Air Pollution, Smoky Days and Hours Worked*

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July 2023

Abstract

This study investigates the impact of air pollution on hours worked in Chile. We construct downwind smoke plumes originating from each wildfire to causally identify the effect of air pollution. Our findings reveal a 2% reduction in hours worked due to increased fine particulate matter from an extra smoky day. The effect is more pronounced for male workers engaged in outdoor tasks and for poor households, where the negative effects of air pollution can be up to four times larger. The study suggests that focusing solely on labor productivity underestimates the economic cost of air pollution by 11-13%.

Keywords: air pollution, hours worked, wildfires, Chile
JEL Codes: Q53, J20, J22, O13, I15

*We would like to thank James Banks, Rachel Griffith, Sefi Roth, Juan Pablo Rud, Eswaran Somanathan, and Jeanne Tschopp for helpful comments and suggestions. We have also benefited from the reactions of several seminar and conference audiences, including participants at the ASSA, AERE, CEA, NAREA, EAERE, CREEA, IZA, Latin American Meeting of the Econometric Society, SEA, ACEGD New Delhi, Manchester, Montreal, Adolfo Ibáñez University, Savoie Mont-Blanc, Indian Statistical Institute, Grenoble, Royal Holloway University of London and Sherbrooke. Siobhan Corbett and Brenda Mosco Martinez provided excellent research assistance. We are grateful to the Manchester School and the Social Sciences and Humanities Institutional Grant at the University of Sherbrooke for their financial support. All remaining errors are of our own.

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1 Introduction

Air pollution has long been recognized as a pressing environmental issue, resulting in an extensive number of regulations aimed at controlling its sources across the world. The economics literature has recently shifted its focus from the health implications of air pollution (e.g., Chay & Greenstone, 2003) to its detrimental effects on labor productivity (e.g., Graff Zivin & Neidell, 2012).[1] However, to comprehensively grasp the true impact of air pollution on the labor market, it becomes crucial to also examine its economic consequences on working hours. By considering the combined effects on both labor productivity and working hours, we can better understand the non-health-related repercussions of air pollution on the labor market, thereby warranting more robust policy interventions (Dechezleprêtre et al., 2019).

The existing literature predominantly explores the impact of pollution on labor productivity while assuming constant working hours. For instance, studies have examined metrics such as the number of hourly crop units harvested (Graff Zivin & Neidell, 2012) or the accuracy of umpire calls in baseball games (Archsmith et al., 2018). However, it is important to recognize that air pollution may also affect working hours through adverse health outcomes or avoidance behaviors. These additional dimensions could magnify the overall economic consequences of air pollution, with far-reaching implications for both the labor market and the broader economy. Despite the potential significance of this topic, the body of research examining the influence of air pollution on working hours remains notably limited (e.g., Hoffmann & Rud, 2022). Thus, the primary objective of this study is to quantify the importance of the working hours channel and shed light on the extent to which focusing solely on labor productivity underestimates the overall impact of air pollution.

In order to answer this question, we examine the impact of air pollution on hours worked using administrative data from Chile, home to some of the most polluted areas in the Americas, including the Santiago metropolitan area and sev-

[1] There has also been many economic studies on other non-health outcomes such as cognitive ability (e.g., Ebenstein et al., 2016) and crime (e.g., Bondy et al., 2020). Aguilar-Gomez et al. (2022) provides the latest summary on the economics literature on the non-health impact of air pollution.

eral southern cities.[2] Examining the causal relationship between pollution and working hours poses challenges, as pollution is endogenous to labor supply and working hours. On one hand, economic activity generates pollution, leading to a significant reverse causality issue. On the other hand, pollution triggers avoidance behaviors and simultaneity, such as adverse health effects. For instance, workers may opt to reduce outdoor exposure when pollution levels are high, or, in the long run, more productive and health-conscious workers may relocate to cleaner neighborhoods. To address these challenges, we use the incidence of wildfires as an exogenous source of variation in emission levels, enabling us to causally identify the impact of air pollution on hours worked.

Wildfires, naturally occurring fires in forests or bushes, have intensified and expanded worldwide over the past decade, driven by factors such as increased temperatures, lightning prevalence, variable precipitation, and overall forest dryness during summer periods (Úbeda & Sarricolea, 2016; Sankey, 2018). This global phenomenon has heightened the importance of understanding the economic ramifications of wildfires, including their impact on working hours.[3] In Chile, the 2017 fire season was notably severe, burning approximately 587,000 hectares of forest – roughly the size of Delaware (CONAF, 2017). These fires not only caused extreme air pollution episodes (visible in satellite images) but also destroyed an entire town, resulting in human casualties, displaced families, cattle, and wildlife.

We obtain data from the National Forestry Corporation (CONAF) in Chile, which publishes statistics on wildfires, including the number of events, affected surface, and the duration of each wildfire event. We construct a proxy for smoke plumes downwind from the origin of each wildfire, considering the weather conditions on the date of the incident, and calculate the area covered in smoke.[4] We combine

[2]The country hosts the most polluted city in America (Coyhaique) and three of the top 10 most polluted cities on the continent (Padre las Casas, Osorno, and Linares) (measured by $PM_{2.5}$, according to WHO, 2022). The annual mean $PM_{2.5}$ levels in the five most polluted Chilean cities range from nearly nine to over thirteen times the recommended WHO guidelines.

[3]The scientific literature has extensively documented the increasing frequency and intensity of wildfires (Westerling et al., 2003; Krawchuk et al., 2009). For instance, Abatzoglou & Williams (2016) attributed half of the forest fire area in the western US over the past three decades to climate change, with the 2018 California wildfires incurring costs amounting to 1.5% of California's GDP (Wang et al., 2021). Bayham et al. (2022) contains a more comprehensive review on the economics of wildfires in the United States.

[4]While certain regions may exhibit a heightened likelihood of encountering wildfires, we maintain that, upon accounting for location-specific fixed effects, the residual variation can be regarded

that with data on hours worked from the Supplementary Income Survey (ESI, *Encuesta Suplementaria de Ingresos*), an additional module of the National Employment Survey from the Chilean Statistics Bureau. This module provides detailed information about a household's income and its sources. Crucially for our study, ESI records the actual number of hours worked by each worker during the week preceding the interview date and the number of contractually obligated hours. In a reduced-form setting, we find that exposure to an average wildfire decreases weekly working hours across all industries by approximately 2.5 percent for the average Chilean worker, equating to roughly one hour per week. While we observe a modest rebound effect in the subsequent week, the aggregate effect of wildfires on hours worked remains negative.

To examine the impact of air pollution on working hours, we gathered remote sensing data on particulate matter from the European Centre for Medium-Range Weather Forecasts (ECMWF) and employed the smoke plume we created as an instrument for the air pollution measure. Our identification strategy hinges on two assumptions: the exogeneity of wildfire occurrences and the random assignment of the week in which each household was interviewed. Since the ESI data are geo-referenced at the *comuna* level, we can associate them to other measures related to the area where each household resides. We control for temperature and precipitations, along with workers' socioeconomic characteristics such as age and education level. Additionally, we account for province fixed effects, region-by-year fixed effects, and industry-by-year fixed effects to address unobserved trends. We explore the short-term (contemporaneous) and medium-term (up to three weeks post-fire) impacts of air pollution. In our analysis, we employ not only particulate matter measurements but also an Air Quality Index (AQI) comprising six distinct pollutants, encompassing particulate matter.

We show that an increase in air pollution levels significantly reduces working hours. In our preferred specification, an exogenous increase in the average $PM_{2.5}$ level by one standard deviation in a week results in a reduction of the average Chilean worker's labor supply by approximately one hour. Alongside the intensive margin (productivity), our findings demonstrate that air pollution also sub-

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as exogenous. Our main identification rests on the random variation on occurrence of fire, wind direction, as well as the random interview date from the labor market survey.

stantially affects the extensive margin (supply) of the labor market.[5] By combining this negative effect on hours worked with the adverse effect on workers' productivity documented in the literature, our results suggest that the total impact on production through the labor market is likely *stronger* than what the literature has proposed thus far. Employing the framework discussed in Dechezleprêtre et al. (2019) and existing nationwide studies on the effect of air pollution on productivity (Fu et al., 2021; Dechezleprêtre & Vienne, 2022), we determine that the economic impact of air pollution on production through the labor market is 11–13% larger than previously thought.

Our data also enable us to distinguish the impact of an increase in air pollution across industries, occupations, and various socioeconomic characteristics. We find that the effect varies substantially across sub-samples. The negative effect of air pollution on working hours is considerably higher for populations working in the agricultural and service sectors, as well as for occupations taking place outdoors. Independent of the nature of the work, we also find that workers who are either male, older, or poorer suffer up to four times more from air pollution compared to the general population. This result sharply contrasts with Hoffmann & Rud (2022), who find that higher-income households suffered more from air pollution in an urban setting (Mexico City). The fact that the most affected workers are poorer and older implies that air pollution mitigation policies can help reduce income inequalities and the burden on the healthcare sector (see Banzhaf et al., 2019).

This paper contributes to the literature in two main ways. First, it enriches the literature on the impact of air pollution on workers' health, labor productivity, and labor supply (see for instance, Graff Zivin & Neidell, 2012; Hanna & Oliva, 2015; Archsmith et al., 2018; Chang et al., 2019; He et al., 2019). Our study offers two distinct advantages in this context. By using a purely exogenous variation in pollution levels, we can identify a causal effect. Rather than relying on fluc-

[5] The fluctuation in hours worked may stem from alterations in labor supply or demand. On the supply side, employees may experience declining health, which hampers their ability to work, or they may opt to stay indoors due to hazardous air quality. Conversely, on the demand side, a store owner might choose to keep their establishment closed on days of heavy pollution, anticipating a reduced influx of patrons. As the goal of this paper is to gauge the economic implications of air pollution, it is unnecessary to differentiate between these two influences; the overall shift in hours worked suffices.

tuations of pollution within a given period, we focus on a significant, exogenous shock to pollution levels due to wildfire incidents occurring upwind of the study areas. Our data structure allows us to observe hours worked during the days when wildfires are active. While most of the literature concentrates on specific industries, we examine the entire economy, enabling us to determine an average impact and industry-specific impacts. A notable exception is Hoffmann & Rud (2022), which estimates the effect of air pollution on hours worked in Mexico City; however, our study emphasizes the effect in rural areas instead of urban ones.[6]

Second, this paper introduces a novel instrument to examine the causal impact of air pollution, particularly in rural settings. Recent studies have begun to quantify the negative consequences arising from increased incidences of wildfires.[7] Pakhtigian (2020) leverages wildfire occurrences in Indonesia to investigate the impact of air pollution on health and behavior, determining that air pollution reduces lung capacity and encourages the adoption of cleaner fuels, such as Liquefied Petroleum Gas (LPG). Borgschulte et al. (2022) examines the influence of air pollution and wildfire smoke on the US economy, using high-resolution satellite remote sensing data to analyze the effect of wildfire smoke on the US labor market. They observed significant reductions in annual income in regions of the US impacted by wildfire smoke. By instrumenting air pollution with wildfire smoke we are able to consistently estimate the dose-response function for policy evaluation. This approach is also related to other studies employing agricultural fires (via straw burning) as an instrument (Graff Zivin et al., 2020; Lai et al., 2022).

The remainder of this paper is structured as follows. Section 2 presents a conceptual framework illustrating how air pollution impacts the economy through the

[6] Sarricolea et al. (2020) find that wildfires in Chile mainly affect the central and central-south area of the country, from the Valparaíso to Araucanía regions. This area is the most populated in the country, encompassing 78.9% of the country's population (18.73 million people, Instituto Nacional de Estadísticas, 2018b). Based on an analysis of 17 fire seasons, from 2000 - 2001 to 2016 - 2017, Sarricolea et al. (2020) found that the most burned land use and land cover types in Chile are savannas, croplands, evergreen broadleaf forests, and woody savannas.

[7] Other papers investigate the economic impact of wildfire exposure. Mead et al. (2018) demonstrated that over 60% of residents in Malaysia experienced harmful air quality levels following episodes of wildfires in Indonesia and neighboring countries. Focusing on the United States, Kochi et al. (2010) emphasized the importance of considering the disutility of wildfire smoke in addition to the detrimental effects of pollutants as by-products. Richardson et al. (2012) found that, accounting solely for the cost of illnesses, the social cost per exposed person per day increases from \$9.5 to \$84.42 after considering disutility and the cost of defensive actions.

labor market. Section 3 provides an overview of the data sources and descriptive statistics. In Section 4, we discuss our empirical strategies and present results for both our reduced-form and instrumental variables models. Section 5 showcases our findings using an alternative wildfire measure derived from remote sensing data. In Section 6, we calculate the economic cost of air pollution, employing the framework introduced in Section 2 along with estimates from the literature and our results from Section 4. Finally, Section 7 offers concluding remarks.

2 Conceptual framework

To elucidate the influence of air pollution on labor supply, we utilize the conceptual framework developed by Dechezleprêtre et al. (2019) as a foundation for interpreting how our findings can predict the impact of air pollution on economic output. In Section 6, this framework will serve to conduct a comprehensive analysis of our results on economic output. Envision a simple economy featuring a representative firm responsible for output production, while a representative consumer maximizes her utility by consuming the final output.

Output Y is produced according to the following production function:

$$Y = Y(K, L, P) \tag{1}$$

where K is the level of capital, L represents the effective labor input, and P denotes the pollution level. We can rewrite the effective labor input as $L = N \times \varphi h$, where N is the total population, φ is the worker's productivity level, and h is the labor hours supplied by each worker. If we denote the total time available for each worker as T and the number of sick days as s, we can rewrite $h \equiv T - s$ and (1) as follows:

$$Y = Y[K, N(P)\varphi(P)(T - s(P)), P] \tag{2}$$

Equation (2) acknowledges that the pollution level can potentially influence the labor market in three distinct ways: (1) the pollution level can impact the number of productive workers N; (2) the pollution level can affect labor productivity φ; and (3) the pollution level can alter the number of hours worked h. Utilizing (2), we can decompose the total effect of pollution on economic output as follows:

$$\frac{d\log Y}{dP} = \psi\left[\frac{\partial \log N}{\partial P} + \frac{\partial \log \varphi}{\partial P} - \theta\frac{\partial \log s}{\partial P}\right] + \frac{\partial \log Y}{\partial P} \tag{3}$$

where ψ and θ denote the elasticity of economic output with respect to effective labor L, and the ratio of sick days to labor supply, respectively. $\frac{d\log Y}{dP}$ can be interpreted as the economic cost associated with a marginal increase in air pollution.

The empirical literature exploring the impact of air pollution on health outcomes provides insights into the magnitude of the first channel (i.e., $\frac{\partial \log N}{\partial P}$). A well-established body of medical research demonstrates the ways in which air pollution can affect lung functions and other health outcomes (e.g., Dockery et al., 1993; Pope III et al., 2002). In Economics, numerous studies have identified a significant negative impact of air pollution on infant mortality (e.g., Chay & Greenstone, 2003; Currie & Neidell, 2005; Jayachandran, 2009; Arceo et al., 2016), suggesting mechanisms through which pollution levels can adversely affect N. Related research also indicates how pollution influences productive labor by examining its effect on migration (Chen et al., 2022; Khanna et al., 2021).

An expanding body of literature in both physical science and economics investigates the ways in which particulate matter can influence labor productivity (i.e., $\frac{\partial \log \varphi}{\partial P}$). Life sciences evidence suggests that $PM_{2.5}$ can impact heart and brain function, potentially affecting labor productivity (Ranft et al., 2009; Calderón-Garcidueñas et al., 2014; Genc et al., 2012). Economists have studied the causal effect of air pollution on labor productivity across various contexts, such as: pear pickers in California (Graff Zivin & Neidell, 2012); farmers in Ghana (Aragón & Rud, 2016); umpires in Major League Baseball (Archsmith et al., 2018); workers in call centers in China (Chang et al., 2019); employees in manufacturing facilities in India (Adhvaryu et al., 2019) and China (He et al., 2019); and members of parliament in Canada (Heyes et al., 2019).

Our empirical findings enrich the understanding of how air pollution influences working hours h. Related research has demonstrated a relationship between school absenteeism and PM_{10} concentration (Ransom & Pope III, 1992; Currie et al., 2009). Additionally, several studies have investigated work absenteeism, revealing that it is often linked to the presence of dependents at home, thereby establishing a connection between school and work absenteeism (Holub et al., 2016; Hanna & Oliva, 2015; Hansen & Selte, 2000; Aragón et al., 2017). By integrating our results with the existing literature on how air pollution affects other aspects of the labor market, we can calculate the economic cost of air pollution using equation (3).

3 Data

In this section, we outline the data utilized in our paper. To conduct our analysis, we gather information from a diverse array of sources. Labor supply data is obtained from the National Statistics Bureau, while air pollution data is sourced from the European Centre for Medium-Range Weather Forecasts (ECMWF). Wildfire data is acquired from the Chilean National Forest Corporation (CONAF), and lastly, weather data is collected directly from the network of Chilean weather stations, which is compiled by the Center for Climate and Resilience Research in Chile.

3.1 Labor data

Labor data comes from the Chilean Income Supplementary Survey (*Encuesta Suplementaria de Ingresos*, ESI), which is collected by the National Statistics Bureau (INE). The survey's primary objective is to characterize labor income for individuals classified as occupied in the National Labor Survey (ENE) and to describe other sources of household income. The ENE is conducted four times annually, with ESI serving as an annual supplementary survey collected during the final data gathering stage of ENE (i.e., in the fourth yearly round of ENE, individuals respond to both ENE and ESI). The theoretical sample size of ESI is approximately 11,900 households per year (Instituto Nacional de Estadísticas, 2018a).[8] The survey encompasses all individuals aged 15 and older within each household. ESI has been conducted on an annual basis since 2001.

ESI is conducted annually between October and December and is representative at

[8]ESI's exact sample size is determined using the average unemployment rates of the 5 previous mobile trimesters, a measure estimated from prior ENE surveys.

the regional level.[9] The survey encompasses all regions of the country, covering both urban and rural areas. Methodological documentation highlights weekly sampling targets during the data collection process to ensure an even distribution across the three months of fieldwork.[10] This methodological aspect of the survey is crucial to our identification strategy and bolsters the assumption of randomness regarding the day each household was interviewed.

We analyze nine cross-sections of the survey, spanning from 2010 to 2018. ESI comprises labor data from the week preceding the interview day (e.g., *"last week, that is from Monday to Sunday, did you work for at least an hour?"*), in-depth income details, and individual and household-level sociodemographic data. Owing to the information provided by INE, we can ascertain the precise day each interview occurred and, consequently, the week to which the respondents' answers pertain.

Our primary variable of interest is the number of hours worked. ESI contains three questions concerning the time spent working: the number of hours typically worked per week, the number of hours effectively worked in the previous week, and the number of weekly work hours stipulated by contract. If the number of hours usually worked differs from the actual hours worked, respondents are asked to explain the discrepancy. Potential reasons include climatic factors or natural disasters, illnesses, and others.

Moreover, ESI labor data encompasses the interviewee's job type (managerial, executive, manual, etc.), the industry in which they are employed, and whether they worked outdoors or indoors during the week preceding the interview. The survey also offers information on whether the individual worked in the week prior to the interview, as well as the reasons for any absence.

Panel A of Table 1 presents descriptive statistics for the dependent variables used in our analysis, which include the effective (actual) number of hours worked in the previous week, the usual number of hours, and the difference between the two. On average, respondents worked approximately three hours less than usual, with 39.55 hours instead of 42.62. Interestingly, these figures remain consistent

[9] Chile comprises 15 regions, with a 16th region added in 2006; however, the analysis in this paper is based on the original 15 regions.

[10] Sampling is randomized across months as per the survey administrator's instructions. We did not detect any specific sampling pattern that could bias our results.

for workers performing their tasks outdoors or indoors. Panel B displays descriptive statistics for our control variables. The average survey respondent resides in a household of around 3.7 members, is nearly 44 years old, has an average of 11 years of education, and lives in a *comuna* encompassing an area of 2.5 thousand square kilometers. Approximately half of the respondents are the primary breadwinners in their households.

3.2 Wildfire data

We develop a measure of exposure to wildfire smoke using detailed data on each wildfire (obtained from CONAF) as well as wind speed and direction data. We concentrate on the initial phase of a fire, particularly the day it ignites, to devise our smoke plume metric. We opt for this approach because households are generally caught off guard by the sudden onset of a fire, resulting in minimal avoidance behavior and limited immediate actions. Figure 1 illustrates how we created a proxy for each fire's smoke plume using this primary data. First, we employ a circle to approximate the area affected by the fire (represented by the orange circle in the figure), utilizing daily information on the fire's size. Second, we construct a 60-degree pie slice originating at the fire's center and extending in the wind's direction, using daily data on wind speed and direction during the fire's occurrence. We correlate the distance traveled by the smoke (i.e., the pie slice's radius) with the fire's size and the maximum wind speed observed each day. Wind speed and direction (at a 10m altitude) are sourced from the ERA5-Land hourly dataset, which comprises data from 1950 to the present at a horizontal resolution of $0.1^\circ \times 0.1^\circ$ and hourly intervals (Muñoz Sabater, 2019).

In our baseline estimation, we concentrate on the top 2% of the wildfire distribution, which includes fires with a minimum radius of 373 meters.[11] Smaller fires do not generate a significant amount of smoke (particularly given Chile's vast uninhabited areas). Moreover, smaller fires often result from burning crop residues in agricultural areas, which may itself be endogenous (Lai et al., 2022). In our baseline measure, we multiply the fire's radius by a factor of 8, plus half the max-

[11] The sample comprises 426 fires with a median radius of 647 meters. To ensure the robustness of our findings, we conduct various tests on this value, extending our analysis to include fires in the top 10% of the distribution, i.e., fires with a minimum radius of 122 meters.

imum wind speed measured in meters per second. The average fire radius in our sample is 927.8 meters, and the average maximum wind speed is 4.22 m/s, yielding an average plume length of approximately 9.3 kilometers.[12] It is important to consider that while these fires in Chile may be extensive in size, their direct impacts on the economy are relatively limited due to the country's low population density. For instance, within our sample, the 426 fires resulted in the evacuation of a total of 1,500 people and the destruction of 280 buildings. To provide a comparison, it is worth noting that the 2022 Mosquito fire in California alone led to the evacuation of over 11,000 people and the destruction of 78 buildings.

The Chilean census divides each *comuna* into districts and each district into neighborhoods (i.e., *manzanas*). Due to confidentiality concerns, the survey provides only the *comuna* of residence and work for each respondent, but not the district or neighborhood. Utilizing population census data from 2017, we first calculate the daily smoke coverage share for each *manzana*. We then compute the population-weighted share of each *comuna* affected by smoke. Finally, we aggregate these shares on a weekly basis. The resulting value represents a *comuna*-week measure of exposure to a wildfire's smoke plume.

3.3 Pollution and weather data

We obtain satellite-based pollution information for each *comuna* using reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) provided by the Copernicus Climate Change Service. For pollution data, we employ the CAMS global reanalysis (EAC4) dataset. This dataset includes pollution data (PM_1, $PM_{2.5}$, PM_{10}, and other pollutants such as sulfur dioxide and ozone) for each $0.75° \times 0.75°$ grid (approximately 75km x 75km at the equator) across the globe every 3 hours. By utilizing the population-weighted centroid for each *comuna*, we calculate the average pollution concentration for each pollutant within each *comuna* and week in our sample. Additionally, using the same air pollution data, we construct Air Quality Indexes (AQI) for $PM_{2.5}$ and PM_{10}, following the methodology of the U.S. Environmental Protection Agency (U.S. Environmental

[12] We perform a series of robustness tests, varying the percentage of the fire sample included, the pie slice angle, the coefficient by which we multiply the fire radius, and the coefficient by which we multiply the wind speed, and the result stay qualitatively the same.

Protection Agency, 2018).

We aggregate daily temperature and precipitation data at the weather station level – obtained from the Center for Climate and Resilient Research in Chile – into weekly measures by averaging the temperature readings and summing precipitation totals for each week and for each *comuna*. Table 1 presents descriptive statistics for precipitation, temperature, and pollution during the weeks preceding the interview day, focusing solely on the months of October, November, and December. These months are characterized by low precipitation levels, averaging less than one centimeter, and moderate temperatures around 15 degrees Celsius.

4 Empirical strategy

In the empirical analysis, we first implement a reduced-form estimation to capture the direct impact of exposure to a smoke plume on hours worked. Second, we employ an instrumental variable approach to quantify the effect of air pollution on hours worked. In this specification, we use exposure to a wildfire plume as a source of exogenous variation in pollution levels.

4.1 Reduced form analysis

Wildfire smoke plumes provide us with a convenient source of exogenous variation in pollution levels. As a result, the first part of our analysis is based on a straightforward reduced-form specification of the following form:

$$Hours_{it} = \beta Wildfires_{it} + X'_{it}\gamma + \alpha_i + \alpha_t + \delta_{it} + \eta_{it} + \varepsilon_{it} \tag{4}$$

where, *Hours* represents the number of hours effectively or usually worked over the week preceding the interview. $Wildfires_{it}$ denotes our smoke exposure measure, which is a weighted sum of the share of the area of *comuna* i covered by wildfire smoke during week t (the week prior to the interview). X is a vector of controls, encompassing average precipitation and temperature, the area of the *comuna*, household size, whether the interviewee is the primary breadwinner, their marital status, age, gender, and years of education. Furthermore, we control for province, month, region-year, and industry-year fixed effects. These fixed effects allow us to capture time-invariant and time-varying regional effects, seasonal effects on labor demand, and distinct industry-specific trends that could impact labor supply. ε represents the error term, clustered at the *comuna* level.

Results

Given the exogeneity of the smoke plumes, these reduced-form results can be interpreted causally. We present these results in Table 2. In column (1), we control only for province and year fixed effects, in addition to the wildfire smoke exposure measure. These controls account for unobserved factors at the province and year levels. We obtain a negative coefficient of -0.01, which is statistically significant at the 1% level. This coefficient suggests that if an entire *comuna* is covered by a smoke plume for a full day, workers will work on average 0.97 hours less, corresponding to a reduction of approximately 2.5% of their working hours. In column (2), we control for region by year fixed effects and month fixed effects, as wildfires may be more frequent in specific months. Working hours in some industries may vary over time; thus, in column (3), we control for a set of industry by year fixed effects. The coefficient on wildfire smoke exposure is smaller in magnitude but remains statistically significant at least at the 5% level across all the specifications. In columns (4) and (5), we incorporate weather controls (temperature and precipitation) and individual-level controls. The coefficient of interest remains largely unchanged. The preferred specification, in column (5), implies that a full day of smoke exposure across a *comuna* results in a reduction of 0.38 hours worked, or a 1 percent decrease.

The first robustness test we perform on our identification involves re-running this specification using contract hours as the dependent variable instead of effective hours worked. If wildfire incidents are indeed randomly assigned, exposure to their smoke plume should not be correlated with contract hours of work. The top panel of Table 3 summarizes the results of this estimation using the same structure as Table 2. Columns (1) and (2) show a statistically significant negative relationship between the exposure measure and contract hours. However, columns (3) to (5) do not display any statistically significant association between exposure to wildfire smoke and contracted hours. This loss of statistical significance occurs after conditioning on industry-year fixed effects. This finding suggests that workers who are more likely to be exposed to wildfire smoke may be employed in industries with lower contracted hours. After conditioning on industry-year fixed effects, our results indicate that wildfire smoke is randomly assigned to workers, validating the empirical design.

We also conduct our analysis using the difference between effective and contract working hours as the dependent variable. In this context, the dependent variable can be interpreted as absenteeism, representing hours missed by a worker in a given week. The results for this regression are presented in the bottom panel of Table 3. These findings are qualitatively similar to those observed in Table 2: during weeks when workers are exposed to wildfire smoke, they record more absences. The magnitude of the coefficient remains highly stable across the various specifications.

4.2 Instrumental variable analysis

Having established that exposure to wildfire smoke has a negative impact on the working hours of Chilean workers, we proceed to quantify the effect of air pollution on their working hours by using exposure to wildfire smoke as an instrument. The relationship between air pollution and hours worked may be subject to endogeneity issues. Hours worked could potentially affect air pollution through increased production, leading to reverse causality and a positive correlation between the two. Furthermore, there may be other omitted variables simultaneously affecting hours worked and air pollution. To isolate the causal effect of air pollution on hours worked, we use exposure to wildfire smoke as an instrumental variable, enabling us to disentangle an exogenous component in the variation in air pollution. We then employ a standard two-stage least squares approach. Specifically, our estimation takes the following form:

$$Pollution_{it} = \mu Wildfires_{it} + X'_{it}\xi + \alpha'_i + \alpha'_t + \delta'_{it} + \eta'_{it} + v_{it} \tag{5a}$$

$$Hours_{it} = \beta \widehat{Pollution}_{it} + X'_{it}\gamma + \alpha_i + \alpha_t + \delta_{it} + \eta_{it} + \varepsilon_{it} \tag{5b}$$

where the definitions of the fixed effects and controls follow those outlined in Section 4.1.

Our benchmark results primarily focus on average $PM_{2.5}$ levels, in accordance with the literature that examines the effect of air pollution on labor productivity. However, we also present results for maximum (hourly) $PM_{2.5}$ levels in the Appendix. Regression models for other pollutants reveal qualitatively similar outcomes when compared to those derived from average $PM_{2.5}$ levels.

Results

We initially show the endogeneity of air pollution on hours worked by estimating equation (5b) without employing any instrument. The results can be found in Table A.1, which follows the same structure as Table 2. In all specifications, air pollution displays a positive and statistically significant correlation with hours worked. This positive correlation may appear counter-intuitive; however, as we previously noted, it can be attributed to reverse causality. Working hours are correlated with economic output, which in turn increases the level of air pollution. This table highlights the necessity of an instrument to isolate an exogenous variation in air pollution levels and estimate its causal effect on hours worked.

In the remainder of this section's analysis, we instrument air pollution using exposure to wildfire smoke. Table 4 presents the first and second stage results.[13] The top panel of Table 4 displays first stage results. Our measure of exposure to wildfire smoke exhibits a robust positive effect on the average $PM_{2.5}$ level in a *comuna*. This effect remains strong and consistent across all five specifications. Furthermore, the first stage F-statistics indicate a powerful first stage. Column (5) suggests that a one-day wildfire smoke exposure in a *comuna* raises the *weekly* average $PM_{2.5}$ level by 7.6 $\mu g/m^3$. This increase is substantial, given the World Health Organization's recommendation of a 5 $\mu g/m^3$ 24-hour mean, published in 2021. This corresponds to a 42.6% increase over the average $PM_{2.5}$ levels observed in our sample or approximately half a standard deviation, as seen in Table 1.

After establishing the strong predictive capacity of wildfire smoke for $PM_{2.5}$ levels, the lower section of Table 4 showcases the outcomes from the second-stage analysis. Contrasting with the OLS-equivalent findings in Table A.1, the impact of air pollution on labor supply now emerges as *negative*. This suggests that air pollution leads to a decrease in hours worked. According to our preferred spec-

[13] In our baseline model, we present the effect of average $PM_{2.5}$ level on hours worked. Employing PM_1, PM_{10}, or their maximum levels instead of averages produces similar outcomes. These results are reported in the Online Appendix.

ification (column 5), a one standard deviation increase in the average $PM_{2.5}$ level within a week (i.e., 15.82 $\mu g/m^3$) leads to a reduction of approximately 0.79 hours (or 2 percent) in hours worked – a notable economic effect.

These findings, when considered alongside the existing literature on air pollution's influence on labor productivity, imply that air pollution affects the labor market through both the extensive margin (hours worked) and the intensive margin (labor productivity).[14] Furthermore, we replicate the reduced-form analysis on contract hours and the disparity between actual and contract hours within an instrumental variable framework. The corresponding outcomes can be found in Table A.3 in the Appendix. These results are consistent with the observations made in the reduced-form analysis.

In order to further assess the validity of our instrument, we follow existing literature (e.g., Arceo et al., 2016) by computing the average daytime thermal inversions throughout the week. The outcomes utilizing this instrument are presented in Table A.4 in the Appendix.[15] In line with the literature, we observe that thermal inversions amplify air pollution, and when accounting for their presence, wildfire smoke demonstrates a comparable effect on air pollution to our baseline findings (without thermal inversion). The overidentification tests cannot be rejected across all specifications, implying that wildfire smoke serves as a valid instrument – even though thermal inversions constitute a weaker instrument relative to wildfire smoke.

When we employ both wildfire smoke and thermal inversions as instruments, air pollution exhibits a more pronounced negative impact on working hours: a one standard deviation increase in the average $PM_{2.5}$ level in a week results in a 2.4 hours reduction in working hours (or 6 percent).[16] For the remainder of this

[14]In Table A.2 of the Appendix, we assess our baseline model employing five alternate pollution metrics: average PM_1, PM_{10}, and maximum levels of PM_1, $PM_{2.5}$, and PM_{10}. All pollutants result in a decrease in hours worked.

[15]A thermal inversion refers to an atmospheric layer where air temperature increases with altitude rather than decreasing, which restricts ventilation and traps pollution. As naturally occurring phenomena not caused by human activities, thermal inversions are considered suitable instrumental variables for air pollution in the literature. For additional information on the construction of this type of instrument, see Arceo et al. (2016) and other sources.

[16]Similar results are obtained when using thermal inversion as the sole instrument (with a considerably smaller *F*-statistic in the first stage). The outcomes involving contract hours and the discrepancy between actual and contract hours are qualitatively akin to our baseline findings.

paper, we opt to concentrate on specifications with wildfire smoke as the exclusive instrument to offer a more conservative estimate of the effect.

Particulate matter is not the sole pollutant with the potential to impact cognitive functions and health outcomes. Thus, it is worthwhile to explore whether other pollutants also influence the number of hours worked. To this end, we construct the Air Quality Index (AQI) for our sample following the standards and formulae employed by the United States Environmental Protection Agency (US EPA). This index incorporates six types of pollutants: $PM_{2.5}$, PM_{10}, carbon monoxide (CO), ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2). We then replicate our analysis, substituting our $PM_{2.5}$ measure with AQI, and present the results in Table 5.[17] Our wildfire instrument effectively predicts AQI, and we obtain similar results indicating that a higher AQI (representing elevated pollution levels) adversely affects actual working hours, but not contracted working hours.

4.3 Dynamic analysis

Our current specification captures the immediate impact of air pollution on working hours; however, our data also enables us to examine potential rebound effects in the weeks directly following a wildfire. We match the air pollution levels from two to four weeks prior to the interview and re-run the baseline IV specification, incorporating one, two, and three lags of the pollution measure. The results from these three regressions, as well as those from our baseline specification, are depicted in Figure 2.[18]

In the figure, the blue dot represents the contemporaneous coefficient, while the red, green, and orange dots correspond to the coefficients from the specifications with one, two, and three lags, respectively. The figure reveals a rebound effect in hours worked during the week following the wildfire, with the impact diminishing thereafter – lags two and three are statistically indistinguishable from zero. The rebound effect amounts to 0.067, and when combined with the contempo-

[17] Alternatively, we can also regress on individual components of AQI within the same specification, with the findings summarized in Table A.5. Four of the six pollutants yield significant first-stage *F*-statistics and second-stage effects on hours worked. We did not observe strong predictive power for nitrogen dioxide and sulfur dioxide levels, which is consistent with the fact that wildfire smoke is not a primary source of these pollutants.

[18] The coefficients can be found in Table A.6.

raneous effect of -0.085, yields a long-term negative impact of -0.018. For a one standard deviation increase in $PM_{2.5}$, this corresponds to an overall reduction of 0.28 hours worked, equivalent to a 0.75% decrease.

4.4 Heterogeneous analysis

Our dataset enables us to explore the heterogeneous effects of air pollution on hours worked. In this section, we introduce various sample divisions and examine how the individuals within these groups are influenced by pollution. The outcomes of these estimations are provided in Table 6, where we present the coefficient for average $PM_{2.5}$ pertaining to each subsample.

The first heterogeneity analysis we conduct focuses on gender. While female workers appear to be unaffected by air pollution, male workers seem to experience significant impacts. This outcome could be attributed to the larger proportion of males engaged in agriculture (74.7%). A one standard deviation increase in $PM_{2.5}$ results in a reduction of 2.7 hours worked for males, corresponding to a 6.5% decrease.[19]

Next, we examine individuals working indoors and outdoors. At first glance, the results may seem surprising, as both coefficients appear to be statistically insignificant. However, the coefficient for individuals working outdoors is negative and an order of magnitude larger than the one for individuals working indoors. The outdoor coefficient is not precisely estimated, whereas the indoor workers' coefficient is closer to zero in value and not statistically significant.[20]

The third set of heterogeneous results we explore pertains to the impact of air pollution across age groups. As expected, we observe more pronounced effects for older workers. For workers below 40 years old, the effect is not statistically different from zero, while it turns negative and statistically significant at the 5% level for workers aged between 40 and 54, and becomes two to three times larger and statistically significant at the 1% level for workers over 55 years old. This

[19]The average actual hours worked for men amount to 41.087 per week.

[20]If we run this estimation without household controls, both coefficients become negative and statistically significant at the 1% level for outdoor workers and at the 5% level for indoor workers. The coefficient for outdoor workers is three times larger than the one for indoor workers: -0.136 versus -0.044.

finding is important since older workers are more likely to require hospitalization and experience other complications, resulting in a proportionally greater burden on the healthcare sector.

Another crucial source of heterogeneity is income. The outcomes regarding whether air pollution may exacerbate income inequality have implications for the environmental justice literature. We present results for three distinct income groups, defined by an individual's income relative to the national income average. We find that the impact of air pollution is concentrated on the poorest (workers earning less than the national income average) and the median workers (workers with income between once and twice the national income average). For both groups, the coefficient is negative and statistically significant at the 1% level, suggesting that a one standard deviation increase in $PM_{2.5}$ reduces hours worked by 1.74 hours per week. The result for the wealthiest households is puzzling, as it appears that an increase in air pollution leads to an increase in hours worked, statistically significant at the 10% level.

To better understand the origin of this result, we divide the sample between large *comunas* (i.e., with more than 100,000 inhabitants, totaling 45 *comunas*) and small *comunas*. Our data do not include information on whether a household resides in an urban or rural area; thus, this division serves as a proxy for that distinction. Table 7 displays descriptive statistics for exposure to wildfire smoke across this sample division. We immediately observe that the majority of the variation in smoke exposure originates from small *comunas*; in large ones, where higher-income individuals are likely more concentrated, there is no variation. This lack of variation implies that we might be unable to correct for endogeneity in larger urban areas, potentially explaining the positive coefficient for the wealthiest segment of the sample. Unsurprisingly, when we run the three income bracket subsamples solely on the smaller *comunas*, the positive coefficient for the richest households loses its statistical significance. We do not report the results for the other part of the sample since the first-stage F-stat is lower than 10. Consequently, our identification does not permit us to draw conclusions about urban areas, and our paper can be viewed as presenting the untold half of the story examined by Hoffmann & Rud (2022).

4.5 Robustness

We conduct two distinct robustness tests. Firstly, we exclude from the sample all regions that are typically unaffected by wildfires. Secondly, we perform a series of placebo tests, in which we randomize the occurrence of wildfires across the sample in various ways.

Regions

In Chile, not all regions are affected by wildfires; some, due to their specific vegetation, never experience them. In Table A.9 in the Online Appendix, we present the baseline estimation in the first column and progressively exclude more of the 15 regions comprising Chile. In column (2), we begin by eliminating the three northernmost regions: Arica and Parinacota, Tarapacá, and Antofagasta, which are virtually never affected by wildfires. In column (3), we exclude an additional five regions: Atacama, Coquimbo, Los Lagos, Aysén of General Carlos Ibáñez del Campo, Magallanes and Chilean Antarctica. Finally, in column (4), we eliminate three more regions: Bío Bío, La Araucanía, and Los Ríos. Our results remain robust to these exclusions.

Placebo

The variation in our instrument is based on the random timing and location of wildfire occurrences. To test this design, we conduct a series of placebo estimations using falsely-assigned wildfire plumes. For these placebo estimations, we randomize exposure to wildfire plumes across the entire sample and replace the baseline specification with this shuffled measure. We perform three distinct randomizations: *i)* over the entire sample, *ii)* within each of the 15 regions, and *iii)* within each of the 9 years. We anticipate that this exercise will produce mostly statistically insignificant estimates for the variable of interest while leaving the statistical significance of the estimates for other variables largely unchanged. We repeat the exercise 1,000 times and, each time, collect the t-statistic for the coefficient of interest.

The results of this exercise are displayed graphically in Figures 3, B.2, and B.3. These figures present the histograms of the distribution of t-statistics for the coefficient of interest across the 1,000 repetitions. The red vertical line represents the t-statistic of the baseline estimation (-2.74). As we can observe, the majority of the distribution falls within the -1.96 and 1.96 boundaries, indicating that most coefficients obtained through the falsely-attributed smoke plumes are statistically insignificant. As expected, given the results of Table A.9, when we randomize the variable within each region, the proportion of statistically significant results increases. This outcome can be attributed to the fact that most wildfires are concentrated within a few regions.

5 Alternative wildfires measure

In this section, we employ an alternative methodology as a proxy for wildfire smoke plumes to assess the robustness of our main findings.

5.1 Burned area data

In this section, we create an alternative representation of wildfire smoke using data from the MODIS Burned Area product. This dataset divides the entire planet into a grid of 500m x 500m cells, indicating whether each cell experienced burning on a specific day. Figure B.1 in the Online Appendix illustrates an example of this data, with red dots representing burned grid cells and marked circles serving to help identify these burned cells. We gather this information for all the weeks in our sample.

We construct a buffer area around the population-weighted centroid of each *comuna*. The population-weighted centroid of a *comuna* is calculated by weighting the latitude and longitude components of the geometric centroid of each *manzana* (neighborhood, as defined by the census) by the share of the *comuna*'s population residing in it. Panel (a) of Figure 4a displays the difference between geometric centroids (red crosses) and population-weighted centroids (blue stars). As can be observed, the larger the surface area of a *comuna*, the more likely there is a difference between the two.[21]

[21] In the robustness section, we address the possibility that in some *comunas*, the population might be dispersed among several hamlets, making population-weighted centroids a less ideal measure.

First, we draw a circle with a radius of two kilometers around each population-weighted centroid. Second, we multiply the horizontal radius of each circle by half of the wind speed (with a lower bound at a speed of 2m/s, i.e., the minimum radius is equal to 2km), resulting in elliptical shapes. Third, we tilt the horizontal radius (the longer one in the ellipse) in the direction of the wind and slide the ellipse along this axis against the wind until the population-weighted centroid is once again two kilometers from the boundary of the ellipse on the downwind side. Panel (b) of Figure 4a depicts these elliptical shapes for a given day in the area around Santiago. One observation is that Santiago experienced very slow winds that day, causing some of the shapes to appear round.

At this stage, we compute the share of the ellipse that is burned for each day by examining the burned raster cells. It is worth noting that, since the cells are square and the buffer is an ellipse, if all cells are burned, the share of the buffer burned could exceed 100%. The utilization of an elliptical shape enables us to capture the probable path of the smoke plumes generated by these fires.

Panel D in Table 1 presents descriptive statistics for the share of the area burned within the elliptical buffers. On average, when a buffer is affected by a wildfire, approximately 6.4% of its area is burned. In our sample, a maximum of 58% of a buffer's area has been burned. From an identification perspective, the challenge with this measure lies in the limited variation in the data, as only 522 observations have a strictly positive value. One alternative would be to simply examine the burned share of the entire *comuna*. However, the problem with this approach arises from the vast size of *comunas* and the extensive uninhabited areas within the country. *Comunas* can encompass up to 49 thousand square kilometers of land. If we solely considered the share of surface burned, we might inadvertently capture wildfires that did not impact any human beings. For this reason, we opt for a more restrictive definition.

5.2 Reduced form analysis

In line with our primary analysis, we conduct a reduced-form analysis as follows:

$$Hours_{it} = \beta BufferShare_{it} + X'_{it}\gamma + \alpha_i + \alpha_t + \delta_{it} + \eta_{it} + \varepsilon_{it} \tag{6}$$

where, *Hours* represents the number of hours worked in the week preceding the interview, and *BufferShare* indicates the proportion of burned area within the elliptical buffers during a wildfire. The control vector X includes average precipitation and temperature for the relevant week, the *comuna*'s area, household size, whether the interviewee is the household's primary breadwinner, marital status, age, gender, and years of education. We also account for province, month, region-year, and industry-year fixed effects to capture time-invariant and time-varying regional influences, seasonal labor demand fluctuations, and industry-specific trends that may impact labor supply. The error term is denoted by ε, and we cluster it at the *comuna* level.

Considering the construction of the burned area variable around each *comuna*'s population-weighted centroid (rather than the simple geometric centroid), we can better ensure that the probability of a respondent living within the buffer is non-zero. Considering the potentially substantial size of *comunas*, we enhance our estimations by devising a set of weights that reflect the probability of an individual living in close proximity to the population-weighted centroid. These weights are based on the proportion of a *comuna*'s population living within a two-kilometer radius circular buffer. We choose a circular buffer for these weights since elliptical buffers vary daily according to wind speed and direction. The weights are calculated as follows:

$$w_i = \frac{\text{Population in the Buffer}_{i,2017}}{\text{Total Population in Comuna}_{i,2017}} \tag{7}$$

Using neighborhood-level population data from the census, we compute these shares, capturing all neighborhoods within a buffer and the proportion inside the buffer for those on the edge, as demonstrated in Figure 5. We employ these weights as estimation weights in all our regressions.

Results

Table 8 presents the results for our baseline estimation, which is based on elliptical buffers surrounding the population-weighted centroid of each *comuna*. In the table, we sequentially include all fixed effects and controls at the *comuna*, household, and individual levels. Column (5) displays the complete baseline specification.

The coefficient of the variable of interest remains consistent in terms of magnitude, sign, and statistical significance across the various specifications, suggesting that when a portion of the elliptical buffer around a *comuna*'s population-weighted centroid is burned, the labor supply for that week decreases. This coefficient corresponds to an approximate 1.8% reduction in hours worked for the average Chilean worker in the aftermath of a typical wildfire.[22] The controls exhibit the anticipated signs.

We also computed circular buffers without considering wind speed and direction at the population-weighted centroid of the *comuna*. By replacing the elliptical buffer with the circular buffer and re-estimating our equation, we obtain the findings presented in Table 8. Although smaller in magnitude, this coefficient corresponds to a reduction of approximately 2.4% in hours worked for the average Chilean worker following an average wildfire, which is closer to our baseline reduced form results using our constructed wildfire smoke plume measure.[23]

The choice of a 2-kilometer radius for both the circular and elliptical buffers (aligned with the downwind direction) has been made ad hoc. The risk associated with a much larger buffer is that it would encompass numerous individuals not directly affected by the fire or indirectly by its smoke. In Table A.10 in the Online Appendix, we demonstrate the effect on the baseline specification when the buffer size varies between 1 and 3 kilometers at 500-meter intervals.[24] As anticipated, the coefficient of interest is larger in magnitude for a smaller buffer, although less precisely estimated. As the buffer expands, the coefficient stabilizes around -4 to -5.

In this analysis, we examine the effect of wildfires on the number of hours typically worked by individuals. We expect no impact, as a sudden increase in pollution levels should not influence contract working hours. Table 8 presents the results for a specification where we replace actual working hours with the difference between contract and real hours worked. This difference can be interpreted as the number of hours an individual chose not to work. A positive effect of simi-

[22]This figure is derived as follows: (-10.9*0.064)/38.4, using the descriptive statistics provided in Table 1.

[23]This figure is derived in the following way: (-4.36*0.213)/38.4, where 0.213 represents the average share of wildfire in the circular buffer conditional on it being positive.

[24]Upon recalculating the buffer size, we also recompute the estimation weights.

lar magnitude to actual working hours is observed, consistent with the hypothesis that wildfires have a limited effect on contract working hours. Comparable results are obtained when using the round buffer instead of the elliptical buffer.

To explore whether workers shifted their working hours to the following week instead of genuinely reducing their labor supply, we add a lagged term for the share of wildfire exposure to our regression analyzing real working hours. The coefficients for the contemporaneous term for wildfire exposure closely resemble those estimated in our baseline specification, as shown in Figure 2.[25] In the specification that includes both the contemporaneous and one-period lagged terms, the one-period lagged term exhibits a positive and statistically significant coefficient, though with a smaller magnitude than the contemporaneous effect. This suggests that workers respond to wildfire exposure by reducing working hours during the affected week and attempt to compensate by working more the following week. However, our findings indicate that the overall effect of wildfires remains negative. When a second lagged term is added, it yields a statistically and economically insignificant result, while the contemporaneous and first lag coefficients are similar to the previous specification, albeit with reduced precision.

In Table A.11, we conduct a robustness check on our baseline results by excluding all *comunas* with weights below 0.2, 0.3, 0.4, 0.5, and 0.6 respectively. The results remain positive and statistically significant at the 1 percent level across all specifications, even with the substantial reduction in sample size. As anticipated, when we exclude *comunas* with lower weights and increase the average weights in our sample – corresponding to a higher probability that individuals are genuinely affected by the fires – the observed effect becomes larger. The magnitude of the coefficient increases from 11 in the baseline to 21 when we only include *comunas* with weights above 0.6.

6 Economic impact analysis

In this section, we conduct a back-of-the-envelope economic impact analysis to estimate the GDP-cost of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ attributable to a decrease in hours worked.

[25] Additional results estimated using the alternative wildfire measure are available upon request.

Our calculations are based on the model developed in Dechezleprêtre et al. (2019), specifically equation (3), which decomposes the effect of air pollution on the economy into four main components: the impact on the number of workers, their productivity, their hours worked, and the direct impact of air pollution on production. According to equation (3), to isolate the impact of air pollution on GDP due to a decrease in the number of hours worked, we need our estimate (i.e., $\frac{\partial \log s}{\partial P}$), the elasticity of output with respect to labor (i.e., ψ), and the ratio of hours missed over hours worked (i.e., θ). From our data, we estimate $\theta = 0.08$ by calculating the average weekly difference between contract and real hours worked divided by the average real hours worked. This number suggests that, on average, 8% of hours are missed for various reasons. We use the standard value used in the literature of $\psi = 0.7$ (e.g., Golosov et al., 2014).

In this final step of the economic impact analysis, we obtain $\frac{\partial \log s}{\partial P}$ by estimating our baseline IV specification, equation (5b), using the difference between usual and real hours worked as the dependent variable instead of real hours worked. This estimation reveals that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ leads to a 0.04 increase in the difference between usual and real hours worked. Considering that the average worker works 38.4 hours per week (see Table 1), the 0.04 increase in the difference between usual and real hours worked corresponds to a 1.3% increase.[26]

Utilizing the Chilean GDP figure from 2020 (252.9 billion US dollars) and equation (3), we calculate the impact on GDP from a decrease in hours worked resulting from a 1 $\mu g/m^3$ increase in $PM_{2.5}$ as follows: $\psi\theta\frac{\partial \log s}{\partial P}GDP$. This calculation yields 0.184, indicating that every 1 $\mu g/m^3$ increase in $PM_{2.5}$ leads to a decrease in GDP by 184 million dollars.

The economic impact analysis reveals a significant number, but it is crucial to compare it with other impacts of air pollution, such as its effects on productivity. In the literature, there are two estimates of air pollution's impact on productivity. Fu et al. (2021), examining the Chinese manufacturing sector, discover that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ decreases productivity by 0.82%. In contrast, Dechezleprêtre & Vienne (2022) find a 0.93% decrease in productivity using data from European firms. By employing equation (3) again, these estimates imply a GDP reduction for Chile between 1.45 and 1.65 billion dollars. This suggests that considering

[26] $\frac{0.04}{0.08x38.4} = 0.013$.

the effect on the equilibrium amount of hours worked increases the labor cost of air pollution by 11-13% – a non-negligible amount. As expected, the impact on productivity is more substantial since it applies to all hours worked.

7 Conclusions

In this paper, we determine the causal impact of air pollution on hours worked by utilizing wildfire occurrences to generate exogenous variations in air pollution levels. We analyze labor supply and wildfire data from Chile, a country with significant pollution. We gather week-comuna level pollution data for the period of interest using satellite reanalysis data. Then, we estimate the effect of air pollution on hours worked, employing wildfire exposures as an instrumental variable. To construct our instrument, we estimate the smoke plume resulting from wildfire exposures by considering the fire's size and data on wind speed and direction.

By instrumenting air pollution using wildfire exposures and leveraging satellite data, we isolate the causal effect of air pollution on hours worked, demonstrating that elevated air pollution levels lead to a substantial reduction in hours worked in Chile, imposing a considerable economic cost. Specifically, the average Chilean worker across all industries reduces their working hours by approximately two percent following an increase in air pollution due to a wildfire. We observe that the effect varies significantly across income groups, age, gender, and types of work performed by the workers. Our results are robust to alternative wildfire measures employing remote sensing data on fire.

While much of the empirical work on air pollution has concentrated on worker productivity (the "intensive margin" of air pollution's impact on labor supply), this paper focuses on hours worked (the "extensive margin"). Combining these two effects suggests that air pollution's impact on production could be considerably larger than previously believed. Our findings emphasize the need for further research and discussion on vulnerable individuals who experience significantly more harm from air pollution.

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Tables

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: Working hours					
Real hours worked	38.40	17.05	0	84	265,124
Contract hours worked	42.62	10.56	1	84	195,876
Difference	3.07	11.48	-67	84	195,876
Panel B: Household characteristics					
Household size	3.69	1.69	1	17	265,124
Years of education	11.63	3.91	0	23	265,124
Age	43.57	14.22	15	99	265,124
Main breadwinner†	0.53	0.50	0	1	265,124
Married†	0.58	0.49	0	1	265,124
Gender†	0.57	0.50	0	1	265,124
Panel C: Weather, pollution and wildfires					
Area comuna ($1000km^2$)	2.522	5.776	0.006	48.695	265,124
Average precipitations	0.684	1.496	0	9.109	265,124
Average temperature	15.26	3.02	6.917	21.80	265,124
Wildfire smoke	0.060	3.595	0	294.8	265,124
Wildfire smoke if > 0	4.878	32.18	0.002	294.8	3,236
Average hourly $PM_{2.5}$	17.84	15.82	0.906	138.2	265,124
Maximum hourly $PM_{2.5}$	41.97	39.61	2.103	702.7	265,124
Average AQI (all pollutants)	77.23	38.59	24.43	192.9	221,317
Average $PM_{2.5}$ AQI	56.34	37.02	3.429	178.6	221,317
Average PM_{10} AQI	22.08	17.58	0.143	104.2	221,317
Average CO AQI	1.75	1.96	0	10.79	221,317
Average O_3 AQI	71.90	35.64	22.5	177.7	221,317
Panel D: Elliptical buffers					
Share of wildfire in buffer	0.0001	0.0059	0	0.5791	247,605
Share of wildfire in buffer if > 0	0.0641	0.1123	0.0063	0.5791	522

Note: † denotes indicator variables.

Table 2: Reduced-form analysis: Real hours worked

	Real hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Wildfire smoke	-0.0097***	-0.0088***	-0.0058***	-0.0060***	-0.0038**
	(0.0017)	(0.0018)	(0.0017)	(0.0016)	(0.0017)
Average precipitations (week)				-0.15***	-0.15***
				(0.046)	(0.045)
Average temperature (week)				0.17***	0.18***
				(0.032)	(0.032)
Area of a comuna (1000 km^2)				-0.018	-0.030
				(0.032)	(0.033)
No. of people in HH					0.36***
					(0.028)
Main breadwinner of HH					2.99***
					(0.097)
Years of education					0.25***
					(0.016)
Married					-0.19***
					(0.031)
Age					-0.0026
					(0.0043)
Gender					4.64***
					(0.12)
Province FE	yes	yes	yes	yes	yes
Year FE	yes	no	no	no	no
Month FE	no	yes	yes	yes	yes
Region-year FE	no	yes	yes	yes	yes
Industry-year FE	no	no	yes	yes	yes
Observations	265,124	265,124	265,124	265,124	265,124

Notes: Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Reduced form analysis: Contract hours

	Contract hours during the week				
	(1)	(2)	(3)	(4)	(5)
Wildfire smoke	-0.0055***	-0.0050***	-0.00050	-0.00051	0.00026
	(0.0013)	(0.0012)	(0.0011)	(0.0011)	(0.0012)
Average precipitations (week)				-0.025	-0.021
				(0.023)	(0.023)
Average temperature (week)				-0.028	-0.022
				(0.017)	(0.017)
Area of a comuna (1000 km^2)				-0.020	-0.022
				(0.017)	(0.017)
	Difference in hours worked during the week				
Wildfire smoke	0.0032***	0.0024*	0.0032***	0.0033***	0.0026**
	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Average precipitations (week)				0.14***	0.14***
				(0.033)	(0.033)
Average temperature (week)				-0.21***	-0.21***
				(0.026)	(0.026)
Area of a comuna (1000 km^2)				0.000034	0.0018
				(0.017)	(0.017)
Province FE	yes	yes	yes	yes	yes
Year FE	yes	no	no	no	no
Month FE	no	yes	yes	yes	yes
Region-year FE	no	yes	yes	yes	yes
Industry-year FE	no	no	yes	yes	yes
Observations	195,876	195,876	195,876	195,876	195,876

Notes: Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Causal effect of air pollution on real hours worked

First stage: PM$_{2.5}$ (μg/m^3)					
	(1)	(2)	(3)	(4)	(5)
Wildfire smoke	0.068***	0.076***	0.077***	0.077***	0.076***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Average precipitations (week)				-0.27***	-0.27***
				(0.074)	(0.074)
Average temperature (week)				-0.60***	-0.60***
				(0.095)	(0.095)
First-stage F-stat	1,217.4	813.3	812.0	810.3	810.8
Second stage: Real hours worked during the week					
	(1)	(2)	(3)	(4)	(5)
Average PM$_{2.5}$ (μg/m^3)	-0.14***	-0.12***	-0.076***	-0.078***	-0.050**
	(0.022)	(0.024)	(0.022)	(0.021)	(0.022)
Average precipitations (week)				-0.17***	-0.16***
				(0.047)	(0.046)
Average temperature (week)				0.12***	0.15***
				(0.035)	(0.035)
Area of a comuna (1000 km^2)				-0.011	-0.026
				(0.037)	(0.036)
HH controls	no	no	no	no	yes
Province FE	yes	yes	yes	yes	yes
Year FE	yes	no	no	no	no
Month FE	no	yes	yes	yes	yes
Region-year FE	no	yes	yes	yes	yes
Industry-year FE	no	no	yes	yes	yes
Observations	265,124	265,124	265,124	265,124	265,124

Notes: All models are estimated using two stage least square using wildfire smoke as the exogenous instrument. The Kleibergen-Paap rk Wald F statistics are reported as first stage F-stat. Standard errors in parentheses are clustered at the comuna level. Some controls in the first and second stage regressions are suppressed for exposition purposes. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Causal effect of the Air Quality Index (AQI)

Dependent variable:	Real hours	Contract hours	Hours difference
	(1)	(2)	(3)
AQI index weekly average	-0.067**	0.0023	0.035***
	(0.027)	(0.0098)	(0.0093)
Average precipitations (week)	-0.27***	-0.024	0.25***
	(0.057)	(0.030)	(0.043)
Average temperature (week)	0.088**	-0.021	-0.14***
	(0.042)	(0.021)	(0.029)
Area of a comuna (1000 km^2)	-0.0019	-0.015	-0.0065
	(0.039)	(0.018)	(0.020)
Estimator	IV	IV	IV
Household controls	yes	yes	yes
Province FE	yes	yes	yes
Year FE	yes	yes	yes
Month FE	yes	yes	yes
Region-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes
First stage F-statistic	284.6	569.9	569.9
Observations	221,691	163,841	163,841

Notes: All models are estimated using two stage least square using wildfire smoke as the exogenous instrument. The Kleibergen-Paap rk Wald F statistics are reported as first stage F-stat. Standard errors in parentheses are clustered at the comuna level. Some controls in the first and second stage regressions are suppressed for exposition purposes. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Heterogenous impact of air pollution on labor supply

Dependent variable:		Real hours worked during the week	
Baseline / Overall sample:		-0.050**	(0.022)
Gender	Female	0.043	(0.031)
	Male	-0.17***	(0.025)
Indoor/outdoor	Outdoor	-0.052	(0.041)
	Indoor	0.0080	(0.024)
Age group	Age below 40	0.0022	(0.089)
	Age 40-54	-0.045**	(0.019)
	Age above 55	-0.12***	(0.045)
Income brackets	Poorest	-0.11***	(0.041)
	Median	-0.10***	(0.040)
	Richest	0.069*	(0.038)
Size of the comuna	Big	0.197[a]	(0.149)
	Small	-0.042*	(0.025)
Income brackets	Poorest	-0.11**	(0.043)
(small *comuna* subsample)	Median	-0.10**	(0.041)
	Richest	0.043	(0.055)
HH controls		yes	
Province FE		yes	
Month FE		yes	
Region-year FE		yes	
Industry-year FE		yes	

Notes: All models are estimated using two stage least square using wildfire smoke as the exogenous instrument. All coefficients in tables are coefficients on the average weekly $PM_{2.5}$ regressor. *Poorest* contains individuals earning less than minimum wage, *Median* includes individual making between minimum wage and twice the minimum wage and, *Richest* contains all individuals making more than twice minimum wage. We define small *comuna* as *comuna* with fewer than 100,000 inhabitants (based on 2002 population census). All other controls are suppressed for exposition purposes. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

[a]: the first-stage F-stat for this coefficient is below 10.

Table 7: Summary statistics for wildfire smoke for *comunas* above and below 100K inhabitants

	Mean	Std. dev.	Min	Max	Obs.
Comunas below 100K	0.112	4.933	0	294.833	140,729
Comunas above 100K	0.0002	0.006	0	0.262	124,395

Notes: The population of the different *comunas* comes from the census of 2002.

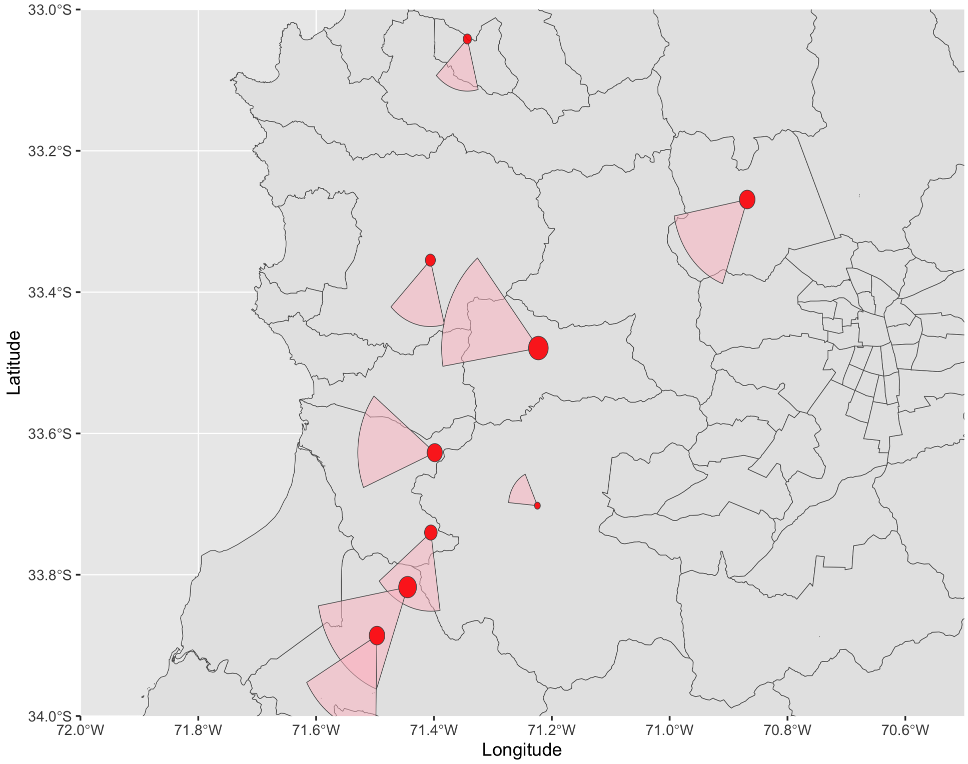
Table 8: Ellipse buffer

	(1)	(2)	(3)	(4)	(5)
	Elliptical buffer – real hours worked				
Share burned	-12.3***	-10.8***	-11.7***	-11.7***	-10.9***
	(3.39)	(2.84)	(3.77)	(4.04)	(2.95)
Observations	247,605	247,605	247,605	247,605	247,605
	Elliptical buffer – difference in hours worked				
	(1)	(2)	(3)	(4)	(5)
Share burned	11.1***	9.40***	9.23***	9.32***	9.27***
	(0.81)	(1.26)	(1.38)	(1.07)	(1.33)
Observations	247,605	247,605	247,605	247,605	247,605
	Round buffer – real hours worked				
	(1)	(2)	(3)	(4)	(5)
Share burned	-4.71***	-4.41***	-4.64***	-4.60***	-4.36***
	(1.10)	(0.90)	(1.20)	(1.27)	(0.96)
Observations	259,824	259,824	259,824	259,824	259,824
	Round buffer – difference in hours worked				
	(1)	(2)	(3)	(4)	(5)
Share burned	4.33***	3.95***	3.86***	3.83***	3.84***
	(0.17)	(0.31)	(0.36)	(0.29)	(0.37)
Observations	259,824	259,824	259,824	259,824	259,824
Weather controls	no	no	no	yes	yes
Household controls	no	no	no	no	yes
Province FE	yes	yes	yes	yes	yes
Year FE	yes	no	no	no	no
Month FE	no	yes	yes	yes	yes
Region-year FE	no	yes	yes	yes	yes
Industry-year FE	no	no	yes	yes	yes

Notes: The introduction of 2 digit industry classification causes the loss of 139,372 observations. All specification contain estimation weights for the probability that an individual is within the buffer affected by the wildfire. Standard errors in parentheses are clustered at the *comuna* level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

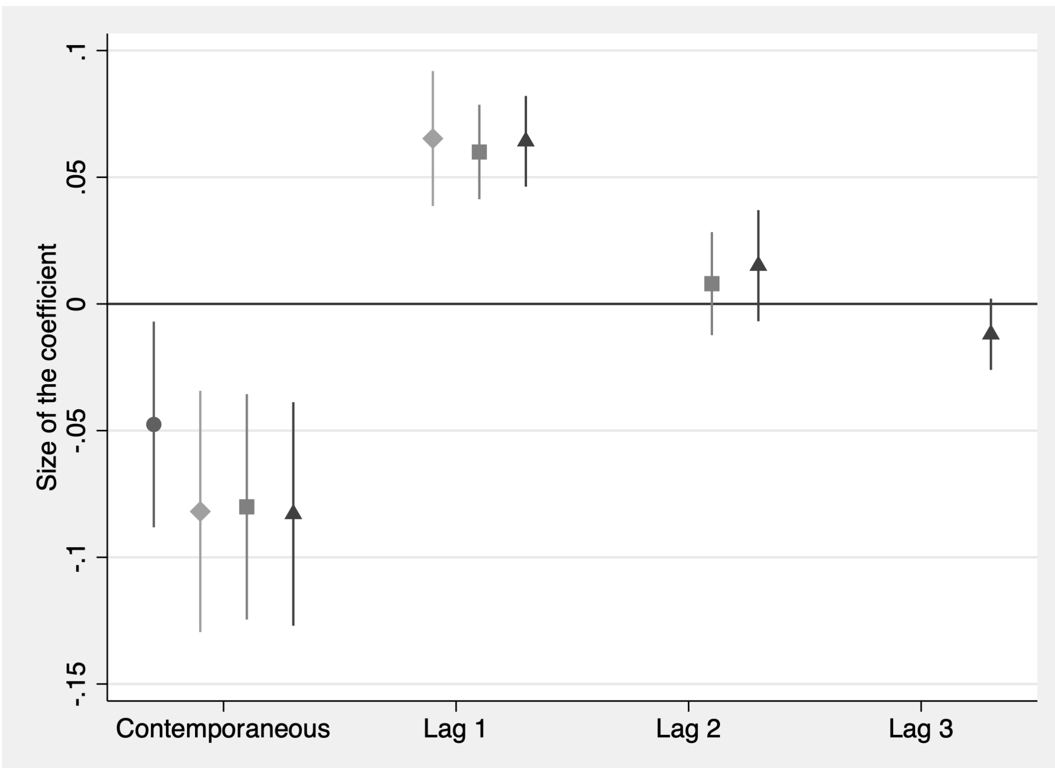
Figures

Figure 1: Smoke plume from wildfires



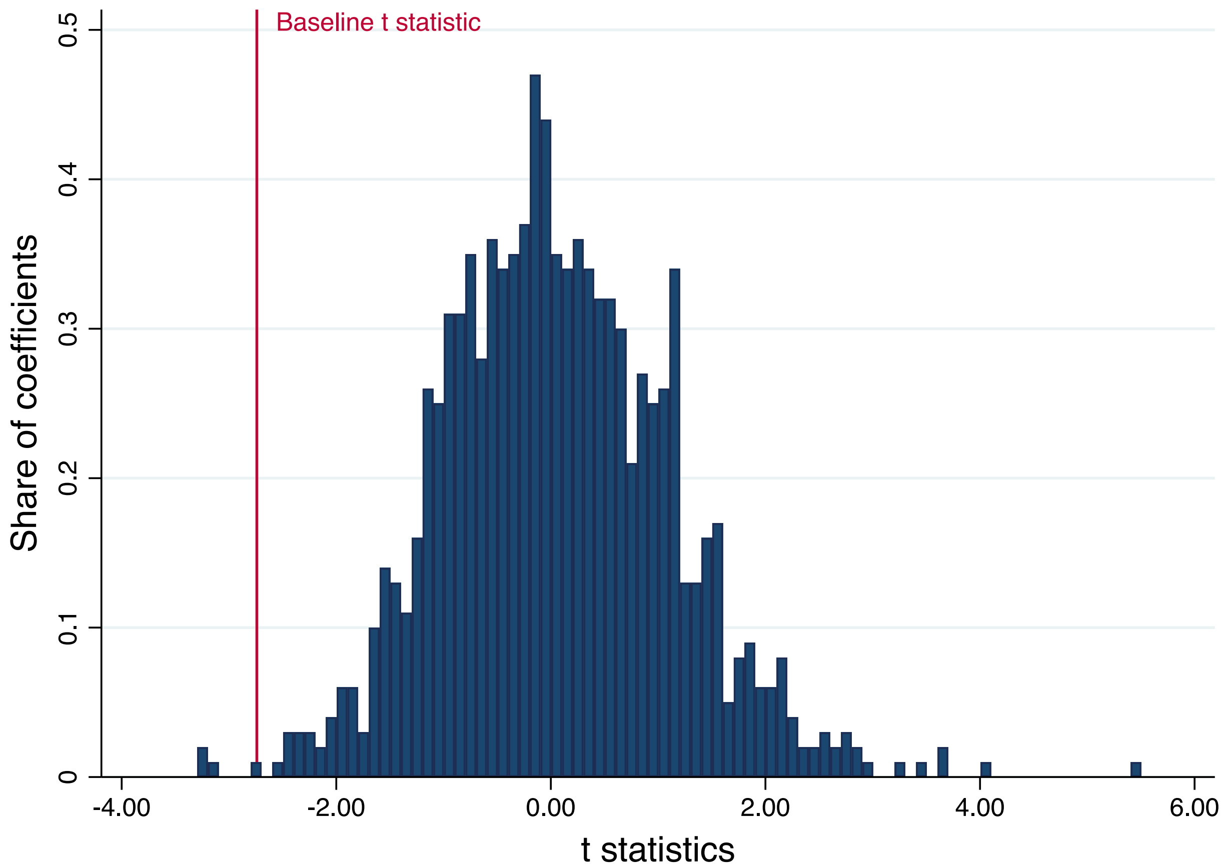
<u>Notes:</u> This figure shows all the wildfires (in red circles) recorded between 18 and 23 December 2016 and the corresponding computed smoke plumes (in pink rays).

Figure 2: Lag coefficients



Notes: The figure reports the coefficients on $PM_{2.5}$ and its lags in different specifications.

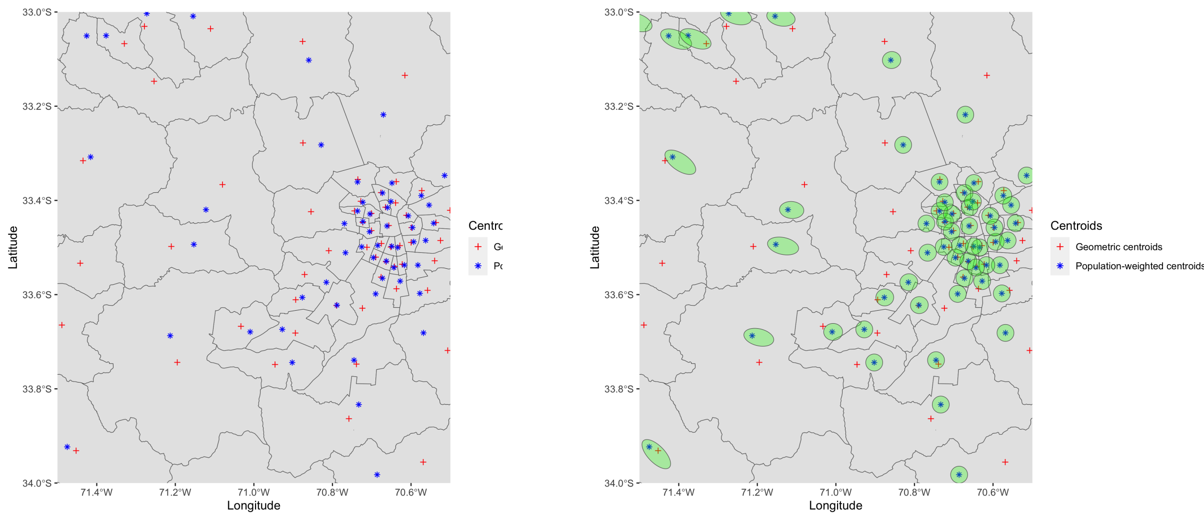
Figure 3: Placebo with randomization over the whole database



Note: The histogram depicts the distribution of the t statistics for the coefficient on the smoke plume for the 1000 placebo replications. In each replication we randomized the occurrences of wildfires over the whole sample. As one can see the largest mass of the histogram falls between -1.96 and 1.96, meaning that the coefficient is not statistically significant at the 5% level. The red line shows the t statistic obtained in our baseline regression (-2.74).

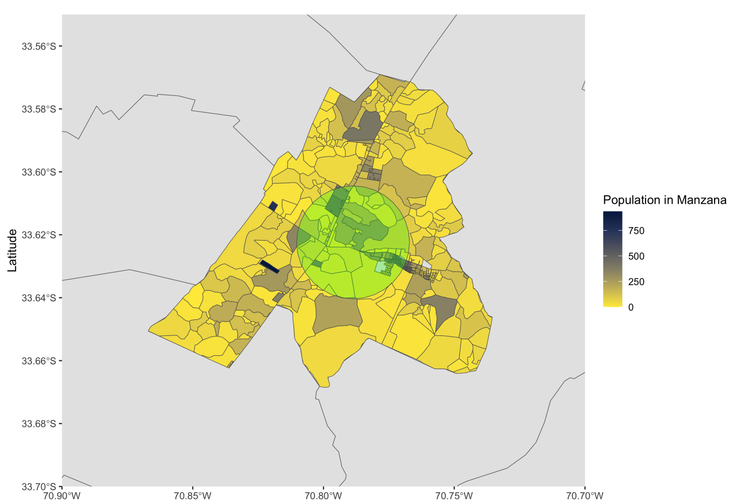
Figure 4: Population-weighted centroids with elliptical buffers

(a) Population-weighted centroids (b) Elliptical buffers



Notes: Geometric (red crosses), population weighted (blue stars) centroids and elliptical buffers of interest for burned areas (green).

Figure 5: Calculation of weights



Notes: Analytical weights are constructed as the share of population of a comuna living inside a buffer zone. The population inside the buffer is constructed started from the population in each manzana.