# Air pollution and labor supply: Evidence from social security data

Felix Holub* Laura Hospido† Ulrich J. Wagner‡

May 22, 2016

***Preliminary and incomplete - please do not quote or cite!***

**Abstract**

We estimate the causal impact of air pollution on the incidence and duration of sickness leaves taken by a representative sample of employees affiliated to the social security system in Spain. Identification derives from day-to-day variation in air pollution concentrations to which the individuals in the sample are exposed in their place of residence. We compute local measures of air quality by interpolating geo-referenced data from almost 900 air quality monitoring stations in all of Spain. These monitoring stations measure and record, at least once per hour, the concentration of various air pollutants that are known to cause harm to human health in the form of cardiovascular and respiratory diseases (SO2, NOx, PM10, CO and O3). We estimate a linear probability model that relates the event of a worker staying at home on a given day in 2009 because of a cardiovascular or respiratory disease to the air quality experienced at the place of residence, controlling for confounding factors such as weather, season and individual effects. Our study contributes new evidence on the impact of pollution on worker productivity.

*Department of Economics, University of Mannheim, Germany.
†Banco de España, Madrid, Spain
‡Department of Economics, University of Mannheim, Germany.

# 1 Introduction

How does air quality affect human capital? There is a sizable body of empirical evidence on this question, especially on the relationship between air quality and human health. In recent years, this literature has grown increasingly sophisticated, relying on ever larger and more detailed datasets, often from administrative sources, covering outcomes relating to infant health (Chay & Greenstone, 2003; Currie & Neidell, 2005; Currie et al., 2009b) and outpatient admissions in hospitals (Karlsson et al., 2015; Schlenker & Walker, 2016). At the same time, some recent studies have extended the scope of the analysis beyond health impacts to investigate how air quality impacts on an individuals' productivity at work or in the classroom. This line of research suggests that bad air quality lowers productivity both at the intensive margin – i.e., the performance on the job (Zivin & Neidell, 2012; Lichter et al., 2015) or in the classroom (Lavy et al., 2014) – and at the extensive margin – i.e., the number of hours worked (Hanna & Oliva, 2015) or spent in school (Currie et al., 2009a).

A fundamental empirical challenge in estimating the short-run impact of air pollution on labor supply arises from unobserved economic shocks that shift air pollution and labor demand simultaneously and thus induce bias in the estimated relationship between air pollution and labor supply (Hanna & Oliva, 2015). In this paper, we exploit rich, individual-level panel data from the Spanish social security system to circumvent this problem. Specifically, we investigate the impact of air pollution on sick leaves taken by workers with full-time employment contracts. Because the terms of these contracts are shaped by a highly rigid collective bargaining process , they are unlikely to respond to short-run economic shocks. We restrict our attention to sick leaves with a medical diagnosis that can be linked to air pollution. Because social security covers more than 95% of employees in Spain, our estimates are presumably close to the population effect and apply to the country of Spain as a whole rather than a particular city as in previous work (Hansen & Selte, 2000; Hanna & Oliva, 2015). Finally, we can control for location fixed effects that mitigate possible sorting bias that would arise e.g. if less polluted places attract individuals with weaker health.

Our econometric approach fits a linear probability model for the event that the individual does not work on a given day because of cardiovascular or respiratory disease. Our model relates this decision to air quality at the place of residence, controling for weather, season and individual effects. In so doing, we seek to estimate the causal impact of air pollution on the incidence of sick leave in a representative sample of members of the general scheme of Social Security in Spain.

# 2 Institutional Background

## 2.1 Temporary disability benefits in Spain

The beneficiaries of temporary disability benefit are those workers who meet the following requirements: (i) receiving health care, (ii) being affiliated to the social security, as a worker or collecting unemployment benefits, and (iii) having covered a minimum contribution period. In case of absence due to illness a contribution period of 180 days is required in the five years immediately preceding the illness. The minimum contribution period is not required in the case of an accident. The benefit consists of a daily subsidy the amount of which depends on the base and the percentages applicable to it. As a general rule, the regulatory base is the result of dividing the amount of the contribution base of the worker in the preceding month by the number of days worked in that month. Of that regulatory base, the worker receives

1. nothing during the first three days,
2. 60% from day four until day 20 (both days included), and
3. 75% from day 21 onwards.

In the case of an accident, the worker receives 75% from the day the entitlement occurs. That entitlement day is, in case of accident or occupational disease, the next day from the beginning of the sick leave (and the employer pays fully the first day of the leave).

In case of common illness, the benefit is paid from the fourth day of the leave. The benefit is paid by the employer from the fourth day to the fifteenth, both included. The first three days the benefit is not perceived, unless the company. Finally, the maximum duration of the benefit is 12 months, renewable for another 6.

Although the payment will always be done by the company, from the sixteenth day the salary is provided by Social Security. That is, the company will claim the wages paid to Social Security.

In addition, some collective agreements complement the temporary disability benefit. Workers receive less money during the sick leave, but if the agreement complements the amount of the disability payment, the difference with the usual salary may not be too big. Some agreements grant matching funds to achieve 100 % of the salary during the temporary disability from day one.

**Example** A worker earns a monthly base salary of €1,340.54 which amounts to €44.68 per day. He has been sick at home for 22 days and his collective agreement does not complement the TD. During days 1 to 3 of the sick leave, the worker earns €0. During days 4 through 15, the company pays a benefit of 60% of the base salary, i.e.

$$€44.68 \cdot 60\% \cdot 12 = €321.73$$

During days 16 through 20, the social security administration pays a benefit of 60%

$$€44.68 \cdot 60\% \cdot 5 = €134.05$$

Finally, the benefit paid by the social security administration rises to 75% during days 21 and 22 (2 days): 75% paid by Social Security

$$€44.68 \cdot 75$$

All amounts are before taxes.

## 2.2 Air quality standards in Europe

In recent years, the European Parliament and the Council have passed a series of directives that aim at harmonizing air quality standards across EU member states Council of the European Union (1999); Council of the European Union and Parliament of the European Union (2000, 2002, 2004, 2008). The directives have established legally binding limits on ambient concentrations for a variety of air pollutants. The most recent one, Directive 2008/50/EC establishes limit values that apply to pollutant concentrations during different time intervals, i.e. a daily mean, the maximum daily 8-hour mean or an hourly mean, and prescribes the maximum number of permitted excee-

Table 1: Air quality standards for selected air pollutants

| Pollutant | Concentration (per $m^3$) | Averaging Period | Legal Nature | Permitted exceed-ences each year |
|---|---|---|---|---|
| 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 | - |
| Particulate Matter | 50 μg | 24 hours | Limit | 35 |
| ($PM_{10}$) | 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 |

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

dences during the course of a year.

Table 1 summarizes the limit values for the pollutants we study in this paper, namely particulate matter smaller than 10 micrometers ($PM_{10}$) , nitrogen dioxide ($NO_2$), sulfur dioxide ($SO_2$), carbon monoxide (CO) and ozone (O3).[1] For example, the daily mean of $SO_2$ shall not surpass 125 μg/$m^3$ more than 3 times a year. In addition, the 1-hour mean may not exceed 350 μg/$m^3$ more than 24 times a year. Similarly, the 24/ daily mean of $PM_{10}$ must not exceed 50 μg/$m^3$ more than 35 times and the 1-hour mean concentration of $NO_2$ may not exceed 200 μg/$m^3$ more than 18 times a year.[2] For pollutants such as CO and $O_3$, the limits apply to average concentrations calculated over the preceding 8 hours. The maximum of these 8-hour means for CO must not exceed 10mg/$m^3$. The corresponding limit for $O_3$ is 120 μg/$m^3$ and may not be exceeded on more than 25 days per year (this standard must be met only over a three-year average).

## 2.3 Related literature

TO BE COMPLETED Ostro (1983); Hausman et al. (1984)...

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

[2]We also report the annual standards for the three pollutants, though this will not be pursued in the analysis below.

# 3 Data

This paper draws on four large data bases that we describe in more detail in this section.

## 3.1 Employment histories

Our primary data come from the Spanish social security administration (*seguridad social*) which administrates both health insurance and pension benefits for more than 95% of the workforce in Spain. Since 2004, the administration maintains a research dataset, the Muestra Continua de Vidas Laborales (MCVL). The MCVL is a representative sample of anonymized individual work histories drawn from the universe of individuals who were affiliated with the social security at some point during the reporting year. An individual record contains information on both current-year and historical employment relations, dating back in time to when the administration began to keep computerized records.

## 3.2 Sick leaves

While sickness leaves are not part of the variables in the MCVL, it is possible to the invididuals sampled in the MCVL, as demonstrated by Alba (2009) and Malo et al. (2012).[3] The linking is done by staff members of the social security administration so as to ensure confidentiality. So far, the administration has matched sickness leaves only for 2009. This is why in the subsequent analysis, we use members of the general scheme from the 2004 to 2009 MCVL samples and combine their information on work days and contribution bases in 2009 with the corresponding information on sick leaves for that year.

## 3.3 Air quality

Data on air quality come from AirBase, an extensive database of measurements of air quality in the Member States of the European Union (EU) and other countries working

[3] Sickness leaves are first processed by the employer's mutual indemnity association who also reports back to the social security administration.

with the European Environment Agency (EEA). Data are collected annually by the EEA under a mandate from the Council of the European Union.[4]

With AirBase the European Topic Centre for Air and Climate Change provides a unified interface for accessing these data through the EEA website.[5] 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. In its current version 8, AirBase contains data of almost 900 air quality measurement stations across in Spain between January 1986 and December 2012. Figure shows a map with the exact location of each air quality monitor in the sample. Apart from location, the monitors differ in terms of the set of air pollutants they monitor and the time window of measurement (the vast majority of stations is still active). The meta-data include information on the municipality where the monitors stations are located, which allows us to construct a dataset on air quality across Spanish towns.

## 3.4 Weather

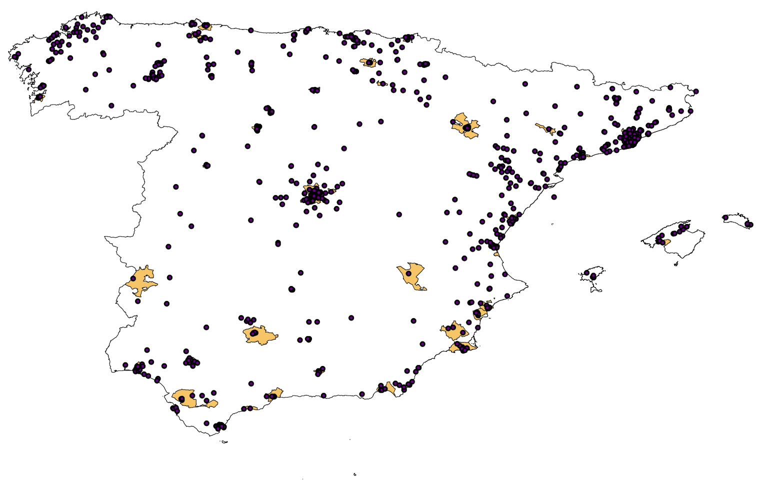
Meteorological data were downloaded from the website of the European Climate Assessment & Dataset project (ECA&D).[6] The ECA&D project collects daily data on twelve essential climate variables provided by national meteorological instutes and research institutions. For Spain, historical information is available from 1896 onwards, and the a number of variables and geographical coverage has been increasing steadily until today. The data are delivered at the level of the weather station and include the geographic coordinates of its location and other relevant meta-data. Based on the geographic coordinates, we assign each of the 117 stations to a municipality using ArcGIS. If more than one weather station is assigned to the same municipality, the variables are averaged across stations. As a result we obtain daily measurements for the key meteorological variables in more than 50 Spanish cities.

[4] Council Decision 97/101/EC of 27 January 1997 establishing a reciprocal exchange of information and data from networks and individual stations measuring ambient air pollution within the Member States, OJ L 35, 5.2.1997, p. 14–22.

[5] Available online at `http://acm.eionet.europa.eu/databases/airbase/`

[6] The ECA&D project was initiated by the European Climate Support Network of GIE-EUMETNE, an association of 31 European national meteorological agencies currently coordinated by the Royal Netherlands Meteorological Institute. The project website is available online at `http://eca.knmi.nl/`

Figure 1: Location of air quality monitors



Note: The map excludes airquality monitors on the Canary Islands.

Figure 2: Duration of sick leaves: Cardivascular and respiratory diseases

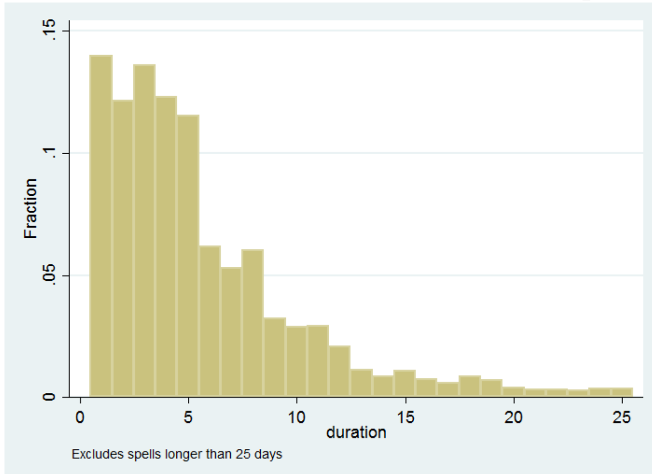



Table 2: Descriptive Statistics: Invididuals

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Variable | mean | std. dev. | min | max | *N* |
| Sick leave | 0.00283 | 0.0266 | 0 | 1 | 207,000 |
| Age | 39.39 | 11.35 | 16 | 77 | 207,000 |
| Female | 0.470 | 0.499 | 0 | 1 | 207,000 |

### 3.5 Descriptive Statistics

As shown in Table 2, the MCVL dataset comprises exactly 207,000 workers, 47% of which are female. The age of workers ranges from 16 to 77 years and the mean is at 39.29 years. For each of these workers, we know whether a sick leave was taken on any given day in 2009. Since our focus is on diseases related to air pollution, we only count sick leaves that are due to cardiovascular or respiratory diseases as air pollution is known to be a possible cause for these diseases. The average propensity to take a sick leave on a given day was 0.283%. Figure 2 plots the duration of these sick leaves.

We merge the worker data to daily pollution and weather data on the basis of the 5-digit municipality code of the workers primary residence. Table 3 summarizes the covariates in the merged dataset which is organized as a worker-by-day structure. Panel A reports daily mean values for $PM_{10}$, $NO_2$, $SO_2$ and maximum daily 8-hour means for

CO and $O_3$. These measures closely correspond to the legally binding limits on short-term concentrations summarized in Table 1, and are reported in the corresponding units of measurement.

In the regressions below, we would like to be able to account for a possible non-linear relationship between health and air quality. Therefore, we follow Currie et al. (e.g. 2009b) and define dummy variables for each pollutant that group the measured concentrations into five bins relative to the EU limit value (between 0% and 25% of the limit, between 25% and 50% of the limit, between 50% and 75% of the limit, between 75% and 100% of the limit, and above the limit). These dummy variables are summarized in Panel B of Table 3. This exercise shows that EU air quality standards were exceeded only for particulate matter (on average 5.55% of worker days) and ozone (on average on 1.52% of worker days). However, this should not be interpreted to mean that ambient concentrations of carbon monoxide, sulphur dioxide and nitrogen oxide were innocuous. In fact, the World Health Organization has recommended much stricter air quality standards than the EU to avoid health problems (WHO, 2006).

Panel C summarizes the weather variables. Cloud cover is measured in integer-valued oktas ranging from 0 (sky completely clear) to 8 (sky completely cloudy). Wind speed is measured in 0.1 meters per second, precipitation in 0.1 millimeters and daily average temperature in 0.1 degrees Celsius.

Finally, as shown in Table 4, some of the pollution measures are strongly correlated.

# 4 Empirical model

We aim to model two salient empirical facts. The first one is the propensity to take a sick leave as a function of time invariant and time-varying factors. The second one concerns the length of a sickness spell leave, conditional on having taken a leave. It is not straightforward to model these to aspects in a standard econometric model. Structural econometric modeling offers ways of doing that though at a substantial cost in terms of the parametric and behavioral assumptions that necessarily enter such a model. Since much of the literature on air quality and health has been focusing on the impact of pollution on wellbeing, we shall start with an econometric approach that

Table 3: Descriptive statistics: Pollution and Weather

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Variable | mean | std. dev. | min | max | *N* |
| *A. Pollution: mean concentrations* | | | | | |
| SO2_day | 6.559 | 4.653 | 0.100 | 72.02 | 51,363,619 |
| PM10_day | 26.40 | 13.38 | 1.143 | 115.4 | 51,363,619 |
| CO_dymax | 0.536 | 0.305 | 0.0110 | 3.983 | 51,363,619 |
| O3_dymax | 68.07 | 25.51 | 0.500 | 160 | 51,363,619 |
| NO2_day | 39.62 | 20.83 | 0.575 | 121.2 | 51,363,619 |
| *B. Pollution: intervals relative to EU standard* | | | | | |
| PM_25_50 | 0.393 | 0.488 | 0 | 1 | 51,363,619 |
| PM_50_75 | 0.314 | 0.464 | 0 | 1 | 51,363,619 |
| PM_75_100 | 0.118 | 0.323 | 0 | 1 | 51,363,619 |
| PM_100_inf | 0.0555 | 0.229 | 0 | 1 | 51,363,619 |
| SO2_25_50 | 0.00200 | 0.0447 | 0 | 1 | 51,363,619 |
| SO2_50_75 | 0.000135 | 0.0116 | 0 | 1 | 51,363,619 |
| SO2_75_100 | 0 | 0 | 0 | 0 | 51,363,619 |
| SO2_100_inf | 0 | 0 | 0 | 0 | 51,363,619 |
| CO_dymax_25_50 | 0.00191 | 0.0437 | 0 | 1 | 51,363,619 |
| CO_dymax_50_75 | 0 | 0 | 0 | 0 | 51,363,619 |
| CO_dymax_75_100 | 0 | 0 | 0 | 0 | 51,363,619 |
| CO_dymax_100_inf | 0 | 0 | 0 | 0 | 51,363,619 |
| O3_dymax_25_50 | 0.290 | 0.454 | 0 | 1 | 51,363,619 |
| O3_dymax_50_75 | 0.419 | 0.493 | 0 | 1 | 51,363,619 |
| O3_dymax_75_100 | 0.192 | 0.394 | 0 | 1 | 51,363,619 |
| O3_dymax_100_inf | 0.0152 | 0.122 | 0 | 1 | 51,363,619 |
| NO2_25_50 | 0.288 | 0.453 | 0 | 1 | 51,363,619 |
| NO2_50_75 | 0.00380 | 0.0615 | 0 | 1 | 51,363,619 |
| NO2_75_100 | 0 | 0 | 0 | 0 | 51,363,619 |
| NO2_100_inf | 0 | 0 | 0 | 0 | 51,363,619 |
| *C. Weather* | | | | | |
| cloud_cover | 3.563 | 2.460 | 0 | 8 | 41,065,158 |
| wind_speed | 30.97 | 17.53 | 0 | 167 | 40,369,944 |
| precipitation | 13.13 | 47.13 | 0 | 755 | 39,805,269 |
| mean_temperature | 165.1 | 72.92 | -47 | 341.5 | 42,142,190 |

Table 4: Correlation of pollution measures

| | PM10_day | SO2_day | CO_dymax | O3_dymax | NO2_day |
|---|---|---|---|---|---|
| PM10_day | 1 | | | | |
| SO2_day | 0.0931 | 1 | | | |
| CO_dymax | 0.253 | 0.4242 | 1 | | |
| O3_dymax | -0.0113 | -0.2479 | -0.3256 | 1 | |
| NO2_day | 0.3484 | 0.4783 | 0.4811 | -0.4043 | 1 |

seeks to consistently estimate the extensive margin decision of whether or not to take a sick leave in response to a bad pollution day. Our approach is data driven and rests on the least restrictive parametric assumptions.

## 4.1 Baseline specification

We specify the probability $P_{imt}$ that individual $i$ living in municipality $m$ takes a sick leave on day $t$ as

$$P_{imt} = x'_{mt}\alpha + w'_{mt}\beta + z'_{im}\gamma + \phi_{\mathrm{m}} + \tau_t + \varepsilon_{imt} \tag{1}$$

where $x_{mt}$ is a vector of ambient pollution concentrations in municipality $m$, $z_{im}$ are time-invariant characteristics of individual $i$, $\phi_m$ is a municipality fixed effect. The vector $w_{mt}$ contains second-order polynomials of average temperature, precipiation, cloud cover, and wind speed. In addition, we include a vector of time effects $\tau_t$ to control for day of week, calendar month, and public holidays.

We estimate equation (1) and all following equations as linear probability models on a subset of the data for which all pollution variables are observed. The vector of air pollution concentrations $x_{mt}$ comprises the pollution variables summarized in panels A and B of Table 3, or subsets thereof.

## 4.2 Count data model

TO BE COMPLETED

Table 5: Particulate Matter: Daily mean effects

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable: sick leave | | | | | |
| PM10_day | 0.215*** | 0.064*** | 0.038*** | 0.213*** | 0.063*** | 0.036*** |
| | (0.013) | (0.014) | (0.014) | (0.013) | (0.014) | (0.014) |
| Constant | -3.410 | -0.946 | -0.099 | 22.5*** | 25.6*** | 26.3*** |
| | (5.13) | (5.22) | (5.22) | (2.31) | (2.38) | (2.38) |
| $R^2$ | 0.000 | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 |
| Weather controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-week FE | No | Yes | Yes | No | Yes | Yes |
| Month FE | No | Yes | Yes | No | Yes | Yes |
| Holiday FE | No | No | Yes | No | No | Yes |
| Noschool FE | No | No | Yes | No | No | Yes |
| Municipality FE | Yes | Yes | Yes | No | No | No |
| Individual controls | Yes | Yes | Yes | No | No | No |
| Individual FE | No | No | No | Yes | Yes | Yes |
| No. of obs. | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 |
| No. of workers | | | | 144,245 | 144,245 | 144,245 |

Notes: All coefficients are scaled by a factor of 10,000 for better readability. Robust standard errors in parentheses, clustered at worker level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

# 5 Results

We estimate the baseline specification (1) on a matched sample comprised of 144,245 workers and more than 37.5 million worker-day observations. Table 5 summarizes the results when particulate matter is the only pollution measures included in the regression. The effect is positive and statistically significant throughout, but it becomes smaller as more time effects are included. Including individual fixed effects hardly changes the estimates which suggests that municipality fixed effects are effective controls for unobserved heterogeneity in the propensity to take a sick leave. According to the most conservative estimate of 0.0000036, a reduction of the daily average concentration by one standard deviation (13.38µg – which happens to be approximately half the average concentration) would reduce the propensity to take a sick leave by 0.005 percentage points from the mean of 0.228%.

Table 6 shows the results from the alternative estimation with dummies for five intervals of PM10 concentrations. These results confirm that PM10 has a positive and significant impact on the propensity to take a sick leave, and that this effect is increasing with the concentrations.

Table 6: Particulate matter: Intervals

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable: sick leave | | | | | |
| PM_25_50 | 2.57*** | 1.99*** | 1.082*** | 2.489*** | 1.959*** | 1.051*** |
| | (0.34) | (0.352) | (0.356) | (0.334) | (0.347) | (0.35) |
| PM_50_75 | 4.07*** | 1.56*** | 0.377 | 3.979*** | 1.569*** | 0.38 |
| | (0.373) | (0.395) | (0.402) | (0.366) | (0.388) | (0.396) |
| PM_75_100 | 8.33*** | 2.79*** | 1.393*** | 8.272*** | 2.736*** | 1.327*** |
| | (0.476) | (0.494) | (0.503) | (0.47) | (0.487) | (0.496) |
| PM_100_inf | 11.3*** | 4.32*** | 2.879*** | 11.149*** | 4.169*** | 2.712*** |
| | (0.755) | (0.78) | (0.79) | (0.741) | (0.765) | (0.775) |
| Constant | -1.53 | -1.04 | -0.040 | 24.389*** | 25.381*** | 26.367*** |
| | (5.14) | (5.24) | (5.236) | (2.32) | (2.391) | (2.391) |
| $R^2$ | 0.000 | 0.001 | 0.0009 | 0.0001 | 0.0005 | 0.0005 |
| Weather controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-week FE | No | Yes | Yes | No | Yes | Yes |
| Month FE | No | Yes | Yes | No | Yes | Yes |
| Holiday FE | No | No | Yes | No | No | Yes |
| Noschool FE | No | No | Yes | No | No | Yes |
| Municipality FE | Yes | Yes | Yes | No | No | No |
| Individual controls | Yes | Yes | Yes | No | No | No |
| Individual FE | No | No | No | Yes | Yes | Yes |
| No. of obs. | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 |
| No. of workers | | | | 144,245 | 144,245 | 144,245 |

Notes: All coefficients are scaled by a factor of 10,000 for better readability. Robust standard errors in parentheses, clustered at worker level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Next we turn to the other pollutants. Table 7 reports the results from a regression of sick leave on mean concentrations of all five pollutants. As before, including worker fixed effects hardly affects the results. While the effect of PM10 found previously vanishes in this specification, a positive and significant coefficient is found for nitrogen oxide concentrations. As reported in Table 4, PM10 and NO2 are correlated with a correlation coefficient of 0.35, so it is possible that the previous regressions picked up a the effect of high nitrogen dioxide concentrations on worker wellbeing. Furthermore, we find that high concentrations of sulphur dioxide and ozone both have a negative impact on sick leaves.

Table 7: All pollutants: Daily mean effects

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | Dependent variable: sick leave | | | |
| PM10_day | 0.019 | 0.005 | -0.004 | 0.014 | 0.002 | -0.008 |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.015) | (0.015) |
| SO2_day | -1.029*** | -0.396*** | -0.365*** | -1.075*** | -0.387*** | -0.356*** |
| | (0.104) | (0.102) | (0.102) | (0.103) | (0.101) | (0.101) |
| CO_dymax | 2.978* | -1.32 | -1.023 | 3.702** | -0.963 | -0.664 |
| | (1.65) | (1.653) | (1.655) | (1.628) | (1.636) | (1.638) |
| O3_dymax | -0.329*** | -0.076*** | -0.082*** | -0.336*** | -0.072*** | -0.078*** |
| | (0.018) | (0.015) | (0.015) | (0.018) | (0.015) | (0.015) |
| NO2_day | 0.165*** | 0.131*** | 0.096*** | 0.163*** | 0.13*** | 0.095*** |
| | (0.021) | (0.022) | (0.023) | (0.020) | (0.022) | (0.022) |
| Constant | 16.145*** | 2.872 | 4.801 | 40.38*** | 28.246*** | 30.206*** |
| | (5.173) | (5.333) | (5.332) | (2.753) | (2.792) | (2.791) |
| $R^2$ | 0.0006 | 0.0009 | 0.0009 | 0.0002 | 0.0005 | 0.0005 |
| Weather controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-week FE | No | Yes | Yes | No | Yes | Yes |
| Month FE | No | Yes | Yes | No | Yes | Yes |
| Holiday FE | No | No | Yes | No | No | Yes |
| Noschool FE | No | No | Yes | No | No | Yes |
| Municipality FE | Yes | Yes | Yes | No | No | No |
| Individual controls | Yes | Yes | Yes | No | No | No |
| Individual FE | No | No | No | Yes | Yes | Yes |
| No. of obs. | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 |
| No. of workers | | | | 144,245 | 144,245 | 144,245 |

Notes: All coefficients are scaled by a factor of 10,000 for better readability. Robust standard errors in parentheses, clustered at worker level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We investigate this further in Table 8 which reports the results from a specification with dummies for different intervals of pollution concentrations relative to the standard. Notice that some interval dummies for $SO_2$ and $NO_2$ are droppped because concentrations remain well below the EU limits. These regressions confirm the positive and significant impact of nitrogen oxide on sick leaves. The magnitude of this effect is about ten times larger when concentrations are at 50%-75% of the EU limit than when they are at 25%-50%, which hints at a very elastic relationship between pollution and worker response. Again we find a negative and significant impact of ozone concentrations on sick leaves, and surprisingly this effect remains very flat at concentrations above 50% of the EU limit. While sulphur dioxide is not systematically related to sick leaves across specifications, we now find a negative and significant coefficient on carbon monoxide.

# 6 Conclusions

TO BE COMPLETED

Table 8: All pollutants: Intervals

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable: sick leave | | | | | |
| PM_25_50 | 0.475 | 1.252*** | 0.469 | 0.376 | 1.237*** | 0.454 |
| | (0.346) | (0.351) | (0.351) | (0.341) | (0.347) | (0.348) |
| PM_50_75 | 0.15 | 0.346 | -0.584 | 0.008 | 0.358 | -0.576 |
| | (0.401) | (0.402) | (0.404) | (0.395) | (0.397) | (0.399) |
| PM_75_100 | 1.75*** | 0.756 | -0.344 | 1.583*** | 0.685 | -0.42 |
| | (0.509) | (0.499) | (0.5) | (0.504) | (0.494) | (0.496) |
| PM_100_inf | 3.962*** | 2.215*** | 1.142 | 3.688*** | 2.074*** | 0.994 |
| | (0.774) | (0.755) | (0.759) | (0.763) | (0.743) | (0.747) |
| SO2_25_50 | -14.26*** | -6.065 | -6.343 | -14.8*** | -6.192 | -6.463* |
| | (3.964) | (3.925) | (3.925) | (3.948) | (3.911) | (3.911) |
| SO2_50_75 | -2.661 | 4.465 | 5.886 | -4.303*** | 2.822 | 4.279 |
| | (8.095) | (7.975) | (7.971) | (8.091) | (7.979) | (7.977) |
| CO_dymax_25_50 | -20.83*** | -14.896** | -14.313** | -19.991*** | -13.566** | -12.99** |
| | (6.391) | (6.357) | (6.356) | (6.298) | (6.266) | (6.265) |
| O3_dymax_25_50 | -7.712*** | -1.797*** | -1.668*** | -8.058*** | -1.715*** | -1.58*** |
| | (0.699) | (0.599) | (0.6) | (0.689) | (0.588) | (0.589) |
| O3_dymax_50_75 | -19.452*** | -5.168*** | -5.069*** | -20.021*** | -5.058*** | -4.946*** |
| | (1.092) | (0.859) | (0.86) | (1.073) | (0.838) | (0.839) |
| O3_dymax_75_100 | -23.458*** | -5.826*** | -5.947*** | -23.988*** | -5.631*** | -5.734*** |
| | (1.229) | (0.973) | (0.973) | (1.205) | (0.949) | (0.948) |
| O3_dymax_100_inf | -23.7*** | -5.197*** | -5.023*** | -24.152*** | -4.927*** | -4.732*** |
| | (1.421) | (1.177) | (1.18) | (1.395) | (1.154) | (1.157) |
| NO2_25_50 | 2.753*** | 1.686*** | 1.141*** | 2.696*** | 1.731*** | 1.179*** |
| | (0.308) | (0.314) | (0.319) | (0.306) | (0.31) | (0.316) |
| NO2_50_75 | 14.028*** | 10.476*** | 10.247*** | 14.089*** | 11.065*** | 10.828*** |
| | (1.716) | (1.646) | (1.648) | (1.713) | (1.642) | (1.644) |
| Constant | 4.983 | -0.003 | 1.052 | 28.431*** | 25.475*** | 26.567*** |
| | (5.151) | (5.265) | (5.264) | (2.383) | (2.462) | (2.461) |
| $R^2$ | 0.0006 | 0.0009 | 0.0009 | 0.0002 | 0.0005 | 0.0005 |
| Weather controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-week FE | No | Yes | Yes | No | Yes | Yes |
| Month FE | No | Yes | Yes | No | Yes | Yes |
| Holiday FE | No | No | Yes | No | No | Yes |
| Noschool FE | No | No | Yes | No | No | Yes |
| Municipality FE | Yes | Yes | Yes | No | No | No |
| Individual controls | Yes | Yes | Yes | No | No | No |
| Individual FE | No | No | No | Yes | Yes | Yes |
| No. of obs. | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 | 37,540,588 |
| No. of workers | | | | 144,245 | 144,245 | 144,245 |

Notes: All coefficients are scaled by a factor of 10,000 for better readability. Robust standard errors in parentheses, clustered at worker level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

## References

Alba, A. (2009). *La incapacidad temporal para el trabajo: análisis economómico de su incidencia y su duración*. Technical report, Universidad Carlos III de Madrid.

Chay, K. Y. & Greenstone, M. (2003). The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *Quarterly Journal of Economics*, 118(3), 1121–1167.

Council of the European Union (1999). Council Directive (EU) 1999/30/EC.

Council of the European Union and Parliament of the European Union (2000). Directive 2000/69/EC of the European Parliament and of the Council.

Council of the European Union and Parliament of the European Union (2002). Directive 2002/3/EC of the European Parliament and of the Council .

Council of the European Union and Parliament of the European Union (2004). Directive 2004/107/EC of the European Parliament and of the Council .

Council of the European Union and Parliament of the European Union (2008). Directive 2008/50/EC of the European Parliament and of the Council.

Currie, J., Hanushek, E. A., Kahn, E. M., Neidell, M., & Rivkin, S. G. (2009a). Does pollution increase school absences? *Review of Economics and Statistics*, 91(4), 682–694.

Currie, J. & Neidell, M. (2005). Air pollution and infant health: What can we learn from California's recent experience? *Quarterly Journal of Economics*, 120(3), 1003–1030.

Currie, J., Neidell, M., & Schmieder, J. F. (2009b). Air pollution and infant health: Lessons from New Jersey. *Journal of Health Economics*, 28(3), 688 – 703.

Hanna, R. & Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics*, 122, 68 – 79.

Hansen, A. C. & Selte, H. K. (2000). Air pollution and sick-leaves. *Environmental and Resource Economics*, 16(1), 31–50.

Hausman, J. A., Ostro, B. D., & Wise, D. A. (1984). *Air Pollution and Lost Work*. NBER Working Papers 1263.

Karlsson, M., Schmitt, M., & Ziebarth, N. R. (2015). The short-term population health effects of weather and pollution. *Working Paper*.

Lavy, V., Ebenstein, A., & Roth, S. (2014). *The Long Run Human Capital and Economic Consequences of High-Stakes Examinations*. NBER Working Paper 20647.

Lichter, A., Pestel, N., & Sommer, E. (2015). *Productivity Effects of Air Pollution: Evidence from Professional Soccer*. IZA Discussion Papers 8964, Institute for the Study of Labor (IZA).

Malo, M. A., Cueto, B., García Serrano, C., & Pérez Infante, J. I. (2012). *La medición del absentismo: Estimaciones desde la perspectiva de las empresas y de las vidas laborales*. Technical report, Ministerio de Empleo y Seguridad Social.

Ostro, B. D. (1983). The effects of air pollution on work loss and morbidity. *Journal of Environmental Economics and Management*, 10(4), 371 – 382.

Schlenker, W. & Walker, W. R. (2016). Airports, air pollution, and contemporaneous health. *Review of Economic Studies*, 83(2), 768–809.

WHO (2006). *WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide*. Geneva, Switzerland: World Health Organization.

Zivin, J. G. & Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7), 3652–3673.