Wildfires, Smoky Days, and Labor Supply *

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Abstract

We study the impact of air pollution on labor supply in Chile. We use the exogenous incidence of wildfires between 2010 and 2018 to identify the causal impact of air pollution on labor supply. We complement the literature that focuses on health or workers' productivity and empirically estimate the economic costs of air pollution. We adopt a reduced form approach to estimate the economic impact of experiencing an additional smoky day on the number of hours worked, based on the random assignment of the day of visit for the National Labor Survey and the exogenous occurrence of wildfires. We find that a marginal increase of air pollution due to an extra smoky day leads to a 2.6 percent reduction in hours worked for the average Chilean worker. The effect is more substantial for male workers, mainly involved in outdoor tasks (such as agriculture) and poor households, where the negative effect of air pollution is up to four times higher. These results complement existing productivity results, suggesting that air pollution may have a more critical impact on production than previously thought.

Keywords: wildfires, labor supply, air pollution, Chile
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1 Introduction

Labor and human capital are two important engines for growth. In addition to studying the impact of an exogenous increase in air pollution on health outcomes (e.g., Chay & Greenstone, 2003), it is also important to understand how air pollution may affect the effective labor supply. This is economically important if we would like to quantify its comprehensive effect on the economy (Dechezleprêtre et al., 2019). A better understanding of the economic cost of air pollution will help us devise an optimal policy for regulating air pollution and its sources, and it will also help promote economic growth by improving labor productivity and investments. Existing evidence shows that air pollution may induce a negative effect on a person's cognitive ability (e.g., Ebenstein et al., 2016) and labor productivity (e.g., Graff Zivin & Neidell, 2012). However, the literature on how air pollution may affect working hours is relatively scant.

In this paper, we study the effect of air pollution on hours worked in Chile using administrative data. Chile houses the most polluted areas of the American continent. Air pollution in Chile is concentrated in the Santiago metropolitan area and southern cities. According to the World Health Organization (WHO) air quality database of 2018 (WHO, 2018), Chile is home to the most polluted city in America (Coyhaique) and to three of the remaining top 10 most polluted cities of the continent (Padre las Casas, Osorno, and Valdivia) (measured by $PM_{2.5}$, according to WHO, 2018). The air quality guidelines of the WHO establish that $PM_{2.5}$ should not have an annual mean higher than 10 $\mu g/m^3$, nor a 24-hour mean greater than 25 $\mu g/m^3$ (WHO, 2005). However, the annual means of $PM_{2.5}$ in the five most polluted Chilean cities range from almost three times to almost seven times the WHO's guidelines.

Studying the causal relationship of pollution on labor supply is challenging because pollution is endogenous to labor supply. On the one hand, pollution derives directly from economic activity, creating an important reverse causality problem. On the other hand, pollution gives rise to avoidance behaviors and simultaneity (such as an adverse effect on health). For instance, workers may choose to reduce their outdoor exposure if pollution levels are high; or in the long run, more productive and health-conscious workers may sort themselves to cleaner neighborhoods. We propose to use the incidence of wildfires in Chilean forests as an exogenous source of variation in the level of emissions to identify the impact of air pollution on labor supply causally.

In order to study the response of workers to pollution, we gather secondary data from the Supplementary Income Survey (ESI, *Eucuesta Suplementaria de Ingresos*), which is an additional module of the National Employment Survey from the Chilean Statistics Bureau. This additional module provides detailed information about a household's income and its sources. More importantly for our study, ESI asks about the effective number of hours worked by each worker over the week preceding the date of the interview and the number of hours due by contract. ESI also records the reason of any discrepancy between the effective number of hours provided and the number of hours contracted in a given week. We match these data to wildfires information from the National Forestry Corporation (CONAF), which is a private entity dependent from the Ministry of Agriculture. CONAF publishes statistics on wildfires, including the number of events, affected vegetation and hectares as well as the duration of each wildfire event. Using the origin of the fire and weather conditions on the date of the incident, we construct a proxy for smoke plumes downwind from their origin for each wildfire. We also gathered remote sensing data on particulate matters from the European Centre for Medium-Range Weather Forecasts (ECMWF).

The identification strategy used in this paper is based on two hypotheses: the exogeneity of wildfire occurrence and the random assignment of the week in which each household was interviewed. Given that the ESI data are geo-referenced, we can match the day of the interview to wildfire incidents and other measures (such as rainfall or temperature) to the area (i.e., *comuna*) where each household is located. It is then straightforward to study the causal link between pollution and the supply of labor across the whole of Chile by regressing wildfire exposure on the actual hours of work supplied in any given week. We control for weather data such as temperature and precipitations and other socioeconomic characteristics of the workers such as age and education level. We also control for province fixed effects, region-by-year fixed effects, and industry-by-year fixed effects to take unobserved trends into account. We study the short-term (or contemporaneous) effect and the medium-term effects of wildfires (up to three weeks after the fire).

In a reduced-form setting, we find that exposure to the average wildfire reduces weekly hours of work across all industries by about 2.6 percent for the average worker in Chile, which corresponds to roughly one hour per week. Combining this negative effect on hours worked with the negative effect on workers' productivity previously found in the literature, our results suggest that the effect on the effective labor supply is probably *stronger* than what the literature suggested so far. We run a battery of robustness tests on the definition and measure of fires (including using an alternative measure of wildfires coming from an alternative database, i.e. the MODIS Burned Area product), on different regions, and, eventually, we also run three separate placebo tests. Our results are robust to all these variations.

We estimate the effect of air pollution on labor supply. First, we construct a proxy of smoke plumes from wildfires to capture the exogeneous variation in air pollution generated by wildfires. Using these smoke plumes as an instrument, we find that an increase in air pollution levels has an economically significant effect on labor supply. In our preferred specification, an exogenous increase in the average $PM_{2.5}$ level in a week leads to a reduction in the average Chilean worker labor supply by roughly one hour. In addition to the intensive margin (productivity), already studied by a large literature (see for instance Hoggsett et al., 1997; Deschenes and Greenstone, 2007 and 2011; Almond et al., 2009; Schlenker and Roberts, 2009; Graff Zivin and Neidell, 2012; Chen et al., 2013; Chang et al., 2016; Neidell, 2017; Archsmith et al., 2018; Bishop et al., 2018), we show that air pollution also has a considerable effect on the extensive margin (supply) of the labor market.

Our data allow us to differentiate the impact of an increase in air pollution across industries, occupations and a variety of socioeconomic characteristics. We find that the effect varies in a sizeable way across sub-samples. The negative effect of air pollution on labor supply is substantially 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 relative to the general population. The fact that the most affected workers are poorer and older, implies that air pollution mitigating policies can help reduce income inequalities and the burden on the healthcare sector (see Banzhaf et al., 2019).

The contribution of this paper is twofold. First and foremost, we contribute to the literature on the impact of air pollution on workers' health and labor supply (see for instance, Graff Zivin & Neidell, 2012, 2018; Archsmith et al., 2018; Chang et al., 2019; He et al., 2019). In this respect, our study presents two advantages. Using a purely exogenous variation in pollution levels allows us to capture a causal effect. Instead of relying on the fluctuations of pollution in a given period, we focus on a large and exogenous shock to the level of pollution due to wildfire incidents that occur upwind of the study areas. Our data structure allows us to observe hours worked during the days in which the wildfire is active. While most of the literature focuses on specific industries, we focus on the whole economy, and we can get an average impact and impact by industry.

To the best of our knowledge, Borgschulte et al. (2022) is the only work that studies the impact of air pollution and wildfire smoke on the overall economy. They use high-resolution satellite remote sensing data to study the effect of wildfire smoke on the US labor market. They find substantial reductions in annual income in regions of the US that are impacted by wildfire smoke. Our project improves their work on two fronts. By using yearly data, Borgschulte et al. (2022) may underestimate the real impact of the variation in pollution resulting from a wildfire. If the fire happens early in the year, people can adjust their behavior to compensate for the negative shock. We observe the number of hours of work missed in a given week, which allows for more precise identification. Thanks to this precision, we can focus on the short- and medium-term response to the pollution due to wildfires. In addition to reduced-form results, we calculate the exogenous increase of pollution (based on the type of wood being burned) to compute a dose-response on how pollution affects the labor supply. We will use this measure to instrument observed pollution and capture the variation due to the wildfire.

Second, we contribute to the literature on the economic impact of wildfires. Wildfires in Chile and around the world have been increasing in frequency and severity (Bowman et al., 2017). This increase is in line with recent findings that global warming has led to an increase in fuel aridity worldwide. Fuel aridity largely increases the likelihood of wildfires. In studying the impact on western US forests, Abatzoglou & Williams (2016) estimated that climate change could explain half of the forest fire area in the past three decades. Therefore, it is crucial to understand the consequences of wildfires to anticipate adverse outcomes, plan avoidance, and provide accurate estimates of the costs of wildfire smoke on affected populations. Both contributions help guide government policies related to air protection and natural disaster prevention.

The rest of our paper is organized as follows. Section 2 gives a background of wildfires and climate change. Section 3 illustrates a conceptual framework. Section 4 outlines the data sources and descriptive statistics. Section 5 discusses our empirical strategies and results for our reduced-form and instrumental variables models. Section 6 calculates the economic cost of air pollution using the framework in Section 3 estimates from the literature as well as our estimates from Section 5. Section 7 concludes.

2 Background: wildfires and climate change

In the last decade, higher temperatures, increased lightning prevalence, variable precipitation, and general forest dryness during summer periods have caused an increase in the intensity and size of wildfire episodes all around the globe (Úbeda & Sarricolea, 2016; Sankey, 2018). In Chile, the year 2017 was a notable fire season, when 587,000 hectares of forest – roughly the size of Delaware – were burned (CONAF, 2017). This fire not only caused severe air pollution episodes (which were visible in satellite images) but also burnt an entire town, left human casualties, and displaced families, cattle and wildlife.

Wildfires have been forecasted to increase due to climate change. Bowman et al. (2017) use data from MODIS to study extreme wildfire events in the United States and Australia, and forecasts that the incidence rate of extreme wildfire events, which have large socioeconomic impacts, will increase by 20-50% in the coming years. Abatzoglou & Williams (2016) studied wildfire incidence in California, and also predict a higher likelihood of wildfires over the next decades as a direct result of global warming. Flannigan et al. (2013) found that climate change has increased the severity of wildfires and that their season may be prolonged and potentially more severe. Sankey (2018) finds that since the 1970s, the area burned annually by wildfires in Canada has more than doubled, and Sandink (2011) estimates that by 2100 the annual burned area will again have doubled in size.

Some more recent studies have begun to quantify the negative impacts resulting from increased incidents of wildfires (e.g. Pakhtigian, 2020; Borgschulte et al., 2022). Pakhtigian (2020) uses wildfires occurrences in Indonesia in order to study the impact of air pollution on health and behavior, finding that air pollution decreases lung's capacity and pushes people toward the adoption of cleaner fuels, such as LPG.[1] Mead et al. (2018) showed that more than 60% of residents in Malaysia have been exposed to a harmful level of air quality following episodes of wildfires in Indonesia and other neighboring countries. Focusing on the United States, Jones (2017) measured the willingness to avoid wildfires using the life satisfaction approach and found that on average, the representative household is willing to pay \$ 373 to avoid one day of wildfire. Kochi et al. (2010) emphasized the importance of taking into account the disutility of wildfire smoke, in addition to harmful impacts of pollutants as by-products. Richardson et al. (2012) found that, if we just account for the cost of illnesses, the social cost per exposed person per day goes from \$ 9.5 to \$ 84.42 after considering the disutility and the cost of defensive actions. The costs associated to wildfires highlighted in this paragraph are related to the smoke they generate. These damages are particularly difficult to quantify and the object of this project is the first step towards understanding the economic damages of wildfires. Nevertheless, one should not forget that wildfire cause many other costs, related to fire suppression, building damages, and loss of life.

Our empirical work focuses in Chile. Because of its geography, Chile has marked weather and land use heterogeneity throughout its territory. According to CONAF (2020), in 2017 23.3% of the country's surface was forestland, which is equivalent to 17.66 million hectares. Of this area, 81.5% are native forests, with the remaining being plantations (Úbeda & Sarricolea, 2016). Plantations (or evergreen forests) primarily consist of pine and eucalyptus (FAO, 2016), both highly flammable non-native species (Peña Fernández & Valenzuela-Palma, 2008). As in many other parts of the world, the fire regime, i.e. pattern, frequency and intensity of wildfires, has increased in the country (Úbeda & Sarricolea, 2016). Peña Fernández & Valenzuela-Palma (2008) found that the increase in wildfires in Chile is closely related to the increase of plantations of these two species.

Sarricolea et al. (2020) find that wildfires in Chile mainly affect the central and central-

[1] LPG stands for Liquefied Petroleum Gas.

south area of the country, from the Valparaíso to Araucanía regions. This area is the most populated of the country: it concentrates 78.9% of the country population (18.73 million people, Instituto Nacional de Estadísticas, 2018). 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. While the authors find that there are wildfire hotspots, they also show that wildfires have a high spatio-temporal variability.

Air pollution in Chile is concentrated in Santiago metropolitan area and in southern cities. According to WHO's air quality database of 2018, Chile is home to the most polluted city in America, Coyhaique, and to three more cities on the top 10 most polluted cities of the continent (Padre las Casas, Osorno and Valdivia) (measured by $PM_{2.5}$, WHO, 2018). The annual means of $PM_{2.5}$ in the five most polluted Chilean cities range from almost three times to almost seven times the WHO's guidelines. Air pollution caused by wildfires not only affects annual concentration means, but it is also a contributor to surpassing the WHO guideline for 24-hour mean $PM_{2.5}$ concentration (25 $\mu g/m^3$).

3 Conceptual framework

To help interpret the effect of air pollution on labor supply, we have adopted the conceptual framework in Dechezleprêtre et al. (2019) to illustrate how our results can be used to predict the effect of air pollution on economic output. Consider a simple economy where there exists a representative firm producing output, and the representative consumer consumes the final output to maximize her utility.

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 is the effective labor input, and P is the level of pollution. 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) recognises the fact that the pollution level can potentially affect the labor market in three different ways: (1) the pollution level can affect the number of productive workers N; (2) the pollution level can affect labor productivity φ; and that (3) the pollution level can affect the number of hours worked h. Using (2), we can decompose the total impact of pollution on economic output as:

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

where ψ and θ are 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 of a marginal increase in air pollution.

Empirical literature studying the effect of air pollution on health outcomes help inform the magnitude of the first channel (i.e., $\frac{\partial \log N}{\partial P}$). There is a longstanding literature on medical science that established how air pollution can affect lung functions and other health outcomes (e.g., Dockery et al., 1993; Pope III et al., 2002). In Economics, several papers have found a significantly negative impact of air pollution on infant mortality (e.g., Chay & Greenstone, 2003; Currie & Neidell, 2005; Jayachandran, 2009; Arceo et al., 2016), suggesting channels in which the pollution level can negatively affect N. Several related studies have also shown how pollution affects productive labor by showing the effect on migration (Chen et al., 2022; Khanna et al., 2021).

There is a growing literature in both physical science and economics showing how particulate matter can affect labor productivity (i.e., $\frac{\partial \log \varphi}{\partial P}$). Evidence from physical science suggests that $PM_{2.5}$ can affect heart and brain function, potentially affecting labor productivity (Ranft et al., 2009; Calderón-Garcidueñas et al., 2014; Genc et al., 2012). Economists study the causal effect of air pollution on labor productivity in various settings: pear pickers in California (Graff Zivin & Neidell, 2012); farmers in Ghana (Aragón & Rud, 2016); umpires in MLB (Archsmith et al., 2018); workers in call centers in China (Chang et al., 2019); workers in manufacturing facilities in India (Adhvaryu et al., 2019) and China (He et al., 2019); members of parliament in Canada (Heyes et al., 2019).

Our empirical results will contribute to the understanding on how air pollution affects the working hours h. Related studies have shown a relationship between school absenteeism and PM_{10} concentration (Ransom & Pope III, 1992; Currie et al., 2009). Other studies also looked into absenteeism from work, finding that often it is related to the presence of dependents at home, creating a nexus between school and work absenteeism (Holub et al., 2016; Hanna & Oliva, 2015; Hansen & Selte, 2000; Aragón et al., 2017). By combining our results and the existing literature on how air pollution affects other margins in the labor market, we are able to derive the economic cost of air pollution using equation (3).

4 Data

In this section we describe the data used in the paper. In order to run our analysis, we collect data from a variety of sources. Data on labor supply come from the National Statistics Bureau, data on air pollution come from the European Centre for Medium-Range Weather Forecasts (ECMWF), data on wildfires come from the National Forest Corporation in Chile, and finally, we collected weather data directly from the network of Chilean weather stations, these data are assembled by the Center for Climate and Resilience Research in Chile. In the appendix, we also describe the data source on burned area from the MODIS Burned Area database, which we use to construct our alternate measure of wildfires.

4.1 Labor data

Labor data comes from the Chilean Income Supplementary Survey (*Encuesta Suplementaria de Ingresos*, ESI), collected by the National Statistics Bureau (INE). The objective of the survey is to characterize incomes from labor for people classified as occupied in the National Labor Survey (ENE), and to characterize other sources of households' income. ENE is collected four times each year, and ESI is a supplementary survey collected in the final data collection process of ENE (this means, in the fourth yearly round of ENE individuals answer both ENE and ESI). ESI's sample size is determined using the average unemployment rates of the 5 previous mobile trimesters, measure estimated from previous ENE surveys. ESI's theoretical sample size is roughly 11,900 households per year (INE, 2018). Within each household, the survey considers all individuals 15 years old and above. The survey has been running on a yearly basis since 2001.

ESI is collected every year in October, November and December and it is representative at the regional level.[2] The survey includes all the regions of the country, including both urban and rural areas.The methodological documents indicate that for the data collection process there are weekly sampling targets, in order to ensure the sampling period is evenly distributed throughout the three months of fieldwork.[3] This methodological aspect of the survey is key to our identification strategy, and supports the randomness of the day each household was interviewed.

We use nine cross sections of the survey, from 2010 to 2018. ESI includes labor information from the week prior to the day of the interview (e.g. *"last week, that is from Monday to Sunday, did you work for at least an hour?"*), detailed income information, and socio-

[2]Chile is composed by 15 regions, a 16th region was added in 2006, but we base the analysis of this paper on the original 15 regions.

[3]Sampling is randomized across months per the instruction of the survey administrator. After a careful analysis we were not able to detect any particular sampling pattern that could have biased our results.

demographic individual and household level data. Thanks to information provided by INE, we are able to identify the exact day during which the interview took place, and therefore the week to which the answers are referring.

Our variable of interest is the number of hours worked. ESI includes three questions regarding time worked: number of hours per week usually worked, number of hours per week effectively worked last week, and number of weekly work hours by contract. In instances in which the number of hours usually worked differs from the time effectively worked, the interviewees are also asked for the reason why this happened. Options to this question include climatic reasons or natural catastrophes, and illnesses, among others.

Labor data in ESI includes the aforementioned amount of hours worked per week, the type of job the interviewee performs (managerial, executive, manual, etc.), the industry in which she works, and whether she worked outdoors or indoors the week prior to the interview. It also provides information on whether the person worked or not on the week prior to the interview, and reasons for job absence.

Panel A of Table 1 reports descriptive statistics for the dependent variables used in our analysis, i.e. the effective (real) number of hours worked last week, the usual number and the difference between the two. On average respondents worked roughly three hours less than usually, 38.54 hours instead of 41.62. Interestingly these numbers do not change for workers performing their activity outdoors or indoors. Panel B shows descriptive statistics for our controls. The average respondent is the survey lives in a household composed of roughly 3.7 members, is almost 44 years old, has an average of 4 years of education and lives in a comuna with an area of 2.7 thousands square kilometres. Roughly half of the respondents are the main breadwinner in the household.

4.2 Wildfire data

We create a measure of wildfire exposure using detailed data on each wildfire (collected from CONAF), as well as wind speed and direction data. We illustrate on our steps to create the smoke plume from these primary data sources in Figure 9. We first draw the areas affected by fire using information on fire and the area that it is burned (shown in the orange circle). Then, using data on wind speed during the occurrence of fire, we construct a 60 degree plume from the origin of the fire towards the direction of the wind. The distance of travel is correlated with the size of the fire and the maximum wind speed observed on the day of the wildfire occurrence.

The Chilean census subdivides each comuna in districts and each district in neighborhoods (i.e., *manzanas*). For confidentiality reasons, the survey only provides the comuna of residence and of work for each respondent, but not the district and neighborhood. We first calculate the percentage of the area in each *manzana* covered by the fire and the smoke for each day of the week. As labor hours are measured at the comuna level, we compute a population-weighted measure of wildfire fire and smoke share during the week for each comuna (using population census data from 2017) and use this as our measure for wildfire exposure. We test this distance measure and present robustness checks to our instrument.

There are two reasons why we believe this wildfire exposure measure will help with the identification in an instrumental variable setting. First, because the remote sensing data are collected from the sky, we cannot distinguish wildfires from man-made fires such as straw burning, which may itself be endogenous (Lai et al., 2022). Second, in addition of burning forest cover, wildfire smoke has been shown to have negative effect on labor market and human behaviors, and it is important to capture the effect of wildfire smoke on air pollution in our sample (Borgschulte et al., 2022; Burke et al., 2021).

4.3 Pollution and weather data

We gather satellite-based pollution and weather information in each comuna using reanalysis data from the Copernicus Climate Change Service from the European Centre for Medium-Range Weather Forecasts (ECMWF). For pollution data, we use the CAMS global reanalysis (EAC4) dataset. The EAC4 dataset contains pollution data (PM_1, $PM_{2.5}$, PM_{10}, and other pollutants such as sulfur dioxide and ozone) on each $0.75° \times 0.75°$ grid globally every 3 hours. Using the population-weighted centroid for each comuna, we construct an average pollution concentration for each pollutant in each comuna and week in our sample.

Other than fire, smoke from wildfires will also increase pollution level in a region. Unfortunately we do not have access to smoke plume data in Chile. Instead, we combine the CONAF wildfire data (with coordinates and duration for each fire) and wind speed and direction data from ECMWF. We measure wind speed and direction (at the 10m altitude) using the ERA5-Land hourly data from 1950 to present with a horizontal resolution of $0.1° \times 0.1°$ at hourly intervals (Muñoz Sabater, 2019). We construct the smoke plume for each fire by drawing a donut around the burned area and proxy the distance and direction the smoke travelled by using the data on wind speed and direction. We measure the wildfire and smoke plume exposure (separately) by calculating the share of the surface area of affected manzanas, before aggregating this to the comuna level using the population in each manzana as weights. We test the robustness of our smoke plume proxy by changing how we construct the donut and distance travelled.

Our weather data are gathered from the Center for Climate and Resilience Research, which collects daily station-level data from the Chilean Meteorological and Water Directorates from 1930 to 2020. It contains around 800 stations for precipitations and 300 stations for (average and extreme) temperature across Chile. Using the longitude and latitude supplied, we are able to map out the location of all these weather stations. However, these weather stations may not be located near population centers, and may not provide data for every day in our sample. We interpolate the available data in order to obtain a standard measure of temperature and precipitations at the comuna level.

We employ the standard radial basis function interpolation method to interpolate weather data for each comuna.[4] Similar to the handling of wildfire data, we approximate the location of households in the comuna using weighted population centroids. For each day in our sample (from September to December form 2010 to 2018), we interpolate temperature and precipitation values for the weighted centroid for each of the 345 Chilean comunas. The interpolation is based on all the available data from weather stations for a particular day. Figure 8 shows the result of this interpolation for average temperature on the 21st of December 2011 using the standard method.

We then aggregate our daily projections of temperature and precipitations into weekly measures by averaging the temperature measures and summing precipitations across each week. Table (2) reports descriptive statistics for precipitations and temperature during the weeks concerned by the interview (i.e. the week before the day of the interview) as well as the pollution measures. These information concern only the months of October, November, and December. These months are characterized by low level of precipitations, less than one millimetre on average, and average temperatures around 15 degrees Celsius.

5 Empirical strategy

In order to capture the causal effect of air pollution on labor supply we proceed in two steps. First, we implement a reduced form estimation in which we use wildfires to identify variations in the pollution level. Second, we use an instrumental variable approach in which we use wildfires alerts in order to capture exogenous variation in the average pollution level.

[4] In the baseline specifications, we have interpolated our weather data using a linear radial basis function. We have tried alternative thin plate spline and the interpolated values are similar, albeit with more extreme values that we had to rule out. Other than radial basis function methods, we have also employed ordinary Kriging methods to interpolate weather data, again obtaining very similar results.

5.1 Reduced form analysis

Wildfires have the advantage of providing us with readily available exogenous variation in pollution levels. For this reason, our analysis is based on a simple 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* denotes the number of hours worked over the week preceding the interview. $Wildfires_{it}$ is a weighted sum of the share of area (in percentage) in comuna i covered in wildfire smoke over the week t (the week preceding the interview). X is a vector of controls, containing average precipitations and temperature (for the week considered), the area of the comuna, the size of the household, whether the person interviewed is the main breadwinner of the household, whether she is married, her age, gender and years of education. Finally, 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, finally, different industry specific trends that could affect labor supply. ε is the error term, and we cluster the error term at the comuna level.

We report our reduced-form results in Table 3. In model (1), we only control for province and year fixed effects in addition to the wildfire smoke measure to condition for unobserved factors in the province and yearly trend. We have obtained a negative coefficient of -0.011 which is statistically significant. This coefficient implies that, if wildfire smoke is present in the entire comuna for one day in the week, the worker will work 1.1 hours less, translating to about 2.8 percent reduction in their working hours. In model (2) we control for region by year fixed effects and month fixed effects as wildfire may be more frequent in some months. Working hours in some industries may change over time so we control for a set of industry by year fixed effects in model (3). The coefficient on wildfire smoke is smaller in magnitude but it remains statistically significant. In models (4) and (5), we control for the precipitation and temperature, as well the socioeconomic status of the worker that we observe in our data, and our coefficient remains unchanged. Our preferred specification (5) implies that one day of wildfire smoke in the comuna will result in a reduction of 0.5 working hours or a 1.3 percent reduction.

To check the random assignment of wildfire smoke in our sample, we have re-run our model using contracted hours as the dependent variable. If the wildfire incidents are indeed randomly assigned, we should see that the wildfire smoke should not be correlated with the contracted hours of work. We report our findings in Table 4 and use the same set of specifications as in the previous analysis. Models (1) and (2) show a statistically negative signs on wildfire smoke on contracted hours, while models (3) to (5) did not display a significant relationship between wildfire smoke and contracted hours after we condition on industry by year fixed effects. This suggests that there is some evidence that workers who are more likely to experience wildfire smoke work in industries with lower contracted hours. After conditioning on industry-specific trends, our results suggest that wildfire smoke is randomly assigned to workers, validating our empirical design.

We repeat our analysis by using the difference between the actual working hours and the contracted working hours as the dependent variable. In other words, we can interpret this dependent variable as the number of 'sick days' or absenteeism that the workers did not work on that particular week. Results for this regression are reported in Table 5. We find a qualitatively similar results as in Table 3: in weeks where there are wildfire smoke in the comuna that they live in, workers have called in for more absences. The magnitude of the coefficient is highly stable across specifications where we include industry by year fixed effects or not.

Before moving on to the instrument variable analysis, we can also test the robustness of our reduced form results by considering some subsample analysis. One interesting feature in our labor market survey is that workers report in the survey whether they spent time outdoor in the week. We have re-run the reduced-form analysis in Table 6 by splitting our sample based on the nature of their work that week. Column (1) reports our preferred specification (Table 3, model (5)) by using only workers who worked outdoor, while column (2) focuses on the workers who worked completely indoor in that week. Table 6 suggests that our reduced-form results are completely driven by workers who work outdoor while wildfire smoke does not display a statistically significant relationship with working hours for indoor workers.[5]

5.2 Instrumental variable analysis

After establishing that wildfire exposures have a negative impact on hours worked by Chilean workers, we proceed to quantify the effect of air pollution on their working hours using wildfre smoke as an instrument. Without using any instrumental variables, hours worked can potentially affect air pollution through an increase of production, leading to reverse causality and a positive correlation between the two. In order for us to isolate the causal effect of air pollution on the labor market, we use wildfire exposure as the instrument using

[5]Given the sensitivity of the nature of work in determining whether workers work outdoor or not, we also run a version of the analysis using the difference in actual and contracted hours (i.e., as in Table 5. Wildfire smoke is found to increase absenteeism for both outdoor and indoor workers, while the coefficient on outdoor workers is larger in magnitude. The results in this regression are qualitatively similar to the ones in Table 6.

standard two stage least squares. Specifically, our estimation equations are as follows:

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

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

where the definitions of the fixed effects and controls follow the ones in Section 5.1.

We use satellite-based pollution data in order to assign the pollution level in each comuna on a given week from ECMWF. We gather pollution level every 6 hours in each comuna (using the population-weighted centroid as the coordinate) and compute maximum and average levels of each air pollutant every week. We are particularly interested in measuring the impact of particulate matters (with diameters less than 1, 2.5, and 10 μm) on labor supply. Our benchmark results are based on average $PM_{2.5}$ levels in line with the literature measuring the effect of air pollution on labor productivity but we are also showing results for maximum (hourly) $PM_{2.5}$ level for that particular week in the appendix. Our regression models for other pollutants yield qualitatively similar results compared to the one for average $PM_{2.5}$ levels.

5.2.1 Results

We first show the endogeneity of air pollution on labor supply by estimating equation (5b) without using any instrument variables. We report our results in Table 7. Across all specifications, presented in the same order as the ones in Section 5.1, air pollution is shown to have a positive and statistically significant correlation with hours worked. The unintuitive positive correlation can be explained by reverse causality: working hours is correlated with economic output which increases the level of air pollution. This justifies the need for an instrument in order to estimate the causal impact of air pollution on labor supply.

Therefore, for the rest of the analysis in this section, we instrument the air pollution measure using the wildfire smoke measure we presented in the reduced form analysis. We present the first and second stage results in Table 8.[6] Our first stage results are shown in the top panel. Our measure of wildfire exposure has a strong positive effect on the average level of $PM_{2.5}$ in a comuna and it remains strong and stable across all five specifications. The effect remains strong after controlling for province fixed effects as well as region and industry specific time trends and the F-statistic indicates a very strong first stage. Our first stage regression implies that a one-day wildfire smoke increases the *weekly* average $PM_{2.5}$ level in

[6] In our baseline model we have presented the effect of average $PM_{2.5}$ level on labor supply. We have obtained a similar result with PM_1 and PM_{10}, or using the maximum level of air pollution in a day instead of its average level. We report them in Appendix A.

the comuna by 7-8 μg/m^3, which is a significant amount considering the 24-hour mean of guideline of 15 μg/m^3 recommended by the World Health Organization.

After establishing a strong prediction of wildfire smoke on $PM_{2.5}$ level, the bottom panel of Table 8 presents the second-stage result. Across all specifications, compared to the OLS-equivalent results in Table 7, the effect of air pollution on labor supply is now *negative*, indicating the air pollution reduces labor supply. In our preferred specification (model 5), a one standard deviation increase in average $PM_{2.5}$ level in a week (i.e., 15.6 μg/m^3) translates to about 1 hour (or a 2.6 percent) reduction in hours worked, which is economically significant. Combining the results in the literature on labor productivity, air pollution affects the labor market through both the extensive margin (labor supply) as well as the intensive margin (labor productivity).

In the appendix, we estimate our baseline model using five other different pollution measures: average PM_1, PM_{10}, as well as maximum levels of PM_1, $PM_{2.5}$, and PM_{10} in a given week in Table A.1. We find that all pollutants reduce the hours worked. We also repeat the reduced-form analysis on contracted hours and the difference between actual and contracted hours in an instrumental variable setting in Tables A.2 and A.3. The results are similar to the ones we find in the reduced-form analysis.

By industry

Next, we study whether the effect is concentrated on certain type of workers by dividing our sample according to their primary industry that they work on: agriculture, manufacturing (and constructions, mining and utilities sector) and other services. We report our findings in 9. Surprisingly, the negative effect of air pollution on agricultural and service sectors is now three to four times higher than our benchmark, suggesting that the effect of air pollution on labor supply is focused on primary occupations and studies that concentrate on a particular set of occupations or industries may provide a misleading figure for an economy-wide effect.[7]

By income groups

The other important source of heterogeneity is the income group of. This has important implications on environmental justice literature on whether air pollution (policies) may exacerbate income inequality. Table 10 report our results for three different income groups, defined by their income relative to the national income. We find that the effect of air pol-

[7]We find that the air pollution leads to an increase in working hours for manufacturing, construction and utilities sector, which is counter-intuitive. One potential reason is that these industries may be correlated with wildfire activities potentially invalidating our instrument. We are currently investigating further.

lution is concentrated on the poorest (workers with less than national income) as well as the poor workers (workers with income between one and two national income levels). Our results suggest that workers in richer households may have access to resources or they are more efficient in mitigating the negative effect of wildfires and air pollution. Our results also imply that air pollution mitigating policies will benefit poor households more than rich households.

Other sources of heterogeneity

We can make sure of our extensive set of observables to study the heterogeneous impact of air pollution on hours worked. We have done three sets of regressions by splitting our sample according to (1) gender of the worker, (2) whether the worker worked outdoor in the week of the survey, and (3) the age of the worker.

Table 11 reports the coefficient on average $PM_{2.5}$ for these three sets of regressions and, similar to our earlier results on industries, occupations and income, we find there exists a significant difference across different types of workers. We find that male workers suffer more from the air pollution exposure which ultimately affects their working hours. For female workers, on the other hand, air pollution does not appear to affect their labor supply decision. Similar to our reduced-form results in Table 6, the negative effect of air pollution is concentrated on workers who work outdoor as we are unable to find a significant effect of air pollution on indoor workers. This can potentially be explained by the exposure of air pollution during work rather than home activities.

Last but not least, we are interested to see if the effect of air pollution is stronger for older workers, and we find some evidence of this. For workers aged 55 or above, we find that air pollution exposure reduces twice as much labor supply relative to younger workers. This is potentially important as aged workers are likely to need hospitalization and experience other complications, leading to a proportionally higher burden on the healthcare sector.

5.2.2 Robustness

Regions

Not all regions of Chile are affected by wildfires, some of them, because of their specific vegetation never experience wildfires. In Table A.4 we present the baseline estimation in the first column, and then we exclude more and more of the 15 regions composing Chile. In the second second column we start by eliminating the three northernmost regions: Arica and Parinacota, Tarapacá, and Antofagasta. In the third column we eliminate an additional 5 regions: Atacama, Coquimbo, Los Lagos, Aysén of General Carlos Ibáñez del Campo, Magallanes and Chilean Antartica. Finally in the fourth column we eliminate an additional three regions: Bío Bío, La Araucanía and, Los Ríos. Our results are robust to these exclusions.

Placebo

Finally, we run a placebo test to verify that the relationships obtained above are not spurious. We shuffle the shared of a buffer burned over the entire sample and replace this shuffled measure in the baseline specification, randomly either (i) across the entire sample, (ii) across sample within region but across different weeks; or (iii) across sample within the same year but across different regions. We repeat the exercise 1000 times and report in columns (1), (2) and (3) of Table 12 the share of replications that produce statistically significant estimates at the 1 percent, 5 percent and 10 percent levels, respectively. In other words, we reassign the share of a buffer burned to either a random observation in our sample or more restrictively to another observation in the same region or same year.

We expect this exercise to produce mostly insignificant estimates on the shuffled variable, while leaving the significance of the estimates on other variables largely unchanged. This is what we observe. Across the three different shuffling methods, i.e. over the whole sample, within each region and, within each year, the results are largely statistically insignificant, in less than 10 percent of the replications we observe statistically significant results at the 5 percent level. Unsurprisingly, given the results of Table A.4, when we reshuffle the variable within region the share of statistically significant results is higher. This is due to the fact that most wildfires are concentrated within a few regions.

6 Alternative wildfires measure

6.1 Burned area data

We also generate wildfires data using the MODIS Burned Area product, which tells us for each 500 metres raster cell whether it burned or not in a given day. Figure 1 shows an example of the data. The red dots represent burned raster cells, while the marked circles help us identify the burned cells. After collecting all 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 computed by taking the geometric centroid of each manzana (neighborhood) as defined by the census and assign to it the share of the comuna's population living in the manzana as a weight. Each centroid is identified by two components, longitude and latitude. We compute a weighted average across the latitutes of each manzana and the same for the longitudes. Figure 2 shows the difference between geometric centroids (red crosses) and population weighted centroids (blue stars). As one can see, the bigger is the surface of a comuna the more likely it is that we observe a difference between the geometric and the population weighted centroids.[8]

The buffer area around each population weighted centroid used in the baseline is a circle of radius 2 kilometres.[9] Once the buffer is defined we compute the share of its surface that is burned by looking at the raster cells. It is worth mentioning that, since the cells are squared and the buffer is a circle, if all the cells are burned, the shared of the buffer burned could exceed 100%.

Table (13) shows descriptive statistics for the share of area burned in a buffer with a 2 kilometres radius (our baseline) and with a 3 kilometres radius (used in some other specifications). On average, if a buffer is affected by a wildfire, roughly 22% of it is burned; while if we increase the size of the buffer to 3 kilometres, only the 12.7% is on average burned. Yet, independently of the size of the buffer, we have cases in which the whole area has been burned.

The way of capturing wildfires used in this paper is restrictive: we capture a wildfire only if it happens around the population weighted centroid of a comuna. The alternative could be to just look at the burned share of the surface of the whole comuna. The problem with this approach is related to the size of the comunas and the large parts of the country that are completely uninhabited. Comunas can cover up to 49 thousand square kilometres of land. If we simply looked at the share of surface burned, we could easily capture wildfires that did not impact any human being. For this reason, we prefer to use a restrictive definition of wildfires.

6.2 Methodology

Similar to the main analysis, we can run 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* denotes the number of hours worked over the week preceding the interview. We focus on 2 kilometres buffers around the population weighted centroids of each comuna. The variable *BufferShare* denotes the share of burned area within these buffers in the event of a wildfire. X is a vector of controls, containing average precipitations and temperature (for the week considered), the area of the comuna, the size of the household, whether the

[8] In the robustness section we deal with the possibility that in some comunas the population might be scattered among several hamlets and, therefore, the population weighted centroids might not be the ideal measure.

[9] We perform a number of robustness tests in which we change the size of the buffer.

person interviewed is the main breadwinner of the household, whether she is married, her age, gender and years of education. Finally, 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, finally, different industry specific trends that could affect labor supply. ε is the error term, and we cluster the error term at the comuna level. Since comunas can be relatively large, we constructed weights that allow us to capture the probability that the person being interviewed lives or works within the area affected by the wildfire.

The Chilean census subdivides each comuna in districts and each district in neighborhoods (i.e., *manzanas*). For confidentiality reasons, the survey only provides the comuna of residence and of work for each respondent, but not the district and neighborhood. The fact that the share of burned area variable is constructed around the population weighted centroid (instead of the simple geometric centroid) of each comuna goes a long way in ensuring that the probability that a respondent lives within the buffer is not null. In order to improve the accuracy of our estimations, we construct a set of weights that give us the probability that an individual lives in the buffer area. The weights are based on the share of population of a comuna i living within a buffer, and constructed in the following way.

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

The shares are computed using neighborhood level population data from the census. We capture all the neighborhoods within a buffer and the share within the buffer of all those at the edge, as shown in Figure 4. We use these weights as estimation weights in all the regressions.

6.3 Results

Table 14 reports results for our baseline estimation, based on 2 kilometres buffers around the population weighted centroid of each comuna. In the table, we progressively add all the fixed effects and the comuna-, household-, and individual-level controls. Column (5) contains the full baseline specification. Standard errors are clustered at the comuna level in all the regressions.

The coefficient on the variable of interest is stable across specifications in terms of magnitude, sign and statistical significance, indicating that if a share of the two kilometres buffer around a comuna's population weighted centroid is burned, the week's labor supply declines. This coefficient implies a reduction of roughly 2.3% in hours worked for the average Chilean worker following an average wildfire.[10] The signs of the controls are as expected.

The size of the buffer has been chosen ad hoc. The risk associated with a much bigger buffer being that we would include many people who are not affected neither directly be the fire nor indirectly by its smoke. In Table 15, we show what happens to the baseline specification by letting the buffer size change between 1 and 3 kilometres at 500 metres intervals.[11] As expected, the coefficient of interest is larger in magnitude for a small buffer, albeit less precisely estimated. Once the buffer expand the coefficient stabilizes around -4.

Let us now look at what happens if we look at the number of hours usually worked by individuals. We do not expect to find any effect, as a sudden increase in pollution levels should not have any impact on usual working hours. If the results from this specification, where we replace real hours worked with usual hours worked, are statistically significant, then our main result could just be the result of a spurious correlation. Table 16 reports results for this specification using the same structure of Table 14. The coefficient of interest, not only is statistically not significant, but is also close to zero.[12] The last set of results we present here relates to the difference between usual and real hours worked. In other words, we can interpret this difference as the number of hours that our respondent chose not to work. Here, if it is true that a sudden increase in pollution decreases labor supply, we should observe an increase in the difference. As shown in Table 17, where we use the difference between usual and real hours worked as dependent variable, we observe a positive effect statistically significant at the 1% level, consistent with our previous two findings.[13]

To investigate if workers shifted their working hours to the following week, rather than an actual reduction in their labor supply, we include a lagged term for the share of wildfire exposure to our regression looking at real working hours. We show the coefficients for the contemporaneous term for wildfire exposure as well as the lagged terms in Figure 5. In the specification that includes both the contemporaneous and one-period lagged terms, the one-period lagged term shows a positive and statistically significant coefficient, albeit with a smaller magnitude than the contemporaneous effect. It suggests that workers react to wildfire exposure by reducing working hours in the week affected by fire, but try to compensate by working more in the following week. Yet, our results show that the aggregate effect of wildfires is still negative. We also add a second lagged term but it shows a statistically and economically insignificant result, while the contemporaneous and first lag coefficients are similar to the previous specification, aside from losing precision.

[10]This number is obtained in the following way (-4*0.222)/38.54 using the descriptive statistics presented in Table 1.

[11]When recalculating the buffer size we also recompute the estimation weights.

[12]Table 26, in the Appendix, shows that this is true also when we change the size of the buffer.

[13]Table 27, in the Appendix, shows that this is true also when we change the size of the buffer.

We also try to further unravel the impact of air pollution on labor supply by looking at its impact on various sub populations and see how they react. First, we will look at where the working activity takes pace, indoor versus outdoors. Second, we will look at the industries and occupations in which the respondents are employed, in order to quantify the impact of air pollution on different industries, instead of just having one aggregate average effect. Third, we will analyse the impact according to the economic status of the workers and, eventually, we will look at the change in hours worked by reason.

Indoor/outdoor

In the baseline analysis we focused on the whole sample of workers. When studying air pollution it is interesting to investigate whether workers performing their activities outside are affected in a different way from workers who conduct their activities indoors. In our data, we are able to observe if our respondents conducted work outdoor or indoor *during the week preceding the interview*. In other words, instead of classifying whether workers work outdoor based on the nature of their occupations or industries, we are able to accurately pin down if a worker had spent time outdoor during the week. For this reason, a first variation consists in running our baseline specification on two separate subsamples. First, we run the specification on the subsample working outdoors, and then on the sample working indoors. We can find descriptive statistics for the two sub samples in Table 1. As one can see, the statistics are quite similar between the two samples.

The results for these two specifications are presented in Table 18. The first thing one notices is that, interestingly, air pollution has a negative impact on real hours worked for both types of workers: the ones working outdoors and the ones working indoors, and both coefficients are statistically significant at the 1 percent level. Yet intuitively, the impact on workers performing their tasks outdoors is 65 percent larger than the ones on the other subsample. For the average share of burned area (22 percent), outdoor workers reduce the number of hours worked by an average of 3.7 percent, while indoor workers only reduce them by 2.3 percent.

Industries and occupations

In this section of the paper we quantify the impact of air pollution by industry, occupation, and skill level. We work with buffers of two sizes, two, and three kilometres. Increasing the size of the buffer allows us to increase the level of identifying variation.[14]

We start by taking a look at different industries when the buffer size is set at two kilo-

[14] We require at least 50 workers to be impacted by a wildfire in order to include an industry/occupation in our analysis.

metres, and we report our results in Table 19. In this case, we are able to analyze only two industries: (1) agriculture, livestock, forestry and fishing; and (2) wholesale and retail, which includes repair of motor vehicles, motorcycles. When we increase the size of the buffer to three kilometres, results in Table 20, we are also able to include manufacturing. Agriculture is the only industry is affected by air pollution in a statistically significant way. Not surprisingly, the impact of air pollution on hours worked in agriculture is similar to the result observed for outdoor workers. The more surprising result is the absence of an effect of air pollution on construction workers. Also these workers perform the majority of their tasks outdoors, yet, they seem unaffected by a sudden change in the level of air pollution.

In Tables 21 and 22, we split the sample according to occupations. Here as well, the number of occupations that we are able to analyze is dictated by the level of variation in the dataset. A two kilometres buffer allows us to analyze only two occupations: (1) service and sales workers; and (2) elementary occupations (unskilled). A three kilometres buffer, instead, allows us to expand to seven occupations, by adding: (3) professionals; (4) technicians and associates; (5) clerical support workers; (6) craft and related trades workers; and (7) plant and machine operators and assemblers. In both cases, we can see that workers in elementary occupations experience a huge reduction in their working hours: exposure to an average wildfire reduces their working hours by 4.2 percent. In the 3 kilometres buffer version, we found that professionals and technicians also experience a large reduction in working hours – this perhaps can be explained by the flexibility in their working hours compared to other types of occupations, such as service and clerical workers. We also found an increase in working hours for plant and machine operators, which include workers in forest management industry.

Finally, in Table 23 we focus on the largest sub-sample, workers employed in elementary occupations. We split this sample between workers performing their tasks indoors and outdoors. The impact of a sudden increase in air pollution for these workers is among the highest observed in our sample, yet it becomes slightly larger in magnitude and more precisely estimated for workers employed outdoors. The similar magnitude between the impact on outdoor and indoor workers may be due to the fact that indoor elementary occupations are probably not performed in well ventilated and enclosed environments. Air quality in most industrial building is likely not much different from outdoor air quality.

Income

In order to further understand the heterogeneous effect of wildfires, we also investigate whether the labor market response differs across the income levels. It is important to understand the effect for households in different income brackets for two reasons. First, the capacity to adapt to wildfires is likely to be correlated with income levels, isolating different income levels allows us to study if richer households are able to dampen the negative effects of wildfires. Second, if the deteriorative effect of wildfires is stronger for poorest households, mitigation measures on wildfires and air pollution can be viewed as a progressive measure, which disproportionally benefits poor households, relative to rich households.

Based on reported income from the primary occupation, we allocate individuals to three income brackets according to the national minimum wage, which is set every year by the Chilean government. Table 24 reports the findings after we split our sample into three subgroups according to their income.[15] The first subsample contains individuals earning less than minimum wage, the second includes individual making between minimum wage and twice the minimum wage and, finally, in the third subsample, we find all individuals making more than twice minimum wage. Surprisingly, the effect is close to zero for the poorest respondents, earning less than the national minimum wage. There are two possible reasons for that. First, these workers work much less compared to workers in richer brackets – the average poorest worker and median worker work for an average of 29 and 42 hours per week, respectively.[16] Second, their choice of occupations may prevent them from choosing their working hours flexibly. The effect of wildfire is the strongest for workers in the median income bracket, which includes respondents earning between one and two times the national minimum wage.

Reasons

The ESI questionnaire asks respondents who declared working a different amount of hours than usual what was the reason for the difference. In Table 25, we first run our baseline specification for everyone who answered this question, in column (1), we then run the same specification only for people who gave as reason either *climatic reasons or natural catastrophes* or *due to illness, temporary disability or accident*. These are the two reasons that could be related to the effects of a wildfire. We use the difference between the real and the usual amount of hours worked as our dependent variable. As expected, since these are workers who admitted working less than usual, the coefficients are positive across all specifications. While the coefficient of interest is statistically significant at the one percent level in both columns, the share of burned area has a much stronger impact on people claiming climatic or health reasons to work less than usual. This difference, indirectly suggests that health reason can explain why workers chose to work less during the week when wildfire occurred.

[15] We have also estimated a single model by interacting income bracket dummies with the share of wildfires, and the results are similar.

[16] The usual working hours are also lower for the poorest households: 30 hours, relative to 44 and 46 hours for workers in the median and richest brackets.

Robustness

In Table 28, we rerun our baseline results by eliminating all comunas with weights below 0.2, 0.3, 0.4, 0.5, and 0.6 respectively. The results are positive and statistically significant at the 1 percent level across all specifications, despite the drastic reduction in sample size. As expected, as we rule out comunas with lower weight and increase the average weights in our sample, which corresponds to a higher probability that individuals are effectively affected by the fires, lead to a larger effect. The magnitude of the coefficient goes from 4 in the baseline, to 9 in the case where we only keep comunas with weights above 0.6.

7 Welfare analysis

(to be completed)

8 Conclusions

In this paper we identify the causal impact of air pollution on labor supply by using wildfire occurrences to generate exogenous variations in air pollution levels. We use labor supply and wildfire data from Chile, a heavily polluted country. The average Chilean worker, across all industries, reduces its working hours by roughly 2.7 percent following the increase in air pollution at the occurrence of a wildfire.

We collected data on pollution at the week-comuna level for the period of interest using satellite reanalysis data. We then proceed in estimating the effect of air pollution on labor supply using wildfire exposures as an instrumental variable. Using satellite data on air pollution, Only when instrumenting air pollution using wildfire exposures, we isolate the causal effect of air pollution on labor supply and show that air pollution level leads to a significant lower number of hours worked in Chile, posing a large economic cost.

Most of the empirical work on air pollution has focused on workers' productivity, which we could call the "intensive margin" of the impact of air pollution on labor supply. In this paper we focus on hours worked, a sort of "extensive margin". Putting this two effects together, tells us that the impact of air pollution on production could be significantly larger than previously thought.

In a next step, we will conduct more analysis using our instrumental variables approach and refine our instrument variables, before computing the economic cost of air pollution and demonstrate the comprehensive effect of air pollution on economic output through the labor market (Dechezleprêtre et al., 2019).

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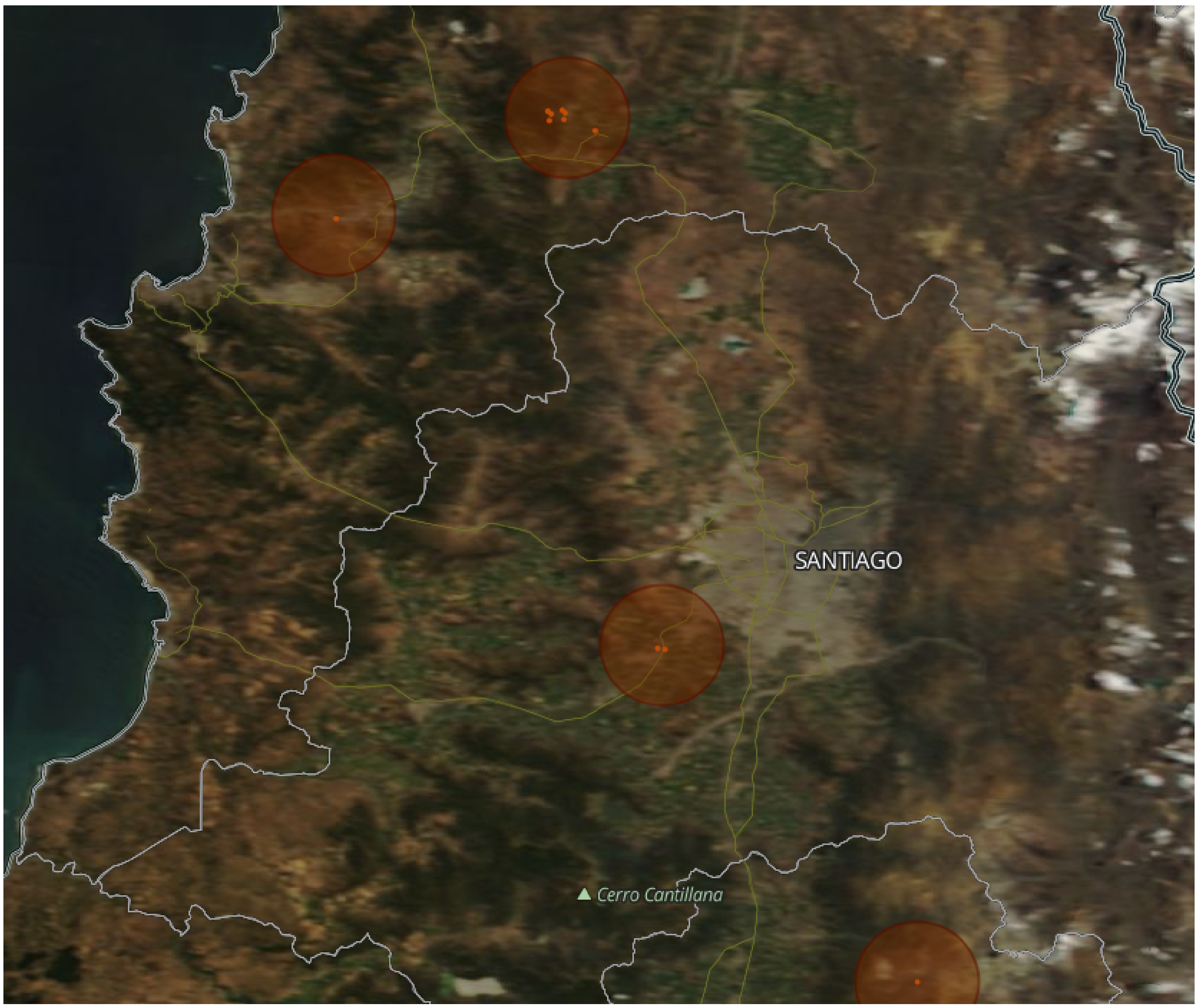
Tables

Table 1: Summary statistics – labor market variables

Variable	Mean	Std. Dev.	Min.	Max.	N
<u>**Panel A:**</u>					
Real hours worked	38.54	17.82	0	168	271,879
Usual hours worked	41.62	15.20	1	168	271,879
Difference	3.07	10.60	-99	126	271,879
<u>*Outdoor:*</u>					
Real hours worked	39.33	18.78	0	168	84,400
Usual hours worked	42.41	15.75	1	168	84,400
Difference	3.07	11.84	-74	126	84,400
<u>*Indoor:*</u>					
Real hours worked	38.19	17.35	0	168	187,479
Usual hours worked	41.26	14.93	1	168	187,479
Difference	3.06	9.98	-99	112	187,479
<u>**Panel B:**</u>					
Household size	3.70	1.69	1	17	221,691
Years of education	4.09	1.90	0	11	221,691
Age	43.49	14.21	15	95	221,691
Area comuna ($1000km^2$)	2.516	5.748	0.006	48.695	221,691
Main breadwinner†	0.53	0.50	0	1	221,691
Married†	0.58	0.49	0	1	221,691
Gender†	0.57	0.50	0	1	221,691

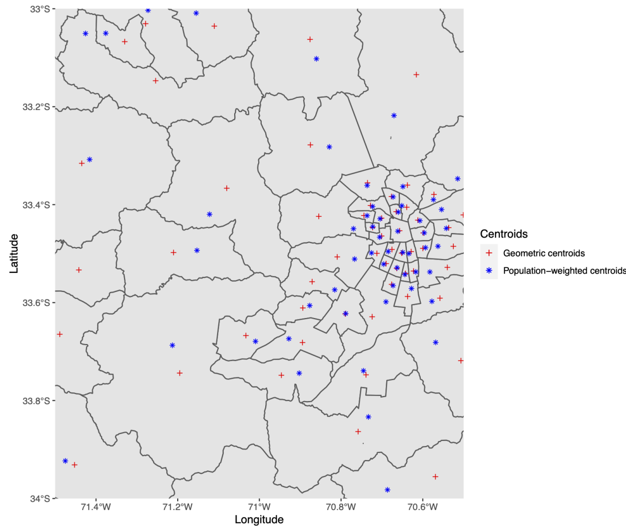
Note: † denotes indicator variables.

Figure 1: Measuring exposure to fire



Notes: MODIS Burned Area product, the red dot are burned raster cells, while the round buffer are meant to help identify the burned areas.

Figure 2: Population-weighted centroids

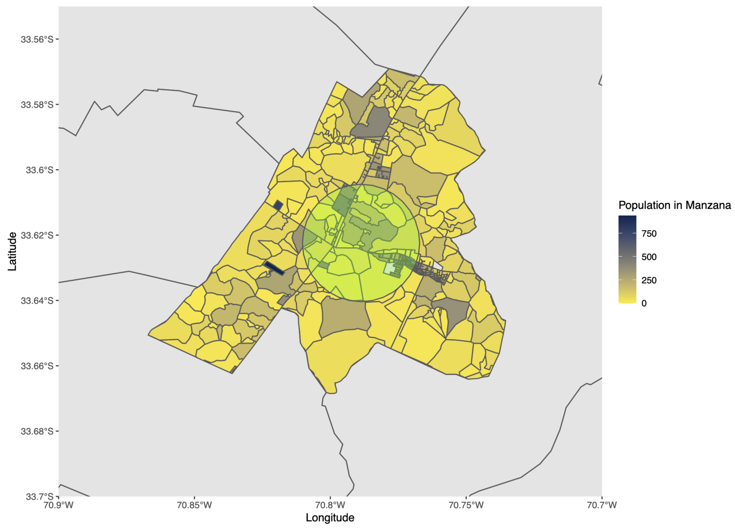


Notes: Geometric (red crosses) and population weighted (blue stars) centroids.

Figure 3: Buffers

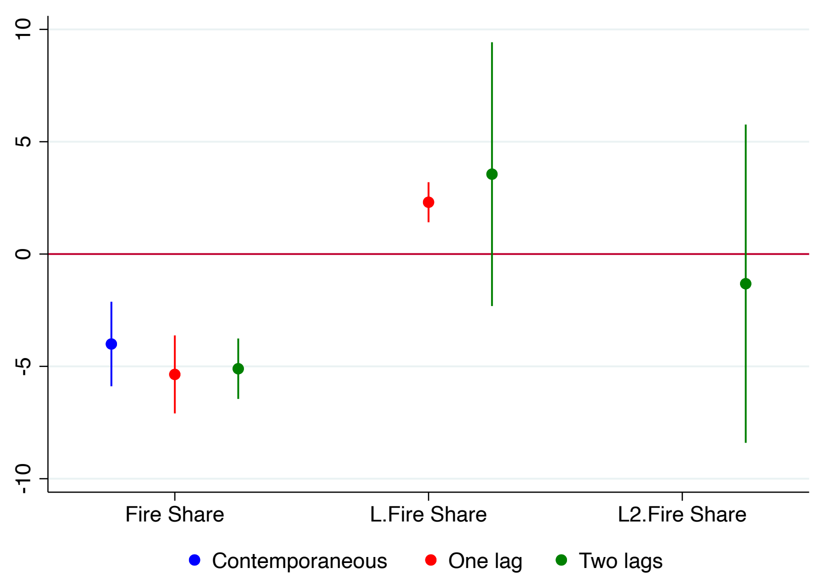
Notes: Geometric (red crosses), population weighted (blue stars) centroids and buffers of interest for burned areas (green).

Figure 4: Weights



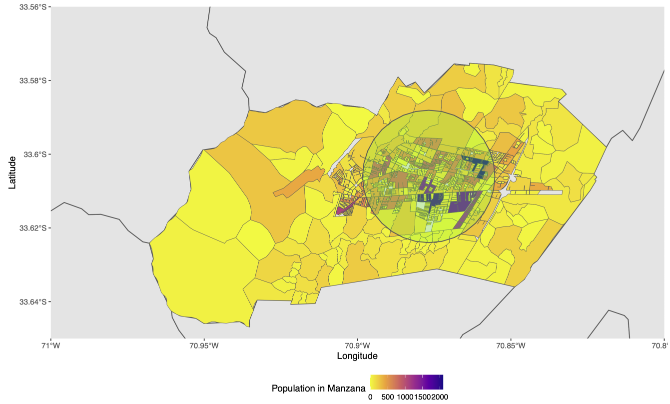
Notes: Weights are constructed as the share of population of a comuna living inside a buffer zone. The population inside the buffer is constructed started from the population in each manzana.

Figure 5: Lag coefficients



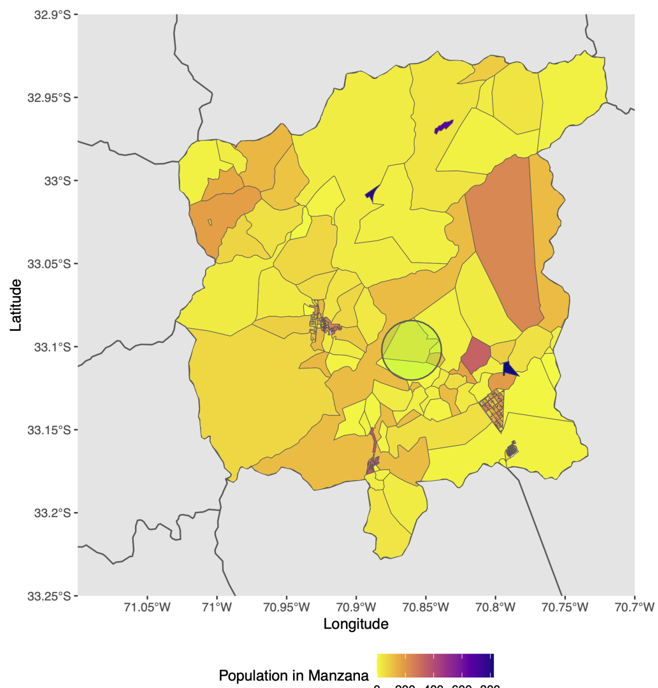
Notes: Coefficients on the *Share of buffer area burned* and its lags.

Figure 6: Population weighted centroids, high accuracy – Peñaflor



Notes: Example of a high accuracy buffer area. The buffer contains a large share of the population of this comuna.

Figure 7: Population weighted centroids, low accuracy – Tiltil



Notes: Example of a low accuracy buffer area. The buffer contains a small share of the population of this comuna.

Table 2: Summary statistics – weather and wildfires

Variable	Mean	Std. Dev.	Min.	Max.	N
Average precipitations	0.681	1.472	0	9.109	221,691
Average temperature	15.30	3.00	6.921	21.80	221,691
Wildfire smoke	0.0663	3.874	0	294.8	221,691
Wildfire smoke if > 0	5.911	36.11	0.002	294.8	2,487
Average hourly PM_1	14.52	14.13	0.540	119.3	221,691
Average hourly $PM_{2.5}$	17.92	15.87	0.926	138.2	221,691
Average hourly PM_{10}	25.89	22.09	1.361	193.9	221,691
Maximum hourly PM_1	35.62	36.65	1.055	608.0	221,691
Maximum hourly $PM_{2.5}$	42.68	41.47	2.103	702.7	221,691
Maximum hourly PM_{10}	61.07	57.27	3.089	986.1	221,691

Note: Temperatures and precipitations are averaged per week.

Table 3: Reduced-form analysis: Real hours worked

	Real hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Wildfire smoke	-0.011***	-0.0099***	-0.0070***	-0.0073***	-0.0051***
	(0.0019)	(0.0020)	(0.0020)	(0.0019)	(0.0018)
Average precipitations (week)				-0.23***	-0.23***
				(0.052)	(0.052)
Average temperature (week)				0.14***	0.14***
				(0.033)	(0.033)
Area of a comuna (1000 km^2)				-0.0044	-0.0091
				(0.031)	(0.031)
No. of people in HH					0.31***
					(0.029)
Main breadwinner of HH					3.03***
					(0.100)
Years of education					0.10***
					(0.024)
Married					-0.23***
					(0.031)
Age					-0.024***
					(0.0047)
Gender					4.65***
					(0.13)
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	221,691	221,691	221691	221,691	221,691
R^2	0.0000063	0.0000049	0.0000025	0.00049	0.028

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

Table 4: Reduced form analysis: Contracted hours

	Contracted hours during the week				
	(1)	(2)	(3)	(4)	(5)
Wildfire smoke	-0.0057***	-0.0051***	-0.00046	-0.00047	0.00038
	(0.0013)	(0.0012)	(0.0011)	(0.0011)	(0.0012)
Average precipitations (week)				-0.033	-0.028
				(0.029)	(0.029)
Average temperature (week)				-0.029	-0.025
				(0.019)	(0.019)
Area of a comuna (1000 km^2)				-0.016	-0.016
				(0.018)	(0.018)
No. of people in HH					0.27***
					(0.020)
Main breadwinner of HH					1.95***
					(0.082)
Years of education					0.12***
					(0.020)
Married					-0.089***
					(0.024)
Age					0.029***
					(0.0036)
Gender					1.84***
					(0.092)
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	163,841	163,841	163,841	163,841	163,841
R^2	0.0000042	0.0000033	0.000000030	0.000033	0.024

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

Table 5: Reduced form analysis: Difference in hours worked

	Difference in hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Wildfire smoke	0.0048***	0.0036***	0.0044***	0.0046***	0.0042***
	(0.0011)	(0.0012)	(0.0012)	(0.0011)	(0.0011)
Average precipitations (week)				0.23***	0.22***
				(0.041)	(0.040)
Average temperature (week)				-0.17***	-0.17***
				(0.028)	(0.028)
Area of a comuna (1000 km^2)				-0.00089	-0.00015
				(0.018)	(0.018)
No. of people in HH					0.059***
					(0.019)
Main breadwinner of HH					0.20***
					(0.063)
Years of education					-0.024
					(0.017)
Married					-0.11***
					(0.024)
Age					0.0061**
					(0.0025)
Gender					-1.48***
					(0.074)
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	163,841	163,841	163,841	163,841	163,841
R^2	0.0000025	0.0000014	0.0000021	0.0012	0.0042

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

Table 6: Reduced form analysis: Indoor versus outdoor

Dep. var.: real work hours	Outdoor (1)	Indoor (2)
Wildfire smoke	-0.014***	0.0016
	(0.0028)	(0.0024)
Average precipitations (week)	-0.34***	-0.18***
	(0.099)	(0.048)
Average temperature (week)	0.071	0.17***
	(0.054)	(0.037)
Area of a comuna (1000 km^2)	0.086*	-0.064***
	(0.051)	(0.023)
No. of people in HH	0.24***	0.33***
	(0.051)	(0.034)
Main breadwinner of HH	2.70***	3.34***
	(0.21)	(0.12)
Years of education	0.0040	0.18***
	(0.035)	(0.029)
Married	-0.22***	-0.29***
	(0.067)	(0.038)
Age	-0.086***	0.0032
	(0.0080)	(0.0050)
Gender	6.94***	4.00***
	(0.30)	(0.14)
Province FE	yes	yes
Month FE	yes	yes
Region-year FE	yes	yes
Industry-year FE	yes	yes
Observations	60,190	152,166
R^2	0.033	0.031

Notes: The dependent variable is the real number of hours worked. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effect of air pollution on real hours worked: OLS

	Real hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
$PM_{2.5}$ (μg/m^3)	0.011**	0.017***	0.016***	0.017***	0.018***
	(0.0050)	(0.0057)	(0.0056)	(0.0055)	(0.0054)
Average precipitations (week)				-0.24***	-0.24***
				(0.054)	(0.054)
Average temperature (week)				0.14***	0.15***
				(0.034)	(0.034)
Area of a comuna (1000 km^2)				-0.0078	-0.013
				(0.030)	(0.031)
No. of people in HH					0.32***
					(0.029)
Main breadwinner of HH					2.99***
					(0.10)
Years of education					0.10***
					(0.025)
Married					-0.22***
					(0.033)
Age					-0.023***
					(0.0047)
Gender					4.68***
					(0.13)
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	202,576	202,576	202,576	202,576	202,576
R^2	0.0059	0.0085	0.034	0.034	0.061

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

Table 8: Causal effect of air pollution on real hours worked

First stage: PM$_{2.5}$ (μg/m^3)					
	(1)	(2)	(3)	(4)	(5)
Wildfire smoke	0.070***	0.078***	0.078***	0.078***	0.078***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Average precipitations (week)				-0.43***	-0.43***
				(0.091)	(0.091)
Average temperature (week)				-0.42***	-0.42***
				(0.090)	(0.090)
First-stage F-stat	1,288.9	856.7	849.2	826.3	830.3
Second stage: Real hours worked during the week					
	(1)	(2)	(3)	(4)	(5)
Average PM$_{2.5}$ (μg/m^3)	-0.16***	-0.13***	-0.089***	-0.093***	-0.065***
	(0.024)	(0.026)	(0.025)	(0.024)	(0.024)
Average precipitations (week)				-0.27***	-0.26***
				(0.055)	(0.054)
Average temperature (week)				0.097***	0.12***
				(0.036)	(0.035)
Area of a comuna (1000 km^2)				0.0060	-0.0018
				(0.036)	(0.034)
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	221,691	221,691	221,691	221,691	221,691
R^2	0.0085	0.0044	0.0023	0.0020	0.027

Notes: All models are estimated using two stage least square using wildfire smoke as the exogenous instrument. 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 9: The causal effect of air pollution, by industry

Dep var. real work hours	Industry		
	Agriculture	Manufacturing	Service
Average $PM_{2.5}$ (μg/m^3)	-0.19***	0.24***	-0.28***
	(0.056)	(0.028)	(0.033)
Average precipitations (week)	-0.43***	-0.16**	-0.29***
	(0.14)	(0.073)	(0.065)
Average temperature (week)	0.20**	0.26***	-0.012
	(0.090)	(0.055)	(0.050)
Area of a comuna (1000 km^2)	0.10	-0.012	0.014
	(0.15)	(0.037)	(0.034)
Estimator	IV	IV	IV
HH controls	yes	yes	yes
Province FE	yes	yes	yes
Month FE	yes	yes	yes
Region-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes
Observations	27,698	50,838	143,154
R^2	0.024	0.034	0.012

Notes: The dependent variable is the real number of hours worked. All models are estimated using two stage least squares using wildfire smoke as an exogenous instrument. The 'Manufacturing' group also includes some primary sectors such as mining, construction and utilities sectors. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: The causal effect of air pollution, by income group

Dep var. real work hours	Income brackets		
	Poorest	Median	Richest
Average $PM_{2.5}$ (μg/m^3)	-0.11***	-0.13***	0.10***
	(0.038)	(0.035)	(0.035)
Average precipitations (week)	-0.23**	-0.33***	-0.13**
	(0.093)	(0.059)	(0.061)
Average temperature (week)	0.13**	0.068	0.24***
	(0.056)	(0.043)	(0.053)
Area of a comuna (1000 km^2)	0.062	-0.084*	0.0042
	(0.074)	(0.050)	(0.034)
Estimator	IV	IV	IV
HH controls	yes	yes	yes
Province FE	yes	yes	yes
Month FE	yes	yes	yes
Region-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes
Observations	60557	80261	80870
R^2	0.015	0.0031	0.0075

Notes: The dependent variable is the real number of hours worked. All models are estimated using two stage least squares using wildfire smoke as an exogenous instrument. The income brackets are based on income from their primary occupation. *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. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Heterogenous impact of air pollution on labor supply

Dependent variable:	Real hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Baseline / Overall sample:					
	-0.16***	-0.13***	-0.089***	-0.093***	-0.065***
	(0.024)	(0.026)	(0.025)	(0.024)	(0.024)
Gender:					
Female	-0.024	-0.015	0.028	0.025	0.018
	(0.029)	(0.030)	(0.034)	(0.033)	(0.035)
Male	-0.26***	-0.20***	-0.19***	-0.20***	-0.17***
	(0.030)	(0.034)	(0.031)	(0.031)	(0.029)
Indoor/outdoor:					
Outdoor	-0.21***	-0.15***	-0.23***	-0.23***	-0.21***
	(0.050)	(0.049)	(0.054)	(0.054)	(0.050)
Indoor	-0.079***	-0.064**	-0.034	-0.037	0.017
	(0.026)	(0.026)	(0.026)	(0.024)	(0.025)
Age group:					
Age below 40	-0.15	-0.12	-0.16*	-0.16**	-0.065
	(0.089)	(0.084)	(0.082)	(0.081)	(0.084)
Age 40-54	-0.14***	-0.12***	-0.050***	-0.051***	-0.042**
	(0.023)	(0.020)	(0.019)	(0.019)	(0.018)
Age above 55	-0.21***	-0.16**	-0.095*	-0.10*	-0.11**
	(0.056)	(0.062)	(0.056)	(0.056)	(0.054)
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

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. All other controls are suppressed for exposition purposes. Standard errors in parentheses are clustered at the comuna level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: Placebo

Dep. var.: real work hours	Share statistically significant at: 1%	5%	10%
Randomization over all sample:			
Wildfire smoke	0.026	0.083	0.146
Randomization within region:			
Wildfire smoke	0.039	0.103	0.178
Randomization within year:			
Wildfire smoke	0.025	0.074	0.140
Weather controls	yes	yes	yes
HH controls	yes	yes	yes
Province FE	yes	yes	yes
Month FE	yes	yes	yes
Region-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes

Notes: Results show the share of statistically significant results over 1000 randomizations, where the wildfire measure is randomized over the entire sample, within regions and, within years. Statistical significance corresponds to clustered standard errors at the comuna levels. The dependent variable is the real number of hours worked.

Table 13: Summary statistics – MODIS

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Share of wildfire in 2 km buffer	0.0003	0.016	0	1.47	271,879
Share of wildfire in 2 km buffer if > 0	0.222	0.381	0.019	1.47	382
Share of wildfire in 3 km buffer	0.0003	0.013	0	1.47	271,879
Share of wildfire in 3 km buffer if > 0	0.127	0.246	0.009	1.49	578

Note: Temperatures and precipitations are averaged per week.

Table 14: Real hours worked – 2 km buffer

	Real hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Share of wildfire in 2 km buffer	-4.60***	-4.05***	-4.40***	-4.33***	-4.00***
	(1.03)	(0.82)	(1.22)	(1.27)	(0.96)
Average precipitations (week)				-0.072**	-0.069**
				(0.034)	(0.034)
Average temperature (week)				0.21***	0.21***
				(0.038)	(0.039)
Area of a comuna (1000 km^2)				0.089***	0.084***
				(0.027)	(0.025)
No. of people in HH					0.33***
					(0.035)
Main breadwinner of HH					3.24***
					(0.12)
Years of education					0.11***
					(0.028)
Married					-0.29***
					(0.038)
Age					-0.013**
					(0.0061)
Gender					4.66***
					(0.15)
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	411,301	411,301	271,929	271,929	271,879
R^2	0.0055	0.0075	0.036	0.036	0.063

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.

Table 15: Real hours worked – 1-3 km buffer

	Buffer size:				
Dep. var.: real work hours	1 km	1.5 km	2 km	2.5 km	3 km
Share of wildfire in buffer	-12.7*	-5.03***	-4.00***	-4.29***	-4.56***
	(6.78)	(1.92)	(0.96)	(1.15)	(1.51)
Average precipitations (week)	-0.052	-0.060*	-0.069**	-0.072**	-0.082**
	(0.036)	(0.034)	(0.034)	(0.034)	(0.034)
Average temperature (week)	0.22***	0.22***	0.21***	0.21***	0.21***
	(0.045)	(0.042)	(0.039)	(0.037)	(0.036)
Area of a comuna (1000 km^2)	0.061	0.069***	0.084***	0.093***	0.10***
	(0.052)	(0.026)	(0.025)	(0.027)	(0.032)
HH controls	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes
Observations	271,530	271,879	271,879	271,935	271,935
R^2	0.064	0.063	0.063	0.063	0.063

Notes: All specification contain estimation weights for the probability that an individual is within the buffer affected by the wildfire, the weights are recomputed every time the size of the buffer changes. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Usual hours worked – 2 km buffer

	Usual hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Share of wildfire in 2 km buffer	-0.90	-0.79	-1.06	-1.04	-0.72
	(1.10)	(0.99)	(1.39)	(1.37)	(1.14)
Average precipitations (week)				0.029	0.032
				(0.028)	(0.028)
Average temperature (week)				-0.020	-0.011
				(0.025)	(0.025)
Area of a comuna (1000 km^2)				0.11***	0.10***
				(0.027)	(0.023)
No. of people in HH					0.40***
					(0.033)
Main breadwinner of HH					3.65***
					(0.11)
Years of education					0.11***
					(0.025)
Married					-0.35***
					(0.034)
Age					-0.012**
					(0.0057)
Gender					-3.79***
					(0.14)
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	411,301	411,301	271,929	271,929	271,879
R^2	0.0061	0.0072	0.058	0.058	0.092

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.

Table 17: Difference in hours worked – 2 km buffer

	Difference hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Share of wildfire in 2 km buffer	3.70***	3.26***	3.34***	3.30***	3.28***
	(0.18)	(0.34)	(0.28)	(0.24)	(0.30)
Average precipitations (week)				0.10***	0.10***
				(0.026)	(0.026)
Average temperature (week)				-0.23***	-0.23***
				(0.026)	(0.026)
Area of a comuna (1000 km^2)				0.019	0.020
				(0.015)	(0.015)
No. of people in HH					0.065***
					(0.017)
Main breadwinner of HH					0.41***
					(0.056)
Years of education					0.003
					(0.014)
Married					-0.063***
					(0.019)
Age					0.001
					(0.0019)
Gender					0.87***
					(0.053)
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	411,301	411,301	271,929	271,929	271,879
R^2	0.0031	0.0071	0.015	0.016	0.018

Notes: The difference in hours worked is computed by subtracting the number of real hours worked from the usual number of hours worked. 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.

Table 18: Indoors/outdoors – 2 km buffer

Dep. var.: real work hours	Outdoor	Indoor
Share of wildfire in 2 km buffer	-6.56***	-3.99***
	(1.59)	(0.58)
Average precipitations (week)	-0.14**	-0.037
	(0.070)	(0.038)
Average temperature (week)	0.18***	0.23***
	(0.055)	(0.043)
Area of a comuna (1000 km^2)	0.27***	-0.064**
	(0.083)	(0.026)
HH controls	yes	yes
Province FE	yes	yes
Month FE	yes	yes
Region-year FE	yes	yes
Industry-year FE	yes	yes
Observations	73,253	187,479

Notes: The dependent variable is the real number of hours worked. 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.

Table 19: Industries – 2 km buffer

Dep. var.: real work hours	Agriculture	Wholesale
Share of wildfire in 2 km buffer	-7.14***	3.40
	(2.04)	(5.94)
Average precipitations (week)	-0.26**	-0.010
	(0.12)	(0.074)
Average temperature (week)	0.23**	0.28***
	(0.092)	(0.075)
Area of a comuna (1000 km^2)	0.33***	0.27***
	(0.11)	(0.088)
HH controls	yes	yes
Province FE	yes	yes
Month FE	yes	yes
Region-year FE	yes	yes
Industry-year FE	yes	yes
Observations	33,472	49,317

Notes: The dependent variable is the real number of hours worked. For an industry to be included, at least 50 observations need to be affected by a wildfire. 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.

Table 20: Industries – 3 km buffer

Dep. var.: real work hours	Agriculture	Manufacture	Wholesale
Share of wildfire in 3 km buffer	-9.31***	0.81	2.26
	(2.79)	(3.46)	(9.57)
Average precipitations (week)	-0.26**	0.019	-0.038
	(0.11)	(0.070)	(0.071)
Average temperature (week)	0.26***	0.22***	0.26***
	(0.084)	(0.079)	(0.068)
Area of a comuna (1000 km^2)	0.38***	-0.13	0.25***
	(0.100)	(0.14)	(0.095)
HH controls	yes	yes	yes
Province FE	yes	yes	yes
Month FE	yes	yes	yes
Region-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes
Observations	33,509	27,446	49,320

Notes: The dependent variable is the real number of hours worked. For an industry to be included, at least 50 observations need to be affected by a wildfire. 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.

Table 21: Occupations – 2 km buffer

Dep. var.: real work hours	Service	Unskilled
Share of wildfire in 2 km buffer	0.81	-7.26***
	(1.25)	(2.54)
Average precipitations (week)	-0.032	-0.024*
	(0.041)	(0.012)
Average temperature (week)	0.18***	0.18***
	(0.067)	(0.052)
Area of a comuna (1000 km^2)	0.16**	0.29***
	(0.064)	(0.078)
HH controls	yes	yes
Province FE	yes	yes
Month FE	yes	yes
Region-year FE	yes	yes
Industry-year FE	yes	yes
Observations	62,073	104,431

Notes: The dependent variable is the real number of hours worked. For an occupation to be included, at least 50 observations need to be affected by a wildfire. 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.

Table 22: Occupations – 3 km buffer

Real work hours	Prof.	Tech.	Cler.	Serv.	Craft.	Plant	Unskilled
3 km buffer	-15.4***	-16.7*	7.63	1.31	-1.73	8.37***	-10.1***
	(2.73)	(9.99)	(10.2)	(2.26)	(4.79)	(2.86)	(3.82)
Avg prec.	0.041	0.026	0.022	-0.040	-0.013	0.027	-0.027**
	(0.040)	(0.023)	(0.031)	(0.033)	(0.014)	(0.030)	(0.012)
Avg temp	0.19***	0.19***	0.17***	0.16**	0.25***	0.17**	0.17***
	(0.055)	(0.051)	(0.049)	(0.062)	(0.060)	(0.071)	(0.048)
Comuna	-0.087	-0.0078	0.033	0.18**	0.058	-0.012	0.32***
	(0.079)	(0.053)	(0.070)	(0.079)	(0.076)	(0.14)	(0.074)
HH controls	yes	yes	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes	yes
Observations	41,234	42,184	35,118	62,085	57,105	36,226	104,499

Notes: The dependent variable is the real number of hours worked. For an occupation to be included, at least 50 observations need to be affected by a wildfire. 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.

Table 23: Unskilled – 2 km and 3 km buffers

	2 km			3 km	
Dep. var.: real work hours	Baseline	Outdoor	Indoor	Outdoor	Indoor
Share of wildfire in 2 km buffer	-9.97***	-10.6***	-9.04**	-14.1***	-14.3*
	(2.26)	(1.50)	(4.50)	(1.96)	(8.11)
Average precipitations (week)	-0.018	-0.019	-0.033	-0.023*	-0.031
	(0.012)	(0.017)	(0.020)	(0.013)	(0.021)
Average temperature (week)	0.20***	0.20***	0.19***	0.19***	0.19***
	(0.053)	(0.076)	(0.062)	(0.064)	(0.060)
Area of a comuna (1000 km^2)	0.24***	0.39**	0.059	0.42***	0.074
	(0.081)	(0.17)	(0.055)	(0.13)	(0.061)
HH controls	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes
Observations	89912	44,163	45,749	44,219	45,761

Notes: The dependent variable is the real number of hours worked. All specification contain estimation weights for the probability that an individual is within the buffer affected by the wildfire, the weights are recomputed every time the size of the buffer changes. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 24: Income

Dep var. real work hours	Income brackets		
	Poorest	Median	Richest
Share of wildfire in 2 km buffer	0.39	-7.76***	-3.67*
	(0.70)	(1.05)	(2.01)
Average precipitations (week)	-0.051	-0.12***	-0.10***
	(0.074)	(0.046)	(0.036)
Average temperature (week)	0.24***	0.21***	0.24***
	(0.058)	(0.042)	(0.048)
Area of a comuna (1000 km^2)	0.13	-0.18***	0.088
	(0.081)	(0.055)	(0.058)
HH controls	yes	yes	yes
Province FE	yes	yes	yes
Month FE	yes	yes	yes
Region-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes
Observations	74271	97803	99799

Notes: The dependent variable is the real number of hours worked. The income brackets are based on income from their primary occupation. *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. 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.

Table 25: Reasons – 2 km buffer

Dep. var.: difference	Any reason (1)	Health & climate (2)
Share of wildfire in 2 km buffer	2.50***	6.64***
	(0.61)	(1.72)
Average precipitations (week)	-0.29***	-0.20
	(0.060)	(0.15)
Average temperature (week)	-0.048	-0.056
	(0.053)	(0.15)
Area of a comuna (1000 km^2)	-0.083	-0.052
	(0.058)	(0.19)
HH controls	yes	yes
Province FE	yes	yes
Month FE	yes	yes
Region-year FE	yes	yes
Industry-year FE	yes	yes
Observations	64,494	7,491
R^2	0.033	0.14

Notes: The dependent variable is the difference between the usual and the real number of hours worked. Column (1) focuses on all individuals who provided a reason, while column (2) only contains individuals that provided *climatic reasons or natural catastrophes* or *due to illness, temporary disability or accident* as reasons. 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.

Table 26: Usual hours worked – 1-3 km buffer

	Buffer size:				
Dep. var.: real work hours	1 km	1.5 km	2 km	2.5 km	3 km
Share of wildfire in buffer	-10.0*	-2.51	-0.72	-0.48	-0.20
	(5.91)	(2.45)	(1.14)	(1.33)	(1.41)
Average precipitations (week)	0.048*	0.039	0.032	0.031	0.024
	(0.028)	(0.028)	(0.028)	(0.027)	(0.027)
Average temperature (week)	-0.019	-0.011	-0.011	-0.011	-0.011
	(0.027)	(0.026)	(0.025)	(0.025)	(0.024)
Area of a comuna (1000 km^2)	0.073	0.096***	0.10***	0.10***	0.11***
	(0.048)	(0.024)	(0.023)	(0.023)	(0.025)
HH controls	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes
Observations	271,530	271,879	271,879	271,935	271,935
R^2	0.092	0.091	0.092	0.092	0.092

Notes: All specification contain estimation weights for the probability that an individual is within the buffer affected by the wildfire, the weights are recomputed every time the size of the buffer changes. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table 27: Difference in hours worked – 1-3 km buffer

	Buffer size:				
Dep. var.: real work hours	1 km	1.5 km	2 km	2.5 km	3 km
Share of wildfire in buffer	2.68	-2.52***	-3.28***	-3.81***	-4.36***
	(2.16)	(0.90)	(0.30)	(0.38)	(0.42)
Average precipitations (week)	0.10***	0.099***	0.10***	0.10***	0.11***
	(0.024)	(0.024)	(0.026)	(0.026)	(0.026)
Average temperature (week)	-0.24***	-0.23***	-0.23***	-0.22***	-0.22***
	(0.029)	(0.027)	(0.026)	(0.026)	(0.026)
Area of a comuna (1000 km^2)	0.012	0.027*	0.020	0.012	0.0024
	(0.028)	(0.016)	(0.015)	(0.017)	(0.020)
HH controls	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes
Observations	271,530	271,879	271,879	271,935	271,935
R^2	0.018	0.018	0.018	0.018	0.018

Notes: The difference in hours worked is computed by subtracting the number of real hours worked from the usual number of hours worked. All specification contain estimation weights for the probability that an individual is within the buffer affected by the wildfire, the weights are recomputed every time the size of the buffer changes. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

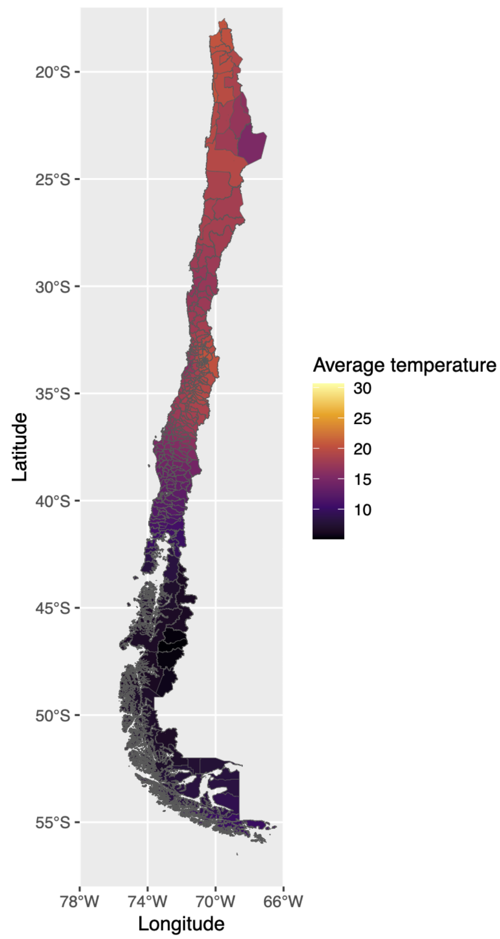
Table 28: Robustness – weights

	Weight >				
Dep. var.: real work hours	0.2	0.3	0.4	0.5	0.6
Share of wildfire in 2 km buffer	-4.27***	-4.32***	-10.2***	-9.93***	-9.11***
	(1.07)	(1.14)	(1.45)	(1.75)	(1.91)
Average precipitations (week)	-0.053	-0.038	-0.022	-0.055	0.00031
	(0.032)	(0.037)	(0.039)	(0.045)	(0.063)
Average temperature (week)	0.22***	0.25***	0.26***	0.25***	0.27***
	(0.041)	(0.042)	(0.046)	(0.056)	(0.062)
Area of a comuna (1000 km^2)	0.062**	0.063**	0.056*	0.060**	-0.81
	(0.029)	(0.026)	(0.031)	(0.026)	(0.55)
HH controls	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes
Observations	209,165	164,871	135,160	85,436	50,444

Notes: The number of observations decreases as we increase the probability that an individual lives within the buffer area considered for wildfires. 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 8: Weather data



Notes: Standard radial basis function interpolation for average temperature on the 21^{st} of December 2011.

Figure 9: Smoke plume from wildfires

Online appendix

A Additional tables and figures

Table A.1: IV results: different pollution measures

Dependent variable:	Real hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Baseline pollution measure:					
Average weekly $PM_{2.5}$ ($\mu g/m^3$)	-0.16***	-0.13***	-0.089***	-0.093***	-0.065***
	(0.024)	(0.026)	(0.025)	(0.024)	(0.024)
Alternative pollution measures:					
Average weekly PM_1 ($\mu g/m^3$)	-0.18***	-0.14***	-0.10***	-0.11***	-0.074***
	(0.027)	(0.030)	(0.029)	(0.027)	(0.027)
Average weekly PM_{10} ($\mu g/m^3$)	-0.12***	-0.092***	-0.065***	-0.067***	-0.047***
	(0.017)	(0.019)	(0.018)	(0.017)	(0.017)
Maximum hourly PM_1 ($\mu g/m^3$)	-0.024***	-0.022***	-0.016***	-0.016***	-0.011***
	(0.0036)	(0.0042)	(0.0042)	(0.0039)	(0.0040)
Maximum hourly $PM_{2.5}$ ($\mu g/m^3$)	-0.021***	-0.020***	-0.014***	-0.014***	-0.0100***
	(0.0032)	(0.0037)	(0.0037)	(0.0035)	(0.0035)
Maximum hourly PM_{10} ($\mu g/m^3$)	-0.015***	-0.014***	-0.0100***	-0.010***	-0.0072***
	(0.0023)	(0.0027)	(0.0027)	(0.0025)	(0.0025)
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	221,691	221,691	221,691	221,691	221,691

Notes: All models are estimated using two stage least square using wildfire smoke as the exogenous instrument. Standard errors in parentheses are clustered at the comuna level. Other controls are suppressed for exposition purposes. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: The effect of air pollution on contracted hours

	Contracted hours during the week				
	(1)	(2)	(3)	(4)	(5)
Average $PM_{2.5}$ (μg/m^3)	-0.058***	-0.048***	-0.0043	-0.0044	0.0036
	(0.013)	(0.011)	(0.010)	(0.011)	(0.011)
Average precipitations (week)				-0.035	-0.026
				(0.029)	(0.029)
Average temperature (week)				-0.031	-0.023
				(0.020)	(0.020)
Area of a comuna (1000 km^2)				-0.015	-0.016
				(0.018)	(0.018)
No. of people in HH					0.27***
					(0.020)
Main breadwinner of HH					1.95***
					(0.082)
Years of education					0.12***
					(0.020)
Married					-0.089***
					(0.024)
Age					0.029***
					(0.0036)
Gender					1.84***
					(0.092)
Estimator	IV	IV	IV	IV	IV
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	163,841	163,841	163,841	163,841	163,841
R^2	0.0029	0.0019	0.000056	0.000021	0.024

Notes: All models are estimated using two stage least squares using wildfire smoke as an exogenous instrument. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: The effect of air pollution on absenteeism

	Difference in hours worked during the week				
	(1)	(2)	(3)	(4)	(5)
Average $PM_{2.5}$ (μg/m^3)	0.049***	0.034***	0.041***	0.043***	0.040***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Average precipitations (week)				0.25***	0.24***
				(0.042)	(0.042)
Average temperature (week)				-0.15***	-0.15***
				(0.028)	(0.028)
Area of a comuna (1000 km^2)				-0.0060	-0.0048
				(0.019)	(0.019)
No. of people in HH					0.059***
					(0.020)
Main breadwinner of HH					0.19***
					(0.063)
Years of education					-0.023
					(0.017)
Married					-0.11***
					(0.024)
Age					0.0060**
					(0.0025)
Gender					-1.48***
					(0.074)
Estimator	IV	IV	IV	IV	IV
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	163,841	163,841	163,841	163,841	163,841
R^2	0.0026	0.00083	0.0012	0.00013	0.0031

Notes: All models are estimated using two stage least squares using wildfire smoke as an exogenous instrument. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Robustness – regions

Dep. var.: real work hours	Baseline	Excluding regions 1, 2, 15	Excluding regions 1, 2, 3, 4, 10, 11, 12, 15	Excluding regions 1, 2, 3, 4, 8, 9, 10, 11, 12, 14, 15
Average weekly $PM_{2.5}$ (μ/m^3)	-0.065***	-0.064***	-0.063***	-0.061***
	(0.024)	(0.024)	(0.023)	(0.020)
Average precipitations (week)	-0.26***	-0.26***	-0.24***	-0.42***
	(0.054)	(0.055)	(0.059)	(0.065)
Average temperature (week)	0.12***	0.12***	0.20***	0.13***
	(0.035)	(0.035)	(0.036)	(0.039)
Area of a comuna (1000 km^2)	-0.0018	0.087	0.11	0.29***
	(0.034)	(0.058)	(0.14)	(0.098)
Estimator	IV	IV	IV	IV
HH controls	yes	yes	yes	yes
Province FE	yes	yes	yes	yes
Month FE	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes
Observations	221,691	198,812	159,576	114,632
R^2	0.027	0.027	0.028	0.026

Notes: The first column contains the baseline. In the second second column we eliminate the three northernmost regions of the country: Tarapacá, Antofagasta and, Arica and Parinacota. In the third column we also eliminate: Atacama, Coquimbo, Los Lagos, Aysén of General Carlos Ibáñez del Campo, Magallanes and Chilean Antartica. In the fourth column we also eliminate: Bío Bío, La Araucanía and, Los Rvíos. All specification is estimated using two stage least square with wildfire smoke as the exogenous instrument. Standard errors in parentheses are clustered at the comuna level. *** p<0.01, ** p<0.05, * p<0.1.