group



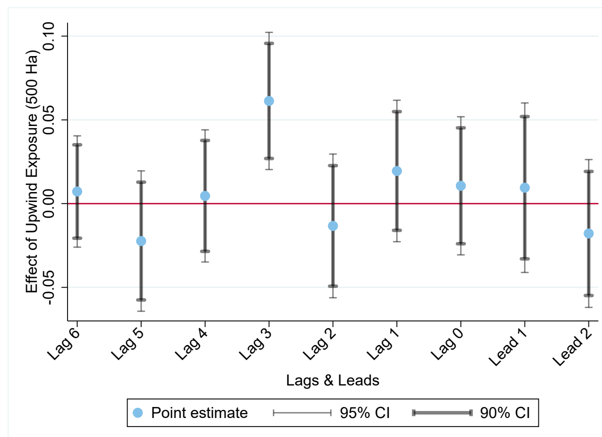

(a) Infants



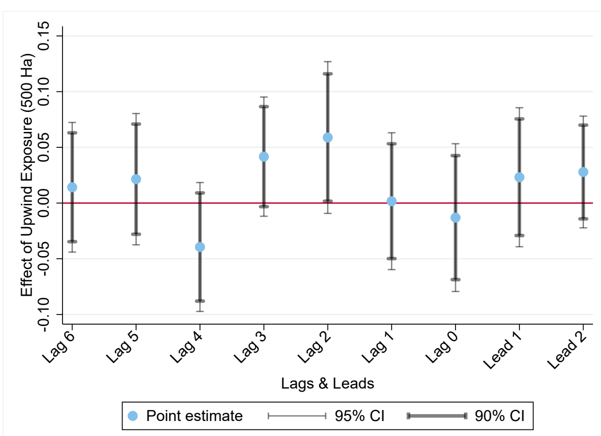

(b) Toddlers



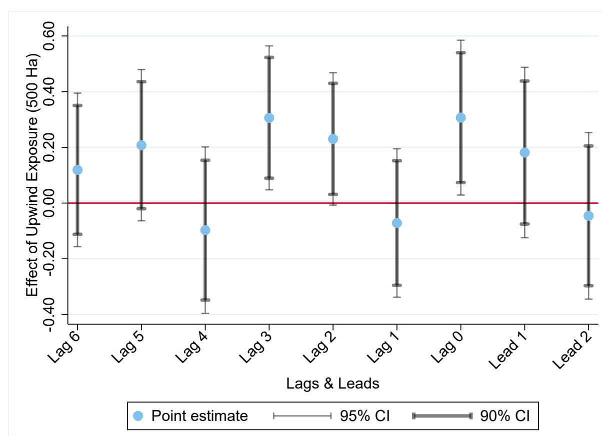

(c) Children




(d) Young Adults




(e) Middle Age




(f) Elderly

Notes: Each coefficient and set of confidence intervals is drawn from a regression model akin to that presented in Table 2 based on municipality and week cells from 2004–2019. These estimates are obtained from running a dynamic model, as in equation (2), with 6 lags and 2 leads. All other details follow those provided in Notes to Table 2.