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Urban Air Pollution and Sick Leaves: Evidence From Social Security Data

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URBAN AIR POLLUTION AND SICK LEAVES: EVIDENCE FROM SOCIAL SECURITY DATA*

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Abstract

We estimate the causal impact of air pollution on the incidence of sick leaves in a representative panel of employees affiliated to the Spanish social security system. Using over 100 million worker-by-week observations from the period 2005-2014, we estimate the relationship between the share of days an individual is on sick leave in a given week and exposure to particulate matter (PM_{10}) at the place of residence, controlling for weather, individual effects, and a wide range of time-by-location controls. We exploit quasi-experimental variation in PM_{10} that is due to Sahara dust advection in order to instrument for local PM_{10} concentrations. We estimate that the causal effect of PM_{10} on sick leaves is positive and varies with respect to worker and job characteristics. The effect is stronger for workers with pre-existing medical conditions, and weaker for workers with low job security. Our estimates are instrumental for quantifying air pollution damages due to changes in labor supply. We estimate that improved ambient air quality in urban Spain between 2005 and 2014 saved at least €503 million in foregone production by reducing worker absence by more than 5.55 million days.

Keywords: air pollution; health; sickness insurance; labor supply

JEL Classifications: I12, I13, Q51, Q53

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1 Introduction

Air pollution poses a major threat to public health by shortening lives (Deryugina et al., 2019) and increasing acute morbidity (Schlenker & Walker, 2016). As a negative externality of many economic activities, air pollution causes additional damage by reducing productivity on the job (Graff Zivin & Neidell, 2012) and by hindering human capital accumulation (Currie et al., 2009a; Ebenstein et al., 2016). The hypothesis that air pollution damages the economy also via reductions in labor supply was first examined by Ostro (1983) and Hausman et al. (1984). Recent research has provided credible evidence in support of this hypothesis in the context of emerging economies (Hanna & Oliva, 2015; Aragón et al., 2017), but little is known so far about this relationship in post-industrial societies where pollution levels are low and productivity is high.

In the G7 countries, the mean population exposure to fine particulate matter ($PM_{2.5}$) fell by 25% between 1990 and 2017, driven in no small part by costly environmental regulations. Over the same period, GDP per hour worked increased by 50% (OECD, 2019). These trends have important implications for cost-benefit analysis of air quality regulations. First, with air quality improving, sub-clinical health impacts such as sick leaves taken gain relative importance compared to severe health impacts which have been the main focus of the health literature so far. Second, higher labor productivity means that work days lost due to air pollution account for larger economic damages. Taken together, this calls for a better understanding of the labor-supply impacts of air pollution.

To shed light on this important issue, this paper provides the first causal estimates of how many work days are lost due to air pollution concentrations typically observed in post-industrial economies. Our empirical analysis is based on a novel administrative dataset that links rich information on personal and occupational characteristics of Spanish workers to the frequency, length, and diagnosis, of sick leaves taken. We estimate the impact of air pollution on workers' propensity to call in sick, based on weekly variation in ambient concentrations of particulate matter (PM_{10}) across 99 cities in Spain. Our baseline model is a linear regression of the share of sick-leave days on the share of high-pollution days and weather variables. To control for non-random assignment of pollution across workers, we include city-by-year, year-by-quarter, and worker fixed-effects. Possible remaining endogeneity is addressed in an instrumental-variables regression that exploits exogenous variation in PM_{10} driven by dust storms in Northern Africa.

Our estimates imply that a 10%-reduction in high-pollution events reduces the absence rate by 0.8% of the mean (2.79%). This effect is robust across a variety of specifications and economically significant when scaled up to the entire work force. The estimates imply that the improvement in ambient air quality in urban Spain between 2005 and 2014 saved at least €503 million in foregone production by reducing worker absence by more than 5.55 million days. In further analysis, we uncover two important sources of treatment heterogeneity. One relates to pre-existing medical conditions that we infer from a worker's sick leave record. We estimate that the health response of vulnerable workers (defined as those belonging to the top-five percentile of the distribution of sick leaves taken during the pre-estimation period) is more than three times stronger than the response of healthy workers. Furthermore, our analysis of treatment heterogeneity across workers and occupations reveals that job security is an important moderating factor in workers' decisions to take a sick leave in response to a pollution shock. Specifically, we estimate that workers with a high predicted risk of losing their job respond less strongly than those with high job security. Using counterfactual analysis, we show that such interactions of behavior and labor market institutions have a large impact on estimates of the external costs of air pollution that arise from changes in labor supply.

This paper makes several substantive contributions to the literature. First and foremost, we provide a comprehensive assessment of the impacts of air pollution on labor supply, an understudied outcome thus far in an otherwise quite extensive empirical literature on the health effects of air pollution.[1] Early research on this relationship uncovered negative correlations between air pollution and labor supply in cross-sectional data (Ostro, 1983), repeated cross sections (Hausman et al., 1984), and case studies (Hansen & Selte, 2000). More recent evidence shows that air pollution reduces hours worked among households in Mexico City, Lima, and Santiago de Chile (Hanna & Oliva, 2015; Aragón et al., 2017; Montt, 2018). Yet there is a lack of causal evidence for developed countries where exposure to ambi-

[1] Previous research has provided credible evidence that air pollution adversely affects health in infants (Chay & Greenstone, 2003; Currie & Neidell, 2005; Currie et al., 2009b, 2014; Arceo et al., 2016; Knittel et al., 2016) as well as in adults, based primarily on hospital records of births, deaths and emergency-room admissions (Neidell, 2009; Moretti & Neidell, 2011; Graff Zivin & Neidell, 2013; Schlenker & Walker, 2016; Deryugina et al., 2019; Currie et al., 2009b). Another strand of the literature investigates how air pollution affects the productivity of workers and students, and finds negative and statistically significant impacts in a variety of settings (Currie et al., 2009a; Graff Zivin & Neidell, 2012; Chang et al., 2016, 2019; Ebenstein et al., 2016; Roth, 2016; Lichter et al., 2017; He et al., 2019).

ent air pollution is much lower. Another fundamental difference is that employment contracts in developed economies are shaped by rigid labor market institutions and a comprehensive social security system. In such a setting, the typical channel of adjusting labor supply in response to a high-pollution event is by taking a (paid) sick leave. By studying this outcome for workers in Spain, a post-industrial economy with universal sickness insurance, our paper fills an important gap in the literature.

Second, our analysis substantially broadens the range of health impacts considered. While the literature has mostly focused on severe health outcomes such as mortality and hospital admissions, our analysis additionally captures all health impairments that workers find troublesome enough to go and seek a sick leave from their general practitioner. Moreover, thanks to having information on the diagnosis, we shed light on the pathology behind the estimated treatment effect by identifying the medical conditions most affected when pollution levels spike, an aspect that is not yet well understood in the literature. We thus contribute new evidence that helps drawing a more complete picture of the pollution-health gradient.

Third, our paper contributes first evidence on how the estimated pollution-sick-leave gradient interacts with features of the labor market. This aspect is new to the literature on air pollution because our outcome variable is much more driven by individual choices than severe health outcomes. Empirical evidence on this is needed because it is not evident how behavior interferes with sick leaves as a health outcome. A sick leave can be regarded as both, a health impact and an investment for improving future health. In the labor market studied by us, sick leaves might also be affected by workers pretending to be sick (moral hazard) or pretending to be healthy (presenteeism). We provide first evidence on this by showing that treatment effects systematically vary with idiosyncratic job security. We discuss the implications of this finding for cost-benefit analysis in the short and long run.

Finally, the strong segregation between employment contracts with high and low job security makes the Spanish labor market a prime example of a dual labor market. Previous research has shown that this duality lowers productivity and reduce welfare (Dolado et al., 2002; Cabrales et al., 2014; Bentolila et al., 2019). Our paper contributes to this strand of research by identifying an additional channel of inefficiency in dual labor markets: Since workers at risk of losing their jobs are found to be less likely to take a sick leave during high-pollution events, exacerbated presenteeism could adversely affect future health outcomes and lower productivity in this tier of the labor market.

2 Policy background

This section sets the stage for the analysis by explaining the institutional background relating to sickness insurance in Spain and air quality standards in Europe.

2.1 Temporary disability benefits in Spain

The vast majority of workers in formal employment relationships are entitled to temporary disability benefits. In particular, all affiliates of the social security system are entitled to sick leave benefits provided that they see a doctor affiliated with the public health care system for treatment and that they have contributed to social security during a minimum contribution period of 180 days in the five years immediately preceding the illness.[2] The benefit consists of a daily subsidy, the amount of which is given by the product of a regulatory base and a replacement rate. The regulatory base is the amount that is used to determine the benefits paid by the social security system (*Instituto Nacional de la Seguridad Social*) in an insured event such as a sick leave, a permanent disability caused by a work accident, unemployment, or retirement. For each of those events, the law stipulates which and how many contribution bases must be taken into account to determine the regulatory base of the pertaining benefit.

The contribution base is calculated according to the total monthly remuneration received by the employee. To this end, all wage components including extra payments are prorated to the monthly level such that every worker has exactly twelve contribution bases per year. The replacement rate changes over the course of the sick leave. In case of common illness, no benefit is paid until the fourth day of the leave. The replacement rate corresponds to 60% from day four until day 20 of the sickness spell, and rises to 75% from day 21 onward. The maximum duration of the benefit is twelve months, renewable for another six.[3] The benefits are always paid by the employer. However, from the sixteenth day of a leave, the employer can claim reimbursement of the benefits paid by the social security administration.

In addition to social security benefits, many employers have schemes in place that complement sick pay to provide more complete coverage, especially during the first three days of an illness. Moreover, some collective labor agreements grant

[2] No minimum contribution period is required in the case of an accident.

[3] In the case of an accident or occupational disease, the employer pays the first day of the leave in full. After that, social security pays a replacement rate of 75%.

matching funds that add to the replacement rate during a temporary disability. As a result, the difference between the regular salary and the amount of the disability payment may be small or even nil.[4]

2.2 Air quality standards in Europe

Over the past two decades, the European Parliament and the Council have passed a series of directives aimed at harmonizing standards for ambient air quality across EU member states. The directives have established legally binding limits on ambient concentrations for a variety of air pollutants.[5] The most recent "Directive on Ambient Air Quality and Cleaner Air for Europe" (2008/50/EC)[6] establishes limit values that apply to pollutant concentrations measured over different time intervals (hour, day, year). These standards are chosen in accordance to a pollutant's potential to cause health damages in the short and long run. Table 1 summarizes the standards that apply to air pollutants such as particulate matter smaller than 10 micrometers (PM_{10}), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and ozone (O_3).[7] The pollutant of main interest in this paper, PM_{10}, is subject to two standards. The annual mean concentration must not exceed 40 micrograms per cubic meter (µg/m^3). In addition, the occurrence of daily mean concentrations

[4]As an example, consider a worker who earns a monthly base salary of €1,340.54 (before taxes) which amounts to €44.68 per day. He has been sick at home for 22 days and his collective agreement does not complement the temporary disability benefit. During days one to three of the sick leave, the worker earns €0. During days four through 15, the company pays a benefit of 60% of the base salary, i.e., €44.68 × 60% × 12 = €321.73. During days 16 through 20, the social security administration pays a benefit of 60%, i.e. €44.68 × 60% × 5 = €134.05. Finally, the benefit paid by the social security administration rises to 75% during days 21 and 22 (2 days), i.e. €44.68 × 75% × 2.

[5]Directive 1999/30/EC of the European Council of 22 April 1999 relating to limit values for sulphur dioxide, nitrogen dioxide and oxides of nitrogen, particulate matter and lead in ambient air. OJ L 163, 29.6.1999, p. 41-60.

Directive 2000/69/EC of the European Parliament and of the Council of 16 November 2000 relating to limit values for benzene and carbon monoxide in ambient air. OJ L 313, 13.12.2000, p. 12-21.

Directive 2002/3/EC of the European Parliament and of the Council of 12 February 2002 relating to ozone in ambient air. OJ L 67, 9.3.2002, p.14-30

Directive 2004/107/EC of the European Parliament and of the Council . Directive 2004/107/EC of the European Parliament and of the Council of 15 December 2004 relating to arsenic, cadmium, mercury, nickel and polycyclic aromatic hydrocarbons in ambient air. OJ L 23, 26.1.2005, p.3-16.

[6]Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe. OJ L 152, 11.6.2008, p. 1-44.

[7]The directive also regulates particulate matter smaller than 2.5 micrometers ($PM_{2.5}$). This pollutant is not considered in the subsequent analysis due to insufficient coverage of $PM_{2.5}$ measurements in the dataset.

Table 1: Ambient air quality standards for selected pollutants

Pollutant	Concentration (per m^3)	Averaging period	Legal nature	Exceedances each year
Particulate matter	50 μg	24 hours	Limit	35
(PM_{10})	40 μg	1 year	Limit	-
Sulphur dioxide	125 μg	24 hours	Limit	3
(SO_2)	350 μg	1 hour	Limit	24
Nitrogen dioxide	200 μg	1 hour	Limit	18
(NO_2)	40 μg	1 year	Limit	-
Carbon monoxide (CO)	10 mg	Max. daily 8-hour mean	Limit	-
Ozone (O_3)	120 μg	Max. daily 8-hour mean	Target	25 days averaged over 3 years

Notes: Abridged from European Environment Agency,
`http://ec.europa.eu/environment/air/quality/standards.htm`

of 50 μg/m^3 or higher must remain below 36 days per year. Since our econometric identification strategy is based on short-run fluctuations in air pollution concentrations, the analysis below will focus on the 24-hour standard of 50 μg/m^3.

3 Research design

3.1 Sick leaves as a health outcome

Previous research into the effects of air pollution on human health has focused on polar cases. On the one hand, an extensive literature has linked air pollution to severe health outcomes such as morbidity and mortality in adults and infants. On the other hand, a recent strand of the literature has established that air pollution affects humans even under seemingly normal conditions by reducing their productivity at work and in school. Sick leaves can be regarded as an 'intermediate' health consequence that is severe enough to prevent people from following their daily routines while not necessarily leading to dramatic consequences such as hospitalization or death.

Although sick leaves cause substantial economic costs beyond the physical health impact, the literature has not yet investigated this outcome in a systematic way. This paper provides the first, nation-wide study of the impact of urban air pollution on work absenteeism. Specifically, we study paid sick leaves taken by workers within the context of a publicly-provided sickness insurance scheme. Given the novelty of this outcome variable in the context of environmental valuation, it is important to emphasize two peculiarities of this outcome variable which bear relevance for the interpretation of the results.

First, a sick leave indicates, at the same time, a negative health shock and an investment in future health. Taking a sick leave may help to prevent a hospitalization during the pollution spell, and may contribute to better health outcomes in the future. This effect is reinforced if exposure to pollution occurs mainly at the workplace as the sick leave reduces exposure.

The second peculiarity relates to the fact that, like other insurance schemes, sickness insurance is vulnerable to moral hazard. That is, workers might pretend to be sick and take a paid leave. How to reign in moral hazard in sickness insurance is a question of great policy interest in itself, which has been the subject of a burgeoning empirical literature (e.g. Johansson & Palme, 1996, 2005; Henrekson & Persson, 2004). In our econometric analysis below, we assume that moral hazard gets absorbed into worker and time fixed-effects and hence cannot confound the impact of air pollution on sick leaves. However, moral hazard might play a role in explaining heterogeneous impact estimates. Because employers cannot observe the true health status of a worker, they may take the frequency and length of sick leaves taken as a signal about the worker's health. All else equal, employers prefer to award permanent job contracts to workers with good health. Therefore, workers with a low level of job protection have a stronger incentive to signal good health — e.g. by reducing moral hazard — than workers with strong levels of job protection. We shall test this hypothesis in Section 6.2 below.

3.2 Empirical model

Our econometric approach focuses on modeling how short-run variation in ambient pollution affects an individual's propensity to take a sick leave.[8] We specify a linear probability model (LPM) for the share of sick days that worker i living in

[8] This is in line with the literature on the impact of pollution on health outcomes, in that it relates ambient pollution concentrations to a binary health outcome.

city (*municipio*) m takes in week t,

$$\begin{aligned} SICK_{imt} &= \alpha p_{mt} & +w'_{mt}\left[\beta_1+\beta_2 \odot w_{mt}\right]+h'_{mt}\gamma+ \\ &+ & \mu_{m,year(t)}+\lambda_{quarter(t),year(t)}+ \\ &+ & \sum_{a=16}^{65}\theta_a \cdot \mathbb{I}\{AGE_{imt}=a\}+\eta_i+\varepsilon_{imt} \end{aligned} \tag{1}$$

where p_{mt} is a measure of ambient pollution concentrations in city m and week t, w_{mt} is a vector of weather variables in city m and week t, and h_{mt} is a vector containing further city-level controls for school vacations, bank holidays and flu prevalence in week t. Furthermore, the equation includes quarter-by-year effects λ and city-by-year effects μ to control for business-cycle effects and for unobserved local shocks, respectively. As worker-level controls, we include a full set of age dummies and individual fixed effects η_i.

The identifying variation in this regression comes from week-to-week changes in local pollution concentrations and sick leaves within a city and year, after netting out worker-specific effects and correcting for weather as well as other reasons for absence such as business-cycle fluctuations. Inference on the parameters in equation (1) is based on robust standard errors with two-way clustering at the week and city levels.

It is widely held that air pollution is not randomly assigned across space and individuals (Graff Zivin & Neidell, 2013). In equation (1), endogeneity of air pollution might arise for a variety of reasons. First, economic fluctuations that affect both employment and pollution might confound the estimates. For example, an unobserved shock to labor demand might induce both an increase in local pollution while also increasing labor supply (Hanna & Oliva, 2015). Second, to the extent that sick workers cause fewer emissions than they do at work (or on their way to the workplace), the causality might go from sick leaves to air quality. Third, individuals that are more susceptible to adverse health impacts of air pollution might choose to live in less polluted areas. Fourth, pollution exposure is likely measured with error because we use average concentrations rather than individual exposure. All of the above sources of endogeneity would bias the estimated health impact of pollution towards zero. Finally, the estimated pollution impact might also be biased away from zero if it picks up the effect of omitted pollutants that are correlated with the pollutant of interest. The direction of the overall bias is thus ambiguous.

Our research design mitigates concerns about endogeneity in the following ways. First, our focus on sick leaves discards variation from extensive-margin adjustments to labor supply which are not related to a temporary disability. Second, the high-frequency nature of the data allows us to control for a variety of time effects that mitigate simultaneity bias. Third, thanks to the longitudinal structure of the data, we are able to purge the estimates from the effects of locational sorting by individuals or firms. These features help to mitigate some causes of endogeneity, but not necessarily all of them. In particular, if pollution is subject to classical measurement error, an instrumental variable is needed to consistently estimate its causal impact on sick leaves. In the next section, we propose such an approach to instrument for PM_{10}, the pollutant of interest in this study.

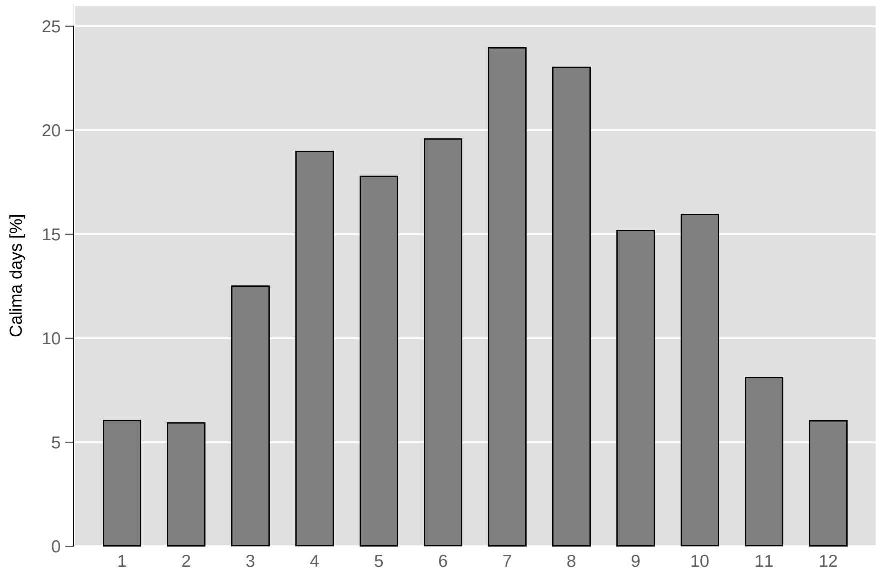
We focus on PM_{10} because no other pollutant exhibited more frequent and more severe violations of the 24-hour limits set by the EU during our study period (cf. Table 3 below). Consequently, PM_{10} is a primary target for air quality management in urban Spain. Estimating dose-response functions for PM_{10} is necessary for designing efficient pollution control regulations, and it is feasible thanks to long-range atmospheric transport of PM_{10} which shifts ambient concentrations in ways that are conditionally independent of local pollution sources.

3.3 Instrumental variable estimation

We address the issue of endogenous pollution in equation (1) within a two-stage least squares (2SLS) estimation framework that exploits quasi-experimental variation in PM_{10} originating from Sahara dust advection. Under certain meteorological conditions, storms in the Sahara desert stir up dust into high altitudes. These dust clouds can travel very long distances and reach European territory several times a year. The arrival of Sahara dust occurs throughout all of Spain, and it is most frequently observed on the Canary Islands, due to their geographical proximity to the Sahara, where the phenomenon is popularly known as 'Calima'. For the sake of brevity, we shall use this term henceforth when referring to episodes of increased PM_{10} concentrations due to long-range transport of African dust. A Calima episode typically lasts several days and is accompanied by regional weather patterns that facilitate atmospheric dust transport. For this reason, the distribution of Calima episodes is not uniformly distributed over the year but peaks during the summer months as depicted in Figure 1.

Figure 2 illustrates how Sahara dust traveled across different regions in Spain during a Calima episode in June 2009. On June 9, the dust plume was building up

Figure 1: Average percentage share of Calima days per month



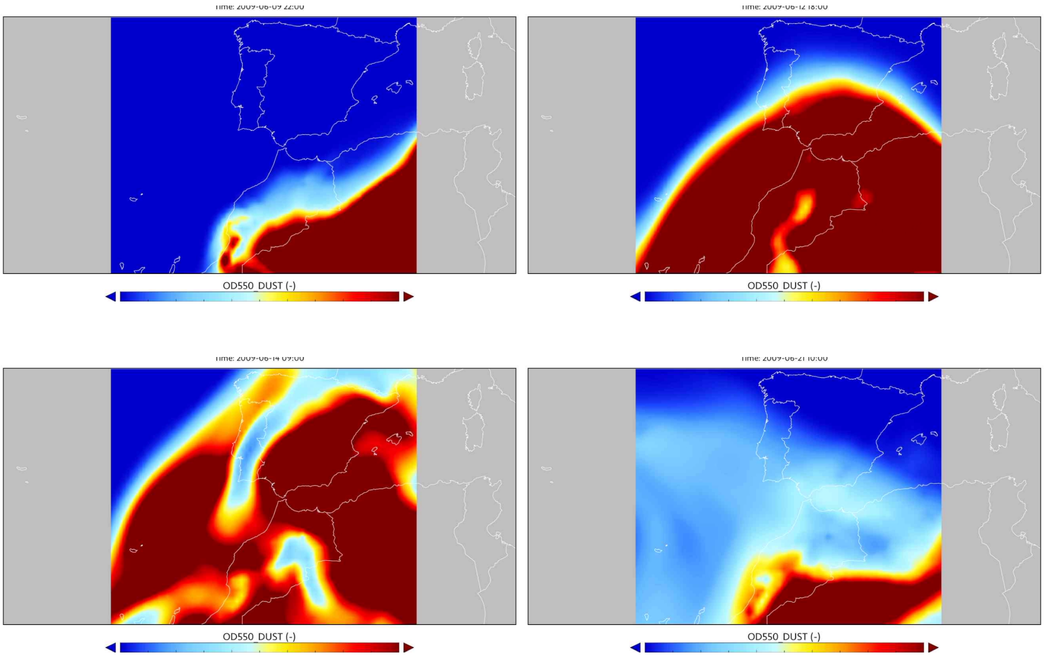
Notes: Each bar represents the average percentage share of days in a given month classified as a Calima episode, based on data from the Spanish Ministry for the Ecological Transition (2018).

over North Africa (Figure 2a). Three days later, the plume had extended to cover the Canary Islands and Southern Spain, but not the Balearic Islands (Figure 2b). On June 14, all of Spain was exposed to Sahara dust, though the intensity varied across regions (Figure 2c). Figure 2d depicts the withdrawal of the dust cloud which was completed at the end of June.

The influence of Sahara dust on ambient PM_{10} concentrations cannot be measured by regular air quality monitors. Therefore, the possible link between ambient pollution and Calima is evaluated *ex post* using data from rural background monitors and meteorological back-tracking models such as the one that generated the data underlying Figure 2. The scientific procedure (Escudero et al., 2007; Querol et al., 2013) behind this attribution is standardized across EU member states and designed to ensure a level playing field across European cities when determining whether they are in compliance with the EU standard for PM_{10} concentrations. Because Calima events substantially increase non-anthropogenic PM_{10} concentrations, the cities affected by this phenomenon are allowed to discount the measured 24-hour-mean concentration for this effect (see Appendix C for more details). Offical PM_{10} discounts constitute a valid instrument for pollution because they shift local PM_{10} concentrations in ways that are plausibly orthogonal to local conditions

Figure 2: Sahara dust intrusion in Spain

(a) June 9, 10pm (b) June 12, 4pm



(c) June 14, 9am (d) June 21, 10am

Notes: Visualization of Sahara dust intrusions on the Iberian peninsula during the month of June 2009. Data and images from the BSC-DREAM8b model, operated by the Barcelona Supercomputing Center (`http://www.bsc.es/earth-sciences/mineral-dust-forecast-system/`)

that drive sick leaves, after conditioning on weather.

Specifically, denote by c_{mt} the weekly share of days for which the city m's applicable PM_{10} discount is strictly positive (Calima days). The first-stage equation for pollution is given by

$$\begin{aligned} p_{mt} &= \widetilde{\alpha} c_{mt} & + w'_{mt}\left[\widetilde{\beta}_1 + \widetilde{\beta}_2 \odot w_{mt}\right] + h'_{mt}\widetilde{\gamma} + \\ &+ & \widetilde{\mu}_{m,year(t)} + \widetilde{\lambda}_{quarter(t),year(t)} + \\ &+ & \sum_{a=16}^{65} \widetilde{\theta}_a \cdot \mathbb{I}\{AGE_{imt} = a\} + \widetilde{\eta}_i + \zeta_{imt} \end{aligned} \tag{2}$$

where all variables other than c_{mt} correspond to those in equation (1). In the second stage, we estimate the outcome equation after substituting predicted pollution $\hat{p}_{mt}$ from equation (2) for p_{mt} in equation (1).

A crucial assumption underlying this approach is that Calima events have no direct effect on sick leaves other than via increased ambient concentrations of

PM_{10}. We flexibly control for local weather to rule out the possibility that particular weather conditions associated with Calima affect the outcome variable. This strategy has proven effective even when the instrument is based on local weather conditions such as wind direction (Hanna & Oliva, 2015; Deryugina et al., 2019) or thermal inversion (Arceo et al., 2016; He et al., 2019). Since our instrument is based on a more regional weather phenomenon, the potential for confounding weather impacts and pollution appears to be small. The exclusion restriction would also be violated if Calima changed behavior. A precondition for this is that workers are aware of Calima while it lasts. On the Canary Islands, located 1,300 kilometers to the south-west of the Iberian peninsula and just 115 kilometers off the Moroccan Atlantic coast, Sahara dust advection is frequent and sometimes visible, hence awareness must be taken for granted. Although we cannot rule out behavioral responses to Calima there *a priori*, robustness checks discussed in Section 5.2.3 below show that our results are not driven by workers from the Canary Islands. In the rest of Spain, Sahara dust events are less frequent and less intense. We found no evidence of the public being alerted to such events during our study period.

Finally, the exclusion restriction would be violated if PM_{10} originating from the Sahara has a substantially different effect on human health than PM_{10} from local sources. Specifically, if the chemical composition of PM_{10} from the Sahara differed substantially from that of non-desert PM_{10}, we should suspect that their health impacts differ, too. Perez et al. (2008, Fig. 3) compare mass-adjusted concentrations of the four group elements in PM_{10} and find that crustal elements are more frequent during Saharan dust days whereas carbon, secondary aerosols, and marine aerosols show no difference. From a study of Madrid, Barcelona and eleven other southern European cities, Stafoggia et al. (2016, p. 418) conclude that “the health effects of dust-derived PM_{10} are of the same (or similar) magnitude as those reported for anthropogenic sources of air pollution”. This lends support to our assumption that the instrumental variable has no direct effect on human health except through raising overall ambient PM_{10} concentrations.

4 Data

For the analysis in this paper, we merge several large datasets that are described in more detail in this section.

4.1 Data sources

4.1.1 Employment histories

Our primary data come from the National Institute of Social Security which administrates both health insurance and pension benefits for more than 93% of the workforce in Spain. Since 2004, the administration maintains a research dataset, the Muestra Continua de Vidas Laborales, henceforth referred to as the MCVL (Spanish Ministry of Employment, Migration and Social Security, 2018). The MCVL is a non-stratified random sample of anonymized individual work histories, covering approximately 4% of all individuals who were affiliated with social security at some point during the reporting year. An individual record contains information on both current-year and historical employment relations, dating back to the time when the administration began to keep computerized records.

4.1.2 Sick leaves

Information on sick leaves taken by social security affiliates is first gathered and processed by the employer's mutual indemnity association which relegates the information back to the social security administration when reimbursements are claimed. While sick leaves are not contained in the MCVL, the social security administration has provided us with a customized dataset that merges individual records of sick leaves to the MCVL during the years from 2005 to 2014. As a result, we have a panel dataset containing daily observations of sick leaves taken by 1.6 million individuals, the diagnosis code based on the International Statistical Classification of Diseases and Related Health Problems (ICD), as well as information on their employment status, wage, age, occupation, and many other characteristics. To the best of our knowledge, we are the first team of researchers to analyze this extraordinary dataset.[9] A caveat is that the dataset is not well-suited to analyze sick leaves taken by unemployed workers. This implies that the analysis to follow has little to say about the impact of air pollution on the unemployed, and on severe health consequences such as permanent disability or death.

[9]Alba (2009) and Malo et al. (2012) have used linked MCVL and sick leave data before, but only for a single year.

4.1.3 Air pollution

Data on air pollution were obtained from the Spanish Ministry for the Ecological Transition (2016). These data are updated on a yearly basis and are also used within the EU framework for reciprocal interchange of information and reporting on ambient air quality (2011/850/EU). The database is comprised of time series data on ambient concentrations of a variety of air pollutants with up to hourly resolution as well as meta-data on monitoring stations. For our analysis, we use readings taken by 784 air quality measurement stations across Spain between January 2005 and December 2014. Apart from location, these stations differ in terms of the set of air pollutants they monitor and the time window of measurement. The vast majority of stations remain active throughout the sample period. The meta-data report the municipality where the measurement station is located. This allows us to link them to construct a dataset of air quality across Spanish cities. When more than one air quality station is located in a municipality, the readings are averaged across stations.

4.1.4 Weather

Meteorological data were provided by the Royal Netherlands Meteorological Institute (2019) as part of the European Climate Assessment & Dataset (ECA&D) project. Within the ECA&D project, national meteorological institutes and research institutions from 31 European countries collect daily data on twelve essential climate variables. For Spain, historical information is available from 1896 onward. The number of variables and geographical coverage has been increasing steadily until today. Based on a total of 193 geocoded weather stations, we assign to each municipality the weather conditions at the station that is closest to the municipality's centroid and has non-missing data. Hence, the assigned weather station is not necessarily located within the boundaries of the municipality.

4.1.5 Calima variables

We downloaded data on PM_{10} discounts from the website of the Spanish Ministry for the Ecological Transition (2018). The data report daily PM_{10} discounts for 29 locations in Spain. We follow the official procedure and assign to each municipality the closest station with available data (see Appendix C for more details).

4.1.6 Other controls

Factors such as epidemics, bank holidays, and school vacations likely affect an individual's propensity to call in sick. To the extent that these factors are correlated with pollution, omitting them from the analysis might result in biased estimates. We thus collected data to control for such factors.

Flu outbreaks are monitored and recorded by the Spanish center for disease control (*Instituto de Salud Carlos III*) under the auspices of its flu surveillance system (*Sistema centinela de Vigilancia de la Gripe en España*). Weekly data for the flu incidence (number of cases per 100,000 inhabitants) are published for each autonomous community,[10] except Galicia and Murcia (Spanish Center for Disease Control, Instituto de Salud Carlos III, 2016).[11] We merge the flu data to our estimation sample at the level of the Autonomous Community. In case of missing observations, data were imputed using the national average.

The dates of school vacations and bank holidays vary at the levels of the autonomous community, province, and even municipality. We gather this information from the various regional "official bulletins" and numerous other sources. The linking is done at the pertinent geographic level.

4.2 Data cleaning

Our dataset contains daily records of individual sick leaves between January 1, 2005 and December 31, 2014. The raw sample is comprised of approximately four billion worker-by-day observations over the full sample period. However, some cleaning steps are necessary in order to use the sample for our purposes. This subsection describes and justifies those steps.

First, we drop all workers living in municipalities with less than 40,000 inhabitants. For these workers, the place of residence is reported only at the level of the province, which is too coarse for accurate spatial matching to pollution and weather data. For all remaining workers, we know the place of residence at the five-digit municipality code level which is required for matching. Since these muncipalities have 40,000 inhabitants or more, we shall henceforth refer to them as cities. We retain just over half of the workers in the raw sample after performing this step.

[10]Spain is not a federation, but a decentralized unitary state comprised of 17 autonomous communities and two autonomous cities.

[11]In a normal year, the monitoring is in place during the flu season, i.e. from week 40 until week 20 of the following year. In 2009, year-round surveillance was in place because of the swine flu.

Second, we impose the following sample restrictions. We only keep worker-by-day observations of individuals aged 16 to 65 who are actively employed and for which we have information on employers and wages. Individuals who are reported to have taken any sick leave of more than 550 days are dropped, as this number exceeds the legal maximum duration. We also remove individuals with reported employment relations after death, negative-length employment durations, as well as duplicate or negative wages. Worker-by-day observations with inflation-adjusted wages in the 99.5th percentile are also excluded.

Third, we drop observations with missing pollution data. In cities where pollution measurements are derived from more than one air quality monitor, failure to account for entry and exit of monitors would lead to incoherent time series. In such cases, we drop all data from monitors reporting less than 120 days of PM_{10} in any reporting year. If this leaves two or more monitors in the data, we require that all monitors report in all years. Finally, we drop all observations on December 31 and January 1 because of the unusually high contamination levels that result from fireworks during the new year's festivities.

Following these cleaning steps, our sample contains between 231 thousand and 263 thousand workers per year who live in 99 cities spread across the Spanish peninsula and the islands. Figure 3a displays a map with all cities included in the estimation sample, and Figure 3b marks the location of each air quality monitor in the sample. The 99 cities included in our sample are home to 55% of the Spanish population and to 51% of all workers affiliated with the general regime of the social security system.

4.3 Descriptive statistics

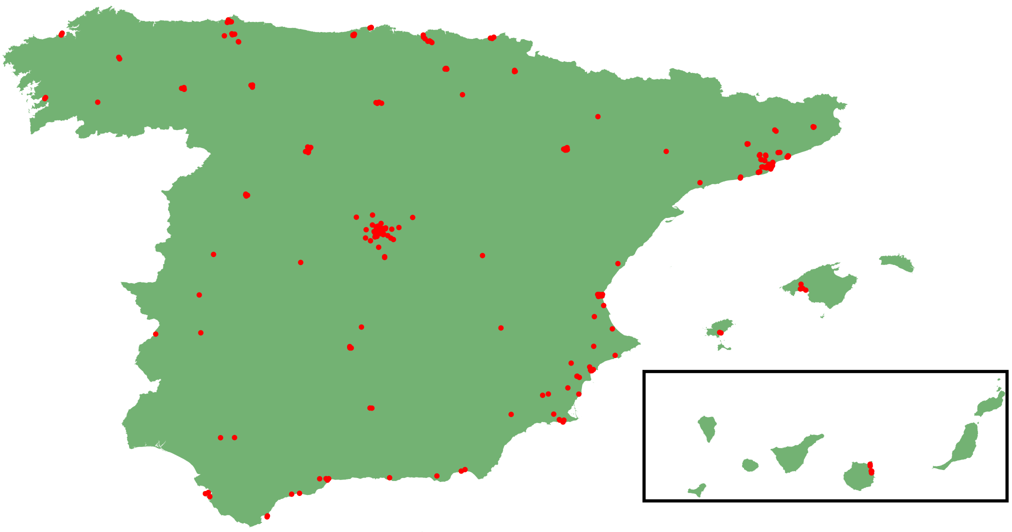
Our sample contains more than half-a-billion daily observations for 466,174 workers aged between 16 and 65 years. To improve computational tractability, we aggregate the data to the weekly level. The first panel of Table 2 provides summary statistics at the worker level. The average propensity to take a sick leave in a given week is 2.79%. The share of female workers is 46%. Figures B.1 and B.2 in Appendix B plot the duration of sick leaves and the frequencies of the main diagnosis codes, respectively.

The remaining panels of Table 2 report descriptive statistics on pollution variables and other covariates, gathered at the city-by-week level. The second panel summarizes the data on particulate matter. The average concentration of PM_{10} is

Figure 3: Geographic coverage

(a) Cities in the sample

(b) Location of air quality monitors



Source: Own representation based on data from Database of Global Administrative Areas (GADM) `https://gadm.org/`

Table 2: Descriptive statistics, 2005-14

Variable	**mean**	**sd**	**min**	**max**	**observations**
1. Social security data (workers)					
Age	37.7	11.5	16	65	466,174
Female share [%]	46	49.8	0	100	466,174
Absence rate [%]	2.79	15.9	0	100	$\geqslant$ 100 million
2. Particulate matter PM_{10} (city-by-week)					
Ambient concentration [μg per m^3]	26.8	13.0	0.0	188.0	38,613
Concentration due to *Calima* event [μg per m^3]	2.1	5.5	0.0	140.6	38,613
Days PM_{10} exceeds 24-hour standard [%]	7	19	0	100	38,613
Calima days [%]	15	25	0	100	38,613
3. Other air pollutants (city-by-week)					
CO [mg per m^3]	0.5	0.3	0.0	5.2	25,279
SO_2 [μg per m^3]	5.5	4.9	0.0	121.6	29,529
NO_2 [μg per m^3]	25.7	14.7	0.0	140.8	33,421
O_3 [μg per m^3]	73.1	25.8	1.0	176.6	31,305
4. Weather data (city-by-week)					
Temperature [°C]	15.9	6.4	-6.7	36.8	38,613
Wind speed [0.1 m/s]	29.4	15.2	0.0	142.9	38,613
Precipitation [0.1mm]	15.5	32.0	0.0	972.0	38,613
Cloud cover [okta]	3.9	1.8	0.0	8.0	38,613
Sunshine [h]	7.3	3.2	0.0	14.5	38,613
Humidity [%]	66.7	13.5	20.0	100.0	38,613
Pressure [hPa]	1,016.7	5.8	978.3	1,041.2	38,613
5. Flu prevalence (region-by-week)					
Flu rate per 100,000 inhabitants	47.1	86.9	0.0	1016.5	11,587

27 µg/m^3, which is well below the EU annual standard of 40 µg/m^3, but higher than 20 µg/m^3, the limit value recommended by the World Health Organization (WHO, 2006). Non-anthropogenic PM_{10} contributes just 2.1 µg/m^3 to this average value. However, the maximum values show that the non-anthropogenic contribution to PM_{10} is very important on high-pollution days. The share of days exceeding the 24-hour standard is 7%, and the share of Calima days is 15%. This means that not every Calima day is a high-pollution day.

The third panel of Table 2 provides descriptive statistics for other air pollutants (CO, SO_2, NO_2, and O_3), and the fourth panel summarizes the weather variables. Daily average temperature is measured in degrees Celsius, wind speed in 0.1 meters per second, precipitation in 0.1 millimeters, and cloud cover in integer-valued oktas ranging from 0 (sky completely clear) to 8 (sky completely cloudy). Sunshine is measured in hours per day, humidity in percent and pressure in hectopascals. The last panel of the table reports the flu rate, in cases per 100,000 inhabitants.

Table 3: Distribution of days per week by pollutant and percent of limit value

	PM_{10}	CO	SO_2	NO_2	O_3
$[50;75)$	26.2	0.0	0.1	22.9	41.0
$[75;100)$	11.5	0.0	0.0	14.9	23.3
$[100;125)$	4.3	0.0	0.0	8.8	4.2
$[125,\infty)$	3.1	0.0	0.0	9.0	0.3

Notes: Each column reports the percentage share of days per week with ambient concentrations for different quartiles of the daily limit value stipulated by the EU. Limit values refer to either 24-hour averages (for PM_{10} and SO_2) or maximum 8-hour averages (for CO and O_3). For NO_2, the bins refer to daily averages evaluated against the annual limit value, as the EU has not defined a daily limit value. All limit values are reported in Table 1.

In some of the regressions below, we examine a possible nonlinear relationship between health and air quality. Following Currie et al. (e.g. 2009a), we partition the support of the distribution of pollution measurements at quartiles of the EU-mandated daily limit value: zero to 50% of the limit, 50% to 75%, 75% to 100%, 100% to 125% of the limit, and above 125% of the limit. Table 3 reports the percentage share of days in each partition. EU air quality standards were exceeded for PM_{10} (with a frequency of 7.4%) and for O_3 (with a frequency of 4.5%). The concentrations for CO and SO_2 hardly ever exceeded half of the respective daily limit values.[12] Since there is no daily EU limit for NO_2, we construct bins for this pollutant using the EU limit for *annual* average concentrations (40 $\mu g/m^3$), which is exceeded on 17.8% of days. This number is reported for completeness and has no immediate interpretation in the context of existing air quality regulations.

5 Results

5.1 Baseline estimates

Figure 4 plots weekly absence rates against ambient levels of PM_{10}. Both the raw data and the residualized data from an OLS estimation of equation (1) at the city-

[12]This is not to say that the ambient concentrations of carbon monoxide and sulfur dioxide are innocuous. In fact, the World Health Organization has recommended much stricter air quality standards than those prevalent in the EU in order to avoid health problems. Municipalities also violated EU standards other than the ones listed here, such as the annual limit value for NO_2.

level suggest that the relationship is positive and increasing. This is also born out by the estimation results for regression equation (1). Table 4 reports OLS estimates (in columns 1 and 4), IV estimates (columns 2 and 5), and respective first stages (columns 3 and 6) for two alternative measures of air pollution.[13] In the first three columns, PM_{10} is measured as the share of days per week on which the daily limit concentration of 50 µg/m^3 is exceeded (PM_{10} exceedance). This identifies the treatment effect of pollution using only high-pollution events. In columns 4 to 6, pollution is measured as average concentrations in µg/m^3. If it was known with certainty that the sick leave response is directly proportional to pollution concentrations, estimating a specification linear in PM_{10} would be more efficient as it exploits variation in pollution over the entire support.

The IV regression is implemented as a two-stage-least-squares (2SLS) procedure where local PM_{10} is first regressed on the Calima variable and controls. This regression is reported in columns 3 and 6 of Table 4 for PM_{10} exceedance and PM_{10}, respectively, and shows that Calima is a strong predictor of ambient PM_{10} concentrations ($R^2 = 0.41$ and $R^2 = 0.65$, respectively). In the second stage, the absence rate is regressed on the predicted PM_{10} variable and controls.

The association between pollution and sick leaves is positive and statistically significant across all specifications, suggesting that higher levels of pollution lead to more sick leaves. The IV estimates exceed the OLS estimates by a factor of 3. This points to attenuation bias that could arise from measurement error in PM_{10} but also due to other sources of bias that were discussed in Section 3.3 above. In the analysis to follow, we thus focus on the IV estimator which allows for a causal interpretation of the estimated relationship. The IV estimates of our baseline regressions imply that, on average, a 10-percentage point reduction in the share of exceedances of the limit value reduces the absence rate by 0.0213 percentage points, i.e. by 0.8% of the mean absence rate (0.0279). Furthermore, a reduction in average PM_{10} concentrations by 10 µg/m^3 reduces the absence rate by 0.03 percentage points.

[13] The estimation of OLS and IV regressions with high-dimensional fixed effects is implemented with the Julia programming language package FixedEffectModels.

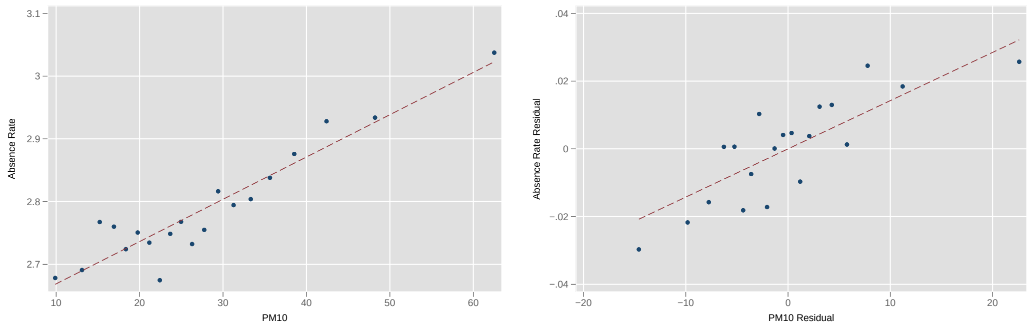
Table 4: Baseline estimates for PM_{10}

	Weekly absence rate		PM_{10} exceedance	Weekly absence rate		PM_{10}
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10} exceedance	0.073***	0.213***				
	(0.016)	(0.067)				
PM_{10}				0.001***	0.003***	
				(0.0004)	(0.001)	
Calima			0.194***			15.5***
			(0.022)			(1.06)
Estimator	OLS	IV	First-stage	OLS	IV	First-stage
Observations	100,739,754	100,739,754	100,739,754	100,739,754	100,739,754	100,739,754
Mean outcome	2.79	2.79	0.08	2.79	2.79	28.04
R^2	0.165	0.165	0.413	0.165	0.165	0.648
First-stage F statistic		80.6		216		

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 4: Sample correlation between sick leaves and PM_{10}

(a) Binned scatter plot (b) Binned scatter plot residuals



Notes: The figures show binned scatter plots after grouping all observations into 20 bins of equal size based on the variable depicted on the x-axis. The dots represent the mean value for each bin. The dashed line shows the predicted relationship based on an OLS estimation for the underlying data. Subfigure (a) plots the relationship between PM_{10} and weekly absence rates at the city-level. Subfigure (b) plots the relationship of the same variables, after controlling for city-year fixed-effects, year-by-month fixed-effects, weather conditions, school holidays, other public holidays, and flu rates.

5.2 Robustness checks

5.2.1 Dynamics

Our main regression equation relates sick leaves to contemporaneous pollution and weather. Previous research has documented that air pollution can have dynamic effects on worker productivity (He et al., 2019). To investigate this, we estimate alternative specifications of equation (1) which include weekly lags of PM_{10} exceedance and use the respective lags of Calima as instrumental variables. The results, reported in Appendix Table A.2, show that the impact of air pollution on sick leaves can last for up to two weeks. Compared to the specification without lags, the contemporary effect of PM_{10} decreases in magnitude by about 15% but the coefficient on the first lag is almost as large. Further lags do not matter empirically.

The lag distribution is open to more than one interpretation, however. When interpreted as a dynamic treatment effect, it implies that a one-off shock to pollution affects health in the current and in the next week. The total effect would then be given by the sum of both point estimates which amounts to twice the contemporaneous effect. Yet this could be confounded by high-pollution episodes that last multiple days. For example, a four-day event can fall either into a single week or extend over two subsequent weeks. In the former case, the event contributes only to identification of the coefficient on contemporaneous PM_{10}, but in the latter case the event also helps to identify the coefficient on lagged PM_{10}. Our regression model cannot disentangle the dynamic effects of two-day pollution event in the previous week from the contemporaneous effects of four-day event that extends over both the previous and current week. In the analysis to follow, we thus focus on the contemporaneous effect only. We acknowledge that this might underestimate the full health impact.

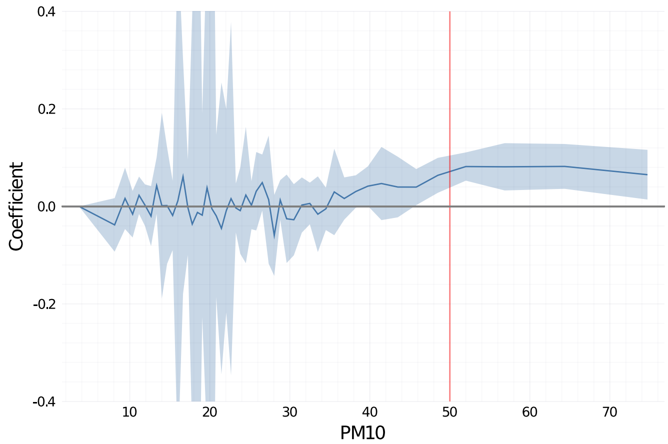
5.2.2 Non-linear effects of pollution

We shed light on the functional form of the pollution-health relationship by re-estimating equation (1) using alternative thresholds to define a high-pollution event. Appendix Table A.3 presents results for OLS and IV regressions where we use the share of week days with pollution exceeding 50%, 75%, 100% (as in the baseline), or 125% of the legal limit of 50 $\mu g/m^3$ on a given day. The IV point estimates show a clear pattern in that (i) higher threshold values for pollution lead to stronger increases in the propensity to take a sick leave, and (ii) the increment in the sick leave impact increases for constant increments in the pollution threshold. The implication is that a linear functional form, which has often been used in the literature, would misrepresent the underlying pollution-health gradient in our application and would lead us to underestimate the health hazard for the right tail of the pollution distribution. The threshold-based approach we use throughout the remainder of this paper circumvents this problem, though it averages over the impacts of high and extremely-high pollution days.

To investigate whether pollution levels below the EU 24-hour standard have a significant impact on sick leaves taken, we estimate a non-parametric version of equation (1) where individual-by-week pollution exposures are sorted into 50 bins of equal size.[14] The share of days in the lowest quantile is omitted. The OLS estimates for the different pollution bins are plotted in Figure 5. The grey area represents the 95% confidence intervals of each indicator. For visual clarity, the 49 estimates and confidence intervals are connected by straight lines. The point

[14] We classify daily city-level PM_{10} into 50 quantiles after weighing each city-day by the number of workers observed in the MCVL to account for different exposure profiles across cities. To avoid a disproportionately large bin at the top, we drop PM_{10} readings in the 99.9th percentile. The 50 indicators for each bin are then averaged at the weekly level. Hence, the resulting variable indicates the share of days in a given city and week in a particular bin. After matching the indicators to the worker-level data, we estimate equation (1), replacing p_{mt} by 49 indicators.

Figure 5: Non-linear impacts of PM_{10} on sick leaves



Notes: The graph depicts point estimates for different bins of PM_{10} concentrations from an OLS regression of sick leave on indicators for each bin and controls. The red line indicates the location of the EU 24-hour standard for PM_{10}. The grey areas indicate 95%-confidence intervals.

estimates are positive and increasing for values of 35 µg/m^3 and higher, and they become statistically significant at 46 µg/m^3 just below the limit value.

5.2.3 Exclusion of Canary Islands

The IV estimation rests upon variation in particulate matter due to Sahara dust advection and transport. Because of their geographic proximity to the Sahara, the Canary Islands are subject to this phenomenon more frequently and with greater intensity than the rest of Spain. This could lead to a violation of the exclusion restriction, e.g., if the local population change their behavior in response to Calima. We therefore estimate the main specification after dropping all cities located on the Canary Islands from the sample. Results reported in Appendix Table A.4 show that the Canary Islands have no particular influence on the estimation results.

5.2.4 Non-linear regression model

Our baseline specification (1) fits a linear probability model to an outcome variable that ranges only between zero and one. The model is thus necessarily mis-specified, but it has the enormous benefit of allowing us to implement high-dimensional fixed-effects and IV estimators in straight-forward ways. Since the realizations of the outcome variable – the share of sick leaves at the city-by-week-level – takes values between 0.38% and 7.02%, we reckon that the bias due to misspecification is not large enough to give up the simplicity and computational tractability of the linear model. We investigate this by estimating a logit model with fractions and worker fixed effects as a non-linear alternative model. This alternative has its own drawbacks as it does not accommodate instrumental variables and, in general, the inclusion of individual fixed effects gives rise to an incidental parameters problem.[15] Results reported in Appendix Table A.5 show that the average marginal effect for the PM_{10} exceedance of 0.063 is smaller than but very close to the OLS baseline estimate of 0.073, while for the PM_{10} in levels, the average marginal effect of 0.001 is almost equivalent to the OLS baseline estimate.

5.3 Estimates by ICD-9 diagnosis group

For a subset of absence spells we observe diagnoses, coded according to the Ninth Revision of the International Statistical Classification of Diseases (ICD-9). This classification scheme subdivides diseases and health-related problems into 17 main categories, referred to as chapters. The three most commonly diagnosed ICD-9 chapters in our sample are "VI: diseases of the musculoskeletal system", "V: mental disorders", and "XVII: injury and poisoning", as reported in Appendix Table B.3. Table 5 reports estimates of 17 IV regressions, using as the dependent variable in equation (1) the chapter-specific absence rate. In those regressions, we drop (i) all spells for which the ICD-9 code is not reported and (ii) all spells with a diagnosis different from the diagnosis group used in the definition of the respective dependent variable, which accounts for the fact that diagnoses are mutually exclusive.[16]

The strongest effect of PM_{10} on sick leaves is found for the diagnosis chapters XVI and V. The former stands for "symptoms, signs and ill-defined conditions" and includes headaches, tachycardia (elevated heart rate), apnea (cessation of breathing), or nausea, among others. The latter (mental disorders) includes, among others, symptoms related to dementia and depression, which have been linked to air pollution in recent research (Bishop et al., 2018; Braithwaite et al., 2019; Fan et al., 2020). A positive effect also emerges for chapter VI (diseases of the nervous and

[15] When the panel is short (T small), noisy estimates of the fixed effects contaminate the estimates of the common parameters and the marginal effects due to the nonlinearity of the model. In particular, the magnitude of the bias of the maximum likelihood estimator would be on the order of $1/T$. However, given that we use weekly data, the average number of observations per worker in our sample is 217.7, suggesting that the incidental-parameter bias will be very small. Simulations by Fernandez-Val (2009) show that the size of the bias is already small when $T = 16$.

[16] Appendix Table A.6 reports the results from an alternative regression where chapter-specific absences are set to zero whenever (i) no diagnosis is reported or (ii) an ICD-9 code does not belong to the diagnosis chapter defining the dependent variable. The results are almost identical to the ones reported in Table 5.

sense organs) which includes Alzheimer's disease, migraine, and eye disorders. In addition, we find a small but statistically significant negative effect for the chapter "diseases of the blood and blood-forming organs". We refrain from a causal interpretation of this point estimate because it is based on very few observations: Less than 0.3% of all sick leaves are classified in this chapter (vs. 11.6%, 13.5%, and 4.2%, respectively, for the above-mentioned diagnosis chapters; cf. Table B.3). Interestingly, we do not find statistically significant effects when looking at diagnosis chapters for respiratory diseases (which includes asthma, bronchitis, and chronic obstructive pulmonary disease) or cardiovascular diseases.[17]

6 Heterogeneity of treatment effects

The richness of our data allows us to investigate the heterogeneity of treatment effects with respect to a wide variety of characteristics of workers and jobs. To do so, we define for each characteristic a categorical variable and split the sample accordingly. In this way, we accommodate heterogeneous reactions not only to air pollution but also to any other variable specified in regression equation (1). First, we analyze heterogeneity with respect to worker characteristics. Next, we study how workers in different occupations react to air quality. We conclude the examination of heterogeneous treatment effects comparing workers with different initial health stocks.

6.1 Heterogeneity across workers

Gender

When splitting the sample by gender, the point estimates are larger for female workers than for male workers (cf. Appendix Table A.7). A 10-percentage point reduction in the share of PM_{10} exceedances reduces the absence rate by 0.026 percentage points for women and 0.017 percentage points for men. However, taking into account the mean absence rates for each group (3.41% for females, and 2.25% for males), the relative effect is 0.8% in both cases.

[17] We can only speculate about the reasons for this. It could be that patients with asthma or respiratory symptoms are more likely to self-medicate in response to a pollution shock, in particular when they know that they have the disease. Bias could also arise due to the fact that ICD codes are not available for all sick leaves, or due to systematic differences in the reporting quality, depending on whether patients were treated in the emergency room or by their general practicioner.

Table 5: Effects of PM_{10} on ICD-9 Diagnosis Groups

	PM_{10} exceedance	Mean	N
I: Infectious and Parasitic Diseases	0.002	0.067	97,528,520
	(0.007)		
II: Neoplasms	0.004	0.097	97,511,232
	(0.005)		
III: Endocrine, Nutritional and Metabolic Diseases, and Immunity Disorders	0.001	0.019	97,432,211
	(0.001)		
IV: Diseases of the Blood and Blood-forming Organs	-0.001***	0.007	97,417,805
	(0.000)		
V: Mental Disorders	0.038***	0.302	97,730,323
	(0.009)		
VI: Diseases of the Nervous System and Sense Organs	0.015**	0.096	97,523,735
	(0.007)		
VII: Diseases of the Circulatory System	0.001	0.091	97,507,524
	(0.002)		
VIII: Diseases of the Respiratory System	0.008	0.137	97,624,631
	(0.012)		
IX: Diseases of the Digestive System	0.010	0.101	97,535,500
	(0.007)		
X: Diseases of the Genitourinary System	-0.004	0.054	97,474,571
	(0.004)		
XI: Complications of Pregnancy, Childbirth, and the Puerperium	0.003	0.080	97,498,058
	(0.003)		
XII: Diseases of the Skin and Subcutaneous Tissue	-0.001	0.026	97,441,348
	(0.003)		
XIII: Diseases of the Musculoskeletal System and Connective Tissue	0.020	0.596	98,073,192
	(0.019)		
XIV: Congenital Anomalies	-0.000	0.006	97,416,810
	(0.001)		
XV: Certain Conditions originating in the Perinatal Period	0.001	0.001	97,412,186
	(0.000)		
XVI: Symptoms, Signs and Ill-defined Conditions	0.042***	0.282	97,745,795
	(0.011)		
XVII: Injury and Poisoning	0.017	0.289	97,733,701
	(0.012)		

Notes: Rows report the IV point estimates for PM_{10} exceedance in separate regressions where (i) the dependent variable is defined on sick leaves with a diagnosis from the ICD-9 chapter indicated in column 1 and (ii) all sick leaves with a diagnosis from another chapter are dropped. Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Age

Appendix Table A.8 reports the regression results after subdividing workers into three age groups of approximately equal size. The point estimates increase with age among young and middle-aged workers. For workers older than 45 years, the increment in the OLS point estimate is less pronounced and the higher mean absence rate in this group implies that the relative impact of high-pollution events is as low as in the group of young workers. When interacting PM_{10} exceedances with worker age we estimate that an additional year increases the pollution impact on absences by 2.8% of the main effect (cf. Appendix Table A.9)

Presence of dependent children

Differences in sick-leave taking across workers could be related to the presence of dependent children in the household. We explore this in Appendix Table A.10 which reports the treatment effects estimated separately for workers with and without children under age twelve in the household.[18] We find that the point estimates are very similar in both groups. The differences are well within the margin of error and, relative to the mean absence rates, the treatment effect is around 0.8% in both groups.

This contrasts with the evidence provided by Aragón et al. (2017) that Peruvian workers with dependent children are more likely to reduce their labor supply during high-pollution episodes in order to take care of their children when air pollution makes them sick. While it is plausible that caregivers in our sample stay at home when their child is sick, such leaves are unlikely to be registered as a sick leave taken by the parent. This is because Spanish labor regulations grant parents at least two days of paid leave per year when a minor child is sick. Unfortunately, we cannot investigate this further as we do not have information on such leaves.

Income and skills

Differences in income might induce heterogeneity in the treatment effects for a variety of reasons. Workers with higher income may attach a higher value to health, they might have access to better health care and more expensive medication, better options to avoid air pollution, or benefit from a collective agreement that comple-

[18] Age twelve is the threshold used in Spanish labor regulations for granting work-hour reductions or leaves for child rearing.

ments sick pay from the social security system. The overall effect of these and other income-related factors on the estimated impact is ambiguous from an ex ante perspective.

The reporting of income is not very precise in our dataset because contribution bases are bottom and top coded. Therefore, we explore the treatment heterogeneity with respect to skill groups that are highly correlated with the salaries that workers received. The Spanish social security system classifies occupations into ten groups, three of which can be considered as high-skilled (Bonhomme & Hospido, 2017). When estimating the treatment effects separately for high-skilled and low-skilled workers, the point estimates, reported in Appendix Table A.11, barely differ.

6.2 Heterogeneity across occupations

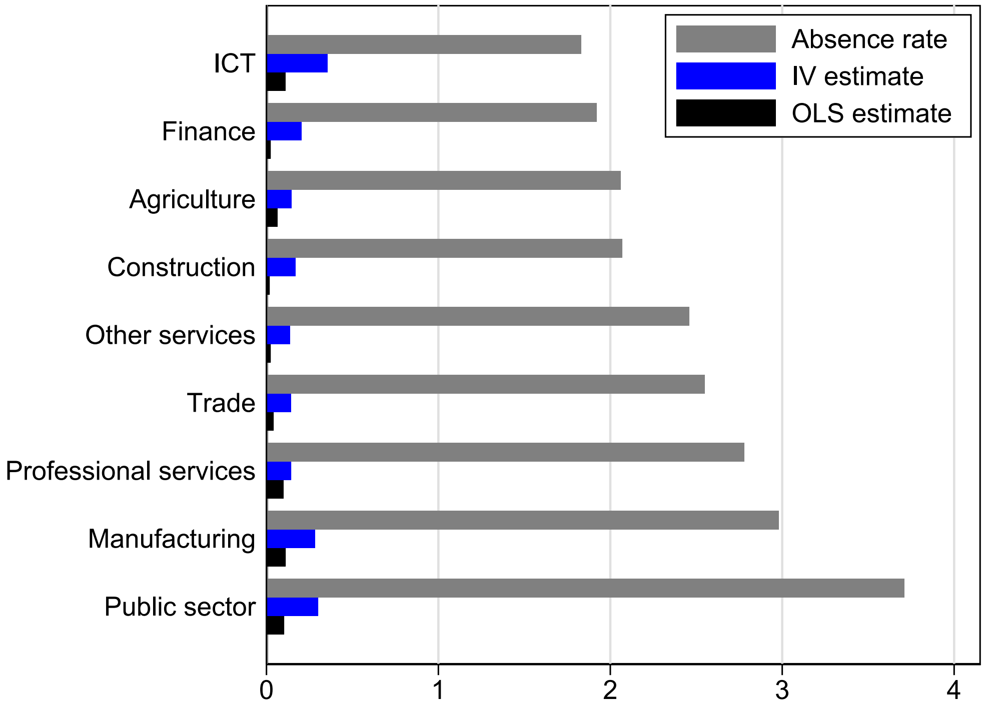
Sector affiliation

We begin our investigation of treatment heterogeneity across jobs with a comparison across sectors. To this end, we split up the sample into nine sectors and estimate equation (1) for each sub-sample. Figure 6 displays the mean absence rates along with the point estimates for PM_{10} exceedance (see Appendix Table A.12 for detailed sector definitions and estimation results).

Three findings emerge from this exercise. First, the estimated impact of high-pollution events on sick leaves is positive in all sectors, and the relationship is statistically significant in all sectors but agriculture. Second, there is meaningful variation in the magnitude of these effects across sectors, with OLS estimates ranging from 0.03 to 0.11 (compared to 0.07 in the full sample) and IV estimates from 0.14 to 0.36 (compared to 0.21 in the full sample). Third, the mean percentage absence rate across sectors is quite heterogeneous and ranges from 1.83 in the information and communication technologies (ICT) sector to 3.71 in the public sector.

Such differences in mean absence rates could arise exclusively because of differences in job characteristics, but in reality they are likely driven also by selection. All else equal, a worker with frail health prefers a job that doesn't expose her to high levels of air pollution or that comes with generous sick leave benefits. Sorting on those characteristics is likely to induce bias in previous, cross-sectional estimates of the impact of air pollution on work days lost (Ostro, 1983; Hausman et al., 1984; Hansen & Selte, 2000). Since we have worker fixed-effects, our esti-

Figure 6: Heterogeneous pollution impacts across sectors



Notes: The chart displays mean absence rates, OLS estimates and IV estimates separately for the following sectors: Information and communication technology (ICT), financial services, agriculture, construction, other services, trade, professional services, manufacturing, and the public sector. All coefficients and absence rates have been multiplied by 100 for better readability. The full results are reported in Appendix Table A.12.

mates are purged of selection bias. Nonetheless, the heterogeneity in the sectoral estimates reflects the joint influence of these and other factors on the decision to take a sick leave. For an illustration, consider the results for the ICT and the public sector. The IV point estimates for these two sectors – 0.355 and 0.301, respectively – are at the top of the range of estimated treatment effects. However, workers in ICT exhibit the lowest average absence rate whereas public sector employees have the highest. This suggests that selection on health cannot alone explain all of the heterogeneity in treatment effects. While the cross-sector comparison of treatment heterogeneities provides clues for the mechanisms driving them, pinning down such mechanisms requires further analysis.

In the remainder of this section, we undertake such an analysis focusing on the role of job security. This is motivated by the fact that both mean absence rates and treatment effects are particularly high in the public sector, where employees enjoy very high levels of employment protection – in particular, civil servants. Compared to workers with low levels of job security, public sectors workers might be more willing to take a sick leave when experiencing a negative health shock because they do not have to fear any consequences for the continuation of their tenure.[19] In contrast, in sectors where precarious employment conditions are more prevalent, such as agriculture and services, workers might take fewer leaves in order to avoid repercussions on the likelihood of remaining employed. Since we cannot rule out that confounding factors other than employment security drive the cross-sector comparison, the subsequent analyses cut the data in different ways to shed more light on this mechanism.

Employment protection in a dual labor market

The Spanish labor market features stark differences in employment protection between temporary and permanent employment contracts. Previous work has shown that this dual labor market affects unemployment, job flows, productivity and welfare (Dolado et al., 2002, 2005; Cabrales et al., 2014; Bentolila et al., 2019). It is conceivable that differences in employment protection could affect the generosity of sick leave benefits (e.g., at the level of collective bargaining) or the worker's willingness to take advantage of those benefits.

We investigate this by splitting the sample into three groups with increasing degree of employment protection: temporary contracts, permanent contracts, and civil servants. The results for each group are reported in Table 6. The IV point estimates imply that, on average, a 10-percentage point reduction in the share of exceedances of the limit value reduces the absence rate by 0.0155 percentage points for workers with a temporary position, and 0.0202 percentage points for workers with a permanent contract. Given the mean absence rates for each group (2.2% for temporary, and 2.9% for permanent), the reaction is similar for both groups (0.7%). However, the implied reaction for civil servants is larger both in absolute terms (0.0497 percentage points) and relative to the mean (1.2%), corroborating the view that the propensity to take a sick leave in this group is not only higher on average but also in response to pollution shocks.

Unemployment risk

Next, we use rich data on individual-level attributes in order to tease apart the potential effect of unemployment risk from other factors driving a worker's decision

[19] In addition, until July 2012, the replacement rates for the daily subsidy were substantially more generous for workers in the public sector than in other sectors.

Table 6: Treatment effects by contract type

	Temporary contract		Permanent contract		Civil servants	
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10} exceedance	0.069***	0.155***	0.066***	0.202***	0.137**	0.497***
	(0.026)	(0.059)	(0.018)	(0.074)	(0.058)	(0.189)
Estimator	OLS	IV	OLS	IV	OLS	IV
Mean outcome	2.238	2.238	2.850	2.850	4.321	4.321
Observations	25,786,038	25,786,038	67,323,069	67,323,069	7,055,193	7,055,193
R^2	0.191	0.191	0.181	0.181	0.180	0.180
First-stage F statistic		86.511		79.280		67.395

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Treatment effects by unemployment risk - interaction

	Weekly absence rate	
	(1)	(2)
PM_{10} exceedance	0.072***	0.212***
	(0.016)	(0.066)
PM_{10} exceedance × unemployment risk	-0.019*	-0.092***
	(0.010)	(0.032)
Estimator	OLS	IV
Mean outcome	2.798	2.798
Observations	100,199,483	100,199,483
R^2	0.165	0.165
First-stage F statistic		34.901

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Standardized within-sector unemployment risk is also interacted with weather variables, city-year dummies and year-quarter dummies. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

to take advantage of sick leave benefits when pollution spikes. Unemployment risk might matter for the following reason. If a worker fears that the frequency of her sick leaves will be taken into account when her employer decides on whether or not to retain her in the event of a mass layoff, it may be rational for her to not take a sick leave even when sick. This is a testable prediction because we can estimate individual unemployment risk from our data and relate this to the propensity to take a sick leave.

In order to predict individual unemployment risk we fit a logit model for the probability of losing a job in a given month for each of the nine sectors above. All regressions control for gender, year, age, age squared, tenure, tenure squared, experience, experience squared, nationality, and province of residence.[20] Using fitted regressions for each sector, we predict the individual unemployment risk for

[20]This approach is inspired by the labor literature. For example, Card (1996) uses predicted wages as a proxy for skills in order to study the impact of unions on workers with different skill levels. As the MCVL contains only limited information on unemployment status, we use missing employment entries in the dataset as proxies for job loss. Since some workers exit the MCVL sample at the end of the year, we include a dummy for the month of December which allows us to control for this effect when predicting job loss. See Appendix D for details.

the first week in which a worker is observed. We then assign workers to one of two groups, depending on whether this prediction lies above or below the sector's median risk. The assignment is made once for the worker's entire time series. In so doing, we capture time-invariant heterogeneity in a worker's risk of job loss while avoiding possible feedbacks of air quality on employment risk. We derive two insights from this classification (summarized in results reported in Appendix Table A.13). First, the average propensity to take a sick leave is lower among those facing a higher risk of losing their job. Second, the increase in this propensity in response to a high-pollution event is higher in the low-risk group than in the high-risk group, an effect that holds in both relative and absolute terms.

We further analyze this using continuous variation in predicted unemployment risk. Table 7 reports regression results from a variant of equation (1) that includes the interaction of PM_{10} exceedance with the individual unemployment risk, standardized relative to other workers in the same sector. The IV coefficient implies that a one-standard deviation decrease in individual unemployment risk is associated with an impact of pollution on sick leaves that is 43% higher.

Our findings imply that estimates of the health damages of air pollution derived from sick leave data may be underestimating the true health effects if workers in jobs with low job security go to work despite being sick. In Section 7 we estimate the magnitude of this divergence for all of Spain.

6.3 Heterogeneity with respect to health status

A long-standing interest in research on the pollution-health gradient has been with the impact on particularly vulnerable individuals. In fact, much of the literature approaches the topic with a focus on vulnerable populations such as infants (Currie et al., 2014) or the elderly (Deryugina et al., 2019).

Thanks to having rich data on workers' health records, we can go beyond the current state of the literature and identify vulnerable individuals in a representative sample of workers aged 16 to 65. To this end, we first construct a straightforward indicator of health as the share of days missed due to the sick leaves taken during the first twelve months that a worker is observed in the sample. We then estimate a variant of equation (1) where PM_{10} exceedances are interacted with this health measure.[21]

[21] In this estimation, we drop the first 18 months of a worker's record to ensure that the spells used to define vulnerability do not extend into the estimation period (a sick leave can last up to six

Table 8: Treatment effects by health status

	Weekly absence rate	
	(1)	(2)
PM_{10} exceedance	0.082***	0.157*
	(0.018)	(0.087)
$\times$ absence share	0.578	2.578***
	(0.354)	(0.698)
Estimator	OLS	IV
Mean outcome	2.915	2.915
Observations	74,706,090	74,706,090
R^2	0.176	0.176
First-stage F statistic		38.440

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8 reports the results. We find that the interaction term is positive and statistically significant in the IV estimation but not for OLS. Two statistics from the distribution of the absence share are helpful to further interpret these results. First, the healthiest 76.5 percent of workers have an absence share of zero. Hence this group responds to high-pollution events according to the main effect. Since the main effect is positive and significant in the OLS regression, but not the interaction effect, attenuation bias due to measurement error seems to be particularly severe for workers with poor health.

Second, we define as vulnerable workers the ones in the top five percent of the absence share distribution who missed at least 12.3% of work days due to illness. The IV estimates imply that the impact of high-pollution events on vulnerable workers is more than 3 times higher than the effect on healthy workers. Therefore, the mean effect masks large effects for particularly vulnerable individuals, a result that has been established thus far only for populations either younger or older than the working-age subjects we consider in our analysis. In further results reported in Appendix Table A.14, we find that the discrepancy between healthy and vulnerable workers is weaker when defining vulnerability based on the length of previous sick leaves.[22] This is consistent with the interpretation that especially workers with chronic conditions but not excessively long sickness spells are harmed by air pollution.

Our results complement the available evidence to support the claim that air pollution imposes a disproportionately large health burden on vulnerable groups of society. Our focus on sick leaves and workers also highlights the perhaps less appreciated fact that universal sickness insurance with a benefit scheme for temporary disability helps to alleviate unequal distributional impacts of air pollution by granting affected workers both access to treatment and time to heal.

7 Aggregate benefits of air quality improvements

The estimation results allow us to compute a lower bound on the benefits of improving urban air quality in Spain. We proceed in two steps. First, we calculate the reduction in sick days caused by a specific improvement in air quality. To translate

months) and thereby have a direct effect on the estimation results.

[22]In particular, the effect size ratio between lower 75 percent and top 5 percent of the distribution is 2.5 when the health indicator is based on the maximum length and 1.2 when it is based on the mean length.

Table 9: Productivity benefits of reducing PM_{10} exposure in urban Spain

	I. Enforcement of 24-hour standards at				II. Reduced exposure	
	50 $\frac{\mu g}{m^3}$		37.5 $\frac{\mu g}{m^3}$		to > 50 $\frac{\mu g}{m^3}$ since 2005	
	Weekly absence [days]	Annual production [€ million]	Weekly absence [days]	Annual production [€ million]	Cumulative absence [days]	Cumulative production [€ million]
Baseline	-8,304 ± 5,107	39.31 ± 24.18	-12,955 ± 8,570	61.32 ± 40.57	-5.55m ± 3.42m	503 ± 309
Adjusted for job security	-11,657 ± 6,433	55.18 ± 30.45	-18,536 ± 11,161	87.74 ± 52.83	-7.80m ± 4.30m	706 ± 389

Notes: Panel I reports counterfactual productivity benefits of strictly enforcing 24-hour standards for PM_{10} in terms of reductions in (i) work days lost per week and (ii) incremental production. Counterfactual air quality improvements are calculated relative to the observed PM_{10} concentrations in each city contained in the sample, weighted by the number of social security affiliates in that city. Enforcing a limit of 50 $\mu g/m^3$ is binding on 8.11% of worker days in the sample whereas a limit of 37.5 $\mu g/m^3$ is binding on 20.73% of days. Panel II reports the cumulative benefits of reductions in worker exposure to daily PM_{10} concentrations of 50 $\mu g/m^3$ or more that have actually occurred in urban Spain since 2005.

this into a monetary benefit, we then multiply this number by the average daily producer wage across workers. Under the assumption that workers are paid their marginal product, this approximates the value of incremental production enabled by the reduction in sick days. While improving air quality yields sizable additional benefits by reducing mortality, human suffering, and medical treatment costs, we focus on foregone production because this component of the social costs of air pollution is directly linked to our outcome variable and has not yet been quantified in previous research.

We start by considering a counterfactual intervention that enforces strict compliance with the 24-hour standard for PM_{10} throughout the sample period. The average share of worker days on which PM_{10} exceeded the EU limit value was 8.11% between 2005 and 2014. The IV point estimate implies that reducing this share to zero would lower the absence rate by 0.017 percentage points (0.624% of the mean). Specifically, we calculate the increase in work attendance as

$$\hat{\Delta} = 0.0811 \cdot 7 \cdot 0.00213 \cdot 6,867,199 = 8,304 \text{ worker days per week}$$

where the product of the first two terms yields the expected reduction in high-pollution days per week, the third term is the IV coefficient and the last term is the average number of social security affiliates in our sample of 99 cities over the period. We multiply this number with the daily producer wage in constant 2018 Euros, averaged across workers and years[23] to obtain annualized benefits of

$$\hat{\Omega} = 52 \cdot \hat{\Delta} \cdot € \, 91.0 = € \, 39.31\text{m}.$$

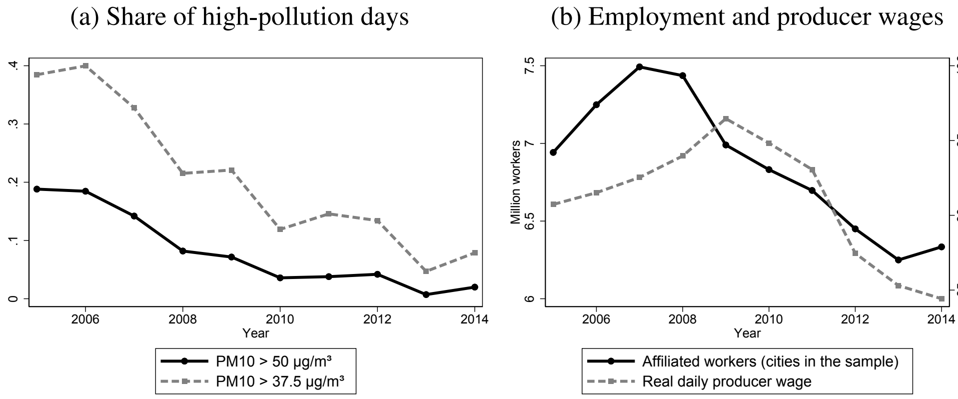
To account for sampling error we include 95% confidence bands for all counterfactual calculations reported in Panel I of Table 9.

Our IV estimate is based on a binary indicator for high-pollution events. In the above exercise, this implies an assumption that PM_{10} concentrations below 50 $\mu g/m^3$ are not harmful to human health. Yet the non-parametric OLS estimates displayed in Figure 5 suggest that pollution increases absence rates even at lower PM_{10} concentrations of less than 40 $\mu g/m^3$. We thus repeat the calculations for a scenario that enforces strict compliance with 75% of the PM_{10} limit value throughout the sample period. This new standard would be binding for 20.73% of worker-days. Using the IV estimate for exceedances above 37.5 $\mu g/m^3$ (reported in Table A.3), we compute a reduction in the absence rate of 0.027 percentage points and an increase in work attendance by 12,955 days per week. The annual benefits in terms of foregone production amount to €61.32 million, which is a 56% increase compared to merely enforcing the EU limit value. Hence, the additional benefits of improving air quality beyond the current EU standard for PM_{10} would be economically significant.

According to our results, high-pollution events cause an increase in sick leaves, but this effect is significantly lower among workers facing a high risk of job loss relative to the sector average. If those workers go to work despite being sick we underestimate the burden of air pollution. To gauge how sensitive our benefit estimates are to such presenteeism, we repeat the above calculations after eliminating idiosyncratic unemployment risk. That is, we replace each worker's estimated unemployment risk by the smallest risk observed in the sector and predict the sick-leave response based on the IV estimates reported in Table 7 which allow for differential responses to pollution depending on unemployment risk. The results for the two counterfactual scenarios are reported in the bottom row of Table 9. This exercise shows that correcting for presenteeism leads to benefit estimates that are

[23] Averaging wages and employment across years is intended to dampen the impact of economic fluctuations on the benefit estimates. As shown by Figure 7 below, such fluctuations were substantial during the ten-year sample period.

Figure 7: Trends in Pollution, Employment, and Wages 2005-2014



Notes: Figure a) displays the share of worker days with PM_{10} concentrations exceeding the EU 24-hour limit of 50 μg/m³ (solid line) and the share of worker days with concentrations in excess of 75% of the limit value (dashed line). The figure is based on our sample of 99 Spanish cities with at least 40,000 inhabitants. PM_{10} concentrations are weighted by the number of social security affiliates in each city and year. Figure b) displays the number of workers affiliated with the General Social Security Regime on our sample of 99 Spanish cities with at least 40,000 inhabitants (solid line) and the daily producer wage, expressed in constant 2018 Euros (dashed line).

more than 40% higher than in the baseline.

With these concepts in mind, we turn to evaluating the benefits of actual air quality improvements that have taken place in urban Spain between 2005 and 2014. Figure 7a shows a strong decline in worker exposure to PM_{10} concentrations exceeding the EU 24-hour limit (or 75% of that limit). In our sample of 99 cities, the share of worker-weighted days with PM_{10} concentrations in excess of 50 $\mu g/m^3$ declined from 18.8% in 2005 to just under 2% in 2014.[24] The cumulative benefit of this development is a reduction in work days lost by 5.55 (± 3.42) million which would have resulted in foregone production worth €503 million (± €309 million). We calculate these numbers by computing for each year from 2006 onwards the reduction in PM_{10} exposure relative to 2005 and summing the associated benefits across years in the sample. It is important to note that this calculation is affected quite strongly by major economic fluctuations that occurred during the sample period, depicted in Figure 7b. The years 2005 to 2007 were the final years of a massive construction boom in Spain, with strong growth in both employment and producer wages. The financial shock and grand recession of 2008 triggered a prolonged economic crisis in Spain which caused dramatic declines in those variables from 2009 onward. If we used 10-year averages of employment and wages to compute benefits as in the counterfactual simulations above, we would likely

[24]This improvement is in line with a broader pattern observed in the G7 countries, where the mean population exposure to $PM_{2.5}$ fell by 25% between 1990 and 2017 (OECD, 2019).

overestimate the value of foregone production because air quality improvements were largest during the crisis years. We account for this by using annual values.

As above, one can adjust the estimated benefits of air quality improvements to account for presenteeism in the impact estimates. This yields a reduction in work days lost by 7.80 (± 4.30) million and a corresponding increase in production worth €706 million (± €389 million). Irrespective of which number one prefers, this exercise shows that the productivity-related benefits of air quality improvements that occurred in Spain between 2005 and 2014 were both economically and statistically significant.

8 Discussion and conclusions

We have conducted the first nation-wide study of the impact of air pollution on work absenteeism. Our application is based on a representative panel of urban workers affiliated with the Spanish social security system. Using naturally occurring variation in Sahara dust advection to instrument for ambient concentrations of PM_{10} we have estimated causal relationships that give rise to a number of policy implications.

First, higher PM_{10} concentrations lead to more work absences, in particular for levels of pollution that exceed the EU-mandated 24-hour limit value of 50 $\mu g/m^3$. This effect is economically significant even when sick leaves are valued only with the foregone production during work days lost, a lower bound on the full social costs which also include cost components related to loss of life, human suffering, and medical treatment. The implication is that policies aimed at reducing particulate matter have non-negligible health benefits that are not accounted for in a sizable literature focusing on severe morbidity and mortality outcomes. Our findings also underline that air pollution damages human health for a broad range of symptoms and diagnosis chapters.

Second, our findings corroborate that air pollution control is needed in particular to protect vulnerable members of society, a policy implication first derived in previous research on infants and the elderly. Our analysis has contributed new evidence for the working population by showing that workers in bad health suffer disproportionately from air pollution. From a public policy perspective, protecting the vulnerable is imperative on the grounds that there are no good substitutes for health. In such a setting, monetary compensation is a blunt instrument for mitigating unequal welfare effects of environmental externalities.

Third, we establish that workers who suffer an adverse health shock due to air pollution are less likely to take a sick leave the higher their individual risk of job loss. As a consequence, such workers might fail to seek adequate treatment for their diseases. This would likely decrease their productivity in the short run and might also have detrimental health consequences in the long run.

We note several caveats. Our study is based on data from the social security system which covers most but not all workers in Spain. Our results may thus not be representative of self-employed, unemployed and permanently disabled workers. Further data limitations imply that our results may not be representative for workers in rural parts of the country.

A cautionary note is due in regards to the use of OLS vs. IV estimates when deriving policy implications. Although our use of high-dimensional fixed effects is well-suited to control for non-random assignment of air pollution in an OLS regression, mismeasured pollution exposure likely causes attenuation bias in our application. Our discussion of the results has predominantly relied on the IV estimates because they mitigate this bias. However, their validity requires that PM_{10} originating from Sahara dust advection affects sick leaves only by shifting local PM_{10} concentrations, conditional on weather and other controls. Based on the evidence available to us, we have argued that violations of the exclusion restriction are unlikely to drive our results. We note, however, that our interpretation of the IV coefficient as a dose-response relationship for urban PM_{10} concentrations is based on the premise that the pathological effects of PM_{10} blown in from the Sahara are identical to those of urban PM_{10}. Previous research on this topic documents small but measurable differences in the chemical and mineralogical composition of those variables (Perez et al., 2008), but also suggests there are no differential health impacts (Stafoggia et al., 2016). We are aware that this does not constitute ultimate proof of identical health effects. Nonetheless, it lends empirical support to an assumption that allows us to derive valuable, additional insights from our empirical results. In making this assumption, we trade-off the remaining scientific uncertainty against the benefits of having point estimates that are not only purged of attenuation bias but also interpretable as dose-response relationships for PM_{10}.[25] Should future research produce new evidence that makes the exclusion restriction

[25]The latter benefit would not arise if we used alternative IVs suggested in the literature which shift several air pollutants at a time.

untenable, this would call for a reassessment of this trade-off and might suggest the adoption of an alternative IV strategy. Even in such a scenario, however, our empirical framework still provides intent-to-treat estimates suitable for evaluating work days lost due to long-range transport of desert dust, which might become more relevant as the problems of global climate change and desertification worsen.[26]

A final caveat to be addressed here concerns the measurement of foregone production due to sick leaves. We have proposed two alternative measures. The first measure only counts sick leaves that were actually taken. This conservative approach likely underestimates the true value of foregone production because it fails to account for the detrimental effects of presenteeism on productivity in the short run (sick workers perform worse on the job; Neidell, 2017), in the medium run (through delayed convalescence), and in the long run (not treating minor conditions can lead to more severe health conditions, as is the case with asthma). Our second measure additionally counts sick leaves that would have been taken if all workers had the maximum level of job protection. This addresses the issue of presenteeism, but it might entail overestimation of work days lost if workers with high job protection are more prone to moral hazard (e.g., because high job security lowers the cost of shirking). Whether or not this matters empirically depends on the margin of shirking. If moral hazard affects the extensive margin, i.e., through more false sick leaves, this should not affect the treatment effect we estimate because the higher baseline absence would be absorbed by worker fixed-effects. In contrast, if workers are able to shirk by taking more sick days for each sick leave, this would provide a competing explanation for observing stronger sick-leave responses to air pollution in jobs with low employment risk. Disentangling moral hazard and presenteeism is beyond the scope of this paper and left as a topic for future research.

Overall, our study has shown that administrative data on sick leaves is very useful for closing an important gap in the empirical valuation of the health impacts of air pollution. We expect that researchers will continue to use this valuable data resource in future work, and find effective ways of dealing with the above-mentioned issues that arise with this new outcome variable.

[26] We report intent-to-treat estimates for the main specifications in Appendix Table A.15.

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Online Appendices (not for publication)

A Additional Tables

Table A.1: Correlation of pollution measures

	PM_{10}	SO_2	CO	O_3	NO_2
PM_{10}	1				
SO_2	0.212	1			
CO	0.383	0.283	1		
O_3	-0.119	-0.201	-0.353	1	
NO_2	0.439	0.191	0.503	-0.479	1

Table A.2: Estimates for PM_{10} with lags

	Weekly absence rate		
	(1)	(2)	(3)
PM_{10} exceedance	0.205***	0.170***	0.177***
	(0.064)	(0.061)	(0.064)
Lag: PM_{10} exceedance		0.167**	0.158**
		(0.066)	(0.064)
Lag 2: PM_{10} exceedance			0.038
			(0.069)
Estimator	IV	IV	IV
Observations	95,732,772	95,732,772	95,732,772
Mean outcome	2.78	2.78	2.78
R^2	0.166	0.166	0.166
First-stage F statistic	81.433	53.929	0.516

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3: Non-linear effects of PM_{10}

	Weekly absence rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PM_{10} > 50\%$	0.027***	0.111**						
	(0.010)	(0.043)						
$PM_{10} > 75\%$			0.060***	0.130***				
			(0.013)	(0.044)				
$PM_{10} > 100\%$					0.073***	0.212***		
					(0.016)	(0.066)		
$PM_{10} > 125\%$							0.061***	0.368***
							(0.022)	(0.111)
Estimator	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Mean outcome	2.791	2.791	2.791	2.791	2.791	2.791	2.791	2.791
Observations	100,739,754	100,739,754	100,739,754	100,739,754	100,739,754	100,739,754	100,739,754	100,739,754
R^2	0.165	0.165	0.165	0.165	0.165	0.165	0.165	0.165
First-stage F statistic		130.461		252.285		80.556		38.747

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4: IV estimates for PM_{10} excluding Canary Islands

	Weekly absence rate			
	(1)	(2)	(3)	(4)
PM_{10} exceedance	0.076***	0.205***		
	(0.016)	(0.07)		
PM_{10}			0.001***	0.003***
			(0.000)	(0.001)
Estimator	OLS	IV	OLS	IV
Observations	98,057,059	98,057,059	98,057,059	98,057,059
Mean outcome	2.769	2.769	2.769	2.769
R^2	0.165	0.165	0.165	0.165
First-stage F statistic		72.4		197

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by municipality and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5: Logit estimates for PM_{10}

	Weekly absence rate	
	(1)	(4)
PM_{10} exceedance	0.028***	
	(0.007)	
	[0.063]	
PM_{10}		0.0004**
		(0.0002)
		[0.0010]
Estimator	Logit	Logit
Mean outcome	2.791	2.790
Observations	100,739,754	100,739,754
Efron's R^2	0.169	0.169

Notes: Coefficients scaled by a factor of 100 for better readability. Mean marginal effects evaluated at the mean in brackets, multiplied by 100 to be comparable to the linear regressions. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors for the coefficients in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: Effects of PM_{10} on ICD-9 Diagnosis Groups

	PM_{10} exceedance	Outcome
I: Infectious and Parasitic Diseases	0.002	0.065
	(0.007)	
II: Neoplasms	0.004	0.094
	(0.004)	
III: Endocrine, Nutritional and Metabolic Diseases, and Immunity Disorders	0.001	0.019
	(0.001)	
IV: Diseases of the Blood and Blood-forming Organs	-0.001***	0.007
	(0.000)	
V: Mental Disorders	0.038***	0.294
	(0.009)	
VI: Diseases of the Nervous System and Sense Organs	0.015**	0.093
	(0.006)	
VII: Diseases of the Circulatory System	0.000	0.88
	(0.002)	
VIII: Diseases of the Respiratory System	0.006	0.134
	(0.012)	
IX: Diseases of the Digestive System	0.009	0.98
	(0.006)	
X: Diseases of the Genitourinary System	-0.004	0.53
	(0.004)	
XI: Complications of Pregnancy, Childbirth, and the Puerperium	0.003	0.77
	(0.003)	
XII: Diseases of the Skin and Subcutaneous Tissue	-0.001	0.025
	(0.003)	
XIII: Diseases of the Musculoskeletal System and Connective Tissue	0.016	0.581
	(0.018)	
XIV: Congenital Anomalies	0.000	0.006
	(0.001)	
XV: Certain Conditions originating in the Perinatal Period	0.001	0.001
	(0.000)	
XVI: Symptoms, Signs and Ill-defined Conditions	0.039***	0.274
	(0.011)	
XVII: Injury and Poisoning	0.015	0.281
	(0.011)	
Observations	100,739,754	

Notes: Each row comes from a separate regression. Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by municipality and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: Treatment effects by gender

	Female		Male	
	(1)	(2)	(3)	(4)
PM_{10} exceedance	0.082***	0.259***	0.064***	0.171***
	(0.027)	(0.092)	(0.016)	(0.056)
Estimator	OLS	IV	OLS	IV
Observations	46,995,784	46,995,784	53,743,967	53,743,967
Mean outcome	3.41	3.41	2.25	2.25
R^2	0.165	0.165	0.163	0.163
First-stage F statistic		77		83.5

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: Treatment effects by age

	≤ 34		> 34 & ≤ 45		> 45	
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10} exceedance	0.055***	0.145***	0.081***	0.221***	0.083**	0.268**
	(0.018)	(0.053)	(0.020)	(0.071)	(0.034)	(0.108)
Estimator	OLS	IV	OLS	IV	OLS	IV
Observations	35,276,558	35,276,558	32,718,271	32,718,271	32,744,309	32,744,309
Mean outcome	2.05	2.05	2.49	2.49	3.90	3.90
R^2	0.141	0.141	0.179	0.179	0.209	0.209
First-stage F statistic		82.918		83.210		74.165

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.9: Treatment effects interacted with age

	Weekly absence rate	
	(1)	(2)
PM_{10} exceedance	0.073***	0.211***
	(0.016)	(0.068)
PM_{10} exceedance × Age	0.002	0.006*
	(0.001)	(0.003)
Estimator	OLS	IV
Mean outcome	2.791	2.791
Observations	100,739,754	100,739,754
R^2	0.165	0.165
First-stage F statistic		37.335

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.10: Treatment effects by household type

	No kids younger than 12		Kids younger than 12	
	(1)	(2)	(3)	(4)
PM_{10} exceedance	0.072***	0.225***	0.090***	0.183**
	(0.017)	(0.069)	(0.024)	(0.078)
Estimator	OLS	IV	OLS	IV
Mean outcome	2.866	2.866	2.561	2.561
Observations	75,836,283	75,836,283	24,902,425	24,902,425
R^2	0.184	0.184	0.182	0.182
First-stage F statistic		78.066		86.966

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.11: Treatment effects by skill level

	High skilled		Low skilled	
	(1)	(2)	(3)	(4)
PM_{10} exceedance	0.079***	0.215**	0.069***	0.207***
	(0.021)	(0.087)	(0.018)	(0.067)
Estimator	OLS	IV	OLS	IV
Observations	24,822,994	24,822,994	75,916,027	75,916,027
Mean outcome	2.02	2.02	3.04	3.04
R^2	0.15	0.15	0.171	0.171
First-stage F statistic		70.9		83.5

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.12: Treatment effects by sector

	Agricultural (1)	Manufacturing (2)	Construction (3)	Trade (4)	ICT (5)	Finance (6)	Professional serv. (7)	Public (8)	Other services (9)
PM_{10} exceedance (OLS)	0.063	0.112***	0.019	0.042**	0.11***	0.025	0.098***	0.103***	0.025
	(0.111)	(0.029)	(0.028)	(0.021)	(0.04)	(0.034)	(0.031)	(0.038)	(0.029)
PM_{10} exceedance (IV)	0.145	0.282**	0.169**	0.142*	0.355***	0.204**	0.144**	0.301**	0.137***
	(0.132)	(0.12)	(0.08)	(0.081)	(0.061)	(0.099)	(0.073)	(0.117)	(0.05)
Observations	786,455	13,151,585	7,833,216	28,884,828	4,099,741	4,329,242	15,294,028	21,820,250	4,530,216
Mean outcome	2.06	2.98	2.07	2.55	1.83	1.92	2.78	3.71	2.46
R^2	0.272	0.186	0.194	0.173	0.176	0.175	0.214	0.178	0.199
First-stage F statistic	54.2	78.5	94.7	80.8	79.3	73	81	72.4	71.2

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The MCVL reports NACE industry classifications based on the Statistical Classification of Economic Activities in the European Community. We form nine sectors based on the NACE level 1 codes as follows: *Agriculture* refers to A: agriculture, forestry and fishing. *Manufacturing* refers to B: mining and quarrying, C: manufacturing, D: electricity, gas, steam and air conditioning supply, and E: water supply; sewerage, waste management and remediation activities. *Construction* refers to F: construction. *Trade* refers to G: wholesale and retail trade; repair of motor vehicles and motorcycles, H: transportation and storage, and I: accommodation and food service activities. *ICT* refers to J: information and communication. *Finance* refers to K: financial and insurance activities and L: real estate activities. *Professional services* refers to M: professional, scientific and technical activities and N: administrative and support service activities. *Public* refers to O: public administration and defence; compulsory social security, P: education, and Q: human health and social work activities. *Other services* refers to R: arts, entertainment and recreation, S: other service activities, T: activities of households as employers, and U: activities of extraterritorial organisations and bodies.

Table A.13: Treatment effects by unemployment risk - split sample

	Low risk		High risk	
	(1)	(2)	(3)	(4)
PM_{10} exceedance	0.098***	0.281***	0.046***	0.146**
	(0.019)	(0.085)	(0.018)	(0.057)
Estimator	OLS	IV	OLS	IV
Observations	50,853,937	50,853,937	49,345,546	49,345,546
Mean outcome	3.13	3.13	2.46	2.46
R^2	0.172	0.172	0.154	0.154
First-stage F statistic		80.2		79.7

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.14: Treatment effects by health status

	Weekly absence rate					
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10} exceedance	0.082***	0.157*	0.084***	0.164*	0.093***	0.192**
	(0.018)	(0.087)	(0.019)	(0.091)	(0.019)	(0.093)
× absence share	0.578	2.578***				
	(0.354)	(0.698)				
× absence max length			0.409	1.878***		
			(0.283)	(0.597)		
× absence mean length					0.463	2.891***
					(0.478)	(0.738)
Estimator	OLS	IV	OLS	IV	OLS	IV
Mean outcome	2.915	2.915	2.915	2.915	2.915	2.915
Observations	74,706,090	74,706,090	74,706,090	74,706,090	74,706,090	74,706,090
R^2	0.176	0.176	0.177	0.177	0.176	0.176
First-stage F statistic		38.440		38.458		38.457

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

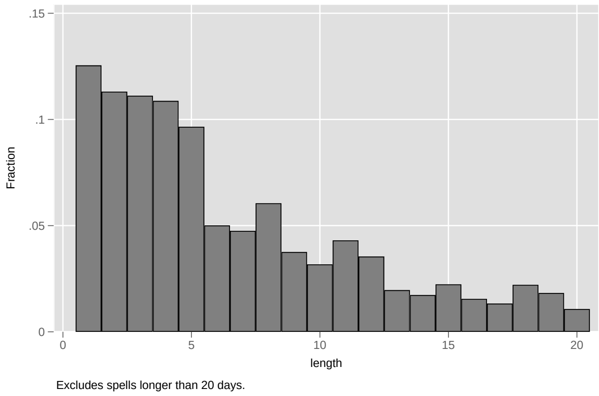
Table A.15: Reduced-form regression for main specifications

	Weekly absence rate				
	(1)	(2)	(3)	(4)	(5)
Calima	0.0412***	0.042***	0.026*	0.028*	0.033**
	(0.0142)	(0.014)	(0.015)	(0.016)	(0.016)
× unemployment risk		-0.018**			
		(0.0006)			
× absence share			0.454***		
			(0.130)		
× absence max length				0.445***	
				(0.143)	
× absence mean length					0.647***
					(0.168)
Mean outcome	2.79	2.80	2.92	2.92	2.92
Worker-by-week observations	100,739,754	100,199,483	74,706,090	74,706,090	74,706,090
R^2	0.165	0.165	0.176	0.177	0.176

Notes: Coefficients scaled by a factor of 100 for better readability. All regressions are estimated by OLS and control for individual fixed effects, age fixed effects, city-year fixed effects, year-quarter fixed effects, flu prevalence and include linear and squared terms of eight weather variables. Robust standard errors in parentheses are clustered by city and by week. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

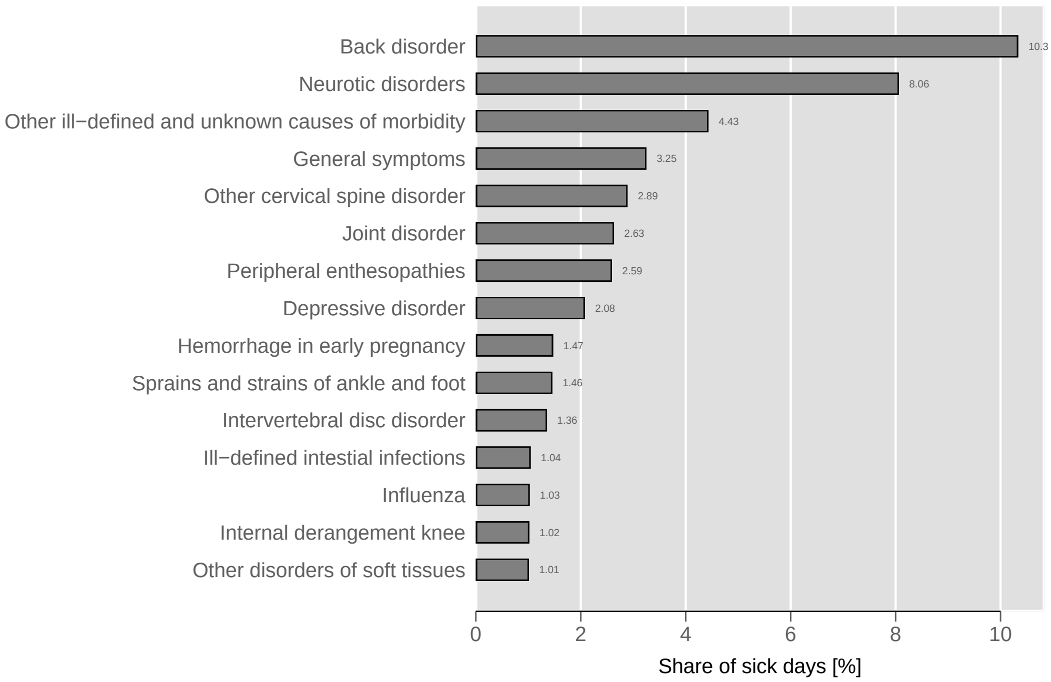
B Additional Figures

Figure B.1: Duration of sick leaves in days



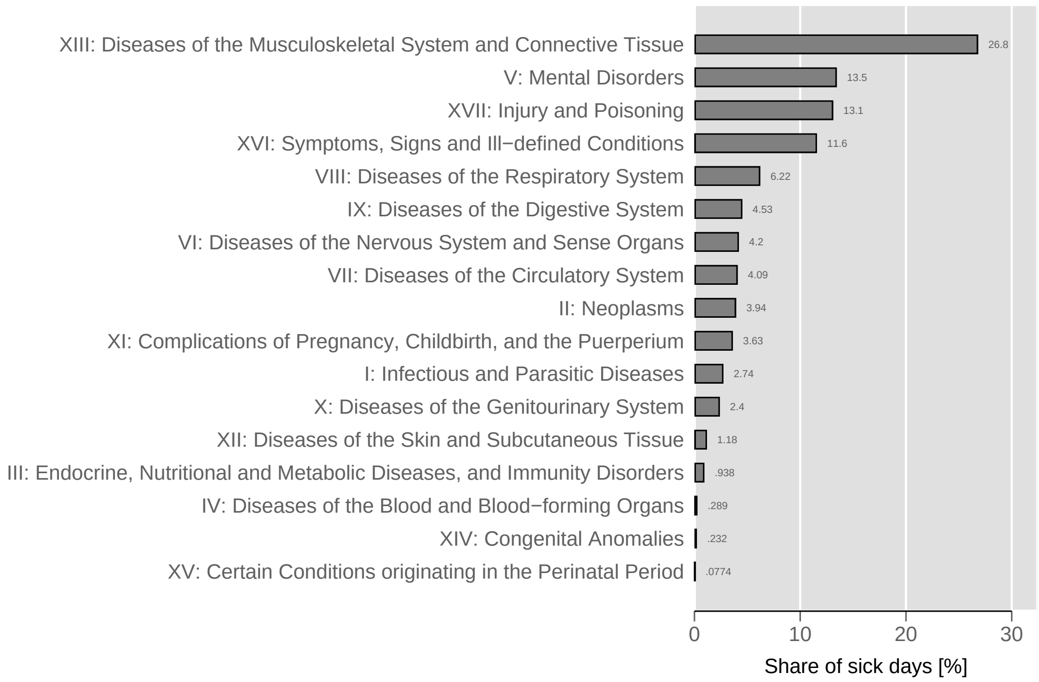
Notes: The figure shows a histogram of the duration of sick leaves in days. Spells longer than 20 days are not depicted. *Source:* Own representation based on data from the Spanish Ministry of Employment, Migration and Social Security (2018).

Figure B.2: Most frequent diagnosis codes



Notes: The figure shows the shares of the 15 most common ICD-9 diagnosis codes for absence spells with a reported diagnosis. *Source:* Own representation based on data from the Spanish Ministry of Employment, Migration and Social Security (2018).

Figure B.3: Distribution of ICD-9 diagnosis chapters



Notes: The figure shows the shares of all ICD-9 diagnosis chapters for absence spells with a reported diagnosis. *Source:* Own representation based on data from the Spanish Ministry of Employment, Migration and Social Security (2018).

C Calima Monitoring

Non-anthropogenic sources, for example wildfires, can influence air quality negatively. Therefore, when determining whether current PM_{10} levels violate EU limit values, observed air pollution may be adjusted downward to account for such effects. In Spain and Portugal, the most important natural factor augmenting PM_{10} is Saharan sand dust advection, known as “Calima”. The magnitude of a Calima event, the PM_{10} discount, may be subtracted from actual PM_{10} readings before determining whether an EU limit value has been exceeded.

A consortium of research institutions (including the Spanish National Research Council’s Institute of Environmental Assessment and Water Research, the Spanish State Meteorological Agency, the Spanish Research Center in Energy, Environment and Technology as well as the Nova University Lisbon and the University of Huelva) generates annual reports which identify exceedances of the daily limit value of PM_{10} caused by Calima events and quantify the PM_{10} discounts. The magnitude of Calima events is quantified using 29 rural background air quality monitors which are located in nine different geographic regions covering Spain and Portugal and measure PM_{10} on a daily level.

The researchers of the consortium identify Calima episodes in each of the nine regions and on each day based on sources like the European Center for Medium-Range Weather Forecasts (ECMWF) or the dust forecast of the Barcelona Supercomputing Center (DREAM). If a day and region is deemed to be affected by a Calima event, PM_{10} discounts are determined using measures from the rural background air quality stations.

The discount can be interpreted as the deviation of PM_{10} on a given Calima day from concentrations observed on days unaffected by Calima. The exact PM_{10} discount at the rural background station is calculated as follows. Based on daily measurements of ambient PM_{10}, one determines the 40th percentile of PM_{10} in a moving time window of 30 days, where the current day lies in the center of the window and all days affected by Calima events are dropped[27]. The PM_{10} discount is the difference between the current day’s observation and the 40th percentile. In the case that the difference is negative, the PM_{10} discount is set to zero. A city then can reduce its compliance-relevant PM_{10} reading by the PM_{10} discount reported by the closest rural background station, but only on days which were deemed to be

[27]The 40th percentile is used because it was found to be the best predictor of local PM_{10} conditional on the day not being affected by sand dust.

affected by Calima events. In addition, we define a daily Calima indicator which takes value one if on a given day a city's applicable PM_{10} discount is strictly positive, and zero otherwise.

D Estimation of Unemployment Risk

We obtain estimates for individual unemployment risk by relating a worker's observed characteristics to the estimated impact of these characteristics on job loss. This approach is inspired by the labor literature. For example, Card (1996) uses predicted wages as a proxy for skills in order to study the impact of unions on workers with different skill levels. In contrast, we aim to quantify an individual's probability of becoming unemployed.

To do so, we first need to define a measure of job loss. As the MCVL contains only limited information on unemployment status, we proxy for job loss by missing employment entries in the dataset. That is, we define job loss by the absence of employment information in the following month. Other than unemployment, there are two principal reasons for why workers may have a missing employment entry in the dataset. First, workers who retire will by definition have no employment entry. Therefore, the estimation excludes all workers aged 65. Second, some workers exit the MCVL sample at the end of the year. To control for this, we include a dummy for the month of December in the estimation of job loss probability.

We define unemployment risk in two steps. In the first step, we regress observed job loss on worker characteristics. In the second step, we use the estimated coefficients to quantify the probability of job loss for each worker.

For step 1, we estimate a logistic regression model of the probability of job loss of worker i living in city (*municipio*) m at the end of year-month t:

$$\begin{aligned} LOSS_{imt} &= f(x_{it}'\beta^s + \theta^s \cdot \mathbb{I}\{month(t) = December\} \\ &\quad + \mu^s_{year(t)} + \psi^s_{province(m)} + \varepsilon_{imt}). \end{aligned} \tag{D.1}$$

Since we expect that unemployment risk varies widely across sectors, we estimate this equation separately for each one of nine sectors s (agriculture, manufacturing, construction, trade, information and communication, finance, professional services, public, and other services; see Figure A.12 for more detailed definitions). Workers who switch sectors will therefore also switch the estimation subset. The vector x_{it} contains dummies for a temporary contract, being female, and for having Spanish nationality. It further includes quadratic polynomials in the worker's age, tenure in the current firm, and total labor market experience. The coefficient θ captures the effect that workers might leave the MCVL at the end of the year for reasons unrelated to job loss. Furthermore, the equation includes year effects μ and province effects ψ.

We quantify each worker's individual unemployment risk by predicting her probability of job loss based on the sector-specific coefficient estimates in equation (D.1). The prediction is evaluated using the first week of data available for the worker, and plugging the respective values of x_{it}, year, and province, into the fitted model for the sector s in which the worker is working. We constrain $\hat{\theta}$ to be zero to obtain a measure of unemployment risk also for observations drawn from the month of December. This results in a single measure of unemployment risk for each worker. We do not re-estimate this measure for all the other weeks, but treat unemployment risk as a fixed worker-specific measure. Hence, even if a worker changes sector, she will keep her initial unemployment risk. Before using this variable for further analysis, we drop all observations that were used to predict worker-level unemployment risk from the sample.

Estimation results for this model are available upon request.