Smoke Signals: Understanding Temporal Dynamics of Wildfire Exposure on Health and Education*

Rubí Arrizaga† Damian Clarke‡ Pedro Cubillos§
J. Cristóbal Ruiz-Tagle¶

January 14, 2026

Abstract

We study the impacts of wildfires in Chile mapping local exposure to over 1,000 large wildfires occurring over 17 wildfire seasons. We consider both how very local exposure patterns owing to changes in ambient conditions – such as wind, atmospheric and topographic conditions – affect exposure to air pollution from wildfires, as well as how this exposure shapes health and educational outcomes both contemporaneously and in the years following exposure. We use tens of millions of population records on admissions to hospital, emergency department visits, birth outcomes (birth weight, size and gestational weeks), and students outcomes (GPA, standardized tests, and attendance rates). We find harmful effects of exposure to wildfires smoke on health, specifically among sensitive groups such as infants, and that these effects are transmitted over the life course onto worsen health and educational outcomes. This findings can be used for quantifying the benefits of fire prevention and suppression efforts as well as early warning and mitigation systems for wildfire smoke.

JEL codes: Q54; I18; R11.

Keywords: Climate Change, Wildfires, Air Pollution, Human Capital, Health, Latin America.

*We are grateful to Ignacio Fernández for excellent research assistance. We gratefully acknowledge support of the Inter American Development Bank, through the project "Implications of Climate Change and Natural Disasters in LAC". We thank participants and organizers of a number of workshops at the Inter American Development Bank for many productive suggestions, and are indebted to two anonymous referees and the editor Klaus Moeltner for their very useful suggestions and feedback. Clarke acknowledges partial support from the Institute for Research in Market Imperfections and Public Policy, MIPP. Arrizaga is grateful to ANID Chile who has supported this work through ANID Fondecyt Iniciación 11260919.

†Departamento de Administración, Universidad de Santiago de Chile. Contact: rubi.arrizaga@usach.cl.

‡Department of Economics, Universidad de Chile & University of Exeter, MIPP and IZA. Contact: dclarke@fen.uchile.cl.

§Department of Economics, University College London. Contact: pedro.cubillos.24@ucl.ac.uk.

¶Global Development Institute, The University of Manchester. Contact: cristobal.ruiztagle@manchester.ac.uk.

1 Introduction

Wildfires have become more frequent and destructive due to increasing severity of droughts, greater frequency of heatwaves, and increased availability of vegetational fuels (Malevsky-Malevich et al., 2008; Gillett et al., 2004; Ellis et al., 2022). Climate change is projected to further exacerbate these drivers, increasing both the frequency and intensity of wildfires in historically fire-prone regions (IPCC, 2022; Abatzoglou and Williams, 2016; Bowman et al., 2017; Flannigan et al., 2009, 2013), and shifting the burden to areas previously unexposed to high levels of fire activity and its associated air pollution (Burke et al., 2021; Moritz et al., 2012). For example, in the United States, wildfires now account for as much as 25 percent of annual exposure to fine particulate matter ($PM_{2.5}$) in some regions, particularly in the west and mountainous areas (Burke et al., 2021).

These developments are particularly relevant in countries such as Chile and many regions around the world where climate-induced extreme heat and prolonged droughts have increased fuel aridity, thus amplifying wildfire risk.[1] These events lead to a cascade of adverse outcomes: immediate losses to human life, infrastructure, and agriculture; harm to economic activity; and acute and chronic health effects due to exposure to wildfire-related air pollution (Flannigan et al., 2009; Bowman et al., 2017; Cancelo-González and Viqueira, 2018).

Understanding the broad and evolving effects of air pollution from wildfires is essential for evaluating the long-term costs of climate change and informing adaptation and mitigation policy. Exposure to wildfire air pollution can affect multiple domains of well-being in ways that unfold over time. Immediate health effects, such as respiratory distress and hospitalizations, represent only one facet of harm. These may later manifest in long-term deficits in health, cognition, and educational attainment, particularly when exposure occurs in utero or during early life (WHO, 2024; Almond et al., 2009, 2018). Quantifying both the short- and long-term effects of exposure to wildfire air pollution is thus central to assessing its full human cost and to designing effective interventions.

In this paper, we study both the short- and longer-term effects of wildfire air pollution on health and human capital, using rich administrative microdata from Chile—a middle-income country that

[1]The Sixth Assessment Report of the IPCC specifically highlights that several regions in South America—such as Southwest South America (Chile), Patagonia, and Central America—will experience growing wildfire risk due to climate change (IPCC, 2022).

has experienced an intensifying wildfire regime. We compile detailed data on 1,121 large wildfires (each burning over 200 hectares) occurring between 2002 and 2021, and match these with administrative records of health at birth, emergency department and inpatient hospital visits, and educational outcomes. We employ detailed data on health and educational outcomes that is both contemporaneous to the occurrence of the wildfires—to capture short and mid-term effects—as well as data throughout individuals' life cycle (i.e. non-contemporaneous)—to capture longer term effects.

Our identification strategy tackles two core challenges in the literature: measuring exposure to wildfire air pollution accurately and establishing causal effects in a setting where exposure is non-random. First, to measure exposure, we use the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model (Stein et al., 2015), which simulates the dispersion of wildfire smoke using meteorological and wind data. This approach moves beyond common proximity-based metrics by providing a more accurate spatial and temporal mapping of air pollution plumes from wildfires and offers a level of granularity and variability not feasible in alternative modelling scenarios. Second, for identification, we rely on quasi-random variation in exposure driven by exogenous atmospheric conditions. Building on recent work using wind direction as a source of variation in pollution exposure (Rangel and Vogl, 2019; He et al., 2020; Rocha and Sant'Anna, 2022; Morello, 2023), we implement a design comparing individuals in geographically proximate areas who nevertheless differ in exposure to wildfire smoke due to differences in space relative to the point of initiation of wildfire, as well as meteorological conditions which determine exposure to smoke. Combining HYSPLIT's dispersion model with rich time- and location-fixed effects allows for a design in which causal effects are inferred from very local variation to contaminants.

A vast extant literature has established that short-term exposure to wildfire smoke increases hospital admissions and mortality, especially among vulnerable populations. In the U.S., recent studies show that wildfire-specific $PM_{2.5}$ increases emergency department visits for asthma and respiratory conditions (Wen et al., 2023; Heft-Neal et al., 2023), hospitalizations for respiratory and cardiovascular diseases (Moeltner et al., 2013), and mortality among elderly populations (Miller et al., 2024). Qiu et al. (2024) estimate that wildfire air pollution led to 15,000 excess deaths per year in the U.S. between 2006 and 2019. Outside the U.S., evidence from Indonesia's 1997 fires shows adverse effects on childbearing (Jayachandran, 2009), child growth and lung function (Rosales-Rueda and Triyana, 2019), and adult height following prenatal exposure (Tan-Soo and Pattanayak, 2019). Similarly, Frankenberg et al. (2005) document health impacts on older adults and prime-age women, while Mead et al. (2018) show widespread exposure in neighboring Malaysia. Health effects have recently been shown to not be limited to physical health, but also mental health (Currie and Saberian, 2025). Moreover, Borgschulte et al. (2024) finds important effects on the earnings and of workers at distant locations from the fire origin. In terms of long-term effects, recent work shows that early-life exposure to wildfire pollution affects years of schooling, adult mortality, and earnings (Arenberg and Neller, 2023; Lo Bue, 2019).

However, mapping out how exposure to wildfires affects human well-being across the short, medium and longer term is challenging, and data limitations often constrain the ability to document each of these margins within the same empirical setting. Whereas most studies focus on short term effects of exposure to wildfire air pollution, long lasting effects of air pollution exposure are usually considerably much larger (Isen et al., 2017). This paper contributes to 'bridging' the literature of short and long-term effects of exposure to wildfire air pollution by examining these effects within the same empirical framework (Currie et al., 2014). Our study addresses this gap and aims to shed some light on how one could translate estimates for short-term effects of exposure to wildfire air pollution—which benefit from data that is relatively easier to obtain—into analysis of mid- and long-term effects, arguably a better indicator of overall effects on human well-being. The clear importance of measuring long-run effects of exposures occurs in many settings (see e.g. Athey et al., 2025), and while assumptions can be made which allow short-run outcomes to act as 'surrogates' of long-run outcomes, in this particular setting we focus on collecting both short, medium and long-term outcomes and hence avoid such auxiliary assumptions.

We make three key contributions to the literature. First, we adopt a more precise, model-based approach to identifying exposure to wildfire smoke by applying HYSPLIT atmospheric dispersion modeling to a novel setting. We argue that this is important in this context, where such atmospheric models point to clear differences in exposure compared with often applied distance-based exposure methods. Second, we provide new evidence linking short-term respiratory health impacts with long-term educational and health outcomes using a single (administrative) sample of individuals, bridging an important gap in the literature. Third, we contribute evidence from Latin America—a region where high-quality administrative data is seldom combined with environmental exposure modeling—thereby broadening the geographical scope of the literature on the long-run effects of early-life conditions (e.g. Aguilar and Vicarelli, 2022; Sanders, 2012).

In doing so, our results are relevant for both the environmental economics literature on pollution and well-being, and the broader human capital literature on early-life shocks and how these are traced-out and reinforce over the life course. Our results point to critical periods of sensitivity early in life, and by empirically mapping short-term impacts onto long-term outcomes, our findings offer a practical contribution to policy evaluation: they can provide a guide to infer long-term consequences of exposure in settings where only short-run data is available, thereby aiding the assessment of long-horizon interventions.

The remainder of this paper is structured as follows. Section 2 lays out a simple theoretical model to illustrate our setting and the relationships we seek to uncover. Section 3 describes key background on the Chilean setting and the outcomes which we study. Section 4 describes the data and construction of the measure of exposure to wildfire air pollution. Section 5 outlines the empirical strategy. Section 6 presents the main results, separated into both short-term effects of wildfire exposure and long term human capital outcomes. Finally, section 7 concludes.

2 A Simple Model of Wildfires Exposure and its Effects on Human Capital Outcomes

We sketch a simple conceptual model to formalize how short-term impacts of wildfire smoke exposure while in the womb and in early life can accumulate into longer-term effects on human capital. This model borrows heavily from Currie et al. (2014), the human capital framework of Grossman (1972) and the early-life origins literature (Almond and Currie, 2011; Almond et al., 2018). The goal is to provide a framework for bridging short-term effects of wildfire air-pollution exposure in early life (e.g. while in utero or during the first year) with long-term effects later in childhood (e.g. during the school years). By bridging, we mean that one can isolate short-term exposure at critical periods in life, and additionally map these into longer-term outcomes – which are typically hard to estimate due to limited long-run data.

Suppose that human capital H (encompassing stocks of both health and education) accumulates over time, and that exposure to air pollution P can affect H at any point in life. Early childhood is a critical period for the accumulation of H (Almond and Currie, 2011; Almond et al., 2018). We divide childhood into three life stages: perinatal (from conception through age 1), toddler years (ages 1 through 3), and preschool- and school-age (ages 4 through 18). We denote by H_N, H_T, and H_S the human capital stock attained at the end of the perinatal N, toddler years T, and preschool- and school-age periods S, respectively. Similarly, let P_N, P_T, and P_S represent air pollution exposure during each of these periods. For simplicity, we assume the following production functions for human capital in each stage:

$$
\begin{aligned}
H_N &= f_N(P_N, Z), \\
H_T &= f_T(H_N,\, P_T), \\
H_S &= f_S(H_N,\, H_T,\, P_S),
\end{aligned}
$$

where Z captures time-invariant family characteristics (endowments) that affect early human capital. In this setup, pollution exposure in any given period can directly affect human capital in that period and may also have indirect effects on later periods by influencing the accumulated stocks H_N and H_T.

These relationships imply that an early-life pollution shock – say, during the perinatal period N – not only affects human capital in period N itself, but can carry over into the toddler and school-age periods through the dependence of H_T and H_S on earlier stocks. We can see this by differentiating the school-age human capital equation with respect to P_N:

$$
dH_S = \frac{\partial H_S}{\partial H_N}\frac{\partial H_N}{\partial P_N}\, dP_N + \frac{\partial H_S}{\partial H_T}\frac{\partial H_T}{\partial H_N}\frac{\partial H_N}{\partial P_N}\, dP_N\,, \tag{1}
$$

which simplifies to

$$
\frac{dH_S}{dP_N} = \frac{\partial H_S}{\partial H_N}\frac{\partial H_N}{\partial P_N} + \frac{\partial H_S}{\partial H_T}\frac{\partial H_T}{\partial H_N}\frac{\partial H_N}{\partial P_N}\,.
$$

Expression (1) represents the total long-term effect of a perinatal pollution exposure (P_N) on human capital at the school-age stage (H_S). The first term is the direct persistence of the perinatal shock (carried forward via H_N), and the second term captures the indirect effect that persists via H_T (since

P_N affects H_N, which in turn affects H_T, and then H_S). In other words, early-life exposure has the well-known "fetal origins" effect that can manifest in later human capital both directly and through intermediary developmental stages.

By contrast, the immediate (within-period) effect of pollution in each childhood stage is given by the partial derivative of H with respect to current exposure P in that stage. Specifically:

$$dH_N = \frac{\partial H_N}{\partial P_N} dP_N \, , \tag{2}$$

$$dH_T = \frac{\partial H_T}{\partial P_T} dP_T \, , \tag{3}$$

$$dH_S = \frac{\partial H_S}{\partial P_S} dP_S \, . \tag{4}$$

Equation (2) represents the short-term effect of perinatal pollution on perinatal human capital (e.g. an in-utero exposure effect on birth or infant health outcomes). Similarly, (3) is the contemporaneous effect air pollution exposure during the toddler years on human capital during that period, and (4) is the contemporaneous effect of school-age pollution on that period's human capital.

The key insight of this model is that, by using an appropriate empirical design, we can estimate many of these parameters directly. In particular, our empirical analysis will yield estimates for: (i) the composite long-run effect of an early-life pollution shock, $\frac{\partial H_S}{\partial H_N}\frac{\partial H_N}{\partial P_N}$ (which comes from the terms in equation (1)), and (ii) the short-run perinatal effect $\frac{\partial H_N}{\partial P_N}$ (equation (2)), the short-run toddler effect $\frac{\partial H_T}{\partial P_T}$ (equation (3)), and (iii) the contemporaneous school-age effect $\frac{\partial H_S}{\partial P_S}$ (equation (4)).

This framework also illustrates the benefit of bridging short- and long-term estimates. If one is able to estimate the immediate perinatal impact $\frac{\partial H_N}{\partial P_N}$ and the propagation factor $\frac{\partial H_S}{\partial H_N}$ (embedded in the composite effect from equation (1)), then one can infer the overall long-term effect of a perinatal exposure, $\frac{dH_S}{dP_N}$. In other words, armed with an estimate of the short-term impact of pollution at birth and an estimate of how strongly early shocks transmit to later human capital outcomes, we can bridge to the long-run effect without directly observing long-run outcomes in every context. Of course, this approach is context-dependent (the transferability of these parameters to other settings may be limited), but it provides a useful blueprint for translating readily available short-run estimates into projections of longer-run impacts.

Finally, for completeness, consider the total effect of pollution across all periods on final human capital. Totally differentiating $H_S = f_S(H_N, H_T, P_S)$ with respect to all three exposure variables yields:

$$dH_S \;=\; \frac{\partial H_S}{\partial P_N} dP_N \;+\; \frac{\partial H_S}{\partial P_T} dP_T \;+\; \frac{\partial H_S}{\partial P_S} dP_S \,,$$

which, after substituting the chain-rule expressions for $\partial H_S/\partial P_N$ and $\partial H_S/\partial P_T$, can be written as:

$$\begin{aligned} dH_S \;=\; & \left(\frac{\partial H_S}{\partial H_N} \frac{\partial H_N}{\partial P_N} \;+\; \frac{\partial H_S}{\partial H_T} \frac{\partial H_T}{\partial H_N} \frac{\partial H_N}{\partial P_N} \right) dP_N \\ & + \left(\frac{\partial H_S}{\partial H_T} \frac{\partial H_T}{\partial P_T} \right) dP_T \;+\; \frac{\partial H_S}{\partial P_S}\, dP_S \,. \end{aligned} \tag{5}$$

Equation (5) highlights that the school-age human capital stock H_S is influenced by pollution shocks not only contemporaneously (via P_S), but also via exposures in previous periods (P_N and P_T). Thus, a comprehensive account of the total impact of pollution on long-run human capital must include these lagged (early-life) exposures. Our empirical strategy is designed to incorporate such cumulative exposure effects when estimating the overall impact of wildfire smoke on health and education outcomes.

3 Background and Context

3.1 Geographic Context, Wildfires and Exposure to their Air Pollutants

Chile is a geographically diverse country, extending across 38 degrees in latitude, and as such 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 of this, 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 Valparaíso to Araucanía districts (Sarricolea et al., 2020).[2] 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).

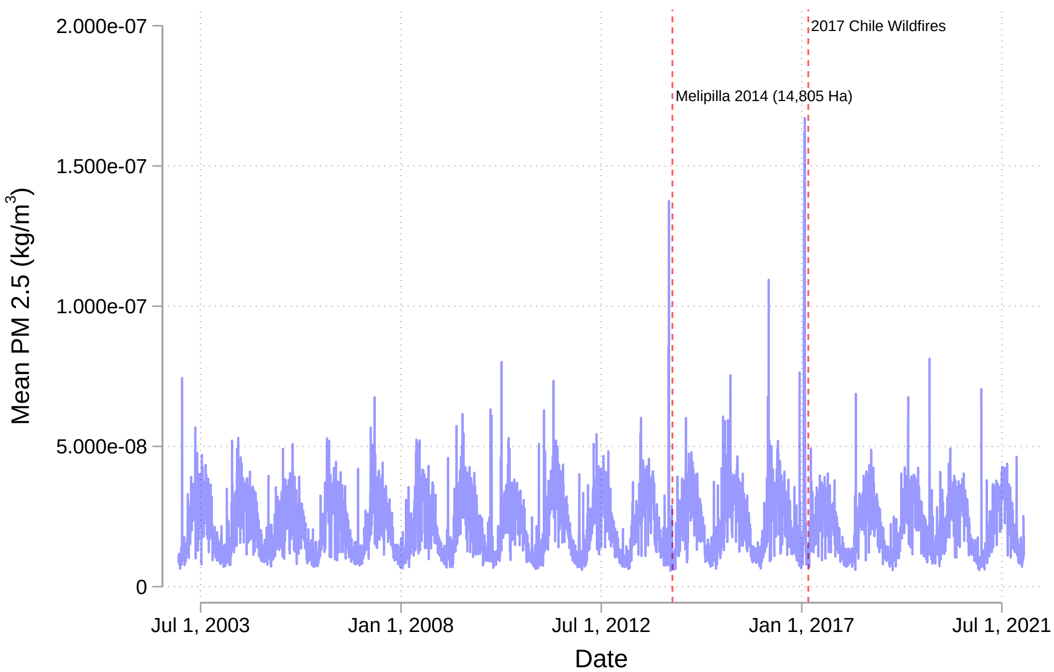
Whereas the majority of wildfires in Chile are started, either directly or indirectly, by human activity (CONAF, 2022), warmer temperatures and droughts make these fires both more frequent and destructive (Westerling et al., 2006). Indeed, the intensity of wildfires in Chile has increased over the last 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 ten times higher than previous yearly averages (CONAF, 2022). The costs owing to wildfires are substantial. According to information from Chile's National Forestry Agency (CONAF, due to 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 support to productive sectors (16 percent), among others.[3]

Prior work has shown that wildfire events in Chile produce significant spikes in air pollution, particularly in $PM_{2.5}$ concentrations, which have well-documented links to morbidity and mortality (Ciciretti et al., 2022). During severe wildfire seasons, urban centers such as Santiago, Concepción, and Temuco have recorded pollution levels that far exceed WHO air quality guidelines. These often result in persistent elevated air pollution, as inversion layers trap smoke in valleys, compounding exposure for days or weeks. Yet to date, few studies have used high-resolution data to link these pollution episodes to health outcomes across space and time. Descriptively, it appears clear that large wildfires are important drivers of elevated air pollution levels. In Figure 1 we present a descriptive plot of mean rates of daily ambient $PM_{2.5}$ in Chile over the period of 2003-2021 based on

[2]This is the most populated region in the country, concentrating 78.9 percent of the population according to censal records (INE, 2018).

[3]Regarding private expenditure 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 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).

Figure 1: $PM_{2.5}$ 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.

remotely sensed data on pollutants from the Climate Change Service of the European Centre for Medium-Range Weather Forecasts (ECMWF). 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 notorious 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.

3.2 Health and Educational System

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 human health, harming cardiovascular and respiratory systems (Heft-Neal et al., 2023; Wen et al., 2023). What's more, there is growing evidence that exposure to air pollution—particularly fine particulate matter ($PM_{2.5}$)—during sensitive developmental windows such as in utero and early childhood can have lasting effects on health, cognitive development and educational attainment (Currie et al., 2014; Carneiro et al., 2024; Chen, 2025; Zhang et al., 2018). These effects may arise through a variety of pathways: reduced birth weight and gestational age, increased incidence of respiratory illness, and school absences due to illness from poor air quality (Rangel and Vogl, 2019; Wen and Burke, 2022). As such, wildfire-related pollution may impose long-run costs not only on physical health but also on human capital formation, with implications for educational trajectories, future earnings and social mobility (Arenberg and Neller, 2023; Borgschulte et al., 2024; Paudel, 2023).

Chile provides a useful setting to study the health and educational consequences of wildfire exposure, in part because of its relatively centralized and comprehensive administrative systems in both sectors. The country has a mixed public-private health care system, with the public system (FONASA) covering about 80% of the population. Health services are delivered through an extensive network of primary care centers, public hospitals, and specialized facilities, with most inpatient care concentrated in the public sector. The Ministry of Health maintains centralized health records covering *both* the public and private system, including detailed information on hospitalizations, diagnoses, and patient demographics, which are systematically recorded by the Department of Health Statistics and Information (DEIS).

The educational system in Chile is also mixed, with a large share of students attending publicly funded schools. Roughly 90% of school-age children are enrolled in either public or subsidized private schools (i.e., voucher schools), both of which follow a national curriculum and are regulated by the Ministry of Education. Importantly, administrative education records in Chile track students longitudinally from early primary, with detailed student-level records of grades as well as attendance, allowing for detailed study of educational trajectories over time.

These features make Chile particularly well-suited for examining the medium- and long-term effects of environmental shocks. First, national coverage and individual-level tracking of health and education outcomes allow for precise identification of vulnerable populations. Second, centralized administrative data allow us to construct course panels with high temporal and geographic resolution. Third, the national scope of these systems ensures that our findings are not driven by selective sample attrition or localized shocks, and can plausibly reflect broader patterns of exposure and resilience.

4 Data

As laid out at more length in section 5, we will work at two principal levels: an aggregate municipal$\times$week level when considering wildfire impacts on short term outcomes (air pollution, hospitalisations, and emergency department visits), and an individual level when considering the impact of longer term or cumulative exposure (birth outcomes, later life health, and later life education). In each case, we will match outcome measures (vital statistics and educational outcomes), with key dependent variables (wildfires) and environmental conditions based on municipal or geographic stratification. Below in Sections 4.1-4.4 we describe key data sources and variable definitions. Then, in Section 4.5 we describe merged municipality- and individual-level datasets and provide summary statistics.

4.1 Wildfires

We access data on all wildfires occurring in Chile between the period of 2003 until 2022 from administrative records maintained by CONAF. 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 of 2019, our final sample used in models laid out below consists of fire seasons 2003-2019. This data contains a record of the precise geo-reference of the fire's point of initiation, the type of land-cover affected, the duration of the wildfire, and the total area burned. We restrict our sample of wildfires to those that burn an area of 200 hectares or larger, as (a) these have been previously identified to cause a significant amount of smoke pollution and greater damage to human health (Jain et al.,

2024) and (b) burn area in these cases is more systematically measured.[4]

In general, over the period under study we observe some evidence of an increase in exposure to fires, particularly among larger fires. Chile has experienced a marked increase in both the frequency and magnitude of wildfires. As shown in Online Appendix Table A1, the total number of reported fires each season is dominated by small events ($<$1 ha), but the occurrence of large fires ($>$500 ha and $>$1000 ha) has been increasingly frequent, especially in recent years. This escalation in fire size is reflected in the pronounced inter-annual variability in total burned area (Online Appendix Figure A1), with catastrophic peaks such as the 2016–2017 season, when over 546,000 hectares were affected. Descriptive statistics (Online Appendix Table A2) confirm that, while the median and mean fire sizes remain below 1,000 ha for most seasons, there is substantial heterogeneity in fire severity, as evidenced by high standard deviations and maximum values exceeding 100,000 ha in extreme years. Notably, only a minority of fires account for the vast majority of the burned area, underscoring the critical importance of large-scale events (i.e., those with burned area greater than 200 ha) in shaping landscape-level fire impacts. In total, 1,121 major wildfire events were included in our exposure modelling discussed in the following section, representing the full set of large-scale fires that most strongly shape inter-annual variability and regional impacts in Chile.

4.2 $PM_{2.5}$ Air Pollution Data

We obtained data on particulate matter with diameter of 2.5 microns or less, $PM_{2.5}$, from two sources. The first set of $PM_{2.5}$ air pollution data comes from a network of air quality monitoring stations of Chile's National Information System for Air Quality (SINCA, due to its acronym in Spanish), of Chile's Ministry of Environment. This network provides detailed data on $PM_{2.5}$ pollution concentrations at a high-level of frequency for selected cities (usually, those large and mid-size cities that have historically been exposed to elevated levels of air pollution). Although this network of monitoring stations has expanded rapidly in recent years, covering more and more cities every year, this data remains very scant for most of the years in our sample and does not provide good data coverage for smaller cities or mid-size cities that lack a long history of high air

[4]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 hectares (hereafter Ha), these are determined based off of 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.

pollution. We observe *at most data* from monitoring stations in 82 municipalities, though in earlier years this number is lower.

To complement this data, we obtained satellite-level data on $PM_{2.5}$ from reanalysis data from the Copernicus program of the European Centre for Medium-Range Weather Forecasts (ECMWF). In particular, the ECMWF's CAMS global reanalysis (EAC4) provides a dataset, every three hours, at the $0.75°\times 0.75°$ latitude-longitude at the earth surface level (more precisely, at atmospheric pressure of 1000 hPa). This is roughly, a 70×70 Km grid for the period 2004 to 2018. By intersecting this with the geographical location of each municipality we calculate weekly average $PM_{2.5}$ pollution for each municipality.[5]

4.3 Health Outcomes

4.3.1 Inpatient hospitalisations

We have collected and systematized administrative records on all inpatient hospitalisation records from the Chilean Ministry of Health's Department of Health Statistics and Information (DEIS) covering the period of 2003, the first year this data is available, and up to 2019. Inpatient hospitalization data are rich, indicating each cause of hospitalization and its duration. These data cover all hospitalizations in the country, whether occurring in the public or the private system.[6] 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 needs not be the same one as the municipality where the individual is hospitalised – which allows us to link individuals to exposure to wildfire air pollution (see Section 5.1 below). We examine all hospitalizations related to respiratory causes (generated from ICD-10 codings), as well as all-cause hospitalizations. When considering immediate impacts of exposure to wildfire, we focus on both hospitalisations at all ages, as well as hospitalization of individuals in specific age groups, such as those less than one year old.

[5]Note that for this measure, there are a small number of observations missing over the entire period, which corresponds to a single municipality (Chilean Antarctica).

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

4.3.2 Emergency department visits

We additionally collect information on all emergency department visits recorded at a municipal level. These emergency departments (EDs) refer to hospital EDs as well as local emergency centres (SAPUs, for their acronym in Spanish), and are available covering virtually the entire country for the period of 2010–2018. These are available by day, and also provide information about ages and health causes for visits (according to ICD-10 codes), and so we consider measures both for specific ages-groups, as well as visits specifically classified as for respiratory causes. We grouped visits to EDs at the municipal level, and calculated the outcomes of interest as the rate of visits per 100,000 inhabitants in the municipality.

4.3.3 Birth data

We use birth records provided also by the DEIS. The dataset includes all children born between 1992 and 2018, with detailed information on sex, birth weight, size, gestational weeks, and the exact date, municipality, and region of birth.[7] This last two variables are key to measure the in utero exposure to wildfire air pollution. It also contains parental demographics such as age, education level, marital status, and municipality of residence. Since our data on wildfires start from 2003, we focus our study on all children born between 2003 and 2018.

4.4 Educational Outcomes

To measure educational outcomes in both the short and long term, we rely on two primary datasets covering primary and secondary education. The first consists of administrative education records provided by the Ministry of Education, that offer detailed information on students' academic trajectories. Using this source, we construct a comprehensive panel dataset at individual level spanning the years 2007 to 2018, which includes annual data on attendance, enrollment, GPA, grade retention, and school characteristics. Particularly we differentiate schools by public,

[7] In Chile, a region is the largest administrative division, while a municipality is a smaller local unit within a province, similar to a district or township.

subsidized private (i.e. voucher schools), and private.[8] Since the academic year starts in March each year and ends in early December, this structure allow us to study the dynamics on education in the year following a wildfire season during the previous summer (which is highly concentrated in December, January, and February). [9]

For the analysis of long-term outcomes, we use our second main dataset: standardized test scores in math and verbal from Chile's *Sistema de Medición de la Calidad de la Educación* (SIMCE), spanning 2012 to 2023. The SIMCE test is a nationwide assessment that evaluates student attainment of Chile's national curriculum through standardized tests administered in selected grades. We focus on 4th-grade scores, as it is the only level consistently assessed across cohorts, ensuring broad comparability over time.[10] We restrict our sample to students born between 2004 and 2008, who typically take the 4th-grade test between the ages of 9 and 11 (see e.g., Bharadwaj et al., 2017). Given the available data until 2018, we focus on the test scores for the years between 2013 and 2018. One limitation of the SIMCE data is that it does not record information on the student's municipality at birth. To address this issue we use as a proxy the municipality at which the student lived when he or she first enrolled in school, usually at age 5 to 7.[11]

4.5 Data Matches and Summary Statistics

We work at two levels depending on the outcome under study. In a first stage, where we wish to consider outcomes for which we only have complete records at the municipal level (air pollution, hospitalization rates), we aggregate by municipality and week. In a second stage, where we are able to observe all outcomes at an individual level (educational outcomes, birth outcomes, births matched to future health outcomes), we work at an individual level.

[8] In Chile, school type – public, subsidized private (voucher), and private – is closely tied to socioeconomic background, resource levels, and academic outcomes. Importantly, both public and subsidized private (voucher) schools receive government funding based on student attendance, creating financial incentives to maintain or improve enrollment and daily presence. This makes school type a key dimension when analyzing education-related effects and disparities.

[9] Thus, effects of wildfire exposure on students' school attendance and annual GPA should not be directly impacted by school closures due to wildfires burning.

[10] Fourth-grade SIMCE is the only test consistently administered every year between 2005–2018 and 2022–2023. SIMCE tests in verbal and mathematics are administered in 4th, 8th and 10th, though tests in grades 8 and 10 occur only on alternating years.

[11] We check the validity of this proxy by combining our birth outcomes dataset and hospitalizations on later years. Specifically, we check whether individuals remain in the same municipality or administrative district where they were born. We find that, after 6 years since birth, approximately 71 percent of students remain in the same municipality and 88 percent in the same administrative district of birth.

For the first of these cases, we generate a balanced panel covering each of Chile's 346 municipalities over time covering the period of 2003-2019, and hence consisting of a maximum of 305,864 cells (52 weeks$\times$17 years$\times$346 municipalities). While data on hospitalizations and wildfire exposure are available for every cell, a ground-level measure of air pollution exposure is only available for the sub-group of municipalities in which monitoring stations exist. The total number of hospitalizations occurring in each municipality are aggregated to municipal level totals, and are calculated as rates per 100,000 individuals using population records provided by Chile's National Institute of Statistics.

In Table 1 below we provide summary statistics for our variables of interest both at the municipality and individual level. Panel A shows wildfire smoke exposure at municipality level for every cell in the data. Wildfire smoke exposure is measured as the number of days in a week where the municipality was exposed to the wildfire smoke. As we lay out at more length in section 5.1, we use different measures of exposure to wildfire based on a formal modeling strategy, where wildfire exposure depends upon a number of factors such as distance from the point of wildfire origin, smoke plume height, and so forth. Our exposure measure captures the total number of days (or portions of days) in which a municipality is exposed to wildfire-induced smoke pollution. While we provide summary statistics here of these main exposure methods, their precise definition is laid out in section 5.1. In general, we can see that the mean exposure, regardless of the measure used, is relatively small, which is explained by exposure to wildfires being highly concentrated only in some regions and during the wildfire season (largely, the summer time). Still, we can see that in some cases municipalities can be exposed up to 2.3 days to the smoke plume during a single week. For $PM_{2.5}$ air pollution, the mean is 22.09 ($\mu g/m^3$) according to the remote-sensed data (ECMWF's Copernicus), and 25 ($\mu g/m^3$) according to the data from the network of air quality monitoring stations (Chile's SINCA). Both measures of air pollution present large standard deviations and peaks surpassing safe levels (according to World Health Organization's guidelines) by more than an order of magnitude.

In the Panel A we also present summary statistics of administrative records covering all hospital admissions and emergency department visits at the municipal by week level. These are all cast as rates per 100,000 exposed population. For the entire population, we observe that admissions due to respiratory causes account for around 10 percent of all hospital admissions — a mean of 21 hospital admissions per 100,000 inhabitants in a week, compared to 182 per 100,000 for all cause hospital admissions. As well as all-cause and cause-specific hospital admissions for all ages, we document rates for specific age groups which are particularly sensitive to health shocks, namely infants (i.e., those individuals younger than one year of age). Unsurprisingly, rates of hospital admissions are around four times higher among infants than for the general population, and about ten times higher when considering those admissions due to respiratory diseases. [12]

In the case of individual-level analyses, each individual can be matched over time using an anonymyzed version of their national identity number (the RUT). This matching process has been documented to have excellent coverage (see, *e.g.* Clarke et al. (2022)). Individual-level linked data is then matched to environmental exposure variables based on municipality of birth or exposure. Depending on the outcome under study we consider environmental exposure measure at differing times: either shorter-term exposure which matches educational data to wildfire conditions in the summer before each school year, or longer-term exposure which links outcomes with conditions to which individuals were exposed while in utero.

Panel B of Table 1 presents descriptive statistics for birth and long-term outcomes covering over 3.3 million individuals, along with wildfire smoke exposure before birth. On average, wildfire exposure during the two-week period prior to birth is 0.004 days, with a maximum of 3 days. For the third trimester of pregnancy, the average exposure rises to 0.024 days, with a maximum of almost 6 full days. Birth-related measures show average birth weight of 3,315 grams and gestational length of 38.5 weeks. Rates of hospital admissions are relatively low, with an average of 0.73 hospitalizations per child across all ages. Although there are some extreme values, is worth noting that 99.9 percent of the sample had less than 10 hospitalizations when they were less than one year old. Short/mid term educational outcomes presented in Panel C are based on over 35 million observations, covering a panel of students across years 2007 and 2018, with high average school attendance (89 percent) and enrollment rates (97). Grade Point Average (GPA) is 5.66 in a scale

[12] 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 (2,600 of 305,864) have no defined rate of hospital admissions, given that there are zero populations in this particular group in a number of very small municipalities. As we lay out in the methods section later in this paper, we will generally weight cells by population size, so findings will not be driven by municipalities with very small populations.

Table 1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Panel A: Municipality-by-Week Measures					
Wildfire Smoke Exposure^a	305,864	0.005	0.093	0	7
PM$_{2.5}$ Air Pollution ($\mu g/m^3$) – ECMWF's Copernicus	304,980	22.09	25.87	0.14	642.24
PM$_{2.5}$ Air Pollution ($\mu g/m^3$) – Chile's SINCA	18,946	25.00	21.78	1	303.97
Hospital Admissions for All Causes (per 100.000)	305,864	181.84	100.81	0	6,061
Hosp. Adm. for Respiratory Diseases (per 100.000)	305,864	21.29	24.38	0	1,667
Hosp. Adm. for All Causes, < 1 year old (per 100.000)	303,010	686.68	894.66	0	175,000
Hosp. Adm. for Resp. Dis., < 1 year old (per 100.000)	303,010	210.82	493.63	0	100,000
Emergency Department Visits for All Causes (per 100.000)	161,928	1502.01	1556.23	0	29,663
ED Visits for Respiratory Diseases (per 100.000)	161,928	447.47	514.74	0	20,169
ED Visits for All Causes, < 1 year old (per 100.000)	160,212	4633.02	6905.32	0	376,737
ED Visits for Resp. Dis., < 1 year old (per 100.000)	160,212	2627.98	4147.09	0	375,929
Panel B: Individual Measures for Long Term Health Outcomes					
Wildfire Smoke Exposure, 1^{st} trimester^a	3,331,299	0.08	0.52	0	17
Wildfire Smoke Exposure, 2^{nd} trimester^a	3,331,299	0.08	0.52	0	17
Wildfire Smoke Exposure, 3^{st} trimester^a	3,331,299	0.09	0.55	0	17
Wildfire Smoke Exposure, two weeks before birth^a	3,331,299	0.01	0.16	0	9
Weight at Birth (grams)	3,331,299	3,315.98	546.98	110	6,440
Size at Birth (cm)	3,331,299	49.27	2.60	16	59
Gestational Weeks	3,331,299	38.47	1.87	15	44
Total Hosp. Adm., < 1 year old	3,331,299	0.40	1.05	0	295
Total Hosp. Adm., $1-3$ years old	3,331,299	0.23	1.18	0	681
Total Hosp. Adm., all ages	3,331,299	0.73	2.22	0	908
Panel C: Individual Measures for Short/Mid Term Educational Outcomes					
Wildfire Smoke Exposure, previous summer^a	33,424,830	0.38	1.16	0	13
School Attendance (percentage)	33,424,830	87.75	21.09	0	100
Student Enrollment Rate	33,424,830	0.95	0.21	0	1
Grade Point Average (GPA)	31,819,851	5.66	0.67	1	7
Panel D: Individual Measures for Long Term Educational Outcomes					
Wildfire Smoke Exposure, two weeks before birth^a	634,117	0.000	0.007	0	2
Wildfire Smoke Exposure, third trimester^a	634,117	0.000	0.029	0	3
Math Test Score at 4th Grade – Chile's SIMCE	620,999	264.22	48.66	91.18	395.59
Verbal Test Scores 4th Grade – Chile's SIMCE	618,809	271.65	51.94	115.71	405.96

Notes: Observations in Panel A cover municipality by week cells for the 346 municipalities and 783 weeks over the period of 2003-2019 (or 2010-2018 in the case of emergency department visits). Measures refers to rates of hospitalizations or visits 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 and for individuals aged 0-1 year. 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. Observations in Panel B covers individuals born from 2005 to 2018, and their hospitalizations between 2005 and 2019. Observations in Panel C for outcomes such as attendance, enrollment, and GPA, cover all students trajectories (panel data) at school from the years 2007 to 2019. In the case of math and verbal test scores (Panel D), we only account of one observation per student at 4th grade who took the test in the years between 2004 and 2008 at 9, 10, or 11 years old. ^{a} As explained in section 5.1 below, we consider certain parameters to model wildfire smoke plume and thus exposure to wildfire air pollution. Particularly, we consider smoke plume heights of up to 50 meters above ground for a municipality to be classified as exposed to wildfire air pollution; modeled injection point (into the atmosphere) for the plume of pollutants from the wildfire at 500 meters above ground at the point of origin of the fire; maximum distance from municipality centroid to wildfire origin of 500 Km; maximum distance of the core of the modeled smoke plume to the centroid of the municipality of 5 Km; and up to 10 days of modeling for wildfire smoke (meaning the number of days a wildfire is assumed to transmit smoke).

that spans from 1 to 7, and considers only those students who actually enrolled. Here the measure of exposure to wildfire's smoke plume considers the whole summer prior to the academic year (specifically the months of December, January, and February prior to the beginning of the school year, in March each year), where the average number of days of exposure is about 0.13, with a maximum of 4.3 days. Finally Panel D shows individual measures of long term educational outcomes, particularly, standardized test scores consider students in 4$^{\text{th}}$ grade who took a test on both math (264) and verbal (272) during the years between 2014 and 2018. Here, the measure of wildfire smoke exposure is analogue to the one in Panel B, but the mean and maximum values are lower, mainly because of the specific years we include.

5 Wildfire Exposure and Empirical strategy

5.1 Modeling of Wildfire Smoke Exposure (HYSPLIT)

While we have rich data on wildfire ignition location and intensity which can provide some proxy of exposure, the environmental consequences of wildfires depend critically on atmospheric conditions. Smoke plumes can travel long distances, often affecting populations far from the fire origin. In Chile, prevailing westerly winds and topographic features such as the Andes Mountains and Chile's central valley basin shape the horizontal and vertical dispersion of wildfire smoke. This makes it difficult to infer population-level exposure using only proximity-based metrics. The use of atmospheric transport models is therefore particularly relevant in Chile's diverse topography, enabling a more precise estimation of exposure windows and the spatial extent of health risk.

To measure exposure to wildfire smoke plumes, we employ the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model (Stein et al., 2015; Draxler and Hess, 1998). HYSPLIT is a widely used atmospheric transport and dispersion model developed by the Air Resources Laboratory of the US National Oceanic and Atmospheric Administration (NOAA) that computes trajectories of air parcels, and thus, the spread of particle air pollutants under realistic meteorological conditions. By using HYSPLIT, we can explicitly model the pathways of smoke from the point of initiation of each wildfire through the atmosphere, rather than relying on crude distance measures or purely observational proxies. This approach provides a physically grounded estimate of where and when smoke travels, which is crucial for accurately assessing exposure to each wildfire in our data.

In our application, we performed forward trajectory simulations from the georeferenced ignition point of each wildfire using the HYSPLIT model and meteorological data covering Chile optimised for use in HYSPLIT described in Stein et al. (2015).[13] For each wildfire, air parcel trajectories were launched every 8 hours from the georeferenced point of ignition. Starting at the time of ignition, trajectories were drawn throughout the duration of the event (up to a maximum of 10 days, or for the actual duration of the fire, if shorter). Each trajectory was initialized at a height of 500 meters above ground level; additional simulations were conducted at 0, 250, 1000, and 1500 meters to assess robustness (see, for example Wen and Burke, 2022). The model provides the position (latitude, longitude, and altitude) of the smoke parcel for every hour, enabling precise mapping of both the spatial and vertical dispersion of the plume during the first days of each wildfire. All trajectories originate from the same fire start location, simulating the continuous release of smoke under realistic atmospheric conditions.

Using the HYSPLIT output, we construct a measure of smoke exposure for each municipality and each wildfire in our data. In essence, we flag a location as "exposed" to the air pollutants from the wildfire at a given moment of time if any simulated trajectory passes sufficiently close to that location under criteria designed to capture meaningful ground-level smoke presence. Specifically, we require that a trajectory segment comes within 5 Km of the location, at an altitude below 50 m (indicating the smoke is near ground level), and remains in the vicinity for at least 1 hour.[14] In our analysis, locations and time periods meeting all these conditions are classified as experiencing wildfire smoke exposure for a period of 8 hours (which corresponds to the frequency of the launching of trajectories). This trajectory-based exposure assignment leverages the full spatiotemporal information from the HYSPLIT simulations: for example, if a smoke plume travels over a city at low altitude for several hours, our method will record exposure for that city on that date, even if the wildfire source is far away or not obvious from simple distance measures.[15]

A key benefit of the HYSPLIT modeling approach is its ability to account for atmospheric transport dynamics when determining smoke exposure. Simple proximity-based metrics (e.g., distance

[13] These data are provided by NOAA, along with the US National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR).

[14] These threshold values (5 Km, 100 m altitude, 1 hour of duration) serve to exclude cases where smoke is aloft or too distant to materially impact ground-level pollution at the location.

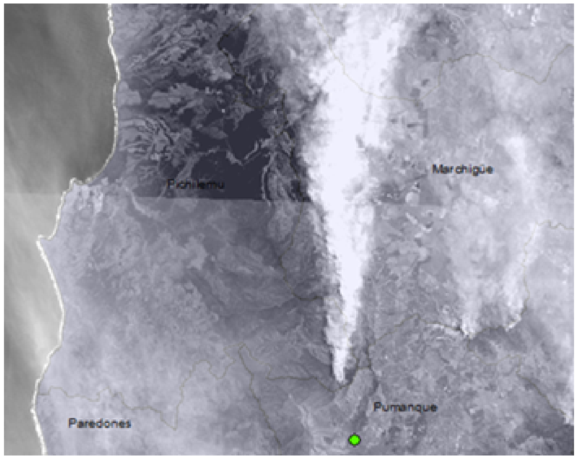
[15] Exposure will of course thus depend upon geographic proximity to wildfires, and in the Chilean case in particular, this exposure is concentrated in the central area of the country in which both substantial vegetational cover is present, but summer conditions are hot and dry (see Appendix Figure A2).

to the nearest fire) are often poor proxies for true smoke exposure because they ignore wind patterns and smoke plume behavior. Wildfire smoke can travel hundreds of kilometers depending on wind direction and stability, sometimes heavily impacting distant communities while sparing closer areas that lie upwind or considerably below the height of the smoke plume. By explicitly simulating trajectories, we capture this heterogeneity: only those downwind areas under the plume's path and height are marked as exposed, which improves attribution of observed impacts to wildfire smoke (Wen et al., 2023).

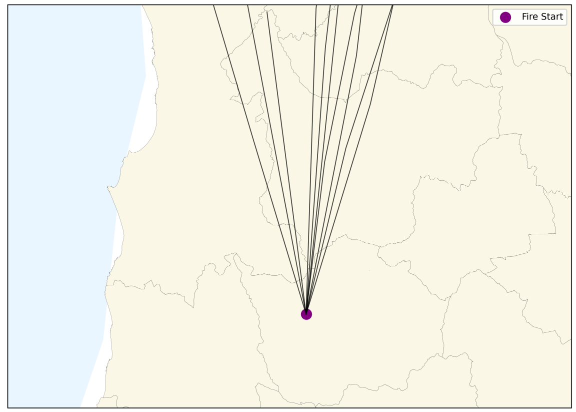
Similarly, satellite-derived measures of particle air pollution, such aerosol optical depth (AOD), provide valuable information on smoke aerosol presence but they have limitations for ground-level exposure assessment. AOD represents the total columnar aerosol load (as observed from above) and does not directly indicate surface-level particle air pollution concentrations that affect human health; satellite observations can also be unavailable or obscured during cloudy conditions or only offer once-daily snapshots. As noted by Reid and Maestas (2019), a high AOD does not always translate to high ground-level smoke pollution (for instance, if smoke remains in the upper atmosphere). In contrast, our HYSPLIT-based approach focuses on smoke at population level and overcomes many data gaps by using a transport model driven by continuous meteorological data.

Another advantage is the improved temporal resolution and source attribution. Trajectory modeling allows us to link pollution events to specific fires and hours, which is valuable for the identification of the impact of exposure to wildfire on downstream (human capital) measures. Traditional exposure metrics in the literature often rely on daily averages from sparse monitoring stations or broad satellite plume maps (e.g., Borgschulte et al., 2024). Those approaches may misclassify exposure (e.g., if a monitor is upwind of a plume or if a satellite detects a diffuse haze that never reaches ground-level). In contrast, the HYSPLIT simulation provides a rich, high-frequency representation of smoke dispersion, enabling us to identify not just whether a location was affected by wildfire smoke, but also to quantify features like the duration of exposure and potential smoke concentrations (with further modeling or assumptions). These improvements in exposure measurement enhance the accuracy of our subsequent analysis of wildfire smoke's economic impacts, helping to address measurement error concerns that are often not captured in the extant literature (Clarke, 2017).

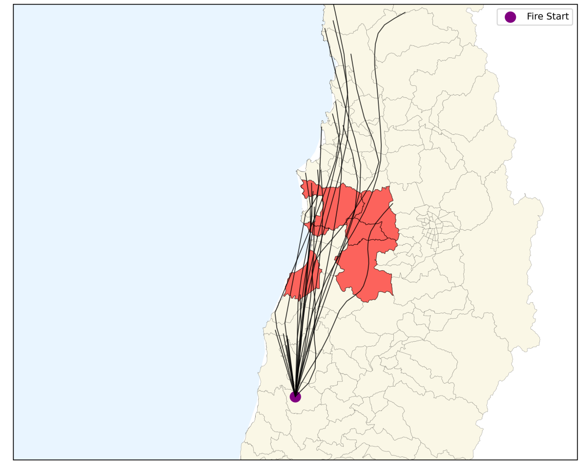
Figure 2: Modelling Smoke Exposure: A Specific Example (Nilahue Barahona wildfire, January 17–28, 2017)



(a) Satellite image 3 days after ignition



(b) HYSPLIT Simulation of Trajectories



(c) Exposed Municipalities

Notes: Panel (a) documents the Nilahue Barahona wildfire based on a satellite image taken 3 days after ignition of the event. Image source: Copernicus Sentinel-1 SAR-2. Panel (b) documents the simulated smoke plumes from the Nilahue Barahona wildfire during the first three days after ignition based on HYSPLIT modelling with atmospheric conditions. Panel (c) documents all simulated smoke plumes and municipalities classified as exposed to the wildfire during the seven days after ignition, created with the HYSPLIT model. Red areas indicate affected municipalities, defined as those that meet the following criteria: plume injection height of 500 meters, the wildfire trajectory passes within 5 km or less of the municipality centroid, the modeled particle is at a height of 100 meters or less, and the distance from the fire origin to the affected commune is less than or equal to 500 km.

Figure 2 provides a concrete example of our exposure modeling approach by illustrating the spatial extent of smoke emissions from a single wildfire (the Nilahue-Barahora wildfire). The red-shaded municipalities are those that meet all of our exposure criteria -— namely, proximity to the municipal centroid, vertical altitude of the smoke parcel, and maximum horizontal distance from the fire origin. The black lines trace the HYSPLIT-simulated trajectories of smoke particles released from the fire. This example highlights how our method captures both the direction and reach of smoke dispersion, allowing us to identify municipalities likely exposed to harmful concentrations of fire-related pollutants during the wildfire's active phase. This also makes clear that a simple distance-based measure would result in a substantially different classification, likely not capturing municipalities quite far north of the source of the fire which are indeed found to be exposed to smoke plumes. We validate this modeling strategy in Section 6.1 where we consider whether modeled exposure does indeed drive $PM_{2.5}$ concentrations at ground level.

5.2 Empirical Strategy for Estimating Effects of Exposure to Wildfire Smoke

5.2.1 Baseline Exposure Models in the Short, Medium and Long-Term

In order to isolate causal effects of exposure to wildfire air pollution, we implement a design which seeks to compare outcomes among individuals in closely-located areas, but where certain individuals were exposed to wildfire particulates—as modeled by HYSPLIT in a specific moment in time—while others were not. To implement such a design, we rely on rich location- and time-specific fixed effects such that, plausibly, the only difference between exposed and unexposed units is their exposure to wildfire air pollutants.[16] The precise specification depends upon the time-horizon and data set-up (e.g., whether municipal or individual-level or short- or long-run). For the case of air pollution and health outcomes in the short run, we begin by estimating:

$$y_{mrt} = \alpha + \beta \cdot \text{Exposure}_{mt} + \varphi_m + \lambda_t + \mu_r \cdot \delta_q + \varepsilon_{mrt} \tag{6}$$

[16]This can be viewed as broadly analogous to designs based on upwind versus downwind exposure in areas which are geographically proximate. In this case, rather than only depending on wind, our design depends upon modeled climate conditions more generally, but maintains the local exposure design of wind-based settings such as (Deryugina et al., 2019; Anderson, 2019; Rangel and Vogl, 2019; Rocha and Sant'Anna, 2022).

where y_{mrt} refers to outcomes in municipality m, in region r and in period t (whereby, for estimating short-run effects, t refers to week-by-year). These outcomes are regressed on the number of days of smoke plume exposure occurring in that particular week in (6). We capture any municipality-specific time-invariant factors, such as geographic location or slowly-evolving demographic characteristics of residents, with φ_m, and any time-specific effects with λ_t. Importantly, we consistently include region-by-quarter-by-year fixed effects, here $\mu_r \cdot \delta_q$. This is key to the design as it allows us to isolate exposure to marginal wildfire air pollution when contrasting municipalities within the same region r and in the same quarter of the year q.[17] Finally, the term ε_{rmt} is a stochastic error term, and standard errors are consistently clustered in 0.75°× 0.75° spatial grid cells (roughly, 70×70 Km).[18] The coefficient of interest β captures the marginal effect of an additional day exposed to wildfires' air pollution.

While (6) considers immediate impacts of wildfire exposure on outcomes of interest, we also estimate a number of richer specifications which allow us to consider both the cumulative impact of prior exposure, as well as provide partial specification checks. As a first consideration, we replace contemporaneous exposure to wildfires $\text{Exposure}_{m,t}$ with exposure averaged over the last eight weeks (the current and seven previous weeks). We then also consider a richer specification based on both lags and leads to wildfire exposure. Specifically we estimate:

$$y_{mrt} = \alpha + \sum_{j=-5}^{6} \beta^j \text{Exposure}_{m,t+j} + \varphi_m + \lambda_t + \mu_r \cdot \delta_q + \varepsilon_{mrt} \tag{7}$$

where all details follow equation (6), with the exception of $j = 5$ lead effects (i.e., pre-wildfire periods), and $j = 6$ lag effects (i.e., post-wildfire periods). This allows us to examine any immediate impacts of wildfire exposure on outcomes (the coefficient β^0), along with any delayed impacts ($\beta^1, \ldots, \beta^6$). What's more, this provides us with a consistency check in that if our specification is indeed capturing differences owing to wildfire exposure—rather than systematic or cyclical differ-

[17] Municipalities are nested within administrative districts (regions). There are 16 such regions in Chile and these are the second level of administrative government.

[18] In a previous working paper version of this study (Arrizaga et al., 2025) we report standard errors clustering by municipality. However, given that many municipalities are small, and, conceivably, there are unobserved geographic shocks which will propogate across space beyond a single municipality, in this version of the paper we take the more conservative approach of using broader grid cells for clustering, which imposes a less demanding covariance structure on error terms, in particular allowing arbitrary correlations between municipalities within larger grid cells. We are grateful to an anonymous referee for suggesting this approach.

ences between areas exposed and unexposed to wildfires—we would expect no differences in the lead up to the fire, which we can test by considering terms $\beta^{-5}, \ldots, \beta^{-1}$.

Our identification strategy relies on the assumption that, conditional on these fixed effects, the wind direction and atmospheric conditions that shape wildfires' smoke plumes should not affect health outcomes other than via changes in exposure to the air pollutants from these wildfires. Thus, we estimate the impact of exposure to wildfire air pollution—i.e. whether an individual's normal area of residence falls within its smoke plume—on a number of health and educational outcomes.

Moreover, for educational outcomes in the short/medium term, we wish to consider the impact of exposure over the prior wildfire season. Noting that wildfire seasons commonly span from December to February of the following year (i.e., the summer season in the southern hemisphere), and that the school year begins in March. Given that we have a measure of yearly academic performance for all students repeated by student over time, we estimate:

$$y_{imt} = \alpha + \beta \cdot \text{Exposure}_{imt}^{Summer} + \varphi_i + \mu_{r(m)} \cdot \delta_b \cdot \lambda_t + \varepsilon_{imt}. \tag{8}$$

Here y_{imt} represent educational outcomes for student i in municipality m and in year t. The coefficient β measures the marginal effect of one additional day of wildfire air pollution during the summer just before the school year starts. Specifically, $\text{Exposure}_{imt}^{Summer}$ sums wildfire smoke plumes across the months December of year $t-1$, and January and February of year t, corresponding to the peak of wildfires and to the months just before classes start (typically on early March). We control for time-invariant characteristics of students with φ_i, and also we aim to compare similar students in the same geographic location and time by interacting year-of-birth b, region r and year t fixed effects, $\delta_b \cdot \mu_{r(m)} \cdot \lambda_t$.

Finally, in the case of long-term effects we seek to determine how exposure in a particularly sensitive period—namely the weeks and months before birth—shape later life health and educational outcomes. In this case, we estimate the effect of each individual's exposure to wildfire smoke during the *in-utero* period. Specifically we estimate the following specification:

$$y_{imb} = \alpha + \sum_{k=1}^{3} \beta_k \cdot \text{Exposure}_{imw(b)}^{IU-Trimester\ k} + \mu_m + \lambda_{t(b)} + \mu_r \cdot \delta_b \cdot \lambda_s + \varepsilon_{imb}, \tag{9}$$

where y_{imb} denotes the health and educational outcomes for individual i born in municipality m and year b. Similarly to the exposure measure in (8), $\text{Exposure}_{imw(b)}^{IU-Trimester\ k}$ sums the in-utero (IU) exposure to wildfire smoke plumes during a specific trimester k, considering the weeks w before birth of individual i at year b. Exposure in this case is defined for each of the three trimesters of gestation, where we follow Persson and Rossin-Slater (2018) in defining exposure based on expected rather than actual gestational weeks from conception.[19] By standardizing the exposure window to a full expected gestation, we avoid the mechanical bias where infants with shorter gestational periods would otherwise appear to have lower cumulative exposure simply due to a truncated observation window.[20] As above, μ_m represents fixed effects at municipality of birth, $\lambda_{t(b)}$ represent fixed effects at calendar-month-by-year-of-birth, and $\mu_r \cdot \lambda_s \cdot \delta_b$ is an interacted fixed effect at region-of-birth $\times$ season $\times$ year-of-birth

Multiple Testing and Over-rejection of Null Hypotheses As we consider the impact of wildfire exposure on multiple outcomes, we should be concerned about over-rejection of null hypotheses if standard test-by-test p-values are used in interpretation of statistical significance. Thus, along with point estimates and standard errors, we present FDR-adjusted p-values. Specifically, we present sharpened q-values as discussed in Anderson (2008), based on Benjamini et al. (2006). We report these p-values across all outcomes for a given independent variable of interest, i.e., we separately adjust p-values for each of short, medium and long-term outcomes.

[19] Specifically, to define exposure in each trimester we impute the approximate date of conception (c) for each individual by subtracting the recorded gestational length of each birth from the actual date of birth. We then calculate the first trimester (weeks 1–13), the second trimester (weeks 14—26), and the third trimester (weeks 27–40). Crucially, following Persson and Rossin-Slater (2018), we calculate the third trimester exposure over a fixed window ending 280 days (40 weeks) post-conception ($e_b = c + 280$), regardless of the actual date of birth. This approach ensures that our measure of exposure is exogenous, determined solely by the timing of conception relative to wildfire events rather than the potentially endogenous length of gestation.

[20] Equation (9) is our preferred measure of in-utero exposure, however this requires data in which we can match individual's birth records, including their gestational length, with long-term outcomes. While we can do this in the case of any long-term health outcomes, for educational outcomes we do not observe an individual's conception length, rather we only observe their birth date. In these cases, we take an alternative approach whereby, rather than counting forward from conception, we count backwards from birth, and define exposure in terms of time immediately preceding birth. Namely, we estimate:

$$y_{imb} = \alpha + \beta \cdot \text{Exposure}_{imw(b)}^{IU} + \mu_m + \lambda_{t(b)} + \mu_r \cdot \delta_b \cdot \lambda_s + \varepsilon_{imb}, \tag{10}$$

where details follow those described in (9), but now exposure is defined in terms of fixed periods before birth. We consider two weeks, one month, and one trimester in separate specification.

5.2.2 Quantifying Exposure to Wildfires in Terms of their Associated $\text{PM}_{2.5}$ Air Pollutants

While our principal interest empirically is in estimating mean effects of exposure to wildfires, we consider two additional analyses focused on quantifying dose responses to air pollutants themselves. A first strategy consists in estimating the *direct* effects of $\text{PM}_{2.5}$ air pollution from wildfires. In this model, we estimate Two-Stage Least Square (2SLS) equations in which $\text{PM}_{2.5}$ is first instrumented by wildfires following our strategy above, and then outcomes are regressed on instrumented $\text{PM}_{2.5}$ in a second stage. Thus, rather than reporting the reduced form model as in (6), we estimate the following two-stage strategy:

$$\text{PM}_{2.5,mrt} = \pi_1 + \pi_2 \cdot \text{Exposure}_{mt} + \varphi_m + \lambda_t + \mu_r \cdot \delta_q + \varepsilon_{mrt} \tag{11}$$

$$y_{mrt} = \alpha + \beta^{2SLS} \cdot \widehat{\text{PM}_{2.5}}_{mt} + \varphi_m + \lambda_t + \mu_r \cdot \delta_q + \varepsilon_{mrt}. \tag{12}$$

Notably, all details follow those in (6). Importantly, if the assumptions of conditional exogeneity, instrument relevance, and an exclusion restriction hold, we can view estimates of $\widehat{\beta}^{2SLS}$ as consistent estimates of the effect of exposure to $\text{PM}_{2.5}$ air pollution on outcomes y. Given the need for consistently measured $\text{PM}_{2.5}$ for each municipality, in this case $\text{PM}_{2.5}$ measures are drawn from remote sensed data.[21]

On the other hand, non-linear patterns of exposure to wildfire air pollution have been suggested by Heft-Neal et al. (2023); Miller et al. (2024). Thereby, a second strategy seeks to examine whether the impact of wildfires varies by *baseline* levels of $\text{PM}_{2.5}$ pollution (i.e., air pollution during periods of time when not exposed to the wildfire smoke plume). We implement this by estimating the following specification:

$$y_{mrt} = \alpha + \beta \text{ Exposure}_{mt} + \gamma \text{ Exposure}_{mt} \times \text{Baseline PM}_{2.5s} + \varphi_m + \lambda_t + \mu_r \cdot \delta_q + \varepsilon_{mrt}. \tag{13}$$

As before, all details follow those laid out in (6). However, the effect of wildfire exposure is now allowed to vary according to baseline levels of $\text{PM}_{2.5}$ in a given municipality. Hence, estimating

[21] While we view ground-sensed data from SINCA as preferable, and use this to document effects of wildfires in $\text{PM}_{2.5}$ in our main analysis, the fact that these cover a maximum of 82 municipalities, and typically far fewer, and corresponding concerns about bias in IV estimates with small sample sizes and weak first stages, makes us prefer remote-sensed data from the Copernicus satellite when obtaining 2SLS estimates.

the parameter γ allows us to test for non-linear effects of wildfire exposure. For this specification baseline $PM_{2.5}$ is measured as the pollution in summer periods in a given municipality when no wildfire smoke plumes are observed. These models are estimated only for short-run outcomes, as is the case with (6).

6 Results

6.1 Wildfires Smoke Modeling (HYSPLIT) and $PM_{2.5}$ Air Pollution

We begin by documenting the estimated impact of wildfire exposure on $PM_{2.5}$ air pollution. Table 2 presents results from (6), where the outcome of interest is the natural logarithm of $PM_{2.5}$ concentrations. This table considers a range of specifications where differences depend upon key parameter inputs into HYSPLIT modeling. Specifically, across columns we vary the maximum distance between municipality centroids and smoke trajectories modeled from HYSPLIT, as well as the maximum distance which trajectories are followed. And across panels A and B we consider exposure defined as cases where municipalities are defined as exposed if smoke is modeled within 50 meters of ground level or within 100 meters of ground level.

One key point from this table is that, regardless of these choices, when combining wildfire initiation points with HYSPLIT exposure modeling, we estimate large effects on $PM_{2.5}$ pollution at ground level. Outcome measures are all captured from ground-level monitoring stations, and so they provide high-quality measurements of $PM_{2.5}$ pollution. These effects are large, ranging from between a 15 to a 30 percent increase in the week average when a municipality is exposed to a 24-hour period of wildfire smoke exposure. A second key point is that while we see clear evidence that our model captures air pollution exposure, the degree to which exposure drives $PM_{2.5}$ pollution does depend on parameters used in HYSPLIT modeling to define exposure. Specifically, we generally see that effects are larger when we consider greater areas over which smoke can travel (i.e., moving from columns 1 to 2, and from columns 3 to 4), and when considering municipalities which are closer to areas where smoke is modeled to pass (columns 1 and 2, as compared to columns 3 and 4). Specifically, effects are observed to be largest when exposure is defined to allow a greater smoke dispersion (500 Km rather than 100 Km), but municipalities are observed to be closer to smoke plumes (within 5 Km rather than 10 Km). Although the Akaike Information Criterion (AIC) is minimized when the smoke trajectory height is set at 100 meters, the results do not differ substantially from the 50-meter case, where coefficients are larger in magnitude. Consequently, and because such specifications are essential for exposure modeling, we utilize the 50-meter parameters for our downstream analysis of health and educational outcomes.

Table 2: Effect of Wildfire Exposure on Log of $PM_{2.5}$ Pollution ($\mu g/m^3$)

	(1) log($PM_{2.5}$)	(2) log($PM_{2.5}$)	(3) log($PM_{2.5}$)	(4) log($PM_{2.5}$)
Panel A: Height of modeled smoke trajectory above ground: $\leq$ 50 meters				
Exposure (8 hrs.)	0.090***	0.100***	0.057***	0.061***
	(0.034)	(0.031)	(0.021)	(0.019)
R-squared	0.787	0.787	0.787	0.787
Akaike I.C.	18,315	18,302	18,316	18,303
Panel B: Height of modeled smoke trajectory above ground: $\leq$ 100 meters				
Exposure (8 hrs.)	0.086***	0.093***	0.052***	0.055***
	(0.030)	(0.028)	(0.018)	(0.017)
R-squared	0.787	0.787	0.787	0.787
Akaike I.C.	18,313	18,299	18,313	18,300
Distance ($\leq$ Km)				
Smoke Traj. to Municipality	5	5	10	10
Municipality to Wildfire	100	500	100	500
Mean $PM_{2.5}$	24.55	24.55	24.55	24.55
Observations	28,333	28,333	28,333	28,333

Notes: Each panel presents a sequence of FE models where the natural logarithm of $PM_{2.5}$ air pollution—as recorded by ground-level monitoring stations—is regressed on the number of HYSPLIT-modeled smoke trajectories that meet the conditions specified for each model and panel. For example, results for column (1) of Panel A considers only those municipalities that are at a distance of up to 5 Km from the nearest HYSPLIT-modeled air parcel trajectory, at a distance of up to 100 Km from the origin of the wildfire, and where the HYSPLIT-modeled air parcel trajectory passes at an elevation of no more than 50 meters above ground. Standard errors, shown in parentheses, are clustered at the level of the municipality. Each model includes municipality, week-year, and region-by-quarter by year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Short-term effects on health and 'Mid-term' effects on education

6.2.1 Estimated Impacts of Wildfire Exposure

We now turn to consider the impacts of exposure to wildfires air pollution on health outcomes as measured by inpatient hospital admission, and educational outcomes as measured by yearly enrollment and grade point average (GPA). In Table 3 we present results for equation (6) including a combination of fixed effects and considering hospital admissions for respiratory causes only (ICD-10 codes J00-J99). Each column considers separate independent variables based on the timing of exposure (i.e., from exposure in the contemporaneous week to exposure during the last eight weeks). We also differentiate by ages, considering particularly all ages, infants (those one year old or younger), and toddlers (1 to 5 years old).

Table 3: Effects of Wildfire Exposure on Rate of Hospital Admissions due to Respiratory Diseases

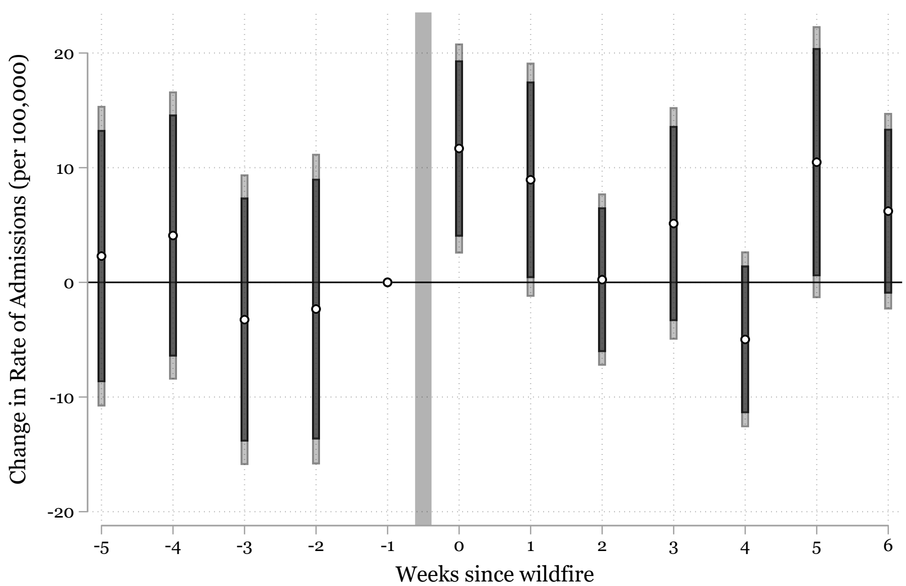
	All Ages		Infants ($\leq$ 1 year old)		Toddlers (1–5 years old)	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure on same week	0.028		7.683**		-0.640	
(8-hour period)	(0.111)		(3.011)		(0.726)	
Exposure over last eight weeks		0.709		44.703**		0.897
(8-hour period)		(0.547)		(17.270)		(3.458)
Mean of Dep. Var.	21.25	21.25	210.93	210.93	52.29	52.29
Observations	304,784	304,784	302,856	302,856	303,742	303,742
R-Squared	0.55	0.55	0.41	0.41	0.29	0.29
FDR-adjusted p-values	0.551	0.248	0.042	0.035	0.373	0.425
Fixed Effects						
Municipality	Y	Y	Y	Y	Y	Y
Week$\times$Year	Y	Y	Y	Y	Y	Y
Region$\times$Quarter$\times$Year	Y	Y	Y	Y	Y	Y

Notes: Each observation correspond to a cell municipality $\times$ week as described in the Section 4. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the $0.75° \times 0.75°$ spatial grid (roughly, 70$\times$70 Km) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the case of respiratory hospital admissions for individuals of all ages, we observe small and non-significant effects on hospitalizations when considering contemporaneous exposure (column 1). This effect turns larger, although still non-significant, when considering exposure over the last eight weeks (column 2). When considering infants (columns 3 and 4), we identify important and statistically significant effects for both measures of smoke exposure. Importantly, when considering contemporaneous wildfire smoke exposure, column 3 shows that, an additional day of smoke exposure, we find an increase of 23.05 (7.683×3 periods of 8 hours) hospitalizations due to respiratory causes per 100,000 infants, which implies an increase of 10.9 percent respiratory hospital admissions over the mean. When we consider the last eight weeks we find that an additional day of smoke exposure leads to 134.1 hospitalization due to respiratory diseases per 100,000 infants, implying a 63.6 percent increase over the mean. This represents the cumulative effect of wildfire smoke exposure on infant's respiratory hospital admission (we will return to this in the paragraph below). Finally, note that we do not find statistically significant effects for children 1–5 years old, demonstrating how important the effects can be for more vulnerable ages, as is the case for infants.

Figure 3: Dynamic Effects of Wildfire Exposure on Infants' Respiratory Hospitalizations



Notes: Point estimates and 95% and 90% CIs are reported on coefficients $\{\beta^{-5}, \ldots, \beta^0, \beta^6\}$ from (7). Unlike other estimates in the paper, the window for accounting for smoke exposure is counted up to 7 days in this case, to avoid significant overlap between weeks for the estimate.

Figure 3 reports the dynamic effects on infants' hospitalizations due respiratory causes following equation 7. We observe statistically significant effects of wildfire smoke exposure. The effects are clearly larger during the contemporaneous week, but we also can also distinguish positive effects one week and 5 weeks after exposure. We notice that before wildfire smoke exposure there are no statistically significant effects, evidencing the existence of no pre-trends, which would be suggestive of more general differences between exposed and unexposed municipalities in our fixed-effects design.

While the prior hospitalization results points to effects on admissions, this may miss cases where individuals feel sick enough to visit an urgent care facility (either a primary care facility or an emergency department unit within a hospital) and are evaluated and discharged without a admission to hospital. Therefore, we additionally present results for urgent care visits in Table 4 below. These results are consistent with our prior findings for hospital admissions. We find that while the effect of wildfire exposure on all-cause urgent care visits remain relatively small in magnitude, urgent care visits specifically for respiratory causes increase substantially for all ages, with relatively larger proportional effects among very young individuals.[22]

Table 4: Effects of Wildfire Exposure on Rate of Urgent Care Visits

	All causes			Respiratory causes		
	All ages (1)	$<$ 1 years old (2)	1-5 years old (3)	All ages (4)	$<$ 1 years old (5)	1-5 years old (6)
Exposure on same week	-3.723	71.485	15.336	8.232**	132.344***	42.423**
	(7.238)	(51.152)	(17.203)	(3.317)	(32.048)	(19.009)
Mean of Dep. Var.	1506.36	4633.02	2647.57	448.77	2627.98	1400.37
Observations	161,460	160,212	160,732	161,460	160,212	160,732
R-Squared	0.87	0.85	0.88	0.78	0.70	0.78
FDR-adjusted p-values	0.437	0.199	0.373	0.042	0.001	0.047
Fixed Effects						
Municipality	Y	Y	Y	Y	Y	Y
Week$\times$Year	Y	Y	Y	Y	Y	Y
Region$\times$Quarter$\times$Year	Y	Y	Y	Y	Y	Y

Notes: Each observation correspond to a cell municipality $\times$ week as described in the Section 4. The sample consider years from 2010 to 2018. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the 0.75°$\times$ 0.75° spatial grid (roughly, 70$\times$70 Km) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Moving on to the effects on educational outcomes, Table 5 shows our main estimates by school type (public, voucher and private). Here we observe that an additional day of wildfire smoke exposure during the summer period led to effectively zero effects attendance, but negative effects on

[22] It has been shown that 'avoidance behavior' may result in reduced visits for non-respiratory causes on days with elevated wildfire air pollution (Heft-Neal et al., 2023). Results shown in column (1) of Table 4, although non-significant, are consistent with such findings. Indeed, noting that respiratory cases actually increase, this, combined with a lack of movement in all cause visits suggests that rates of non-respiratory visits must decrease.

enrollment rate and GPA in the following school year. Effects on enrollment are small in magnitude (but statistically significant), with a marginal effect of an additional day of wildfire smoke exposure on dropout rate of 0.08 percentage points and 0.05 percentage points. While these values are small, they are noteworthy when considering the enrollment rates are high (over 95% of students who should be enrolled are), and that dropout is quite an extreme outcome.[23] Regarding effects on GPA, we find a negative marginal effect in public and voucher school of approximately 0.06 and 0.05 points, respectively, or approximately 0.1 percent of the mean GPA presented in table footers.[24] Again, we find no statistically significant effects on GPA for private schools

It is somewhat puzzling that we do not find effects on attendance, but we do find effects on performance. While there are a number of possible explanations, such as cognitive effects of exposure to smoke (Grennan et al., 2023) or economic impacts of wildfire exposure which spillover into educational performance (Borgschulte et al., 2024; Chan et al., 2023), it is important to note that the vast majority of wildfires occurring in Chile occur during school summer vacations, with quite little overlap with the school calendar year (refer to Appendix Figure A3). We further investigate whether we observe evidence of impacts of wildfire exposure on school attendance focusing specifically on a small number of fires which occurred during the school period. In particular, we examine the June 2013 wildfire season in the V and VII regions, which include 38 and 30 municipalities, respectively. The spatial variation in smoke exposure within these regions enables a comparison of attendance between students who were exposed to the wildfires and those who were not. Figure A4 shows attendance trend between treated and control students. Despite some baseline differences in trends, we observe small divergence in attendance rate immediately following the wildfire. We estimate a simple TWFE model at student–month level to test this difference (see Table A3). While point estimates are negative in this case, these are not statistically significant. Thus, in general, our results point to relatively limited effects of wildfires in this particular setting. However, the fact that most wildfires occur *outside of the school calendar*, and correspondingly that much avoidance behaviour may be limited in this setting, suggests that these results should likely be viewed as a lower bound.

[23] Dropout rates are measured as 100 minus the enrollment rate.

[24] GPA is reported on a scale of 1.0 (lowest possible grade) to 7.0 (highest possible grade), with 4.0 being a passing score. In the interests of presentation, we have multiplied GPA by 100 in this table.

Table 5: Mid-Run Effects of Wildfire Exposure on Educational Outcomes, by School Type

	Attendance			Enrollment			GPA		
Type of school:	Public (1)	Voucher (2)	Private (3)	Public (4)	Voucher (5)	Private (6)	Public (7)	Voucher (8)	Private (9)
Summer Smoke Exposure	-0.0078	0.0022	0.0103	-0.0282**	-0.0168**	-0.0174	-0.0217***	-0.0163***	0.0064
(8-hours period)	(0.016)	(0.010)	(0.027)	(0.011)	(0.007)	(0.021)	(0.006)	(0.006)	(0.010)
Mean of Dep. Var.	87.197	90.851	92.748	95.968	97.835	98.276	55.655	56.723	60.889
Observations	13,319,764	15,929,606	2,448,075	13,319,764	15,929,606	2,448,075	12,694,089	15,506,012	2,399,482
R-Squared	0.53	0.51	0.41	0.45	0.44	0.37	0.72	0.77	0.82
FDR-adjusted p-values	0.790	0.853	0.790	0.029	0.038	0.719	0.004	0.019	0.790
Fixed Effects									
Year-of-birth×Year×Region	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Sample consists of all students (individual measures) between 2007-2018. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. For a clearer interpretation of the results and standard errors, the coefficients for enrolment are multiplied by 100, and those for GPA by 10. Standard errors clustered by school are displayed in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.2.2 Effects of $PM_{2.5}$ Air Pollution Associated to Wildfires

While the main focus of our paper is in documenting the effect of exposure to wildfires themselves, given the recent evidence of the effect of $PM_{2.5}$ air pollution from wildfires on mortality and health outcomes (Heft-Neal et al., 2023; Miller et al., 2024; Wen and Burke, 2022), we seek to examine the impact of such pollutant in a number of ways. Our first approach seeks to directly quantify the effect of $PM_{2.5}$ exposure on the outcomes of interest. Here, as discussed in Section 5 we focus on short run health outcomes, following the two-stage least squares (2SLS) approach outlined in equations (11) and (12). This instrumental variables (IV) approach lets us compare our results with the broader literature. However. this is not our main analysis given that this relies on an exclusion restriction which we may not want to impose. Results from the second stage of the 2SLS regressions are presented in Table 6. In line with our reduced form effects presented earlier, here we observe significant effects of $PM_{2.5}$ pollution on increased respiratory hospital admissions among infants. However, given the increased variance of IV models, these results, while relatively large in magnitude, are not significant at typical levels if considering FDR adjusted p-values presented in the table footer. Nevertheless, the effect sizes are relevant. A one-point increase in $PM_{2.5}$ from wildfires is estimated to increase respiratory hospitalizations of infants by 1.6 per hundred thousand. In percentage terms, each point increase in $PM_{2.5}$ is estimated to increase respiratory hospitalizations for this group by 0.76% and a one standard deviation (Std. Dev. = 21.78, as shown in Table 1) is estimated to increase by 16.5% . These effects provide a useful benchmark, and also tend to be in magnitude with other effects of $PM_{2.5}$ reported in the literature (Dominici et al., 2014; Li, 2021).

Finally, following equation (13), we test whether the marginal effect of wildfire exposure varies with baseline levels of $PM_{2.5}$ pollution in these municipalities. Recent literature has found a concave relationship between $PM_{2.5}$ air pollution from wildfires and emergency department visits (Heft-Neal et al., 2023) as well as mortality outcomes among the elderly population, both for US populations (Miller et al., 2024). Although we do not evaluate non-linearities directly for $PM_{2.5}$ pollution – due to data limitations – we assess whether our measure of wildfire exposure responds non-linearly when interacted with baseline $PM_{2.5}$ pollution. The results are reported in Table 7. Columns 1 and 3 provide evidence of non-linearities whereby baseline $PM_{2.5}$ pollution *augments* the adverse effect of wildfire exposure on infant's respiratory hospital admissions. Although the

Table 6: Effects of $PM_{2.5}$ Pollution Exposure on Respiratory Hospital Admissions

	Respiratory causes		
	All ages	<1 years old	1-5 years old
	(1)	(2)	(3)
$\widehat{PM_{2.5}}$	0.006	1.600**	-0.132
	(0.023)	(0.793)	(0.150)
Mean of Dep. Var.	21.25	210.93	52.29
Observations	304,784	302,856	303,742
First stage F-Test	23.93	23.50	23.93
FDR-adjusted p-values	1.000	0.163	0.617
Fixed Effects			
Municipality	Y	Y	Y
Week×Year	Y	Y	Y
Region×Quarter×Year	Y	Y	Y

Notes: Each observation correspond to a cell municipality × week as described in the Section 4. Estimates report parameters from a 2SLS specification in which PM 2.5 is instrumented with wildfire exposure. Standard errors clustered at the 0.75°× 0.75° spatial grid (roughly, 70×70 Km) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

estimated marginal effects are small and statistically indistinguishable from zero at low baseline $PM_{2.5}$ concentrations, they increase sharply at higher levels of ambient pollution. This pattern is observed both for all-age respiratory hospitalizations and for hospitalizations among children aged 1–5 years. Unlike Heft-Neal et al. (2023) and Miller et al. (2024) these results do not suggest a concave relationship between wildfire $PM_{2.5}$ pollution and health nor mortality outcomes.

In contrast, for infants we estimate deleterious effects of wildfire exposure across the entire support of baseline $PM_{2.5}$, with no statistically significant evidence of non-linearities. For the former groups, the estimates imply the existence of "turning points" at which wildfire exposure begins to increase hospitalization rates. These turning points correspond to baseline $PM_{2.5}$ concentrations of 25.4 μg/m^3 in column 1 (0.966 / 0.038) and approximately 30 μg/m^3 in column 3 (4.66 / 0.154). Notably, these values are close to the sample mean of $PM_{2.5}$ (as shown in Table 1), suggesting that a substantial share of the population resides in pollution conditions under which wildfire exposure generates adverse average effects on respiratory health.

Table 7: Non-linear Effects of Wildfire Exposure on Infants' Respiratory Hospital Admissions

	Respiratory causes		
	All ages (1)	$<$ 1 years old (2)	1-5 years old (3)
Exposure on same week	-0.966*	1.953	-4.666**
	(0.552)	(8.180)	(2.315)
Exposure on same week $\times$ Baseline $PM_{2.5}$	0.038*	0.230	0.154*
	(0.022)	(0.271)	(0.079)
Mean of Dep. Var.	21.12	208.21	51.86
Observations	287,040	285,115	285,998
R-Squared	0.55	0.41	0.30
FDR-adjusted p-values (β)	0.144	0.372	0.144
FDR-adjusted p-values (γ)	0.141	0.154	0.141
Fixed Effects			
Municipality	Y	Y	Y
Week$\times$Year	Y	Y	Y
Region$\times$Quarter$\times$Year	Y	Y	Y

Notes: Each observation correspond to a cell municipality $\times$ week as described in the Section 4. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the 0.75°$\times$ 0.75° spatial grid (roughly, 70$\times$70 Km) in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.3 Long-term Effects on Health and Education

We now turn to the analysis of long-term outcomes using the model presented in equation (9). Specifically, we study how in-utero exposure to wildfire smoke plumes affects birth outcomes, early childhood hospitalizations, and educational outcomes in the longer run. Table 8 below presents the estimated effects of wildfire smoke exposure on birth outcomes, specifically birth weight, birth size, and gestational weeks. We vary the window of exposure by trimester of pregnancy, whereby each trimester is calculated since conception as explained in Section 5.

When exposure occurs during the second trimester of pregnancy we observe consistently negative effects across all outcomes. For instance, the second row of column 1 shows that one additional day of smoke exposure during this period reduces birth weight by approximately 6.4 grams, equivalent to a 0.2 percent decrease relative to the mean. Likewise, column 2 shows that one additional day of wildfire smoke exposure is associated with a 0.05 cm reduction in birth size—roughly a 0.1 percent decrease compared to the average. Similarly, in column 3, we find that an extra day of exposure shortens gestational weeks by about 0.036, or 0.1 percent relative to the mean.

We also present in Online Appendix Table A4 evidence of heterogeneous effects by maternal education. Across all outcomes, we find consistently larger impacts among children whose mothers have lower levels of education. Specifically, the effects are substantially larger for children whose mothers completed only primary or only secondary education, compared to those whose mothers attained a college degree. These results suggest that more vulnerable households are disproportionately affected. This highlights the potential importance of targeting social support policies toward vulnerable households to help mitigate the adverse effects of wildfire smoke. Also, these results may reflect the findings by Hoffmann and Rud (2024), where unequal effects may be due to the limited ability of more vulnerable individuals to react to episodes of high air pollution and limit their exposure and its associated adverse effects.

Table 9 presents the effects of in-utero exposure to wildfire smoke on early-life hospitalizations. For each individual, we calculate the number of hospital admissions within different age ranges: infants (<1 year old), toddlers (1–3 years old), and all ages (i.e., the cumulative number over the life span). Similar to the birth outcomes, the estimated effects are consistently positive but less precise. Column 1 shows, for a one-day exposure during the second trimester of pregnancy, infant hospitalizations increase by 0.62 per hundred thousand.

While the overall evidence is not robust across specifications, the results do suggest a potential link between prenatal exposure and increased hospitalization during early childhood. This is particularly evident when we examine heterogeneous effects by maternal education. Focusing again on exposure in the second trimester, Online Appendix Table A5 shows that children of mothers without a college education experience notably more hospitalizations following wildfire exposure during pregnancy.

Additionally, we replicate these results following equation 10. We do this in order to compare and validate the results that we show below for educational outcomes. Table A6 and Table A7 show the results using exposure in utero two weeks and one trimester before birth as independent variables. The results are consistent, showing negative effects on birth outcomes and positive effects

Table 8: Effects of In-Utero Exposure to Wildfire on Birth Outcomes

	Birth Weight (1)	Birth Size (2)	Gestational Weeks (3)
Smoke Exposure IU [1rd trimester]	0.737	0.003	-0.002
(8-hours period)	(0.586)	(0.005)	(0.002)
Smoke Exposure IU [2rd trimester]	-2.142**	-0.016***	-0.012***
(8-hours period)	(0.846)	(0.003)	(0.002)
Smoke Exposure IU [3rd trimester]	-0.591	-0.001	-0.005*
(8-hours period)	(0.541)	(0.003)	(0.003)
Mean of Dep. Var.	3315.984	49.266	38.466
Observations	3,331,299	3,331,299	3,331,299
R-Squared	0.01	0.02	0.01
FDR-adjusted p-values (β_1)	0.814	0.814	0.814
FDR-adjusted p-values (β_2)	0.018	0.001	0.001
FDR-adjusted p-values (β_3)	1.000	1.000	0.802
Fixed Effects			
Municipality	Y	Y	Y
Month×Year	Y	Y	Y
Year×Season×Region	Y	Y	Y

Notes: Sample consists of all births (individual measures) between 2005-2018. Trimesters of pregnancy are calculated since conception, such that the first two trimesters are thirteen weeks each, whereas the third trimester may vary according to the actual week of birth. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the 0.75°× 0.75° spatial grid (roughly, 70×70 Km) in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

on the number of hospitalizations at an early age.[25]

Finally, we focus on the long-term effects in-utero wildfire smoke exposure on educational attainment. Focusing on column 1 of Panels A and B of Table 10, we find that in-utero exposure to wildfire smoke during the two weeks prior to birth is associated with a negative but statistically insignificant effect on standardized test scores in both math and verbal test scores. While the heterogeneous effects by school type (column 4) suggest some evidence of negative and statistically significant impacts on verbal test scores—particularly for students attending public and private schools—we believe that these results should be interpreted with caution.

First, in-utero exposure to wildfires is heavily concentrated in 2008, with a few additional cases in 2007, but none between 2004 and 2006. This leaves us with a relatively narrow temporal window

[25] One potential interpretation of these findings is that wildfire smoke exposure may lead to more premature births, which in turn result in worse birth outcomes such as lower birth weight and shorter length at birth.

Table 9: Effects of In-Utero Exposure to Wildfire on Lifetime Hospital Admissions

	Infants ($\leq$ 1 years old) (1)	Toddlers (1-3 years old) (2)	All ages (3)
Smoke Exposure IU [1rd trimester]	0.160	0.001	0.119
(8-hours period)	(0.110)	(0.160)	(0.233)
Smoke Exposure IU [2rd trimester]	0.210*	0.005	0.168
(8-hours period)	(0.122)	(0.095)	(0.289)
Smoke Exposure IU [3rd trimester]	0.138	0.057	0.147
(8-hours period)	(0.199)	(0.171)	(0.309)
Mean of Dep. Var.	40.249	22.536	73.256
Observations	3,331,299	3,331,299	3,331,299
R-Squared	0.01	0.00	0.01
FDR-adjusted p-values (β_1)	0.814	0.989	0.814
FDR-adjusted p-values (β_2)	0.071	0.473	0.290
FDR-adjusted p-values (β_3)	1.000	1.000	1.000
Fixed Effects			
Municipality	Y	Y	Y
Month$\times$Year	Y	Y	Y
Year$\times$Season$\times$Region	Y	Y	Y

Notes: Sample consists of all births (individual measures) between 2005-2018. Trimesters of pregnancy are calculated since conception, such that the first two trimesters are thirteen weeks each, whereas the third trimester may vary according to the actual week of birth. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Outcome variables are multiplied by 100 for an easier interpretation of the coefficients. Standard errors clustered at the 0.75°$\times$ 0.75° spatial grid (roughly, 70$\times$70 Km) in parentheses, ***p $<$ 0.01.

for analysis. Second, among students in this sample, the maximum number of wildfire smoke plumes observed during the two-week pre-birth window is just 2, corresponding to approximately 16 hours of wildfire smoke exposure, which is less than a full day. And third, as we explained before, we do not have a precise identification of the municipality of birth of each students, but only a proxy of it. Therefore, interpreting, for example, the coefficient in Column 4 of Panel B as implying that one additional day (24 hours) of exposure would reduce verbal scores by 3×20.13 points in public schools may be misleading.

Indeed, Table A8 in the Online Appendix shows that when we expand the exposure window to include more weeks prior to birth, the estimated coefficients become more imprecise and in some cases even positive. Taken together, these findings suggest that the two weeks prior to birth may be a particularly sensitive period for fetal development, consistent with the health-related results presented earlier, but we must interpret the results with caution. Still, this remains a preliminary insight. There is substantial room for future work to deepen our understanding – particularly once data becomes available for later birth cohorts, when wildfire activity in Chile increased significantly and exposure levels were likely higher and more prolonged.

Table 10: Effects of In-utero Exposure to Wildfire on Standardized Test Scores at 4th grade

Panel A: Math Test Score				
	All	Public	Voucher	Private
	(1)	(2)	(3)	(4)
In-Utero Exposure [Last two weeks]	-4.48	-1.09	-3.76	-4.47
(8-hours period)	(6.93)	(9.59)	(13.01)	(3.45)
Mean of Dep. Var.	264.216	248.705	266.192	298.235
Observations	620,999	208,167	337,517	75,266
R-Squared	0.28	0.19	0.22	0.18
FDR-adjusted p-values	1.000	1.000	1.000	1.000
Panel B: Verbal Test Score				
	All	Public	Voucher	Private
	(1)	(2)	(3)	(4)
In-Utero Exposure [Last two weeks]	-7.14	-11.20	8.39	-20.13**
(8-hours period)	(7.67)	(10.41)	(11.53)	(9.65)
Mean of Dep. Var.	271.652	258.149	273.304	301.514
Observations	618,809	207,335	336,318	75,106
R-Squared	0.19	0.14	0.14	0.09
FDR-adjusted p-values	1.000	1.000	1.000	0.473
Fixed Effects				
Municipality of birth	Y	Y	Y	Y
Year of test	Y	Y	Y	Y
School	Y	Y	Y	Y
Month×Year	Y	Y	Y	Y
Region×Season×Year	Y	Y	Y	Y

Notes: Sample consists of students (individual measures) born between 2004 and 2008 taking the exam at 9, 10, or 11 years old. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the school's municipality level in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Discussion and Concluding Remarks

In this paper we seek out to gain a better understanding of the broader effects of wildfires on human well-being in a context of increased severity and frequency of fires due to soil aridity linked to climate change. Looking at Chile as a case study, we empirically examine temporal dynamics of wildfire smoke exposure on a range of human capital outcomes. Our results highlight both clear short run effects on environmental conditions and health outcomes, particularly among very young individuals, as well as varying longer-term effects on both health and educational outcomes, suggesting that these initial effects unfold over a substantial period of time over the life course.

We make a number of contributions to the literature. The first is to highlight the utility of rich model-based measures of wildfire exposure in quantifying the environmental impacts of such wildfire exposure. In applying these methods in the context of Chile we show that modeled wildfire smoke exposure, as determined from a leading atmospheric model (HYSPLIT), is quite different to simple distance-based measures of exposure. The second is to seek to provide a framework to better understand, and empirical evidence speaking to, the way which exposure to air pollutants from wildfires maps out over the life course in a multi-dimensional and non-linear fashion. And a third contribution is to consider this in a setting which is well-suited to such analysis, with both rich linked microdata and increasing exposure to wildfires over time, but for relatively understudied geographical region in the empirical literature, which is often based in the US or the global north.

While our results do point to the existence of important persistent effects on human capital, we also face a number of limitations, particularly in settings based on longer-term educational outcomes, where we can only consider impacts on relatively early cohorts exposed to wildfire smoke while in-utero, given that educational attainment is only observed nearly a decade later. This is a relevant limitation when considering that more recent cohorts have been exposed to wildfire seasons with increasing intensity. And although a broader set of even longer-term educational outcomes could be explored such as school completion, college enrollment, or university admission test scores, such analyses are left for future work. This also applies to examining other dimensions of wildfire exposure on education, including exposure at different ages or during later stages of schooling.

Nevertheless, our findings point to the importance of building in the long-term impact on human well-being to the calculus of the social returns to fire-prevention and suppression programs, which are becoming a central component of government environmental protection programs both within and outside of Latin America. They additionally point to the importance of both early-warning and mitigation systems for wildfire smoke, and suggest that such systems will be most effective when accounting for groups which are particularly vulnerable and less capable to adapt to limit their exposure.

References

Abatzoglou, J. T. and A. P. Williams (2016). Impact of anthropogenic climate change on wildfire across western us forests. *Proceedings of the National Academy of Sciences 113*(42), 11770–11775.

Aguilar, A. and M. Vicarelli (2022). El niño and children: Medium-term effects of early-life weather shocks on cognitive and health outcomes. *World Development 150*, 105690.

Almond, D. and J. Currie (2011, September). Killing me softly: The fetal origins hypothesis. *Journal of Economic Perspectives 25*(3), 153–72.

Almond, D., J. Currie, and V. Duque (2018, December). Childhood Circumstances and Adult Outcomes: Act II. *Journal of Economic Literature 56*(4), 1360–1446.

Almond, D., L. Edlund, and M. Palme (2009). Chernobyl's subclinical legacy: Prenatal exposure to radioactive fallout and school outcomes in sweden. *The Quarterly Journal of Economics 124*(4), 1729–1772.

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association 103*(484), 1481–1495.

Anderson, M. L. (2019, 10). As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality. *Journal of the European Economic Association 18*(4), 1886–1927.

Arenberg, S. and S. Neller (2023). Ashes to ashes: The lifelong consequences of early-life wildfire exposure. Technical report.

Arrizaga, R., D. Clarke, P. Cubillos, and C. Ruiz-Tagle (2025, Nov). Smoke signals: Understanding temporal dynamics of wildfire exposure on health and education. IZA Discussion Papers 18256, Institute of Labor Economics (IZA).

Athey, S., R. Chetty, G. W. Imbens, and H. Kang (2025). The surrogate index: Combining short-term proxies to estimate long-term treatment effects more rapidly and precisely. *Review of Economic Studies*, rdaf087.

Benjamini, Y., A. M. Krieger, and D. Yekutieli (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika 93*(3), 491–507.

Bharadwaj, P., M. Gibson, J. Graff Zivin, and C. Neilson (2017). Gray matters: Fetal pollution exposure and human capital formation. *Journal of the Association of Environmental and Resource Economists 4*(2), 451–491.

Borgschulte, M., D. Molitor, and E. Y. Zou (2024). Air Pollution and the Labor Market: Evidence from Wildfire Smoke. *Review of Economics and Statistics 106*(6), 1558–1575.

Bowman, D. M., G. J. Williamson, J. T. Abatzoglou, C. A. Kolden, M. A. Cochrane, and A. Smith (2017). Human exposure and sensitivity to globally extreme wildfire events. *Nature ecology & evolution 1*(3), 1–6.

Burke, M., A. Driscoll, S. Heft-Neal, J. Xue, J. Burney, and M. Wara (2021). The changing risk and burden of wildfire in the united states. *Proceedings of the National Academy of Sciences 118*(2), e2011048118.

Cancelo-González, J. J. and F. D.-F. Viqueira (2018). Incendios forestales y salud pública. In *Anales de la Real Academia Nacional de Farmacia*, Volume 84.

Carneiro, J., M. A. Cole, and E. Strobl (2024). Foetal exposure to air pollution and students' cognitive performance: Evidence from agricultural fires in brazil. *Oxford Bulletin of Economics and Statistics 86*(1), 156–186.

Chan, H. R., M. Pelli, and V. Vienne (2023). Air pollution, smoky days and hours worked. *Smoky Days and Hours Worked (May 22, 2023)*.

Chen, P. (2025). Industrialization and pollution: The long-term impact of early-life exposure on human capital formation. *Journal of Public Economics 241*, 105270.

Ciciretti, R., F. Barraza, F. De la Barrera, L. Urquieta, and S. Cortes (2022). Relationship between wildfire smoke and children's respiratory health in the metropolitan cities of central-chile. *Atmosphere 13*(1), 58.

Clarke, D. (2017, Sep). Estimating difference-in-differences in the presence of spillovers. MPRA Paper 81604, University Library of Munich, Germany.

Clarke, D., N. L. Bustos, and K. Tapia-Schythe (2022, September). Estimating Inter-Generational Returns to Medical Care: New Evidence from At-Risk Newborns . IZA Discussion Papers 15593, Institute of Labor Economics (IZA).

CONAF (12 de October de 2022). https://www.conaf.cl/incendios-forestales/incendios-forestales-en-chile/estadisticas-historicas/.

Currie, J., J. Graff-Zivin, J. Mullins, and M. Neidell (2014). What do we know about short-and long-term effects of early-life exposure to pollution? *Annual Review of Resource Economics 6*(1), 217–247.

Currie, J. and S. Saberian (2025, June). Wildfire, Smoke and Mental Health in Canada. Working Paper 33912, National Bureau of Economic Research.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2019, December). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review 109*(12), 4178–4219.

Dominici, F. et al. (2014). Ambient pm2.5 and risk of hospital admissions. *Environmental Health Perspectives*. Short-term PM2.5 exposure associated with increased cardiovascular and respiratory hospitalizations.

Draxler, R. R. and G. D. Hess (1998). An overview of the HYSPLIT_4 modeling system for trajectories, dispersion, and deposition. *Australian Meteorological Magazine 47*(4), 295–308.

Ellis, T. M., D. M. Bowman, P. Jain, M. D. Flannigan, and G. J. Williamson (2022). Global increase in wildfire risk due to climate-driven declines in fuel moisture. *Global change biology 28*(4), 1544–1559.

Flannigan, M., A. S. Cantin, W. J. De Groot, M. Wotton, A. Newbery, and L. M. Gowman (2013). Global wildland fire season severity in the 21st century. *Forest Ecology and Management 294*, 54–61.

Flannigan, M., B. Stocks, M. Turetsky, and M. Wotton (2009). Impacts of climate change on fire activity and fire management in the circumboreal forest. *Global change biology 15*(3), 549–560.

Frankenberg, E., D. McKee, and D. Thomas (2005). Health consequences of forest fires in Indonesia. *Demography 42*(1), 109–129.

Gillett, N., A. Weaver, F. Zwiers, and M. Flannigan (2004). Detecting the effect of climate change on Canadian forest fires. *Geophysical Research Letters 31*(18).

González, M., R. Sapiains, and S. e. a. Gómez-González (2020). Incendios en Chile: Causas, impactos y resiliencia. *Centro de Ciencia del Clima y la Resiliencia (CR)2, Universidad de Chile, Universidad de Concepción y Universidad Austral de Chile. 1*(2), 43–46.

Grennan, G. K., M. C. Withers, D. S. Ramanathan, and J. Mishra (2023, 01). Differences in interference processing and frontal brain function with climate trauma from California's deadliest wildfire. *PLOS Climate 2*(1), 1–17.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy 80*(2), 223–255.

He, G., T. Liu, and M. Zhou (2020). Straw burning, pm2. 5, and death: Evidence from china. *Journal of Development Economics 145*, 102468.

Heft-Neal, S., C. F. Gould, M. L. Childs, M. V. Kiang, K. C. Nadeau, M. Duggan, E. Bendavid, and M. Burke (2023). Emergency department visits respond nonlinearly to wildfire smoke. *Proceedings of the National Academy of Sciences 120*(39), e2302409120.

Hoffmann, B. and J. P. Rud (2024). The unequal effects of pollution on labor supply. *Econometrica 92*(4), 1063–1096.

INE (12 de October de 2018). https://www.ine.cl/estadisticas/sociales/censos-de-poblacion-y-vivienda.

IPCC (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability; Chapter 12: Central and South America*. Sixth Assessment Report (AR6), Intergovernmental Panel on Climate Change (IPCC).

Isen, A., M. Rossin-Slater, and W. R. Walker (2017). Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970. *Journal of Political Economy 125*(3), 848–902.

Jain, P., Q. E. Barber, S. W. Taylor, E. Whitman, D. Castellanos Acuna, Y. Boulanger, R. D. Chavardès, J. Chen, P. Englefield, M. Flannigan, et al. (2024). Drivers and impacts of the record-breaking 2023 wildfire season in Canada. *Nature Communications 15*(1), 6764.

Jayachandran, S. (2009). Air quality and early-life mortality: evidence from Indonesia's wildfires. *Journal of Human Resources 44*(4), 916–954.

Li, J. e. a. (2021). Individual exposure to ambient pm2.5 and hospital admissions for copd in 110 hospitals: a case-crossover study in guangzhou, china. *Environmental Epidemiology*. 10 μg/m^3 PM2.5 associated with 1.6% increase in COPD hospitalizations.

Lo Bue, M. C. (2019). Early Childhood during Indonesia's Wildfires: Health Outcomes and Long-Run Schooling Achievements. *Economic Development and Cultural Change 67*(4).

Malevsky-Malevich, S., E. Molkentin, E. Nadyozhina, and O. Shklyarevich (2008). An assessment of potential change in wildfire activity in the Russian boreal forest zone induced by climate warming during the twenty-first century. *Climatic Change 86*(3), 463–474.

Mead, M. I., S. Castruccio, M. T. Latif, M. S. M. Nadzir, D. Dominick, A. Thota, and P. Crippa (2018). Impact of the 2015 wildfires on Malaysian air quality and exposure: a comparative study of observed and modeled data. *Environmental Research Letters 13*(4), 044023.

Miller, N. H., D. Molitor, and E. Zou (2024). The nonlinear effects of air pollution on health: Evidence from wildfire smoke. Technical report, National Bureau of Economic Research.

Moeltner, K., M.-K. Kim, E. Zhu, and W. Yang (2013). Wildfire smoke and health impacts: A closer look at fire attributes and their marginal effects. *Journal of Environmental Economics and Management 66*(3), 476–496.

Morello, T. F. (2023). Hospitalization due to fire-induced pollution in the Brazilian Amazon: A causal inference analysis with an assessment of policy trade-offs. *World Development 161*, 106123.

Moritz, M., M. Parisien, E. Batllori, M. Krawchuk, J. Van Dorn, D. Ganz, and K. Hayhoe (2012). Climate change and disruptions to global fire activity.

Paudel, J. (2023). Do environmental disasters affect human capital? the threat of forest fires. *Economics of Education Review 94*, 102463.

Persson, P. and M. Rossin-Slater (2018, April). Family ruptures, stress, and the mental health of the next generation: Reply. *American Economic Review 108*(4-5), 1256–63.

Qiu, M., J. Li, C. F. Gould, R. Jing, M. Kelp, M. Childs, M. Kiang, S. Heft-Neal, N. Diffenbaugh, and M. Burke (2024). Mortality burden from wildfire smoke under climate change. Technical report, National Bureau of Economic Research.

Rangel, M. A. and T. S. Vogl (2019, October). Agricultural Fires and Health at Birth. *The Review of Economics and Statistics 101*(4), 616–630.

Reid, C. E. and M. M. Maestas (2019). Wildfire smoke exposure under climate change: impact on respiratory health of affected communities. *Current Opinion in Pulmonary Medicine 25*(2), 179–187.

Rocha, R. and A. A. Sant'Anna (2022). Winds of fire and smoke: Air pollution and health in the Brazilian Amazon. *World Development 151*, 105722.

Rosales-Rueda, M. and M. Triyana (2019). The persistent effects of early-life exposure to air pollution evidence from the Indonesian forest fires. *Journal of Human Resources 54*(4), 1037–1080.

Sanders, N. J. (2012). What doesn't kill you makes you weaker: Prenatal pollution exposure and educational outcomes. *Journal of Human Resources 47*(3), 826–850.

Sarricolea, P., R. Serrano-Notivoli, M. Fuentealba, M. Hernández-Mora, F. De la Barrera, P. Smith, and Ó. Meseguer-Ruiz (2020). Recent wildfires in Central Chile: Detecting links between burned areas and population exposure in the wildland urban interface. *Science of the Total Environment 706*, 135894.

Stein, A. F., R. R. Draxler, G. D. Rolph, B. J. B. Stunder, M. D. Cohen, and F. Ngan (2015). NOAA's HYSPLIT atmospheric transport and dispersion modeling system. *Bulletin of the American Meteorological Society 96*(12), 2059–2077.

Tan-Soo, J.-S. and S. K. Pattanayak (2019). Seeking natural capital projects: forest fires, haze, and early-life exposure in Indonesia. *Proceedings of the National Academy of Sciences 116*(12), 5239–5245.

Wen, J. and M. Burke (2022). Lower test scores from wildfire smoke exposure. *Nature Sustainability 5*(11), 947–955.

Wen, J., S. Heft-Neal, P. Baylis, J. Boomhower, and M. Burke (2023). Quantifying fire-specific smoke exposure and health impacts. *Proceedings of the National Academy of Sciences 120*(51), e2309325120.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam (2006). Warming and earlier spring increase western US forest wildfire activity. *Science 313*(5789), 940–943.

WHO (2024). *Compendium of WHO and other UN guidance in health and environment, 2024 update*. Geneva: World Health Organization.

Zhang, X., X. Chen, and X. Zhang (2018). The impact of exposure to air pollution on cognitive performance. *Proceedings of the National Academy of Sciences 115*(37), 9193–9197.

Online Appendix – Not for Print

Smoke Signals: Understanding Temporal Dynamics of Wildfire Exposure on Health and Education

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

Appendix Figures and Tables

Table A1: Number of wildfires reported in Chile by season and burned area range

Season	< 1 ha	1-10 ha	10-100 ha	100-200 ha	200-500 ha	500-1000 ha	> 1000 ha
2004-2005	4457	1766	343	38	28	10	11
2005-2006	3831	1312	218	16	14	4	1
2006-2007	3723	1205	167	16	13	10	10
2007-2008	4706	1869	327	36	26	6	3
2008-2009	4099	1597	369	32	37	11	12
2009-2010	2763	1016	202	25	38	12	13
2010-2011	3339	1311	234	31	24	5	7
2011-2012	3789	1368	285	31	22	6	8
2012-2013	3941	1435	248	15	11	1	0
2013-2014	4246	1615	364	44	37	15	19
2014-2015	5100	2173	617	72	66	28	17
2015-2016	4466	1829	426	27	24	5	7
2016-2017	3178	1490	419	40	58	32	57
2017-2018	3814	1729	468	40	22	6	2
2018-2019	4726	1899	450	51	29	14	14
2019-2020	5274	2127	568	72	48	21	17
2020-2021	5120	1614	311	28	20	5	3
2021-2022	4788	1571	445	45	53	17	28

Table A2: Descriptive statistics of selected wildfires by season (only fires with area affected greater than 200 ha)

Season	N	Mean	Median	Std	Min	Max	P25	P75	Total
2002-2003	34	648.31	345.00	765.16	220.00	3583.00	280.00	676.25	22042.57
2003-2004	48	620.90	424.50	524.18	206.00	2200.00	278.50	657.78	29803.13
2004-2005	45	613.33	420.00	480.01	203.80	2154.00	255.00	800.00	27600.00
2005-2006	14	422.84	325.00	304.07	201.00	1300.00	223.25	465.50	5919.69
2006-2007	32	1025.77	742.23	917.33	200.00	5046.00	450.00	1498.00	32824.10
2007-2008	30	620.08	382.76	855.81	208.50	3740.00	277.50	461.75	18602.31
2008-2009	56	695.15	412.50	788.68	201.00	3975.91	253.75	662.82	38928.58
2009-2010	59	749.44	400.00	808.72	201.00	3500.00	250.00	840.00	44216.96
2010-2011	36	701.43	375.00	811.03	210.00	3891.60	268.75	703.00	25251.47
2011-2012	4	7469.73	2380.13	11757.05	223.00	24895.65	468.25	9381.60	29878.90
2012-2013	12	296.35	270.00	104.14	203.00	523.40	206.75	348.10	3556.20
2013-2014	69	1209.64	482.00	2432.43	202.00	14805.00	300.00	1050.00	83465.09
2014-2015	111	830.21	395.00	1593.80	200.49	13833.00	268.50	618.96	92153.14
2015-2016	35	573.48	353.00	491.89	205.00	2082.10	233.75	746.00	20071.80
2016-2017	144	3792.21	689.50	14402.29	203.00	159812.58	339.50	2280.45	546077.82
2017-2018	28	428.57	296.22	357.18	200.50	2069.00	262.70	478.72	12000.04
2018-2019	56	950.21	504.82	1999.83	207.00	15145.00	302.18	949.95	53211.61
2019-2020	85	796.54	439.20	1642.91	208.96	14987.90	273.76	826.52	67706.08
2020-2021	27	615.65	311.43	751.68	202.89	3420.03	256.79	577.08	16622.42
2021-2022	96	1034.47	445.85	1693.76	203.17	13768.00	253.72	1066.49	99309.45

Note: This table reports descriptive statistics by wildfire season, considering only wildfires with an affected area greater than 200 hectares. Only the wildfires included in the atmospheric trajectory modeling using HYSPLIT are reported here.

Table A3: Effects of Wildfire Exposure on Students' Attendance

	Attendance	
	(1)	(2)
Wildfire Exposure	-0.4312	-0.4187
	(0.507)	(0.591)
Number of students	389,492	389,492
Mean of Dep. Var.	88.846	88.846
Observations	3,894,920	3,894,920
R-Squared	0.47	0.47
Fixed Effects		
Student	Y	Y
Month	Y	
Month×Region		Y

Notes: Each observation correspond to a student in all grades in 2013 from regions V and VII, which experienced wildfire exposure in June. Within region, the exposure differs between municipalities, and therefore students. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the school's municipality level in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Heterogeneous Effects of In-Utero Exposure to Wildfire on Birth Outcomes, by Mother's Education Level

	Birth Weight			Birth Size			Gestational Weeks		
Mother's education level:	College (1)	Secondary (2)	Primary (3)	College (4)	Secondary (5)	Primary (6)	College (7)	Secondary (8)	Primary (9)
Smoke Exposure IU [1rd trimester]	3.481***	-0.438	0.960	0.011**	0.002	0.001	0.006**	-0.003	-0.004
(8-hours period)	(0.769)	(1.358)	(2.931)	(0.005)	(0.010)	(0.016)	(0.002)	(0.003)	(0.009)
Smoke Exposure IU [2rd trimester]	-2.200	-0.625	-7.125***	-0.012***	-0.012***	-0.039***	-0.007**	-0.008***	-0.032***
(8-hours period)	(1.352)	(0.683)	(2.601)	(0.004)	(0.004)	(0.012)	(0.003)	(0.003)	(0.010)
Smoke Exposure IU [3rd trimester]	0.654	-1.610	3.317**	0.002	-0.002	0.010	-0.002	-0.005	0.001
(8-hours period)	(0.868)	(1.197)	(1.586)	(0.005)	(0.007)	(0.010)	(0.005)	(0.004)	(0.008)
Mean of Dep. Var.	3273.625	3332.116	3349.322	49.105	49.334	49.362	38.283	38.532	38.624
Observations	1,038,390	1,872,869	419,041	1,038,390	1,872,869	419,041	1,038,390	1,872,869	419,041
R-Squared	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.01
FDR-adjusted p-values (β_1)	0.001	1.000	1.000	0.203	1.000	1.000	0.203	1.000	1.000
FDR-adjusted p-values (β_2)	0.173	0.365	0.022	0.022	0.012	0.012	0.026	0.022	0.012
FDR-adjusted p-values (β_3)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Fixed Effects									
Municipality	Y	Y	Y	Y	Y	Y	Y	Y	Y
Calendar Month-of-birth×Year-of-birth	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-of-birth×Season×Region	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Sample consists of all births (individual measures) between 2005-2018. Trimesters of pregnancy are calculated since conception, such that the first two trimesters are thirteen weeks each, whereas the third trimester may vary according to the actual week of birth. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3 Standard errors clustered at the 0.75°× 0.75° spatial grid (roughly, 70×70 Km) in parentheses. *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

Table A5: Heterogeneous Effects of In-Utero Exposure to Wildfire on Lifetime Hospitalizations, by Mother's Education Level

	Infants ($\leq$ 1 years old)			Toddlers (1-3 years old)			All ages		
Mother's education level:	College (1)	Secondary (2)	Primary (3)	College (4)	Secondary (5)	Primary (6)	College (7)	Secondary (8)	Primary (9)
Smoke Exposure IU [1rd trimester]	0.133	0.232	0.391	0.270	-0.112	-0.087	0.488	-0.080	-0.018
(8-hours period)	(0.218)	(0.151)	(0.609)	(0.486)	(0.109)	(0.222)	(0.551)	(0.205)	(0.702)
Smoke Exposure IU [2rd trimester]	-0.024	0.385	0.354	-0.050	0.028	0.250	-0.104	0.244	0.750
(8-hours period)	(0.214)	(0.317)	(0.388)	(0.182)	(0.237)	(0.286)	(0.221)	(0.566)	(0.492)
Smoke Exposure IU [3rd trimester]	-0.077	0.271	0.509	0.122	0.134	-0.252	0.125	0.146	0.381
(8-hours period)	(0.196)	(0.282)	(0.336)	(0.199)	(0.166)	(0.230)	(0.310)	(0.401)	(0.426)
Mean of Dep. Var.	33.160	41.470	52.310	21.651	22.404	25.323	64.778	74.361	89.290
Observations	1,038,390	1,872,869	419,041	1,038,390	1,872,869	419,041	1,038,390	1,872,869	419,041
R-Squared	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.01	0.02
FDR-adjusted p-values (β_1)	1.000	0.905	1.000	1.000	1.000	1.000	1.000	1.000	1.000
FDR-adjusted p-values (β_2)	0.698	0.318	0.365	0.698	0.698	0.365	0.668	0.668	0.190
FDR-adjusted p-values (β_3)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Fixed Effects									
Municipality	Y	Y	Y	Y	Y	Y	Y	Y	Y
Calendar Month-of-birth×Year-of-birth	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-of-birth×Season×Region	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Sample consists of all births (individual measures) between 2005-2018. Trimesters of pregnancy are calculated since conception, such that the first two trimesters are thirteen weeks each, whereas the third trimester may vary according to the actual week of birth. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the 0.75°× 0.75° spatial grid (roughly, 70×70 Km) in parentheses. *p $<$ 0.10, **p $<$ 0.05, ***p $<$ 0.01.

Table A6: Effects of In-Utero Exposure to Wildfire on Birth Outcomes

	Birth Weight		Birth Size		Gestational Weeks	
	(1)	(2)	(3)	(4)	(5)	(6)
Smoke Exposure IU [Last two weeks]	-3.635*		-0.019		-0.015**	
(8-hours period)	(2.097)		(0.015)		(0.006)	
Smoke Exposure IU [Third trimester]		-0.655		-0.001		-0.005*
(8-hours period)		(0.518)		(0.003)		(0.003)
Mean of Dep. Var.	3315.984	3315.984	49.266	49.266	38.466	38.466
Observations	3,331,299	3,331,299	3,331,299	3,331,299	3,331,299	3,331,299
R-Squared	0.01	0.01	0.02	0.02	0.01	0.01
FDR-adjusted p-values	0.122	1.000	0.149	1.000	0.101	0.964
Fixed Effects						
Municipality	Y	Y	Y	Y	Y	Y
Month×Year	Y	Y	Y	Y	Y	Y
Year×Season×Region	Y	Y	Y	Y	Y	Y

Notes: Sample consists of all births (individual measures) between 2005-2018. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the 0.75°× 0.75° spatial grid (roughly, 70×70 Km) in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7: Effects of In-Utero Exposure to Wildfire on Lifetime Hospitalizations

	Infants (≤ 1 years old)		Toddlers (1-3 years old)		All ages	
	(1)	(2)	(3)	(4)	(5)	(6)
Smoke Exposure IU [Last two weeks]	0.006*		0.009*		0.005	
(8-hours period)	(0.003)		(0.005)		(0.007)	
Smoke Exposure IU [Third trimester]		0.001		0.001		0.001
(8-hours period)		(0.002)		(0.002)		(0.003)
Mean of Dep. Var.	0.402	0.402	0.225	0.225	0.733	0.733
Observations	3,331,299	3,331,299	3,331,299	3,331,299	3,331,299	3,331,299
R-Squared	0.01	0.01	0.00	0.00	0.01	0.01
FDR-adjusted p-values	0.122	1.000	0.122	1.000	0.183	1.000
Fixed Effects						
Municipality	Y	Y	Y	Y	Y	Y
Month×Year	Y	Y	Y	Y	Y	Y
Year×Season×Region	Y	Y	Y	Y	Y	Y

Notes: Sample consists of all births (individual measures) between 2005-2018. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the 0.75°× 0.75° spatial grid (roughly, 70×70 Km) in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

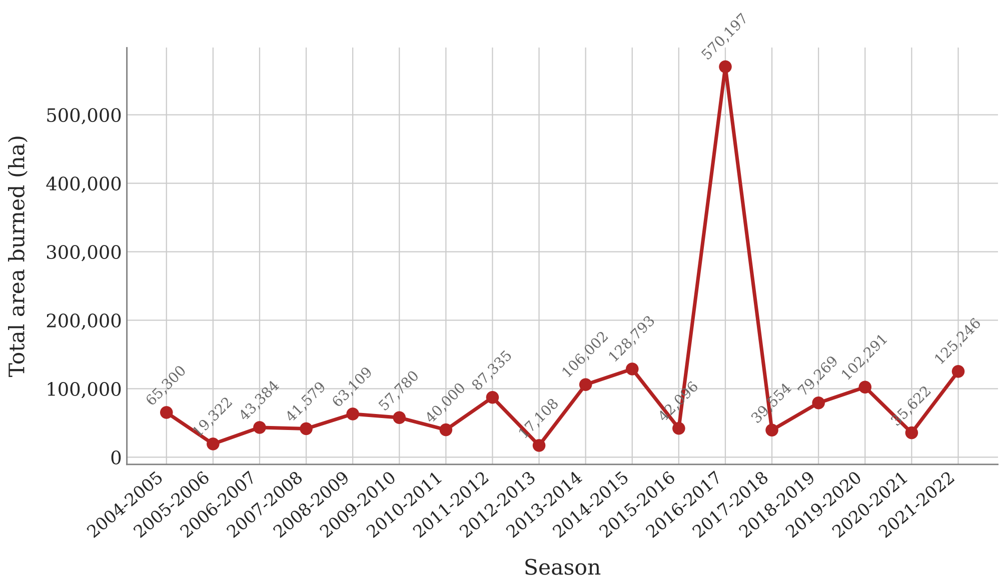
Table A8: Effects of In-Utero Wildfire Exposure on Standardized Test Scores at 4th grade by Different Weeks of Exposure

	Math Test Scores			Verbal Test Scores		
	(1)	(2)	(3)	(4)	(5)	(6)
Smoke Exposure IU [Last two weeks]	-4.48			-7.14		
(8-hours period)	(6.93)			(7.67)		
Smoke Exposure IU [Last Month]		5.22			5.35	
(8-hours period)		(3.78)			(5.67)	
Smoke Exposure IU [Third trimester]			0.98			0.52
(8-hours period)			(1.79)			(1.71)
Mean of Dep. Var.	264.216	264.216	264.216	271.652	271.652	271.652
Observations	620,999	620,999	620,999	618,809	618,809	618,809
R-Squared	0.28	0.28	0.28	0.19	0.19	0.19
FDR-adjusted p-values (X1)	1.000	0.506	1.000	1.000	0.506	1.000
Fixed Effects						
Municipality of birth	Y	Y	Y	Y	Y	Y
Year of test	Y	Y	Y	Y	Y	Y
School	Y	Y	Y	Y	Y	Y
Calendar Month-of-birth $\times$ Year-of-birth	Y	Y	Y	Y	Y	Y
Region$\times$Season$\times$Year-of-birth	Y	Y	Y	Y	Y	Y

Notes: Sample consists of students (individual measures) born between 2004 and 2008 taking the exam at 9, 10, or 11 years old. The independent variable measures exposure to wildfire smoke plumes in 8-hour intervals. To interpret the estimated coefficients as the effect of an additional full day of exposure (i.e., 24 hours), the coefficients should be multiplied by 3. Standard errors clustered at the school's municipality level in parentheses.

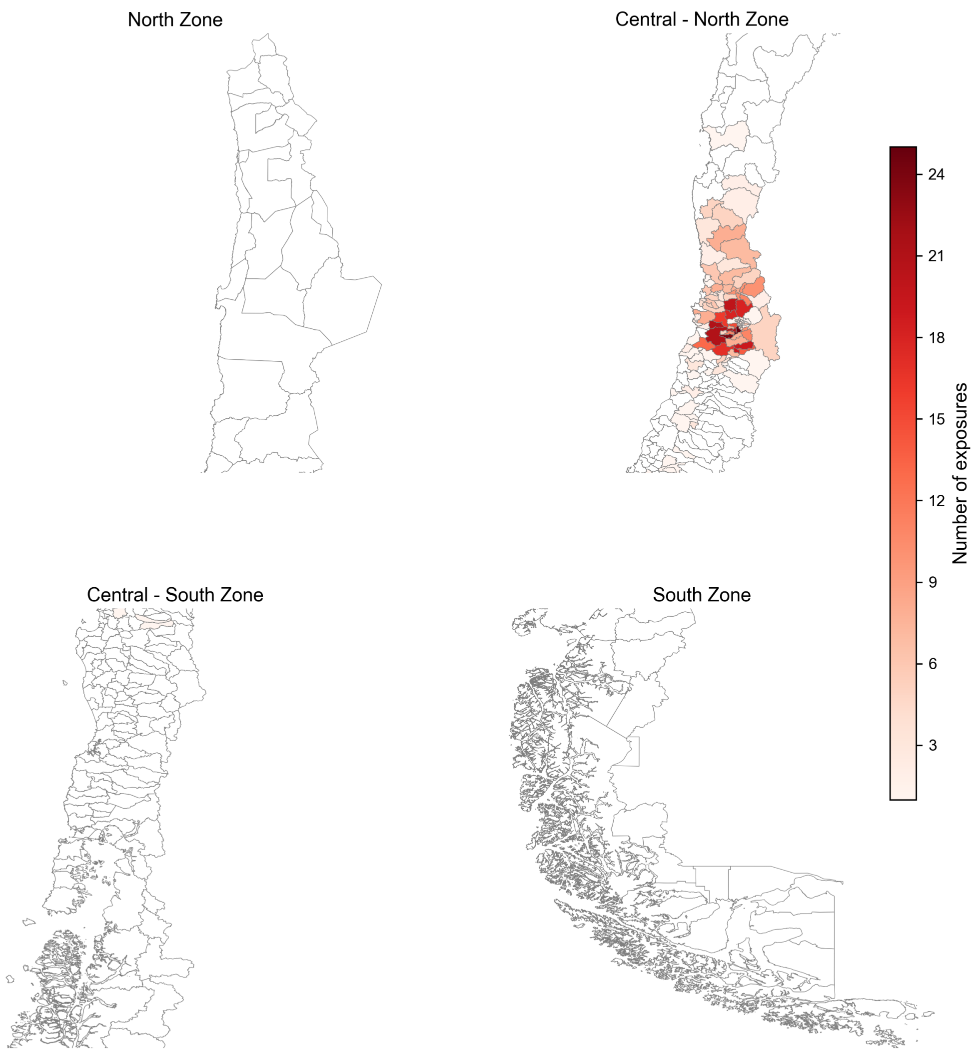
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Total area burned by wildfires per season in Chile (2004-2022).



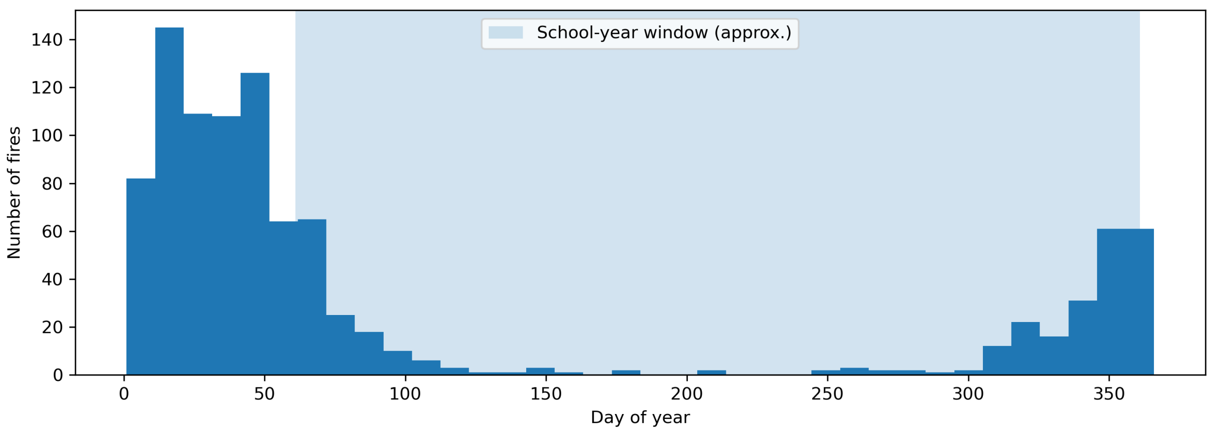
Notes: The figure reports the total area burned (ha) by wildfire season in Chile. Each point corresponds to the national total for the indicated season (e.g., 2016–2017). *Source:* CONAF. *Authors' calculations.*

Figure A2: Wildfire exposure by municipality – season 2016-2017

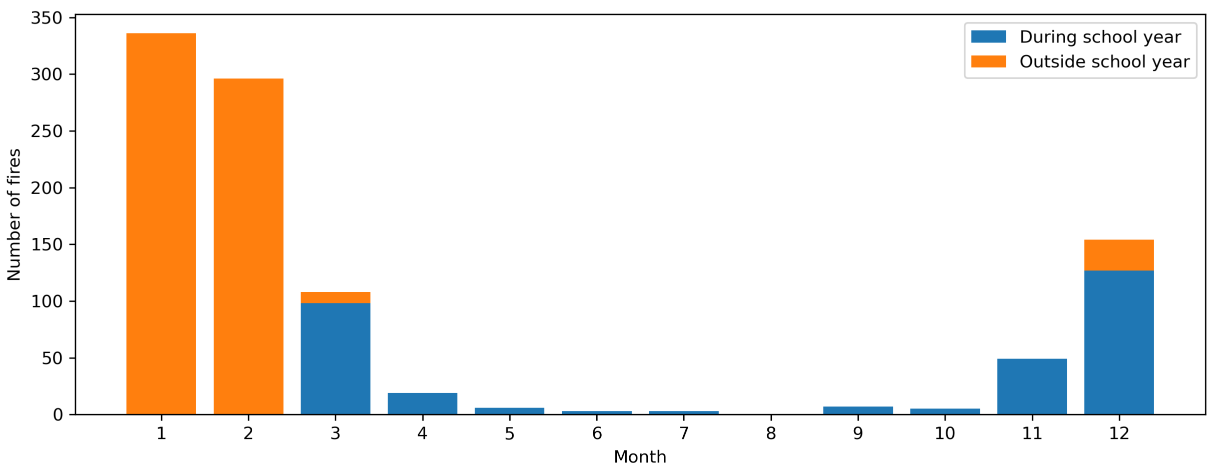


Notes: Heat map present the municipal exposures to wildfire smoke during the 2016–2017 season as modelled by HYSPLIT. A municipality is considered exposed when the particle plume, injected at 500m above the fire origin, lies within a 500km horizontal radius of the municipality, passes within 5km of its centroid, and remains at or below 100m altitude.

Figure A3: Wildfires and the school calendar



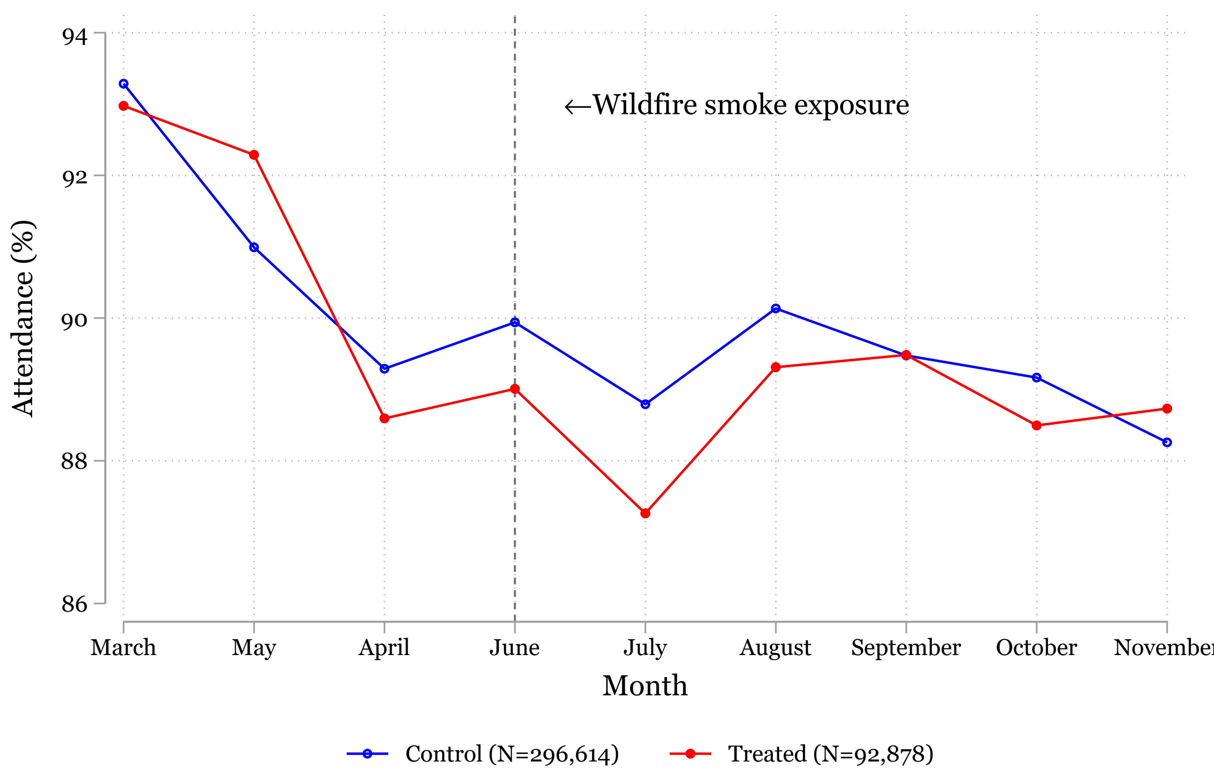
(a) Date of fire initiation and school calendar



(b) Monthly fires and school calendar

Notes: Wildfire ignition dates in Chile, 2002–2022 (CONAF). Panel (a) shows ignitions by day of year; the shaded area marks the school-year window (first Monday of March to the Sunday of the third week of December; shown approximately). Panel (b) reports monthly counts, split by whether ignitions occur during versus outside the school year. Fires with total burned area $\geq$ 200 ha are included when burned-area information is available. *Source:* CONAF. *Authors' calculations.*

Figure A4: Students' Attendance Relative to Wildfire Exposure



Notes: The sample includes students across all grades in 2013 from regions V and VII. These parameters were selected because they represent one of the few instances where wildfire exposure occurred during the school year. Consequently, the analysis compares treated and non-treated municipalities within these treated regions.