The Cost of Air Pollution for Workers and Firms

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Abstract

This paper shows that even moderate levels of air pollution, such as those found in Europe, harm the economy by decreasing firm performance. We estimate the causal effect of fine particulate matter pollution ($PM_{2.5}$) on monthly firms' sales and worker absenteeism in France, using administrative data on 160,000 firms representing half of the country's GDP. We exploit within-municipality variation in air pollution induced by changes in monthly wind direction. We find that a 10 percent increase in firms' monthly $PM_{2.5}$ exposure decreases sales in the following two months by 0.4 percent on average, with heterogeneous effects across economic sectors. Concurrently, sick leave increases by 1 percent, highlighting the negative effects of air pollution on workers' health. Yet sales losses are an order of magnitude larger than we would expect if pollution-induced worker absenteeism was the main underlying channel. We provide suggestive evidence that air pollution also affects firm performance via a decrease in the productivity of non-absent workers and in local demand. Our results suggest that reducing air pollution in line with the World Health Organization's guidelines would generates economic benefits largely exceeding the cost of environmental regulation in Europe.

Keywords: Cost of air pollution, Absenteeism, Firm performance

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1 Introduction

It is widely acknowledged that air pollution has detrimental effects on human health.[1] Air pollution exposure causes higher emergency admissions and mortality (Schlenker and Walker, 2016; Deryugina et al., 2019), higher medical expenditures (Barwick et al., 2024), and a higher number of work loss days (Holub et al., 2021). Cognitive functions and intellectual performance may also be impaired (Aguilar-Gomez et al., 2022). These large health costs directly affect the utility of many individuals and are sufficient to justify public intervention. Yet, there might be even wider economic costs if air pollution's impacts on individuals translate into substantial production losses for firms. While several papers have examined how air pollution affects workers and firms using detailed data on a handful of production sites or for specific occupations, there is limited evidence at the scale of an entire economy.

In this paper, we estimate the causal effect of air pollution exposure on firm production in France, using confidential firm- and worker-level data covering half of the country's private sector (excluding agriculture and financial services). We examine how much of the observed sales losses arise due to workers entering sick leave and missing work, as opposed to effects on worker productivity or demand, based on our analytical framework describing how firms can be impacted by pollution shocks.

We assemble a unique dataset which combines the monthly sales of 160,000 firms with the sickness leave episodes of a representative sample of their workers, granular measures of air pollution, and weather conditions at the workplace between 2009 and 2015. We focus on exposure to fine particulate matter pollution ($PM_{2.5}$) since this pollutant can penetrate deep into the respiratory tract and enter the brain, with particularly detrimental health effects.[2] It can also easily penetrate indoors, thus affecting most workers. Two key challenges with identifying the causal effects of pollution exposure on firms' sales and work absenteeism are that air pollution is often a co-product of production, and individual exposure to pollution exposure is always measured with noise.[3] To circumvent these challenges, our analysis leverages variation in air pollution induced by changes in monthly wind directions at the postcode area level – there are 6,328 such postcode areas in France, which we will refer to as municipalities in the remainder of the paper.

The identifying assumption of our instrumental variable (IV) approach is that, after flexi-

[1] Exposure to fine particulate matter ($PM_{2.5}$), for instance, is associated with approximately 4.2 million premature deaths every year globally (WHO, 2014). Even in Europe, where air pollution has been regulated for several decades, an annual 307,000 premature deaths are attributed to $PM_{2.5}$ pollution (European Environment Agency, 2020).

[2] The 2.5 subscript in $PM_{2.5}$ means that these particles have a size lower than 2.5 μm.

[3] In an ideal setting, pollution exposure would be measured by multiplying pollution levels from each location where an individual spend some time by the number of hours spent in each location. In this paper, we proxy pollution exposure by pollution levels measured at the municipality of the workplace, where workers spend most of their waking hours.

bly controlling for firm-year, month-by-year-by-industry and quarter-by-region fixed effects and weather variables, changes in a municipality's monthly wind direction are unrelated to changes in the sales of firms located in the same municipality except through their influence on air pollution. The benefit of our approach is that it does not require identifying the sources of pollution in each area. Instead, we allow wind directions to influence pollution differently for each municipality in metropolitan France. Our analysis thus employs a similar strategy to Graff Zivin et al. (2023), inspired by Deryugina et al. (2019). While workers' absenteeism is observed at the establishment level, a unique location for which we can easily assign a pollution exposure measure, monthly sales are only observed at the firm level. Thirty-six percent of firms own several establishments in different municipalities, rendering the previous IV approach inapplicable. We therefore exploit another IV approach by computing a weighted average of predicted pollution exposure at the firm-month level, taking into account pollution exposure at each of the locations where a firm owns establishments.

We develop an analytical framework highlighting three channels through which air pollution can influence sales: i) a decrease in labor supply, as measured by an increase in work absenteeism in our context; ii) a decrease in productivity among non-absent workers, which can result from non-absent workers suffering from mild health symptoms or reduced cognitive capacities, as well as from the potential disruptions in production value chains when their co-workers take sick leaves; and iii) a decrease in demand.[4] We use the sick leave data to quantify the contribution of the first channel to the sales decrease. The difference between the magnitude of this channel and the total sales effect is informative on the magnitude of productivity and demand effects.

Our study has four main results. First, firm-level exposure to $PM_{2.5}$ has widespread negative effects on sales in the private sector. We estimate that a 10 percent increase in firm-level pollution exposure in month $t-1$ decreases firm-level sales by 0.40 percent on average in the two following months. The effects differ by economic sector: manufacturing sales and sales in business-to-business trade and services decrease by about 0.20 percent, construction sales by 0.12 percent, while the effect is larger for business-to-consumer industries serving a local demand, with sales decreases around 0.70 percent. An analysis of dynamic effects using a polynomial distributed lag specification suggests that sales decrease until two to three months after the pollution increase, and that the effect dies down after five months, without rebound. These results also hold for the sub-sample of single-establishment firms, for which pollution exposure is measured more accurately in only one location. They are robust to excluding months with air quality alerts, replacing $PM_{2.5}$ with a multi-pollutant air quality index, winsorizing the outcome variable and changing the

[4]In our study, we define the labor supply response in terms of whether or not a worker calls sick to work, which, in France, requires a medical certificate signed by a general practitioner. If a worker chooses to go to work while shortening his number of hours per day, we consider that the channel is lower productivity.

specification of weather controls.

Second, we find that air pollution decreases labour supply by increasing the number of workers in sick leave: our estimates imply that a 10 percent increase in monthly $PM_{2.5}$ exposure increases sickness leave episodes by 1 percent within the month of exposure. The effect of air pollution on work absenteeism is also heterogeneous across economic sectors: it is mostly driven by sick leave increase in manufacturing firms, while we cannot rule out a null effect in the business-to-business trade and services sector. Since the effect of air pollution on sales is similar in these two sectors, we conclude that the decrease in labour supply cannot be the only channel via which air pollution affects firms' sales. We also proxy the sales losses associated with pollution-induced lost days of work in manufacturing (assuming that worker absenteeism does not affect co-worker productivity). We find that this cost is several orders of magnitude smaller than our estimate of pollution-induced manufacturing sales loss. We conclude that the productivity and demand channels must play an important role in decreasing sales.

Third, to disentangle the productivity channel from the demand channel, we compare the effect of pollution on sales in manufacturing industries with high versus low stock levels. We expect that firms with high stock levels are better able to smooth temporary supply-side shocks by selling existing stocks, such that these shocks do not result in sales decrease. On the other hand, they have no reason to be less affected by demand-side shocks. Thus, comparing how air pollution affects sales in the two groups of firms provides a test for whether the air pollution shock is more a supply-side shock affecting workers' productivity or a demand-side shock. Importantly, air pollution increases worker absenteeism by the same amount in the two groups of firms, so we can rule out that any difference in the sales effects is driven by the absenteeism channel. We find that sales in firms with low stock levels experience a 0.3 percent decrease for a 10% increase in pollution, while the effect is close to zero and not significant for firms in industries with high low stock levels. We conclude that at least in manufacturing, air pollution negatively affects the productivity of non-absent workers, and that this productivity effect is an important driver of sales losses.

Fourth, we quantify the benefits associated with reducing pollution levels so as to meet the World Health Organization (WHO)'s recommendations of not exceeding 15 $\mu g/m^3$ for daily $PM_{2.5}$ exposure. In our sample, meeting the recommendations implies reducing pollution levels by 25%. Based on our estimates, bringing pollution levels down to 15 $\mu g/m^3$ every day would have avoided around 27 billion euros of foregone sales (1.5% of total private sector sales) every year between 2009 and 2015. Assuming an average profit share of 30%, this gives 8 billion euros of foregone value added. While there is no readily available estimate for the cost of meeting the WHO threshold, a scenario reducing $PM_{2.5}$ emissions by 33% has been estimated to cost 0.77 billion euros annually. Although the regulatory cost may exceed the benefits from reduced air pollution for a share of firms, our results suggest that the average effect would be a large net benefit.

To the best of our knowledge, this paper provides the first countrywide estimates of the effect of air pollution on firms' performance and their workers in a high-income country. Previous literature has examined how pollution affects workers, in terms of productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Lichter et al., 2017; Meyer and Pagel, 2017; He et al., 2019; Chang et al., 2019; Adhvaryu et al., 2022) and decision-making (Meyer and Pagel, 2017; Dong et al., 2019), based on specific settings where workers are paid by the hour or productivity is easy to observe. Other studies have examined pollution effects on labor supply (Aragón et al., 2017) or firms' performance (Fu et al., 2021) using representative data at the country level in the context of developing countries. We expect pollution to affect workers' health, labor supply and productivity differently in high-income countries, where the levels and saliency of pollution are lower, the sectoral composition of the economy is different, and workers often benefit from institutionalized sickness leave. Average pollution levels in France are similar to those in Europe and slightly above those in the US.[5] Thus, we expect our results to have external validity for other high-income countries.

A closely related study by Holub et al. (2021) estimates the effects of PM_{10} on sickness leaves in Spain and derive an economic cost associated with pollution-induced work loss days by multiplying the number of work loss days with workers' daily wage. We differ from this study in the type of pollutant, in the choice of instrument – adopting wind directions instead of episodes of Sahara wind –, but more importantly in the combination of employer-employee data that allows us to estimate the cost of pollution in terms of foregone sales, which we find to be much larger than the cost related to work absenteeism only. Furthermore, another related study by Borgschulte et al. (2022) finds that air pollution shocks induced by wild-fire smoke in the US reduce per capita earnings in the medium run, using county-level data. Combining worker- and firm-level data, our study sheds light on two possible mechanisms at play: first, workers may not be fully compensated for the income loss associated with taking a sickness leave; second, lower sales in some sectors may reduce the demand for labor.

Our paper contributes to the literature that evaluates the cost of air pollution based on micro-level data. This literature has focused almost exclusively on the health costs to individuals (Deryugina et al., 2019; Mink, 2022; Barwick et al., 2024). For instance, Mink (2022) estimates that reducing nitrogen dioxide concentrations by 27% would save at least €5.2 billion in healthcare costs in France. Our results suggest that considering only the health effects from pollution while ignoring its effects on firms may widely underestimate the economic costs associated with pollu-

[5] In 2015, population-weighted $PM_{2.5}$ exposure was 13 µg/m^3 in France, 8 µg/m^3 in the US, 11 µg/m^{3}in Spain and the UK, 13 µg/m^3 in Germany, and 17 µg/m^3 in Italy. Source: https://www.who.int/data/gho/data/themes/air-pollution/modelled-exposure-of-pm-air-pollution-exposure.

tion shocks. This corroborates the findings in Dechezleprêtre et al. (2019) that a 10% increase in annual $PM_{2.5}$ decreases real GDP by 0.8%, based on GDP data from European regions. By using micro data, our study highlights the heterogeneous effects across economic sectors and provide suggestive evidence of the channels underlying the output loss.

More broadly, our paper adds to the literature on the effects of environmental shocks on workers and firms. Previous literature has examined the effects of high temperatures on workers' productivity (Somanathan et al., 2021), labor supply (Graff Zivin and Neidell, 2014), firms' sales (Addoum et al., 2020), and work accidents (Park et al., 2021) in the context of climate change. In contrast to our findings using pollution shocks, Addoum et al. (2020) fails to detect a significant impact of temperature shocks on US firms' economic performance. This difference may arise from the fact that temperature shocks are salient, which may trigger a private adaptation response which consists in using air conditioning at the workplace, whereas air pollution shocks are largely unnoticed in our context and adaptation is limited.

The rest of the paper is organized as follows. Section 2 provides a brief background on the effect of fine particulate matter on health and describes the data sets. Section 3 presents an analytical framework that formalizes the potential channels through which pollution can affect firms' sales and describes our empirical strategy. Section 4 presents the main results. Section 5 discusses the channels, and section 6 concludes.

2 Background and Data

2.1 Air Pollution, Health, and Productivity in the French Context

As in many high-income countries, air quality in France has been improving in the last decades (Champalaune, 2020; Sicard et al., 2021; Currie et al., 2023). Air pollution is regulated via command and control taking the form of maximum concentration thresholds defined at the European level. Depending on the pollutant, the thresholds are defined at the annual and/or 24-hour level. While the European Union annual threshold of 25 $\mu g/m^3$ for $PM_{2.5}$ is rarely exceeded, the workers in our sample are exposed to daily concentration exceeding the WHO recommended threshold of 15 $\mu g/m^3$ for 37% of worker-days.[6] Due to recurrent non-compliance with EU air quality standards, the European Commission recently referred the French government to the Court of Justice of the EU for systematic failure to meet EU rules and adopt plans to reduce air pollution.[7]

[6] See the 2021 recommendations from the World Health Organization (WHO) at https://apps.who.int/iris/handle/10665/345329.

[7] The legal thresholds are defined in the EU legislation and transposed into French law. The French government must comply with these thresholds or risks incurring sanctions. France was referred to the Court of Justice of the European Union for exceeding the daily thresholds for nitrogen dioxide (NO2) in 2019 (Commission against France, C-636/18) and for particulate matter PM_{10} in 2020 (European Commission, 2020).

Particulate matter with a diameter below 2.5 micrometers ($PM_{2.5}$) enters the lungs and can pass into the bloodstream, resulting in significant health problems such as increased mortality and cardiovascular diseases (World Health Organization, 2016; European Environment Agency, 2020).[8] A large literature has shown the negative effects of short- and long-term exposure to $PM_{2.5}$ on human health, even at low levels of exposure. For instance, Deryugina et al. (2019) found that, in the US, a 1 µg/m^3 increase in $PM_{2.5}$ exposure for one day causes 0.69 additional deaths per million elderly individuals over the three following days. $PM_{2.5}$ also readily penetrates indoors (Chang et al., 2016; Krebs et al., 2021), thereby being likely to affect individuals in their working environment. Exposure to fine particulate matter can temporarily affect cognitive functions: mounting toxicological evidence suggests that it can enter the brain and increase neuro-inflammation and oxidative stress in the central nervous system. Furthermore, $PM_{2.5}$ can travel far (hundreds of kilometres) and remain in the atmosphere for a long period of time (US EPA, 2018).

The recent literature has identified different ways through which air pollution can affect workers' productivity and firms' performance. In the context of developing countries or in settings where workers are paid by the hour, several studies find that pollution reduces workers' productivity primarily through a decrease in output per hour (Graff Zivin and Neidell, 2012; Chang et al., 2016; Adhvaryu et al., 2022; Chang et al., 2019; He et al., 2019). Other papers find that air pollution reduces labor supply, both in the short run (Hanna and Oliva, 2015; Aragón et al., 2017; Holub et al., 2021; Hoffmann and Rud, 2024) or in the medium run (Borgschulte et al., 2022). By reducing non-absent workers' productivity or by reducing labor supply, air pollution will likely also reduce firms' output and sales. Fu et al. (2021) shows that air pollution decreases annual firm-level productivity for a large representative sample of Chinese manufacturing firms. However, in few cases where firms' response could be explored, studies find that firms can dampen the productivity loss from their most affected employees by reallocating tasks among all employees (Adhvaryu et al., 2022), by hiring new employees (Fu et al., 2021), or by asking unaffected workers to work longer hours.

We expect that labor market institutions, industry, and the saliency of pollution shocks influence how workers and firms respond to these shocks. In particular, workers may benefit from different levels of job protection across countries, sectors, and firms, which will lead to different abilities to take sick leaves when being ill. In France, private sector employees are entitled to relatively generous sickness allowances, under some conditions. Sickness allowances consist of three

[8] $PM_{2.5}$ is related to other air pollutants. In particular, it is by definition included in PM_{10} concentration levels, but it is deadlier because smaller-sized particles penetrate deeper into the respiratory system. $PM_{2.5}$ can be either directly emitted as "primary" particles, for which the main contributors are the residential and tertiary sector (52%), transportation (20%), manufacturing (18%) and agriculture (11%) (CITEPA, 2021) or formed in the atmosphere as "secondary" particles from the chemical reactions of gaseous pollutants, including SO_2 and NO_2.

parts, all conditioned on providing a medical certificate and having worked at least 150 hours in the past three months. First, workers receive publicly funded benefits from the fourth day of a sickness leave episode (hereafter, SLE), which amount to roughly 50% of their gross daily wage. Second, they receive an allowance from mandatory employer-funded funds from the eighth day of leave, which amounts to 40% of their gross daily wage for the first 30 days.[9] Third, they receive an optional employer-funded allowance that is negotiated in collective agreements and generally covers the difference between the gross daily wage and the publicly-funded plus mandatory employer-funded benefits. According to survey evidence (Pollak, 2015), two-thirds of private sector employees receive this optional allowance and are granted a 100 percent replacement rate from the first day of leave.

While developing countries such as India or China face very high air pollution levels that may render pollution shocks more visible to managers and firms, the moderate levels of pollution in high-income countries such as France have ambiguous effects on the severity of economic consequences for firms. On the one hand, few workers may suffer severe health symptoms or impaired productivity under such moderate pollution levels. This would suggest that firms would experience small decline in their productivity and output. On the other hand, pollution shocks being less salient implies that managers are less able to respond appropriately by mitigating the reduction in output.

2.2 Data

We combine nationwide gridded reanalysis pollution and weather data, a representative panel dataset of French private sector employees affiliated to France's universal sickness-leave insurance, and value added tax records for the universe of French firms above a certain size, over the period spanning 2009 to 2015.

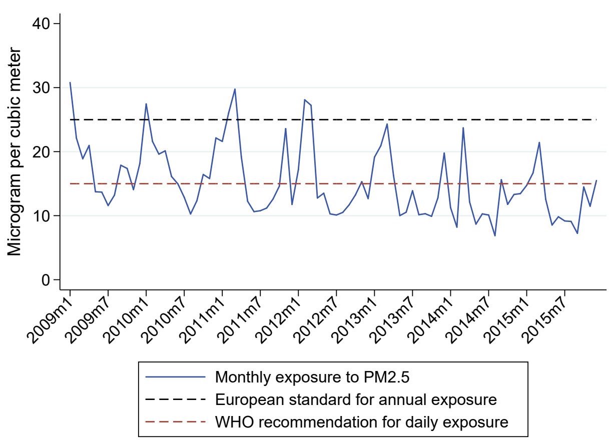
Pollution. We use air pollution data from the French National Institute for Industrial Environment and Risks (INERIS), which provides gridded reanalysis historical pollution data for metropolitan France (Real et al., 2021). The dataset combines background measurements of air quality from monitoring stations with modelling from the chemistry-transport model CHIMERE, using a kriging method (Real et al., 2021). It contains hourly concentrations of $PM_{2.5}$, PM_{10}, NO_2, and O_3 with a spatial resolution of approximately 4 km x 4 km for the period 2000-2018. We aggregate $PM_{2.5}$ data at the monthly level for all 33,252 grid cells located in metropolitan France.

Gridded reanalysis pollution data are better suited to capture the average pollution exposure of local residents than pollution-monitor readings. Indeed, monitors are sparse and sometimes

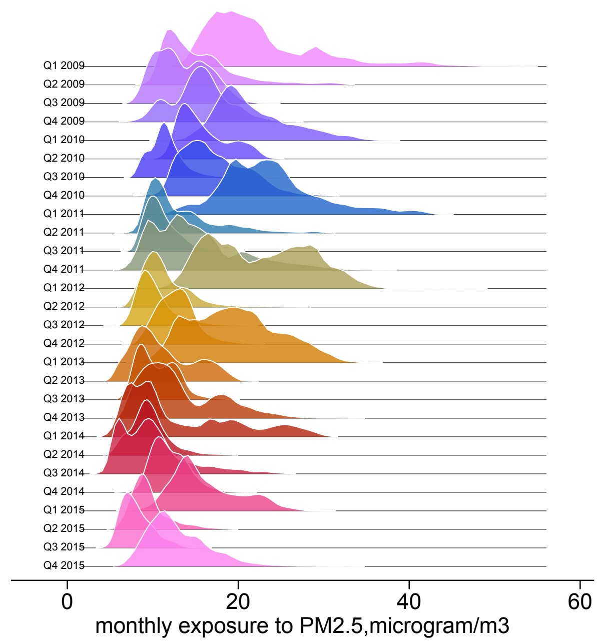
[9] The allowance then decreases to 16% after 30 to 90 days, and is paid for a maximum of 60 to 180 days, depending on the workers' seniority in the firm.

strategically placed to capture locally produced emissions (e.g., from a highway).[10] As a result, monitor readings may not be informative of the average pollution exposure in a given grid cell. By contrast, reanalysis data combine these monitor readings with a chemistry-transport model that takes account of all sources of pollution to give a measure of average exposure.

During our study period 2009-2015, the average $PM_{2.5}$ exposure of French workers, based on the municipality of their workplace, is 15.4 µg/m^3. Figure **??** shows the spatial distribution of annual exposure at different points in time [had to be removed due to maximum size of submission] whereas panel (a) Figure 1 shows the average monthly exposure over the period. Although pollution is quite seasonal, there is substantial variation in monthly exposure within a given quarter x year, as illustrated on panel (b) in Figure 1.



(a) Monthly average exposure to $PM_{2.5}$ (µg/m^3)



(b) Distribution from Q1 2009 to Q4 2015

Figure 1: Monthly average exposure to $PM_{2.5}$ (µg/m^3) in 2009-2015 and distribution of monthly exposure in each quarter from Q1 in 2009 to Q4 in 2015

Notes: Figure a) presents the monthly average of workers' exposure to $PM_{2.5}$ measured at the municipalities of their workplace for 2009-2015, using the sample of workers from the Hygie dataset. Figure b) presents the unweighted monthly distribution of exposure to $PM_{2.5}$ measured at the municipality level, using the sample of municipalities with at least one worker from the Hygie dataset.

[10] The network of $PM_{2.5}$ background monitoring stations is particularly sparse in France. Over the study period, there are between 62 and 105 stations for this pollutant, to be compared with between 173 and 251 for PM_{10}, between 318 and 385 for ozone, and between 282 and 337 for NO_2. The reanalysis data take into account the correlation between $PM_{2.5}$ and PM_{10} using a co-kriging method to exploit the higher density of PM_{10} monitoring stations for estimating $PM_{2.5}$.

Weather. We use gridded reanalysis weather data derived from the ERA5 dataset of the Copernicus Climate Change Service (C3S).[11] We obtain hourly precipitations, surface temperatures, wind direction, and wind speed at the 0.25° x 0.25° resolution (approximately 28 km by 28 km). We compute monthly averages for daily maximum temperatures and hourly wind speeds, and sum hourly precipitation over each month. For wind direction, we compute for each month the share of hours when the wind blows from each of four directions: North (below 45° or above 315°), East (between 45° and 135°), South (between 135° and 225°) and West (between 225° and 315°).

Firm-level sales. We use detailed monthly sales data at the firm level from Value Added Tax records collected by the French administration. We restrict the sample to firms that declare their VAT every month, with at least one worker observed in the absenteeism dataset, and from four broad sectors of activity based on the activity reported at the firm level: manufacturing, construction, business-to-consumer trade and services, and business-to-business trade and services.[12]

The final sample includes 158,223 firms totalling €1.9 sales in 2013, which represents 52% of French firms' sales (excluding the agriculture and financial sectors). Panel a of table 1 shows that the average firm employs 59 workers. 20% of firms belong to the manufacturing sector, 16% to the construction sector, 31% to business-to-business trade and services, and 33% to business-to-consumer trade and services. Average monthly sales amount to €1,316,300 whereas median monthly sales amount to €145,372.

Whereas each establishment can easily be matched to air pollution and weather data through its municipality,[13] the existence of multi-establishment firms represents a challenge. We observe that 36% of the firms – representing 75% of total sales– own more than one establishment in the VAT sample of 2015. We leverage an administrative identifying code which allows us to identify all establishments owned by the same firm.[14] When firms own multiple establishments, we build a firm-level measure of weighted-average exposure to pollution and weather characteristics, where the weights are the annual number of workers in each plant owned by the firm. To compute these weights, we exploit exhaustive matched employer-employee data called *DADS-Postes*, which

[11] We acknowledge using the ERA5 dataset (Hersbach et al., 2018) downloaded from the Copernicus Climate Change Service (C3S) Climate Data Store. See `https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview`

[12] The French tax administration imposes monthly declarations to firms with annual sales above €818,000 for the manufacturing sector and the hospitality industry, and those with annual sales above €247,000 for the other sectors. Firms below this threshold are allowed to fill declarations on a quarterly basis. Firms with monthly VAT declarations represent 66% of French firms, but 91% of total sales (France Stratégie and Inspection générale des Finances, 2021).

[13] To match datasets, we proceed by identifying the Chimere (for air pollution data) and Copernicus (for weather data) grid cells which include each municipality's centroid.

[14] French administrations have created a unique identifier for each establishment composed of 14 digits, of which the first 9 digits correspond to the unique identifier of the firm that owns the establishment (denoted SIREN).

records the number and location of establishments owned by a firm and the number of workers in each of these establishments.

Sickness leave episodes. We obtain data on sickness leave episodes (SLE) from the Hygie dataset, which is a representative sample of private sector employees born between 1935 and 1989 and affiliated to France's universal sickness-leave insurance.[15] This dataset reports for each worker the exact start date and duration of each SLE that occurred during the period 2009-2015, the associated state-funded sickness benefits, and characteristics such as age, gender, annual wage, contract type, and annual medical expenditures. We have three measures of absenteeism: an indicator for an individual starting a SLE in a given month, which we use as a main outcome variable, a count of sick days associated with SLEs that started in a given month, and the total sickness leave spending associated with SLEs that started in a given month. In the main analysis, we only consider SLEs lasting less than three months, which represent 93% of the spells.[16]

We restrict our dataset to employees that we can match to their exact workplace via an establishment-level identifier denoted SIRET (see Appendix B for more details). This restriction allows us to match employees information from the Hygie panel to both air pollution and weather data and to firm-level datasets. As a result, our measurement of pollution exposure is determined by the workplace, and we verify using the exhaustive matched employer-employee data (*DADS-Postes*) that the distributions of $PM_{2.5}$ exposure at the workplace and at the place of residence almost overlap.[17]

We obtain two samples, one that is representative of French private sector employees, and one that we restrict to workers employed by a firm for whom we have monthly sales data. This restriction implies that we discard workers employed by small firms not reporting sales every month, and workers employed in industries excluded from the firms sales sample: not-for-profit, finance and real estate, transport, and hotels.

Panel b of table 1 shows descriptive statistics for the second sample. It includes around 400,000

[15]The Hygie dataset combines administrative data on health from the organization managing the public health insurance (CNAM) with administrative data on employees' careers from the organization managing the public pension system (CNAV).

[16]In our data, the average sickness leave episode lasts 29 days whereas the median duration is only 9 days. Figure B.18 shows the small proportion of SLEs that last more than 3 months and their strong influence on the average number of sick days. We therefore focus on SLEs lasting less than 3 months to avoid that our results for the number of sick days are driven by long-term illnesses.

[17]Individual exposure depends on the location of residence, the location of work, transportation between the two, as well as the location of leisure activities. Based on the 2015 population census, we note that 27% of employees actually live and work in the same municipality. Additionally, the median commuting distance was only 9.2 kilometres in 2017 (INSEE, 2021). Comparing the distributions of pollution exposure at the workplace and at the place of residence for the population of French workers using exhaustive matched employer-employee data (*DADS-Postes*), we find that the two distributions almost overlap, both for the full population and by income quintile.(see Figure A.1)

individuals working in 353,155 private sector establishments over the period 2009-2015. Employees are 40 year old on average; they earn an average annual gross wage of €28,542. On average, roughly 25 workers per 1,000 start a sickness leave episode in a given month, included 23 per 1,000 for whom the sickness leave episode lasts less than 93 days.

Table A.1 in Appendix compares this workers' sample to the representative sample of workers, before conditioning on being employed by a firm included in our sales data. Due to the restriction of sample based on firm size and sector of activity, workers in our main workers sample earn on average more than those in the representative sample. However, the average demographic characteristics, sickness leave status and pollution exposure are similar across the two samples.

Table 1: Summary Statistics, 2009-2015

	Mean	Sd	Count
Panel a: Firms' characteristics			
Single-establishment	0.64	0.48	9,832,620
Number of workers	59.07	477.96	9,832,620
Monthly sales (k€)	1316.30	18153.87	9,831,760
Share in: Manufacturing	0.20	0.40	9,832,620
Construction	0.16	0.37	9,832,620
Business-to-business trade and services	0.31	0.46	9,832,620
Business-to-consumer trade and services	0.33	0.47	9,832,620
Monthly exposure to $PM_{2.5}$ (µg/m^3)	15.17	6.22	9,832,620
Panel b: Workers' characteristics (sample aggregated at establishment level)			
Age	40.19	8.74	8,233,440
Annual wage (euros €)	28541.97	20576.10	8,233,440
Annual medical expenditures (€)	442.02	809.78	8,233,440
Annual out-of-the-pocket expenditures (€)	139.88	172.21	8,233,440
Works in a single-establishment firm	0.40	0.49	8,239,344
Nb workers falling sick per month, per 1,000 workers	24.70	113.44	8,239,344
incl: for <93 days	23.00	109.24	8,239,344
Nb of associated sick days per 1,000 workers	758.91	9404.01	8,239,344
incl: for <93 days	363.52	2655.22	8,239,344
Share in: Manufacturing	0.28	0.45	8,239,344
Construction	0.12	0.32	8,239,344
Business-to-business trade and services	0.33	0.47	8,239,344
Business-to-consumer trade and services	0.27	0.42	8,239,344
Monthly exposure to $PM_{2.5}$ (µg/m^3)	15.34	6.33	8,239,344

Notes: For panel b, the data at the establishment level is weighted by the number of workers.

3 Empirical Strategy

3.1 Analytical Framework

To illustrate how pollution shocks might affect workers and their employing firms, we build a stylized model that connects individual exposure to air pollution with firms' sales.

Demand. Consider an economy in which a representative consumer divides expenditures between a set of differentiated products available in different industries $i \in \{1, ..., \mathcal{I}\}$. The representative consumer aggregates consumption in two tiers. In the top tier, the consumer aggregates consumption in a Cobb-Douglas function across industries, which implies that expenditures on each industry i, Y_{it}, are determined as fixed shares of total expenditures, Y_t: $Y_{it} = \nu_i Y_t$. The second tier aggregates consumption via a Constant Elasticity of Substitution (CES) function across the set of varieties available in each industry i at time t, Ω_{it}. We have

$$U_t = \prod_i \left[\left(\sum_{f \in \Omega_{it}} (X_{fit} e^{u_{fit}})^{\rho_i} \right)^{1/\rho_i} \right]^{\nu_i}, \tag{1}$$

where X_{fit} denote the consumption at time t of variety f in industry i, u_{fit} is an *ex post* variety-specific demand shock (realized at the point of sales), and ρ_i is a parameter that governs the substitutability of varieties within the industry, with constant price elasticity of demand $\sigma_i = 1/(\rho_i - 1) < -1$.

We assume that pollution shocks can affect consumers in two ways. First, if they get sick, they might decide to change their consumption behaviors, notably by staying home and postponing purchases. Denoting by c the level of air pollutant concentration experienced by consumers, this channel is reflected in the *ex post* demand shock being a function of pollution concentration: $u_{fit} = u_{fit}(c)$, with an ambiguous sign for $u'_{fit}(c)$ as consumers may decide to buy more or less of varieties f when exposed to higher pollution concentrations. Second, if they get sick and decide to be absent from work, they incur an income loss due to the fact that social security systems do not necessarily fully compensate workers taking sick leaves: hence, $Y_t(c) = \big(1 - \zeta \bar{a}_t(c)\big) w L_t$, where ζ corresponds to the income loss associated with sick leaves (where full compensation implies that $\zeta = 0$) and $\bar{a}_t(c)$ represents the average absence rate of workers (across firms). We expect that $\bar{a}'_t(c) \geq 0$ as an increasing concentration level of air pollutant can trigger acute negative health effects and a higher absence rate.

The representative consumer's objective is to maximize her utility (1) given her budget constraint. The CES structure yields an expression for expenditures y_{fit} on each variety f at time

t:

$$y_{fit} = (p_{fist})^{\frac{\rho_i}{\rho_i - 1}} (P_{it})^{\frac{\rho_i}{1-\rho_i}} e^{\frac{u_{fit}(c)}{1-\rho_i}} Y_{it}(c), \tag{2}$$

where p_{fit} is the price of variety f at time t and P_{it} corresponds to the CES price index at the industry level, which is defined in the usual way:

$$P_{it} = \left[\sum_{f \in \Omega_{it}} (p_{fit})^{\frac{\rho_i}{\rho_i - 1}} e^{\frac{u_{fit}(c)}{1-\rho_i}} \right]^{\frac{\rho_i - 1}{\rho_i}}. \tag{3}$$

Production. Each firm produces a single differentiated variety, so f can be used interchangeably to index both varieties and firms. Production requires one factor, effective labor, L^A, to produce output Q. Firms have heterogeneous productivity and their production technology is[18]

$$Q_{fit} = L^A_{fit} \exp(\omega_{fit}) = \lambda_{fit}(c)[1 - a_{fit}(c)]^{\theta} L_{fit} \exp(\omega_{fit}), \tag{4}$$

where ω is a Hicks-neutral productivity shock that is known to the firm when making its period t decisions and is exogenous to pollution shocks, and L_{fit} is the number of workers employed by firm f at time t. Effective labor, L^A_{fit}, responds to air pollution concentration through $\lambda_{fit}(c)$, which is the marginal productivity of workers in firm f at time t without absenteeism, and $a_{fit}(c)$, which is the average absence rate of workers in firm f at time t, with θ being a parameter reflecting the attendance impact on marginal productivity. As air pollution concentration increases, workers can suffer from productivity losses while at work, with $\lambda'_{fit}(c) \leq 0$, or they can suffer strong health effects that trigger the decision to take a sick leave, with $a'_{fit}(c) \geq 0$.

Each firm faces a residual demand curve with constant elasticity $\sigma_i = 1/(1-\rho_i)$ within industry i and thus chooses the same profit maximizing markup equal to $1/\rho_i$. While firms hire L_{fit} employees, the marginal cost of labor depends on their absence rate and on the fact that the social security system covers part of the sick leave benefits. This yields the pricing rule

$$p_{fit} = \frac{w[1 - \eta a_{fit}(c)] e^{-\omega_{fit}}}{\rho_i \lambda_{fit}(c)[1 - a_{fit}(c)]^{\theta}}, \tag{5}$$

where w is the common wage rate (assumed to be exogenous to pollution shocks) and η is the social security system's contribution to employees' sick leave benefits (with $\eta = 1$ if the social security system covers all sick leave benefits, and $\eta = 0$ if the firms fully compensate their absent workers).

[18]The production function is similar to the one-worker-type production function in Zhang et al. (2017).

Effects of Pollution Shocks on Firms' Sales. Combining (2) with (5) yields the following expression for firm f's sales at time t:

$$y_{fit} = \left(\frac{w[1 - \eta a_{fit}(c)] e^{-\omega_{fit}}}{\rho_i \lambda_{fit}(c)[1 - a_{fit}(c)]^{\theta}} \right)^{\frac{\rho_i}{\rho_i - 1}} (P_{it})^{\frac{\rho_i}{1-\rho_i}} \, e^{\frac{u_{fit}(c)}{1-\rho_i}} Y_{it}(c), \tag{6}$$

Taking logs, assuming that the absence rate is quite small (hence, $\log(1-x) \approx -x$) and reorganizing terms yields

$$\begin{aligned} \log y_{fit} &= \frac{\rho_i}{1-\rho_i}\omega_{fit} + \frac{\rho_i}{1-\rho_i}\log P_{it} + \frac{\rho_i}{\rho_i - 1}\log\left(\frac{w}{\rho_i}\right) \\ &+ \underbrace{\frac{\rho_i}{1-\rho_i}\log\lambda_{fit}(c)}_{\text{Productivity effect}} + \underbrace{\frac{\rho_i(\eta-\theta)}{1-\rho_i}a_{fit}(c)}_{\text{Absenteeism effect}} + \underbrace{\frac{u_{fit}(c)}{1-\rho_i} + \log Y_{it}(c)}_{\text{Demand effect}}. \end{aligned} \tag{7}$$

From equation (7), we can identify three main channels through which pollution affects firms' sales. First, there is a productivity effect: air pollution may affect the marginal productivity of workers even when all workers are present (though symptoms such as headaches, fatigue, trouble concentrating, and deteriorated cognitive function). Second, there is an absenteeism effect: if workers take sick leaves following a pollution shock, their absence may disrupt the overall production process. The magnitude of this response will depend on the parameter θ—which reflects the effect of being present on the marginal productivity of labor— and on the compensating mechanism that firms do not have to pay for their full sickness leave benefits due to the social security system's contribution reflected by η. Hence, public sickness leave benefits mitigate the cost of absenteeism for firms. Third, there is a demand effect that arises from both behavioral changes experienced by consumers exposed to air pollution shocks and an income effect incurred when workers take sick leaves, in the absence of full compensation from either the social security system or their employer.

From this model, we can draw three main implications for the empirical analysis. First, sales will decrease when pollution is high either if all three channels move together or if the productivity and absenteeism effects dominate an opposite demand effect. Second, the absenteeism effect might be limited in our context as the social security system's contribution can be large relative to estimates of parameter θ alone.[19] Third, we also expect the income effect on demand to be limited because two thirds of French private sector employees are granted a full replacement rate when on sickness leave. Yet, the behavioral demand effect on sales can be either positive or negative, and it may be large in some specific sectors.

[19] For a 5-day sickness leave episode with full replacement rate, the public contribution share approximates 0.2. Zhang et al. (2017) obtain an estimate of θ equal to 0.46 on Canadian private sector employees. These figures would imply that absenteeism reduces firms' sales by a factor -0.26 * $\rho_i/(1-\rho_i)$.

3.2 Econometric Specification

Baseline model at the firm level. Our objective is to identify the short-term causal effect of $PM_{2.5}$ on firms' sales and on their employees' absenteeism. The latter is one of the three channels identified above that we observe directly. It serves the purpose of uncovering the adverse health effects of air pollution on workers.[20] There may be unobserved time-invariant determinants of both local air pollution and firms' and workers' characteristics, such as the local level of economic activity, or time-varying factors that simultaneously affect air pollution and firms' sales, such as weather conditions or infrastructure developments. To address these concerns, we build an empirical strategy that relies both on a comprehensive set of time-varying weather and holidays controls and a rich set of fixed effects, as well as on an instrumental variable.

First, we estimate the effect of monthly average air pollution concentration on monthly firm-level sales. We model this relationship using the following regression equation:

$$Y_{fisgyt} = \beta PM_{2.5gyt-1} + W'_{gyt-1}\gamma_1 + W'_{gyt}\gamma_2 + W'_{gyt+1}\gamma_3 + \nu_{fy} + \theta_{isyt} + \delta_{dq} + \epsilon_{fisgyt}, \tag{8}$$

where the unit of observation is firm f producing in industry i in sector s and located in municipality g on month t in year y. The outcome Y_{fisgyt} is the logarithm of the average sales recorded by firm f for month t and $t+1$ in year y. This aggregation nets out idiosyncratic variability in the assignment of sales to a specific month, since firms may shift the recordings of their sales to the following month in some instances.[21] The parameter of interest is β, the coefficient on lagged monthly $PM_{2.5}$ levels, as measured in municipality g where a single-establishment firm f is located. We consider below the case of firms owning multiple establishments, for which the assignment of air pollution shocks is more complex. Our preferred specification includes firm-by-year (ν_{fy}), industry-by-month-by-year (θ_{isyt}), and quarter-by-departement (δ_{dq}) fixed effects. Firm-by-year fixed effects ν_{fy} isolate variation in pollution exposure around the mean exposure of a firm at the annual level, thereby absorbing any annually invariant firm characteristics while also controlling for annual shocks jointly affecting exposure to pollution and sales. Such shocks include any productivity shock or any change in the number or location of establishments belonging to

[20] We expect the absenteeism channel to represent a lower bound of the health effects. Indeed, private sector workers must show a medical certificate to their employers to benefit from sickness leave allowances, hence they need to see a doctor. Additionally, individual worker characteristics and worker-firm-specific contract conditions can influence the decision to take a sick leave given a health shock.

[21] For example, firms whose accountants are absent at the end of the month are allowed to make a guess on their monthly sales and correct this guess with the help of the accountant the month after. Also, the rules defining the business month when the firm must declare sales and the VAT to the tax administration differ across goods and services. Specifically, the VAT on the sales of domestic goods has to be declared in the month where the good is delivered to the buyer; the VAT on the sales of domestic services has to be declared when the service is paid for; the VAT on exported goods and services within the EU has to be paid one month after the delivery. See https://entreprendre.service-public.fr/vosdroits/F31412.

a firm, which we only observe at the annual level. Industry-by-month-by-year fixed effects θ_{isyt} (or, sector-by-month-by-year fixed effects θ_{syt}) capture monthly shocks that are common across all firms in the same industries (or sectors). We use the 2-digit level of the European Union industry classification to identify 88 industries (A88 codes), which we group into 4 sectors, namely manufacturing (including manufacturing industries, mining, and utilities), construction, business-to-business services (including communication and IT, wholesale trade, professional services and cleaning services), and business-to-consumer services sector (including groceries and supermarkets, restaurants, hairdressers, sales of durable goods such as clothing, furniture, etc., and car sales and repair). Quarter-by-departement fixed effects capture seasonality in pollution (or wind patterns for the instrumented version) specific to a departement which may be correlated with local seasonal fluctuations in economic activity. It captures for instance the seasonal demand variation in ski or sea resort areas.

To address the link between both pollution and weather (different climatic conditions can lead to different air pollution levels) and between sales and weather (due to a decrease in activity on hot days for instance) within firm-years, we also include contemporaneous and lagged weather controls in the sets of controls W'_{gyt-1}, W'_{gyt}, and W'_{gyt+1}. Specifically, we generate indicators for monthly averages of daily maximum temperatures, wind speed and precipitation in each municipality.[22] We then generate a set of indicators for all possible interactions of these weather controls and include it in all our regressions. We also include the count of days in each month associated with school holidays in municipality g.[23] Indeed, economic activity and pollution are typically lower during these holiday periods. Since we want to isolate the specific effect of a one-month change in air pollution at t-1, on outcome observed at t and t+1, our OLS regressions also include monthly $PM_{2.5}$ at t and t+1, while our IV regressions include instrumented monthly $PM_{2.5}$ at t and t+1. Since future air pollution shocks should have no effect on current sales, we provide a placebo check by studying the effect of pollution at time $t + 2$ on sales at time t, while including pollution and weather controls for the period t to $t + 2$.

Wind instruments. Despite the use of high-dimensional fixed effects, OLS estimates of equation (8) are prone to bias due to the potential influence of reverse causality, measurement errors in air pollution exposure, and omitted variables. Indeed, higher sales are likely to increase pollution as a by-product of higher production. Also, when the effects of pollution on sales are channelled through workers' productivity and labor force, there are measurements errors arising from the fact

[22] Monthly average of daily maximum temperatures falls into 12 potential bins. The bins span 3°C each, except for the first bin including all negative temperatures, and for the twelfth bin including all temperatures above 33°C. For wind speed and precipitation, we compute indicators for each quintile of these variables.

[23] Beside the July-August and Christmas school breaks, which occur at the same time for all schools in France, the two-week school breaks in the Fall, Winter, and Spring are staggered by region.

that we only measure pollution exposure based on the workplace location, thereby not capturing pollution exposure at other places (e.g., location of residence and leisure activities) where workers spend time during the month. Assuming that the measurement error is classical —mean zero and i.i.d— this gives rise to an attenuation bias, which can be exacerbated by the use of fixed effects (Griliches and Hausman, 1986). Another potential source of bias pertains to unobserved local shocks that may influence pollution concentration while also affecting workers' absenteeism and sales (e.g., road work).

To address these remaining potential biases, we rely on an instrumental variable approach exploiting month-to-month variation in wind direction at the municipality level, in the spirit of Deryugina et al. (2019) and Graff Zivin et al. (2023). We instrument monthly pollution in a municipality g with a combination of the share of hours in a month where wind blows from each of the four directions (South, West, East, and North) and a pollution intensity factor for each direction in each municipality. This flexible approach acknowledges that a given wind direction might not affect pollution in the same way in all municipalities in France. Following Graff Zivin et al. (2023), we compute four instruments Z_{jgyt}, one for each wind direction as follows:

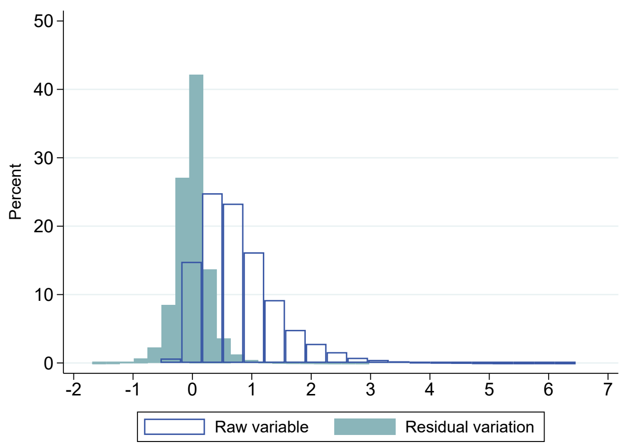
$$\mathrm{Z}_{jgyt} = \mathrm{WIND}_{jgyt} \left(\frac{1}{N_j} \sum_{d \in T_j} PM_{2.5gd} - \frac{1}{N} \sum_{d \in T} PM_{2.5gd} \right) \tag{9}$$

where WIND_{jgyt} identifies the share of hours in month t in year y where the wind blows from direction j (with $j = 1$ indicating South, $j = 2$ West, $j = 3$ East, and $j = 4$ North) in municipality g, while the term in the brackets reflects the deviation from daily mean pollution levels on days where the dominant wind blows from direction j in municipality g. N_j and T_j are the number and set of days where the dominant wind blows from j, while N and T are the total number and set of days over the period of analysis. Figure A.2 shows how this deviation from mean pollution varies for a given wind direction across municipalities in France. Winds blowing from the East and West have a rather homogeneous effects, with East winds increasing pollution concentrations and West winds (from the Atlantic ocean) decreasing them in the vast majority of municipalities. On the other hand, winds blowing from the North and the South have heterogeneous effects on pollution across regions: North (South) winds increase (decrease) pollution in the Northern half of the country, while having moderate effects in the Southern half of the country.

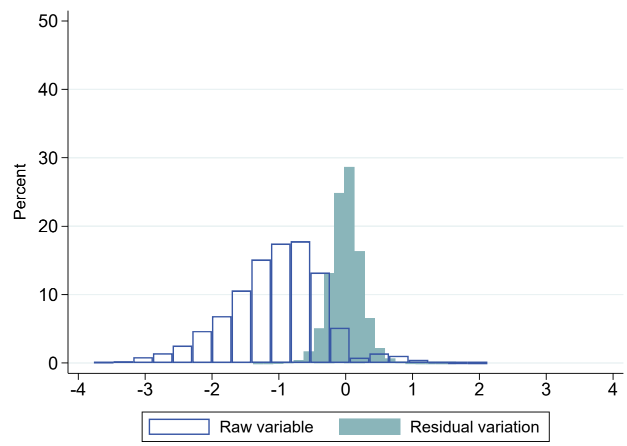
The specification of our first stage is:

$$PM_{2.5gyt} = \sum_{j=1}^{4} \beta_j \mathrm{Z}_{jgyt} + W'_{gyt}\gamma + \nu_{fy} + \theta_{isyt} + \delta_{dq} + u_{gyt}, \tag{10}$$

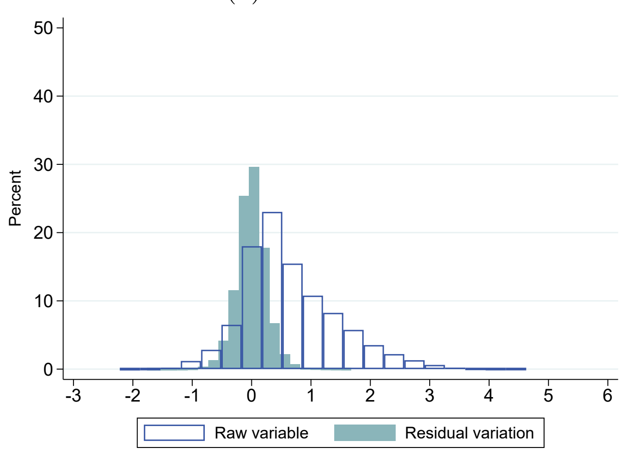
where the parameters of interest are β_js. For a given wind direction j, β_j captures the effect of a marginal increase in air pollution associated with wind blowing from j given municipality-specific changes in pollution associated with each wind direction. The identifying variation is the quasi-random change in wind direction intensity around the mean exposure of each firm within a year, after partialling out quarter- and departement-specific variation, industry-specific trends in this exposure at national level, and conditional on weather parameters other than wind direction. Figure 2 show the identifying variation graphically by plotting the distribution of each wind instrument, both as a raw variable and after residualizing with the fixed effects and controls. Even after controlling for all the fixed effects and control variables, there remains substantial variation in each instrument.



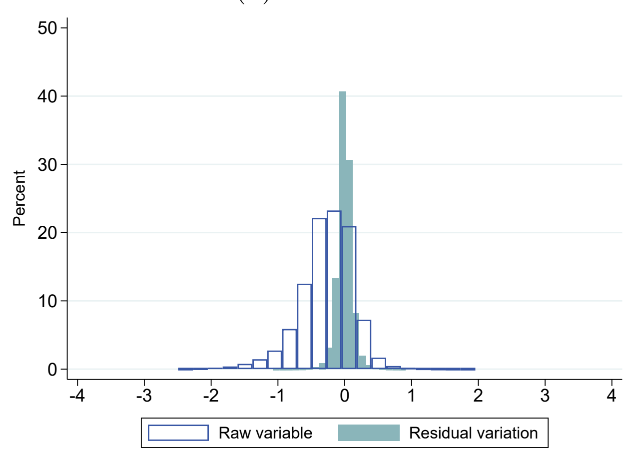
(a) East wind



(b) West wind



(c) North wind



(d) South wind

Figure 2: Identifying variation - Distribution of raw and residualized wind instrument

Notes: residualized variable obtained by regressing each wind instrument value on the right-hand side variables of equation 10: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-departement fixed effects, and firm-by-year fixed effects

For the identification of the β_js, we rely on within-municipality variation in wind direction and its associated variation in pollution, where wind direction is observed at the Copernicus grid cell level. Therefore, we cluster standard errors at the Copernicus grid cell level.

The validity of our research design requires three assumptions: first, our set of wind instruments should be correlated with $PM_{2.5}$ (instrument relevance). Second, it should be uncorrelated with the error term from the second stage, ϵ_{fisgyt} (instrument validity). Third, the assumption of constant treatment effects is not plausible in our setting: we expect the effect of $PM_{2.5}$ on sales to vary by firm characteristics such as the industry and demographic composition of their workforce, which will affect workers' vulnerability to pollution. Under heterogeneous treatment effects, we can only interpret our two-stage-least-square estimate as a local average treatment effect (LATE) if the monotonicity assumption holds. Below we discuss the plausibility of instrument relevance, validity and monotonicity in our setting.

Instrument relevance: Table 2 report the first stage results in a baseline specification at the municipality level. The estimated coefficients $\widehat{\beta_j}$ are all positive, because Z_{jgyt} takes a negative value when wind from direction j decreases pollution in municipality g.[24] All the coefficients are positive and significant. We test for weak-IV using the effective F-statistic (Montiel Olea and Pflueger, 2013) after aggregating the data at the municipality level.[25] The effective F-statistic is 490, wile in our setting the critical values for a 5% worse case bias is of 29.37 and that for a 10% bias is 23. Thus we do not have a weak instrument issue.

Instrument validity hinges on two assumptions. First, they need to be as-good-as-randomly assigned: there should be no weather or seasonal patterns influencing sales co-varying with the instrument value. It is hard to think of a weather characteristic other than wind speed, temperature and precipitation – all flexibly controlled for – which may be correlated with wind direction and influence sales. We control for humidity in a robustness check and find that results are unaffected. Another violation of the exclusion restriction would be if wind direction changes are driven by local seasonal fluctuations that also influence sales. Our control for quarter-by-department fixed effects should capture such correlation. Figures A.3 and A.5 illustrate that there is substantial within-municipality variation in monthly wind directions taking as an example the two largest French cities, Paris in the North and Marseille in the South-East.

Second, the exclusion restriction must hold: the wind instruments should only affect firms sales

[24] A one-unit increase in Z_{jgyt} can correspond to different combinations of wind j frequency in municipality j and how polluting wind j is in municipality g: for example, a 10 pp increase in the share of North wind in municipality A where North wind's deviation from mean pollution is 0.1µg/m^3 and a 20 pp decrease in the share of North wind in municipality B where North wind's deviation from mean pollution is -0.05µg/m^3 will increase both $\mathrm{Z}_{NorthAyt}$ and $\mathrm{Z}_{NorthByt}$ by one unit.

[25] We are unable to run the weakivtest command of Pflueger and Wang (2015) from the secure data server because the version of Stata available there does not accommodate weakivtest after reghdfe. We can only test for weak iv after exporting the data to a local computer. For data protection reasons this can only be one after aggregating the data municipality level

Table 2: First stage results

	(1)
	mean $PM_{2.5}$
$Z_{\text{South}gyt}$	1.468***
	(0.152)
$Z_{\text{West}gyt}$	0.575***
	(0.148)
$Z_{\text{North}gyt}$	1.231***
	(0.055)
$Z_{\text{East}gyt}$	1.610***
	(0.0748)
Holiday and weather controls	Yes
Firm-by-year FE	Yes
Month-by-year-by-industry FE	Yes
Quarter-by-departement FE	Yes
N	6,322,128
R-squared	0.93

Notes: Table reports the first stage results for the sample of single-establishment firms. We report standard errors in parentheses, clustered at the Copernicus grid cell. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

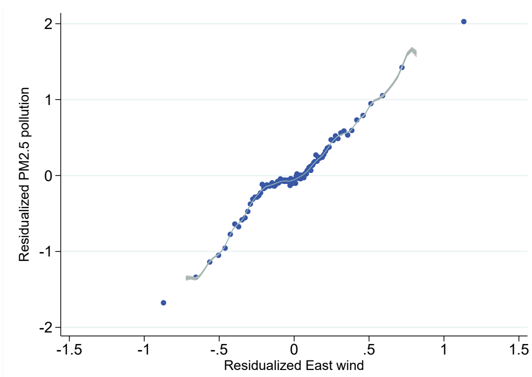
via their impact on $PM_{2.5}$. This assumption is violated if other pollutants that also affect health and productivity outcomes co-vary with wind direction. Of the four other regulated air pollutants (SO_2, NO_2, PM_{10} and ozone), SO_2 and NO_2 are primary pollutants that convert to particulate matter within two to three days. By aggregating pollution concentration at the monthly level, we cannot estimate their effect independently. Additionally, PM_{10} is highly correlated with $PM_{2.5}$ (Pearson correlation coefficient: ρ=0.93) and actually includes $PM_{2.5}$. As a result, caution should be taken in interpreting our causal estimates as reflecting only the effect of $PM_{2.5}$. By contrast, ozone is a pollutant that is typically anti-correlated with other pollutants due to how it is formed in the atmosphere.[26] To address the concern that our effects partly capture the effect of wind on ozone and the effect of ozone on absenteeism and sales, we perform a robustness test using a multi-pollutant air quality index as endogenous variable, instead of $PM_{2.5}$. A one standard deviation increase in the air quality index has about the same effect on worker absenteeism as a one standard deviation increase in $PM_{2.5}$, indicating that ozone is not an important threat to the exclusion restriction (see Table 8).

Instrument monotonicity: Figures 4 shows the distribution of residualized wind variation for each wind direction, and its relationship with residualized $PM_{2.5}$ exposure, using the firm-level panel of single-establishment firms (see the discussion on multi-establishment firms below). The relationship is monotonically increasing for each wind direction, except at the tails of the distribution, and approximately linear. Monotonicity also seems to hold at the individual municipality level: figures A.8, A.10 and A.12 show a residualized binned scatter plot in the same spirit for individual municipalities using three examples in Paris, Marseille and a rural area in the centre of France.[27]

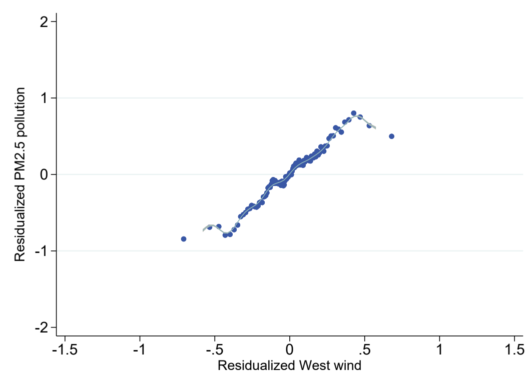
Multi-establishment firms. One challenge we face in the analysis of pollution effects on firms' sales is that firms often own several establishments located in different municipalities. Since we observe sales only at the firm level, we compute firms' exposure to pollution as a weighted average of pollution exposure at each establishment owned by the same firm, where the weights correspond to the relative number of workers in each establishment in each year. Furthermore, we instrument firms' observed pollution exposure by their average predicted pollution exposure according to equation (10) averaged across establishments, weighted by the share of employees. Specifically, we run equation (10) with municipality fixed effects instead of firm-year fixed effects, save the

[26]Ozone results from the chemical reaction between solar radiation, nitrogen oxide and volatile organic compound (Nasa Earth Observatory, 2003). In our data, the Pearson correlation coefficient between monthly $PM_{2.5}$ and ozone is -0.3. Figures 1 and A.7 illustrate this anti-correlation by showing the reverse seasonality of ozone vs $PM_{2.5}$ and NO_2 concentrations.

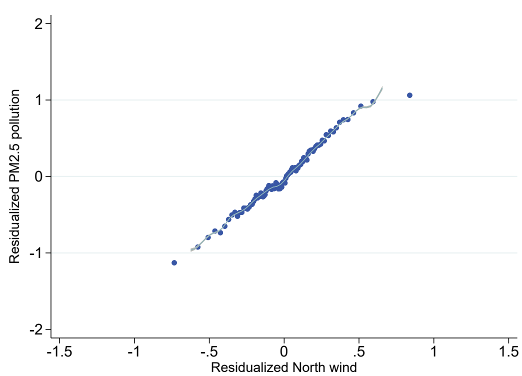
[27]In that case, the variation in each instrument's value only comes from its time-varying component, the frequency WIND_{jgyt} of wind coming j in month t. To adjust to the times series nature of the data, the fixed effects entering the residualization are only quarter and year fixed effects.



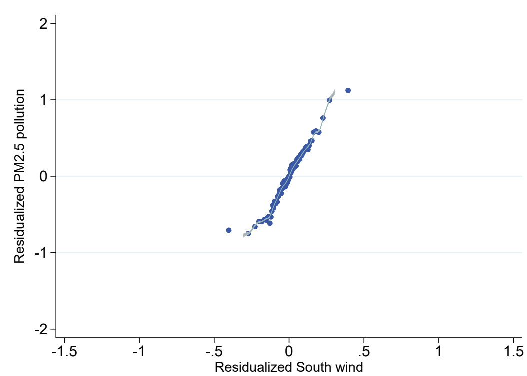
(a) East wind



(b) West wind



(c) North wind



(d) South wind

Figure 4: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations and local polynomial fit

Notes: Figure is based on the sample of single-establishment firms. x-axis residuals (resp. y-axis residuals) are obtained by regressing each wind instrument value (resp. $PM_{2.5}$) on the right-hand side variables of equation 10: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-departement fixed effects and firm-by-year fixed effects. Observations are grouped in equal-sized bins (centiles) based on the value of the x-variable. Each dot shows the mean value of that bin for the x-axis and y-axis residuals. The solid blue line shows a local polynomial regression fit of residualized $PM_{2.5}$ on residualized wind direction, with the grey area around showing 95% confidence bands (leaving out the top and bottom 1% of the distribution).

vector of estimated $\widehat{\beta}_j$, and compute the predicted pollution exposure as $\widehat{PM_{2.5gyt}} = \sum_{j=1}^{4} \widehat{\beta}_j \mathrm{Z}_{jgyt}$. Weather controls and other variables beside wind directions from equation (10) are not used to build the instrument in this specification. Otherwise, the exclusion restriction assumption would not hold. We then compute the firm-level predicted pollution exposure as the weighted average of $\widehat{PM_{2.5gyt}}$ across locations g for each establishment owned by firm f in year y. After doing so, we regress the following regression at the firm level:[28]

$$Y_{fisyt} = \beta \overline{PM_{2.5fyt-1}} + \overline{W'_{fyt-1}}\gamma_1 + \overline{W'_{fyt}}\gamma_2 + \overline{W'_{fyt+1}}\gamma_3 + \nu_{fy} + \theta_{isyt} + \delta_{dq} + \epsilon_{fisyt}, \tag{11}$$

where variables $\overline{PM_{2.5fyt-1}}$, $\overline{W'_{fyt-1}}$, $\overline{W'_{fyt}}$, and $\overline{W'_{fyt+1}}$ correspond to the weighted averages of pollution exposure, contemporaneous and lagged weather and holidays controls across establishments owned by firm f. As before, we also include $\overline{PM_{2.5fyt}}$ and $\overline{PM_{2.5fyt+1}}$ in our OLS regressions, and instrumented pollution exposure in our IV regressions. We cluster the standard errors at the firm level, the scale at which the instrument varies. Figure 6 shows the distribution of residualized predicted $\mathrm{PM}_{2.5}$, and its relationship with residualized $\mathrm{PM}_{2.5}$ exposure, using the sample combining single-establishment and mult-establishment firms. Our main regressions are run on this sample using predicted $\mathrm{PM}_{2.5}$ as an instrument. We check the robustness of this approach by comparing our estimates with estimates for the sample of single-establishment firms from equation (8) using the set of wind instruments.

Analysis of absenteeism at the establishment level. To explore the absenteeism channel, we amend our empirical strategy to the fact that we attribute a geographical location to each worker through its workplace (that is, its work establishment) and to the data restriction of a representative sample of French private sector employees that does not cover all employees in the same establishment. As a result, after aggregating sickness leave outcomes at the establishment-month-of-sample level, we use the following regression equation:

$$Y_{eisgt} = \beta^A PM_{2.5gyt} + W'_{gyt}\gamma + \nu_e + \theta_{isyt} + \delta_{dq} + \epsilon_{eisgt}, \tag{12}$$

where the dependent variable Y_{gyt} is the sickness leave outcome measured in month t in year y in establishment e. β^A is the coefficient of interest. Contemporaneous pollution exposure $PM_{2.5}$ and control variables W are defined as in equation (8). The fixed effects are similar to the ones used for the firm-level regression, except that the firm-year fixed effect is replaces with an establishment fixed effects ν_e, which isolates monthly variation in pollution exposure within an establishment

[28]In OLS models, inference using predicted regressors should be corrected for first-stage sampling variance. When the predicted regressor is used as an instrumental variable, like we do here, the standard errors of the 2SLS regression are unbiased under a set of weak assumptions (Wooldridge, 2010). Predicted regressors have similarly been used as instruments in Schlenker and Walker (2016) and Dahl and Lochner (2012).

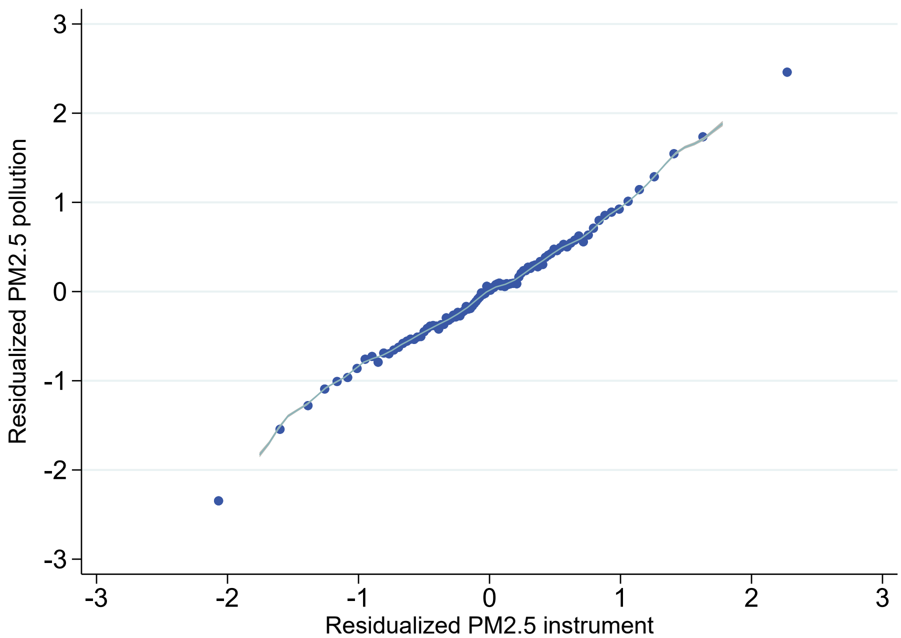


Figure 6: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations and local polynomial fit

Notes: Figure is based on the sample of all firms. x-axis residuals (resp. y-axis residuals) are obtained by regressing the predicted $PM_{2.5}$ variable $\widehat{PM_{2.5}}_{gyt}$ (resp. the endogeneous $PM_{2.5}$ variable on the right-hand side variables of equation 10: weather and holiday controls, industry-by-month-by-year fixed effects, and firm-by-year fixed effects. Observations are grouped in equal-sized bins (centiles) based on the value of the x-variable. Each dot shows the mean value of that bin for the x-axis and y-axis residuals. The solid blue line shows a local polynomial regression fit of residualized $PM_{2.5}$ on residualized wind direction, with the grey area around showing 95% confidence bands (leaving out the top and bottom 1% of the distribution).

and absorbs any time-invariant establishment-specific characteristic. Compared to a firm whose pollution exposure can change from one year to another due to selling or buying establishments, an establishment has a fixed location over time, so we do not need to use establishment-by-year fixed effects. We assess the plausibility of the linearity assumption from equation (12) by looking at a residualized binned scatter plot of the two variables—number of SLEs for each equal-sized bin and monthly average $PM_{2.5}$ levels. The scatter plot suggests that the effect of $PM_{2.5}$ on sickness leave episodes is approximately linear. Since absenteeism at the establishment level is often based on a a sample of just one or two workers, we also run a similar analysis after aggregating establishments at the municipality level.

4 Effects of PM 2.5 on Firms' Sales

4.1 Impact of Lagged $PM_{2.5}$ on Contemporaneous Sales

Effect For All Sectors. Table 3 shows that the effect of lagged monthly $PM_{2.5}$ on contemporaneous firm-level sales is substantial and consistent across alternative specifications with instrumented pollution. Column (1) reveals a positive association between lagged $PM_{2.5}$ and contemporaneous sales when the model is run with OLS. This likely reflects a reverse causality: within a firm-year and controlling for country-wide time-varying shocks, months with a greater local economic activity are more polluted and also bring more sales to the firm. In contrast, when pollution is instrumented with the change in wind directions as in column (2) and above, the effect of pollution on sales becomes negative and statistically significant at the 1% level.

In columns (3) and (4) we include sector-by-month-by-year fixed effects and industry-by-month-by-year fixed effects, respectively, instead of controlling only for monthly-varying shocks that are common across all sectors. We find that the effects on firm-level sales are almost identical to column (2). In columns (5) and (6), we add the quarter-by-departement fixed effects, with our baseline specification appearing in column (6). Looking across specifications, we find that a one unit (1 $\mu g/m^3$) increase in firm-level $PM_{2.5}$ exposure decreases firm-level sales by between 0.26 and 0.53 percent in the two following months. Taking column (6) as the baseline specification, our results imply that a 10% increase in pollution exposure (a 1.5-unit increase) decreases sales by 0.40 percent on average.

Table A.2 displays similar results based on the sample of single-establishment firms. Pollution exposure only depends on one location for these firms. Therefore, instead of using the two-step method and the predicted pollution instrument $\widehat{PM_{2.5gyt}}$, we are able to directly estimate equation 8 in a two-stage least square regression using the four wind direction instruments Z_{jgyt}. Although single-establishment firms may differ from multi-establishment firms in many dimensions (e.g., in size, productivity, capacity to export, capacity to innovate), the IV point estimates of table A.2 have the same direction and order of magnitude as those for the entire sample of firms. Finding similar results across specifications gives some credibility to our empirical strategy where multi-establishment firms' exposure to pollution is measured by a weighted average of establishments' exposure.

Table 3: The Effect of Lagged $PM_{2.5}$ on Firm-level Sales in the next Two Months, All Sectors

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
$PM_{2.5t-1}$	0.0320***	-0.535***	-0.499***	-0.493***	-0.263***	-0.259***
	(0.00992)	(0.0274)	(0.0274)	(0.0272)	(0.0264)	(0.0264)
Firm-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	No	No	No	No
Month-by-year-by-sector FE	No	No	Yes	No	Yes	No
Month-by-year-by-industry FE	No	No	No	Yes	No	Yes
Quarter-by-departement FE	No	No	No	No	Yes	Yes
N	9,412,093	9,412,093	9,403,419	9,403,173	9,403,293	9,403,047
R-squared	0.9457	0.9456	0.9460	0.9468	0.9462	0.9470

Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation (11) for all firms in all sectors. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at t and $t+1$. The confidence intervals are based on standard errors clustered at the firm level. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Heterogeneous Response by Sector. We expect these economic losses associated to air pollution to differ across sectors for multiple reasons. First, sectors in which workers breathe a more polluted air while at work, either because they are working outdoors or because they breathe specific work emissions (as in construction and manufacturing activities), either could face stronger negative effects from air pollution due to the cumulative exposure or could have adapted to a more polluted environment. Second, different sectors have different proportion of high-skilled versus low-skilled workers who may have heterogeneous vulnerabilities of their cognitive skills and health conditions to pollution shocks. Third, some sectors may face a strong demand effect from pollution, while others are immune to it. The estimates from Table 3 capture demand effects only through the response of local demand, that is, only for consumers who live and purchase a specific good or service that was produced in the same location (identified by municipality). Consumers located further away than the location of production are likely to be exposed to different air pollution shocks, and changes in their demand are captured in the industry-month-of-sample fixed effects. Our sectoral classification allows us to identify two sectors for which demand is likely to be local—namely, construction and business-to-consumer trade and services— and two sectors for which demand is likely to be coming from different regions in France and from abroad—namely, manufacturing and business-to-business trade and services.

Table 4 shows that the effect of lagged monthly $PM_{2.5}$ on contemporaneous firm-level sales is negative and substantial across all sectors of activities. Column (1) reveals a negative association between lagged $PM_{2.5}$ and contemporaneous sales for manufacturing, construction, and business-to-business trade and a positive association for business-to-consumer trade and services when the model is run with OLS. When pollution is instrumented with the change in wind directions as in column (2), (3) and (4), using respectively month-by-year fixed effects, month-by-year-by-industry fixed effects, or the latter and quarter-by-*departement* fixed effects, the effect of pollution on sales is negative and statistically significant at the 1% level (except for the construction sector in column (4)).

With our baseline specification shown in column (3), we find that a one unit increase in firm-level $PM_{2.5}$ exposure decreases firm-level sales in the two following months by 0.14 percent in manufacturing, by 0.08 percent in construction, by 0.13 percent in business-to-business trade and by 0.46 percent in business-to-consumer trade and services. Retail sectors directly serving final consumers tend to respond more strongly to air pollution shocks than production sectors, such as manufacturing or construction. The results imply that a 10 percent increase in pollution exposure in month $t-1$ decreases firm-level sales in the two following months by 0.21 percent in manufacturing, 0.12 percent in construction, 0.19 percent in business-to-business trade and services and 0.71 percent in business-to-consumer trade and services.

Running the analysis on the subsample of single-establishment firms using the four wind IV instruments give similar results, as shown in table A.3. Sales decrease is slightly larger for single-establishment firms in the construction sector.

These impacts represent substantial losses to economic production on months with high levels of pollution. To illustrate, we provide back-of-the-envelope calculation of the benefits of meeting the daily $PM_{2.5}$ WHO target in terms of avoided lost sales. Over our 7-year study period, the 15µg/m^3 threshold is exceeded for 37% of the worker-days. Bringing each day above the threshold to 15µg/m^3 would decrease monthly average pollution exposure from 15.4 to 11.5µg/m^3, a 25% decrease compared to the levels observed over 2009-2015. Based on our estimates,this decrease in pollution could have avoided 27 billion euros of foregone sales annually in an average year between 2009 and 2015, which is equivalent to 1.5% of total sales in the French private sector. To provide a rough comparison with the costs of bringing $PM_{2.5}$ to this WHO threshold, we follow Dechezleprêtre et al. (2019) in using the cost of reducing $PM_{2.5}$ emissions—rather than concentrations—obtained from a report published by the European Commission for a scenario reducing emissions by 33% (option 6D): it would cost €0.77 billions annually.[29] Although our

[29]The estimated cost can be found in part 3, page 43 of the following report:

benefit measure is expressed in terms of foregone sales and not in terms of profits, and the costs are not precisely estimated, the comparison provides suggestive evidence that the economic gains from meeting the WHO targets probably largely exceed the potential costs of doing so.

Table 4: Heterogeneous Sales Responses to Lagged $PM_{2.5}$ by Sector

	(1) OLS	(2) IV	(3) IV	(4) IV
Panel A: Manufacturing				
$PM_{2.5t-1}$	-0.0207	-0.321***	-0.283***	-0.137***
	(0.0210)	(0.0495)	(0.0491)	(0.0462)
N	1,880,573	1,880,573	1,880,491	1,880,387
R-squared	0.9632	0.9632	0.9640	0.9641
Panel B: Construction				
$PM_{2.5t-1}$	-0.116***	-0.248***	-0.252***	-0.0802*
	(0.0201)	(0.0473)	(0.0472)	(0.0480)
N	1,531,685	1,531,685	1,531,685	1,531,685
R-squared	0.9347	0.9347	0.9349	0.9351
Panel C: Business-to-Business Trade and Services				
$PM_{2.5t-1}$	-0.0181	-0.338***	-0.310***	-0.127***
	(0.0197)	(0.0491)	(0.0490)	(0.0469)
N	2,875,303	2,875,303	2,875,221	2,875,221
R-squared	0.9332	0.9332	0.9338	0.9339
Panel D: Business-to-Consumer Trade and Services				
$PM_{2.5t-1}$	0.174***	-0.859***	-0.859***	-0.463***
	(0.0172)	(0.0538)	(0.0531)	(0.0498)
N	3,124,507	3,124,507	3,124,507	3,124,507
R-squared	0.9382	0.9382	0.9457	0.9459
Firm-by-year FE	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	No	No
Month-by-year-by-industry FE	No	No	Yes	Yes
Quarter-by-departement FE	No	No	No	Yes

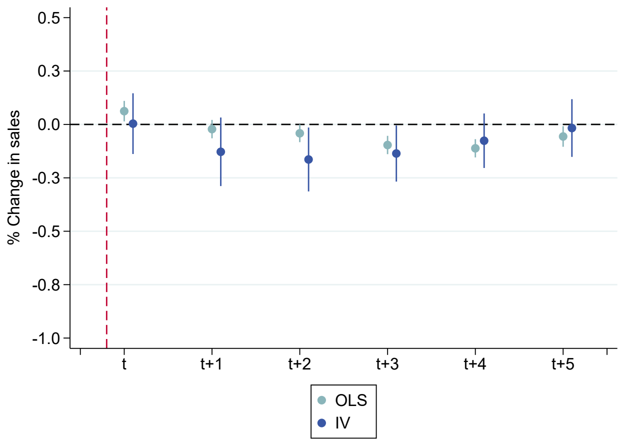
Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation (11) for all firms by sector. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at t and $t+1$. The confidence intervals are based on standard errors clustered at the firm level. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

https://ec.europa.eu/environment/archives/air/pdf/Impact_assessment_en.pdf. The respect of the WHO threshold is equivalent to a decrease of 25% of $PM_{2.5}$ concentrations on average in France, hence the scenario reducing $PM_{2.5}$ emissions by 33% is the closest.

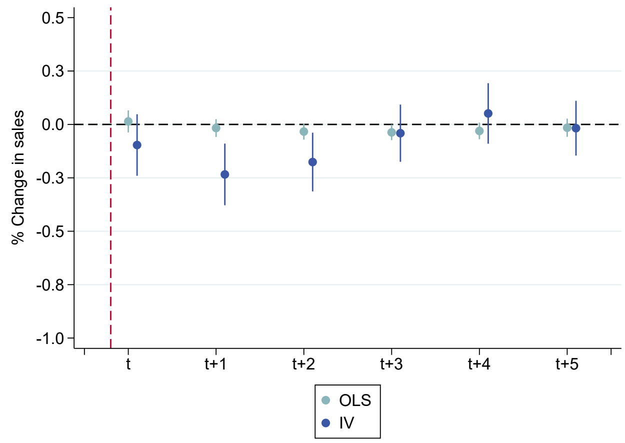
4.2 Dynamic Effects on Sales

Given the granularity of our data at the monthly level, we explore the dynamic effects of air pollution by sector. Figure 7 reports both the OLS and IV estimates of the dynamic effects of air pollution by sector.

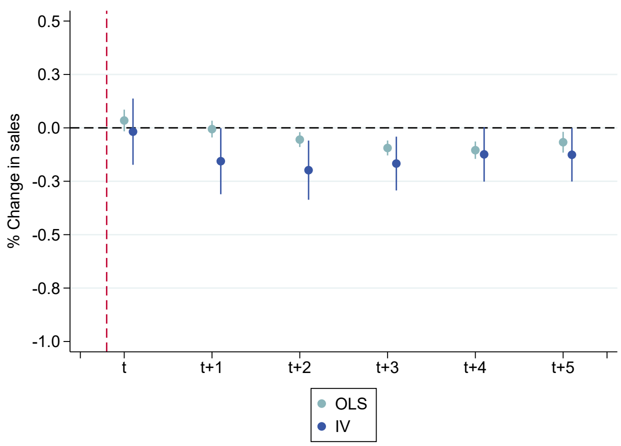
To reduce the noise due to the serial correlation in wind direction and pollution exposure over time, we use a polynomial distributed lag (PDL) (Schwartz, 2000; He et al., 2019), where we impose a smooth polynomial function on the lag structure to discipline the coefficients. Assuming a cubic polynomial functional form, we examine in a single regression the effects of pollution at t, $t-1$,... up to $t-5$ on sales at t by sector. It implies that we impose the following relationships on the coefficients β_l, for $l \in \{0, .., 5\}$: $\beta_l = \sum_{k=0}^{3} \gamma_k l^k$, resulting in $\beta_0 = \gamma_0$, $\beta_1 = \gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$, and $\beta_2 = \gamma_0 + 2\gamma_1 + 4\gamma_2 + 8\gamma_3$ for the first parameters. Using these relationships, we rewrite the regression equation as a function of γ_ks and estimate by OLS and by 2SLS the coefficients γ_1, γ_2, and γ_3. Combining these point estimates and associated standard errors, we recover the point estimates β_ls and associated standard errors by sector. We report in figure 7 the estimates for β_0 with label t, β_1 with label $t+1$, up to β_5 with label $t+5$. The IV results at $t+1$ are generally larger than in main results described above, and the effects for construction become closer to those for manufacturing. But the relative effects across the different sector is generally the same, with orders of magnitude twice to thrice as large for the business-to-consumer services sector compared to the rest. Focusing on the IV estimates, adding more time periods reveal that the negative effect of pollution on sales can worsen over time (up to months $t+2$ and $t+3$) and slowly fades out until it reaches zero at month $t+4$ or $t+5$ depending on the sector. Figure A.14 reports the result for the subsample of single-establishment firms, which are very similar to the results for the whole sample.



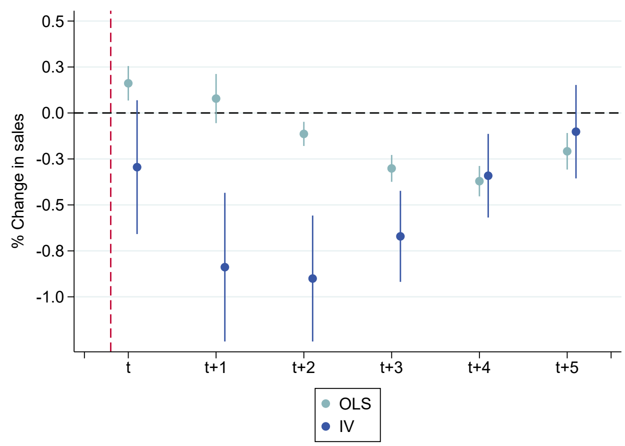
(a) Manufacturing



(b) Construction



(c) Business-to-Business Trade & Services



(d) Business-to-Consumer Trade & Services

Figure 7: Dynamic effects of $PM_{2.5}$ on sales for all firms, by sector

Notes: Figure shows the OLS and IV point estimates and 95% confidence intervals from equation (8) for the effect of contemporaneous and lagged $PM_{2.5}$ (up to $t-5$) firms' sales at t by sector, using the polynomial distributed lag method. All regressions include month-by-year-by-industry fixed effects, firm-by-year fixed effects, quarter-by-departement fixed effects, weather controls, and holidays controls. Controls for weather and holidays at all the relevant leads and lags are added. The confidence intervals are based on standard errors clustered at the Firm level.

4.3 Falsification test

Table 5 shows dynamic specification coefficients that reflect the effect of future exposure to $PM_{2.5}$ measured in $t + 2$ on current outcomes (average sales in months t and $t + 1$) as placebo check. The only sector in which we find a marginally significant effect, with a low magnitude, is the business-to-business trade and services sector.

Table 5: Placebo Checks Using Future Pollution Shocks, by Sector

	Manuf	Const.	B2B	B2C
$PM_{2.5t+2}$	0.0150	0.0713	0.0871*	0.0346
	(0.0465)	(0.0517)	(0.0487)	(0.0381)
Firm-by-year FE	Yes	Yes	Yes	Yes
Month-by-year-by-industry FE	Yes	Yes	Yes	Yes
Quarter-by-departement FE	Yes	Yes	Yes	Yes
N	1,848,438	1,500,852	2,815,435	3,063,255
R-squared	0.9649	0.9363	0.9347	0.9470

Notes: Table reports the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t + 2$ on the sales outcome at t from equation (11) for all firms, by sector. All regressions include weather and holidays controls at t, $t + 1$ and $t + 2$, as well as instrumented pollution at t and $t + 1$. The confidence intervals are based on standard errors clustered at the firm level. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

4.4 Robustness checks

We perform a series of robustness check to assess the risk that our effect is driven by the way we specify control variables, idiosyncrasies in the time period considered, or extreme values in our sample.

Column (1) of table 6 shows the main result when firms of all sectors are pooled together, using our main specification with firm-by-year fixed effects and month-by-year-by-industry fixed effects. In column (2), we assess whether we can interpret our estimates as the causal effects of $PM_{2.5}$ given that other pollutants harming human health, and potentially productivity, may also be influenced by wind directions while being omitted from our main specification. Given our specification of monthly concentration in $PM_{2.5}$, we are not able to disentangle the independent effects of SO_2, NO_2 and PM_{10} from those of $PM_{2.5}$. By contrast, ozone (O_3) is anti-correlated with $PM_{2.5}$ and its transport could be affected by wind direction. If ozone also significantly affects sickness leave, the exclusion restriction could be violated and our estimates may pick up the joint effect of wind-induced changes in ozone and $PM_{2.5}$ on absenteeism. We use a multi-pollutant index instead of $PM_{2.5}$ as our measure of pollution to address this concern. The French air quality index is a synthetic index based on the daily concentrations of different pollutants (SO_2, NO_2, PM_{10}, $PM_{2.5}$ and ozone), ranging from 1 (best air quality) to 6 (worst air quality). We build the index using daily data for four pollutants available in the CHIMERE dataset and take the monthly average in each municipality.[30] The magnitude of the coefficient is not directly comparable to our main estimate using PM2.5, given the difference in the scale of AQI index and PM2.5. Expressing the results in terms of standard deviations gives estimates of the same order of magnitude: a 1-SD increase in lagged PM2.5 (sd=6.2µg/m^3) decreases sales by 1.6 percent, and a 1-SD increase in the AQI index (sd=0.41) decreases sales by 1.3 percent. The lower point estimate for the AQI index could be explained by the fact that an increase in the AQI index corresponds half of the year to an increase in PM2.5 and half of the year to an increase in ozone. If ozone has no significant impact on sales, the effect of PM2.5 becomes diluted when we use AQI as a measure of pollution.

In column (3), we discard observations subject to a PM_{10} air quality alert, to make sure that our results are not driven by consumers' and firms' responses to air quality alerts. Air quality alerts do not exist for $PM_{2.5}$ in France but are issued for PM_{10}. Owing to the high correlation between PM_{10} and $PM_{2.5}$, we use the regulatory thresholds for the issuance of PM_{10} alerts.[31] For each municipality-month we build a variable corresponding to the number of days where a PM_{10} air quality alert was issued, and we re-run the IV regression after excluding all the municipality-months with at least one day of air quality alerts. The estimated coefficient is close to the main result.

In column (4), we winsorize the sales outcome by replacing values in the bottom 2% and top 2% of the monthly sales distribution with values for the 2th percentile and 98th percentile respectively. The result is very close to our baseline coefficient. In column (5), we control for weather using simple and quadratic terms for average daily maximum temperature, average wind speed, and average daily rainfall, instead of using all possible interactions between these variables' bins. The estimated coefficient on pollution is larger, suggesting that our estimate is conservative. In column (6), we cluster standard errors two-way at the firm and month-by-year level, to account for the potential correlation in the error term across observations of the same month. While the

[30] Following the method used by the regional air quality agencies, we first create a sub-index ranging from 1 to 6 for each pollutant based on official thresholds; then we allocate the maximum value of all sub-indices to the air quality index that day. In the data, $PM_{2.5}$ takes the maximum value of all sub-indices 70% of the days from October to March, while ozone takes the maximum value 80% of the days From April to September.

[31] Two levels of alerts exist: level 1 provides information on air pollution levels and advises vulnerable individuals to avoid physical activities outside and recommends decreasing driving speed to mitigate pollution; level 2 adds strict enforcement measures such as driving restrictions (see https://www.airparif.asso.fr/procedure-dinformation-et-dalerte for more information). Until November 2014, level 1 was triggered when daily average PM_{10} exceeded 80 µg/m^3 and level 2 when it exceeded 125 µg/m^3. From November 2014 onwards, the thresholds were lowered to 50 µg/m^3 for level 1 and 80 µg/m^3 for level 2. Even in the most polluted city of France, Paris, air pollution alerts for PM_{10} – which involve recommendations from the health authorities targeting the most vulnerable individuals – were issued on 4% of the days in our study period. More severe alerts involving restrictions in car traffic were issued on 0.7% of the days only.

effect of pollution on sales becomes less precisely estimated, it remains significant at the 5% level.

Table 6: The Effect of Lagged $PM_{2.5}$ on Contemporaneous Firm-level Sales, All Sectors, robustness checks

	(1) Baseline	(2) AQI	(3) No PM_{10} alert	(4) Winsorized outcome	(5) continuous weather	(6) Two-way clustering
$PM_{2.5t-1}$	-0.259***		-0.272***	-0.270***	-0.424***	-0.259**
	(0.0264)		(0.0298)	(0.0262)	(0.0280)	(0.105)
AQI index$_{t-1}$		-3.192***				
		(0.438)				
N	9,403,173	9,411,803	8,959,529	9,411,935	9,411,803	

Notes: Table reports the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation (11) for all firms in all sectors. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, instrumented pollution at t and $t+1$, firm-by-year fixed effects, quarter-by-departement fixed effects and industry-by-month-by year fixed effects. The confidence intervals are based on standard errors clustered at the firm level, except for column (5) where they are double-clustered at the firm level and across time. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

5 Identifying Channels

The temporary decline in economic production following a month of high $PM_{2.5}$ levels can arise due to different channels explored in our analytical framework: workers may become sick and stay home, they may suffer from mild symptoms that allow them to work but with lower productivity, other workers may face disrupted work tasks due to the absence of their co-worker, and finally demand can change due to behavioral changes in high pollution contexts. In this section, we explore these channels. We consider that evidence of work absenteeism—which requires a medical certificate in the French context—reveals more broadly the health impact of air pollution.

5.1 Pollution-induced sickness absenteeism

Table 7 reports the main OLS and IV estimates of the effect of $PM_{2.5}$ on sickness leave outcomes, for the sample of workers whose firm is included in our sales data. Columns (1) and (2) report the estimates based on equation (12) using establishment (SIRET) fixed effects. The OLS estimate indicates that a one-unit increase in monthly average $PM_{2.5}$ concentrations is associated with a 0.07 increase in the number of workers starting a sickness leave that month, per 1,000 workers. The IV estimate is twice as large, consistent with the OLS estimate being downward bias due to omitted variable and attenuation bias from classical measurement error. The IV estimate corresponds to a 0.6 percent increase given the baseline average of 23 per 1,000 workers, and if we translate it to an elasticity, it means that a 10 percent increase in monthly PM2.5 increases absenteeism by 1 percent.

Columns (3) and (4) report estimates for the sample at the municipality level, replacing establishment fixed effects and industry-by-month of sample fixed effects with municipality fixed effects and month of sample fixed effects. The OLS estimate is about the same as in column 1. The IV estimate is larger in magnitude and also points to a significant increase in sick leave.

Table 7: The Effect of PM2.5 on the number of Workers entering Sick Leave in the Same Month (per 1,000 Workers), All Sectors

	Establishment-level sample		Municipality-level sample	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$PM_{2.5t}$	0.0716***	0.147***	0.0609**	0.273***
	(0.0211)	(0.0603)	(0.0260)	(0.0897)
N	8,238,888	8,238,888	369,190	369,190
R-squared	0.0636	0.0636	0.2516	0.2516
Dep. var. mean	23	23	23	23
First-stage effective F-statistic		490		490

Notes: Table reports OLS and IV estimates from equation (12) for the effect of $PM_{2.5}$ on the number of workers starting a sick leave per 1,000 workers using a sample aggregated at the establishment level (columns 1 and 2), and at the municipality level (columns 3 and 4). All regressions include quarter-by-departement fixed effects and weather and holidays controls. Columns 1 and 2 also includes industry-by-month-of-sample fixed effects and establishment fixed effects, while columns 3 and 4 include month-of-sample fixed effects and municipality fixed effects. Observations are weighted by the number of workers in each establishment (columns 1 and 2) or municipality (columns 3 and 4). Standard errors in parentheses are clustered at the Copernicus grid cell level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

To be able to compare our results on the relationship between pollution exposure and sick leave to the existing literature, we also run the analysis for the entire representative sample of workers. Figure A.16 shows the OLS and IV estimates for the representative sample compared to our sample of interest. The results are very close across the two samples. Our estimate translates into an elasticity of sick leave flows to pollution of –0.10. In contrast, Holub et al. (2021) examines a representative sample of Spanish workers and shows that a 10% reduction in weekly PM_{10} concentration in the main urban areas in Spain reduces weekly sickness-related absenteeism by 0.8% of the mean, implying an elasticity of the labor supply of –0.08. While our study differs in the type of pollutant studied and the time horizon considered (monthly vs. weekly), the order of magnitude is similar.

Figure 8 highlights the heterogeneous effects of pollution on absenteeism by sector. The effect appears to be driven by workers employed in the manufacturing sector and to some extent in the construction sector. By contrast, the effect of air pollution on sick leave is small the service sector. These heterogeneous effects do not necessarily reflect differences in worker vulnerability to of air pollution by sector. They may reflect differences in the ability to work from home or be absent from work without a medical certificate, conditional on a given pollution-induced health shock. The cost of being in sick leave may also differ by sector, given that employer-funded sickness leave benefits depend partly on industry-specific collective agreements.

For our purpose of uncovering the mechanisms via which air pollution affects firms' sales, the take-away from this graph is that there is no correlation between the magnitude of the absenteeism effect and the magnitude of the pollution effect. For example, the two sectors with the highest and lowest absenteeism response to pollution, manufacturing and business-to-business services, have a similar sales response to air pollution. Heterogeneity across sectors in the ability to cope with absenteeism shocks can also not entirely explain the heterogeneity in the sales decrease. Otherwise, we would expect to find no sales decrease in business-to-business services, where the absenteeism effect is zero.

Assuming that absenteeism causes no disruption to the production process beside the lost output of the sick workers, we can proxy foregone sales due to pollution-induced absenteeism by multiplying our estimates on how pollution affects the number of sick days by sales per worker.day. For the average manufacturing firm, we estimate that a one-unit increase in $PM_{2.5}$ increases the number of sick days per 1,000 workers by 5.5 days. The average firm has 90 workers, so our estimates implies 0.5 days of work lost in the month. Average monthly sales per full-time worker per day are €1,170. So for the average firm the pollution-induced output loss due to absenteeism is around €585 worth of sales. In contrast we find that a one unit increase in $PM_{2.5}$ decreases manufacturing firms sales by 0.137%, which correspond to €3,173 for the average firm. Therefore, even in the sector where the air pollution increases absenteeism the most, sales losses caused by this absenteeism channel represent only 18% of total sales losses due to pollution.

To conclude, while worker absenteeism is affected by air pollution and contributes to sales losses, it cannot be the only and even the main channel via which air pollution decreases firms' sales.

Robustness Checks. We perform the same set of robustness checks as for the effect on sales to validate the evidence of a causal effect of $PM_{2.5}$ concentrations on sickness leave episodes.

Column (1) of table 8 shows the baseline estimate for the specification with establishment fixed effects (same as column (2) of table 7), where the magnitude implies that a one-SD increase in $PM_{2.5}$ increases absenteeism by 0.93 spells per 1,000 workers. Column (2) shows that a 1-unit increase in the AQI index increases the number of workers entering sick leave that month by 2.1

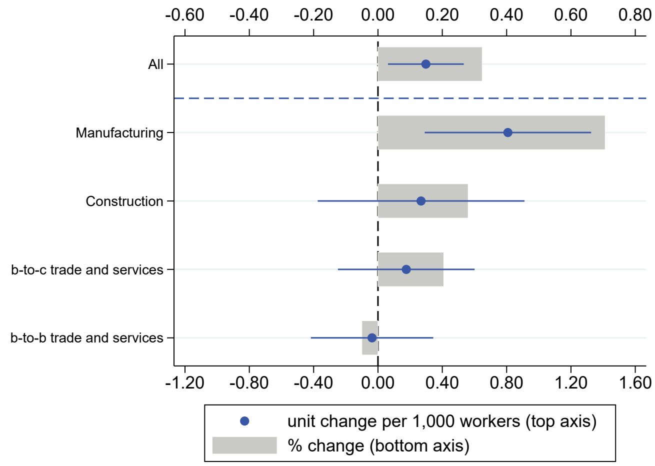


Figure 8: Contemporaneous effect of a one-unit increase in $PM_{2.5}$ on sick leave episodes

per 1,000 workers. The standard deviation of monthly AQI is 0.40, so a one-SD increase in AQI increases absenteeism by 0.86 spells per 1,000 workers. The two effects are of a similar order of magnitude. Columns (3) to (5) show that the estimated effect of PM2.5 on the number of workers starting a sick leave is robust to discarding months with PM_{10} alerts, winsorizing the absenteeism outcome and changing the specification of weather controls. Column (6) shows that two-way clustering at the Copernicus grid cell and time level, which is quite conservative, renders the estimated coefficient less precise.

Table 8: The Effect of $PM_{2.5}$ on worker absenteeism, all sectors, robustness checks

	(1) Baseline	(2) AQI	(3) No PM_{10} alert	(4) Winsorized outcome	(5) continuous weather	(6) Two-way clustering
$PM_{2.5t}$	0.147**		0.156**	0.157***	0.154**	0.147*
	(0.0603)		(0.0650)	(0.0496)	(0.0610)	(0.0874)
AQI index$_t$		2.149**				
		(0.868)				
N	8,238,888	8,238,888	7,890,564	8,238,888	8,238,888	8,238,888

Table reports IV estimates from equation (12) for the effect of $PM_{2.5}$ on the number of workers starting a sick leave, per 1,000 workers. All regressions include industry-by-month-by-year fixed effects, quarter by departement fixed effects, establishment fixed effects, weather controls, and holidays controls. Observations are weighted by the number of workers for which we observe sick leave status in each establishment. Standard errors in parentheses are clustered at the Copernicus grid cell level, except in column (6) where they are clustered by Copernicus grid cell level and by month-year. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

5.2 The role of productivity and demand

Productivity: While we are unable to quantify the productivity channel, we provide suggestive evidence that pollution directly affects worker productivity by decomposing effects by industry within the manufacturing sector. We classify industries by whether they are above or below the median in terms of their quantity of stock, using a survey on manufacturing plants conducted in 2004.[32] To the extent that stock levels is orthogonal to worker absenteeism due to pollution, we expect that firms operating with low stock levels should have their sales more impacted by pollution than firms operating with high stock levels only if air pollution directly impacts worker productivity: while firms with high stock levels can buffer any shock in production by selling some existing stocks, firms with low stock levels are not able to compensate and decrease sales.

Table 9 reports the results. Columns (1)-(3) indicate that the sales decrease is driven by firms belonging to industries operating with low stock levels, while the effect is close to zero for firms belonging to industries operating with high stock levels. At the same time, Columns (4)-(6) suggest that the tow types of firms experience a similar increase in worker absenteeism. Average sales and number of employees are also relatively similar across the two groups of firms, suggesting that heterogeneous vulnerabilities to air pollution by firm size is not the channel driving the difference in the magnitude of the sales response. All in all, this heterogeneity by stock level suggests that air pollution affects sales at least partly via an effect on workers' productivity.

Demand: We would expect demand responses to be stronger in the consumer retail and services sector. We do find larger magnitudes for the effect of $PM_{2.5}$ on sales in that sector. These larger magnitudes reveal that consumers whose health is deteriorated may avoid grocery shopping or going to a restaurant. By contrast, customers of professional services or manufacturing products are less likely to live in the vicinity of sellers, which implies that they probably will not be exposed to the same pollution shocks. We provide suggestive evidence that the demand channel is at play by comparing the effect of pollution on sales for retail firms specialised in staples – that is to say essential goods which consumption is hard to forego, such as food, – and retail firms selling more discretionary goods such as furniture or clothing. Table 10 shows that pollution decreases sales slightly more for firms selling discretionary goods than for firms selling staples. However, the point estimates are quite imprecise and we cannot reject that the effects are the same. Furthermore,

[32] Unfortunately we do not have firm-level data on stocks or more recent data. The manufacturing industries with high stock levels are: production of textile; clothing; shoes and leather; chemicals; pharmaceuticals; other non metallic mineral products; machine and equipment; transport material outside car industry; furniture; other manufacturing industry; repair and installation of machines. The manufacturing industries with low stock levels are: food industry; production of beverages; tobacco products; wood products; paper; printing and recording industry; refineries; plastic and rubber; metal industry; other metal products; electronic, optic and IT equipment; electric equipment; car industry. Extractive and utility industries, while included in our main manufacturing sector, are not included here

Table 9: Heterogeneous effects of air pollution on sales and worker absenteeism in the manufacturing sector, by stock level

	Sales effect			Absenteeism effect		
	All firms	Low stock levels	High stock levels	All firms	Low stock levels	High stock levels
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5t-1}$	-0.137***	-0.219***	-0.026	0.404***	0.316*	0.378*
	(0.0462)	(0.0545)	(0.0888)	(0.132)	(0.179)	(0.230)
Nb. employees	90	83	96	90	83	96
Avg. sales	2,315,972	2,160,235	2,368,296	2,315,972	2,160,235	2,368,296
N	1,880,491	1,151,904	629,098	1,428,984	865,415	486,670
R-squared	0.9640	0.9708	0.9530	0.1368	0.1367	0.1370

Notes: Columns 1-3 report the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation (11) for manufacturing firms. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at t and $t+1$, and firm-by-year, quarter-by-departement and industry-by-month-by-year fixed effects. Columns 4-6 report the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at t on absenteeism outcome at t for manufacturing firms. All regressions include weather and holidays controls at t. The confidence intervals are based on standard errors clustered at the firm level. Column (2) and (3) show heterogeneity by industry based on whether that industry operates, on average, with low or high stock levels. Stock level information comes from a 2004 survey on 2,058 manufacturing establishments and is measured in days of production. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

the two types of firms differ in size, which could explain the difference in how sales respond to air pollution. All in all, our results are suggestive of a negative effect of air pollution on consumer demand at least in some industries.

Table 10: Heterogeneous effects of air pollution on sales and worker absenteeism in the business-to-consumer services sector, staples vs discretionary goods

	Sales effect			Absenteeism effect		
	All firms	Discretionary	Staples	All firms	Discretionary	Staples
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5t-1}$	-0.463***	-0.522***	-0.321***	-0.125	-0.047	-0.350
	(0.0498)	(0.0604)	(0.0736)	(0.119)	(0.137)	(0.239)
Nb. employees	48	41	72	48	41	72
Avg. sales	883,728	690,286	1,567,431	883,728	690,286	1,567,431
N	3,124,507	2,430,024	694,278	1,428,984	1,424,001	458,241
R-squared	0.9459	0.938	0.9530	0.1368	0.1367	0.1370

Notes: Columns 1-3 report the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation (11) for manufacturing firms. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at t and $t+1$, and firm-by-year, quarter-by-departement and industry-by-month-by-year fixed effects. Columns 4-6 report the IV estimates of the effect of a one unit increase in $PM_{2.5}$ at t on absenteeism outcome at t for firms in the business-to-consumer trade and services sector. All regressions include weather and holidays controls at t. The confidence intervals are based on standard errors clustered at the firm level. Column (2) and (3) show heterogeneity by industry based on whether that industry operates, on average, with low or high stock levels. Stock level information comes from a 2004 survey on 2,058 manufacturing establishments and is measured in days of production. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

6 Conclusion

In this paper, we show that an increase in monthly firm-level exposure to fine particulate matter causes a decrease in sales in the French private sector in the following months. We also show that air pollution exposure for workers increase their sickness-related absenteeism. We find that the economic cost of pollution associated with these firm-level sales losses exceeds by far the monetary value of pollution-induced absenteeism valued at the marginal product of labor.

Our analysis has several implications for research and policy. First, our analysis suggests that productivity and demand effects play an important role in the transmission of pollution shocks to firms' sales. Based on the sectors where the gaps between sales losses and absenteeism are the largest, we attempted to characterize the relative importance of these two channels. Developing research designs to better understand the underlying mechanisms for each affected sector could be a promising path for future research.

Second, there is a large literature in economic geography and urban economics that relates high density with a high productivity, one of the benefits of agglomeration (Combes et al., 2012; Ahlfeldt and Pietrostefani, 2019). Recent work separately shows that high density also causes high levels of air pollution (Carozzi and Roth, 2023). Our work suggests that pollution levels may be an important omitted variable in the estimation of agglomeration effects. This omitted variable is expected to bias the effect of density on productivity downward, given the positive relationship between density and pollution and the negative relationship between pollution and productivity. Revisiting estimates of agglomeration effects on productivity net of pollution effects would be an interesting avenue for urban and environmental economists.

Third, ex-ante cost-benefit analyses of environmental regulation that do not account for the negative effect of pollution on firms' performance will significantly underestimate the net benefits of these regulations. As the European Commission is currently in the process of updating its regulatory standards to bring them closer to the WHO recommendations, it seems all the more important to properly quantify the costs and benefits of doing so. In our analysis, we provide an estimate of the benefits of bringing daily exposure to $PM_{2.5}$ down to the WHO recommendations that is much larger than available cost estimates. Adding health benefits for the entire population to our estimates—which depend exclusively on work loss days and sales losses—the benefits will significantly exceed the costs.

References

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2020). Temperature Shocks and Establishment Sales. *The Review of Financial Studies 33*(3), 1331–1366.

Adhvaryu, A., N. Kala, and A. Nyshadham (2022). Management and shocks to worker productivity. *Journal of Political Economy 130*(1).

Aguilar-Gomez, S., H. Dwyer, J. Graff Zivin, and M. Neidell (2022). This Is Air: The "Nonhealth" Effects of Air Pollution. *Annual Review of Resource Economics 14*(1), 403–425.

Ahlfeldt, G. M. and E. Pietrostefani (2019). The economic effects of density: A synthesis. *Journal of Urban Economics 111*, 93–107.

Aragón, F. M., J. J. Miranda, and P. Oliva (2017). Particulate matter and labor supply: The role of caregiving and non-linearities. *Journal of Environmental Economics and Management 86*, 295–309.

Barwick, P. J., S. Li, D. Rao, and N. B. Zahur (2024). The Healthcare Cost of Air Pollution: Evidence from the World's Largest Payment Network. *The Review of Economics and Statistics*, 1–52.

Borgschulte, M., D. Molitor, and E. Zou (2022). Air Pollution and the Labor Market: Evidence from Wildfire Smoke.

Carozzi, F. and S. Roth (2023). Dirty density: Air quality and the density of American cities. *Journal of Environmental Economics and Management 118*, 102767.

Champalaune, P. (2020). Inequality in Exposure to Air Pollution in France: Measurement and Impact of a City-Level Public Policy. pp. 67.

Chang, T., J. Graff Zivin, T. Gross, and M. Neidell (2016). Particulate Pollution and the Productivity of Pear Packers. *American Economic Journal: Economic Policy 8*(3), 141–169.

Chang, T. Y., J. G. Zivin, T. Gross, and M. Neidell (2019). The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China. *American Economic Journal: Applied Economics 11*(1), 151–172.

CITEPA (2021). Secten – le rapport de référence sur les émissions de gaz à effet de serre et de polluants atmosphériques en France.

Combes, P.-P., G. Duranton, L. Gobillon, D. Puga, and S. Roux (2012). The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection. *Econometrica 80*(6), 2543–2594.

Currie, J., J. Voorheis, and R. Walker (2023). What Caused Racial Disparities in Particulate Exposure to Fall? New Evidence from the Clean Air Act and Satellite-Based Measures of Air Quality. *American Economic Review 113*(1), 71–97.

Dahl, G. B. and L. Lochner (2012, May). The Impact of Family Income on Child Achievement:

Evidence from the Earned Income Tax Credit. *American Economic Review 102*(5), 1927–1956.

Dechezleprêtre, A., N. Rivers, and B. Stadler (2019). The economic cost of air pollution: Evidence from Europe. Technical report, OECD, Paris.

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

Dong, R., R. Fisman, Y. Wang, and N. Xu (2019). Air Pollution, Affect, and Forecasting Bias: Evidence from Chinese Financial Analysts. *Journal of Financial Economics 139*(3).

European Commission (2020). Air quality: Commission decides to refer France to the Court.

European Environment Agency (2020). Air pollution: how it affects our health.

France Stratégie and Inspection générale des Finances (2021). Comité de suivi et d'évaluation des mesures de soutien financier aux entreprises confrontées à l'épidémie de covid-19 - Rapport final. Technical report.

Fu, S., V. B. Viard, and P. Zhang (2021). Air Pollution and Manufacturing Firm Productivity: Nationwide Estimates for China. *The Economic Journal 131*(640), 3241–3273.

Graff Zivin, J. and M. Neidell (2012). The Impact of Pollution on Worker Productivity. *American Economic Review 102*(7), 3652–3673.

Graff Zivin, J. and M. Neidell (2014). Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labor Economics 32*(1), 1–26. Publisher: [The University of Chicago Press, Society of Labor Economists, NORC at the University of Chicago].

Graff Zivin, J., M. Neidell, N. J. Sanders, and G. Singer (2023). When Externalities Collide: Influenza and Pollution. *American Economic Journal: Applied Economics 15*(2), 320–51.

Griliches, Z. and J. A. Hausman (1986). Errors in variables in panel data. *Journal of Econometrics 31*(1), 93–118.

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

He, J., H. Liu, and A. Salvo (2019). Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China. *American Economic Journal: Applied Economics 11*(1), 173–201.

Hersbach, H., B. Bell, P. Berrisford, G. Biavati, A. Horányi, J. Muñoz Sabater, J. Nicolas, C. Peubey, R. Radu, I. Rozum, D. Schepers, A. Simmons, C. Soci, D. Dee, and J.-N. Thépaut (2018). Era5 hourly data on single levels from 1959 to present. *Copernicus Climate Change Service (C3S) Climate Data Store (CDS) (Accessed on 20-JUL-2022).*

Hoffmann, B. and J. P. Rud (2024). The unequal effects of pollution on labor supply. *Econometrica Conditionally Accepted.*

Holub, F., L. Hospido, and U. Wagner (2021). Urban Air Pollution and Sick Leaves: Evidence from Social Security Data.

INSEE (2021). Déplacements domicile-travail – Même sur de très courts trajets, l'usage de la voiture reste majoritaire - Insee Flash Provence-Alpes-Côte d'Azur - 70.

Krebs, B., J. Burney, J. G. Zivin, and M. Neidell (2021). Using Crowd-Sourced Data to Assess the Temporal and Spatial Relationship between Indoor and Outdoor Particulate Matter. *Environmental Science & Technology 55*(9), 6107–6115. Publisher: American Chemical Society.

Lichter, A., N. Pestel, and E. Sommer (2017). Productivity effects of air pollution: Evidence from professional soccer. *Labour Economics 48*, 54–66.

Meyer, S. and M. Pagel (2017). Fresh Air Eases Work – The Effect of Air Quality on Individual Investor Activity. Technical Report 24048, National Bureau of Economic Research, Inc. Publication Title: NBER Working Papers.

Mink, J. (2022). Putting a price tag on air pollution: the social healthcare costs of air pollution in France.

Montiel Olea, J. L. and C. E. Pflueger (2013). A Robust Test for Weak Instruments. *Journal of Business and Economic Statistics*.

Nasa Earth Observatory (2003). Chemistry in the Sunlight. Publisher: NASA Earth Observatory.

Park, R. J., N. Pankratz, and A. P. Behrer (2021, July). Temperature, Workplace Safety, and Labor Market Inequality. Technical Report 14560, Institute of Labor Economics (IZA). Publication Title: IZA Discussion Papers.

Pflueger, C. E. and S. Wang (2015). A Robust Test for Weak Instruments in Stata. *Stata Journal 15*(1), 216–225.

Pinna, M. (2022). Binned scatterplots with marginal histograms: binscatterhist. *The Stata Journal 22*(2), 430–445. Publisher: SAGE Publications.

Pollak, C. (2015). L'effet du délai de carence sur le recours aux arrêts maladie des salariés du secteur privé.

Real, E., F. Couvidat, A. Ung, L. Malherbe, B. Raux, and A. Colette (2021). Historical reconstruction of background air pollution over france for 2000–2015. *Earth System Science Data preprint, in review.*(https://doi.org/10.5194/essd-2021-182).

Schlenker, W. and W. R. Walker (2016). Airports, Air Pollution, and Contemporaneous Health. *Review of Economic Studies 83*(2), 768–809.

Schwartz, J. (2000). The distributed lag between air pollution and daily deaths. *Epidemiology (Cambridge, Mass.) 11*(3), 320–326.

Sicard, P., E. Agathokleous, A. De Marco, E. Paoletti, and V. Calatayud (2021). Urban population exposure to air pollution in Europe over the last decades. *Environmental Sciences Europe 33*(1), 28.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political*

Economy 129(6), 1797–1827. Publisher: The University of Chicago Press Chicago, IL.

US EPA (2018). EPA Report on the Environment - Particulate Matter Emissions. Technical report.

WHO (2014). 7 million premature deaths annually linked to air pollution.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press.

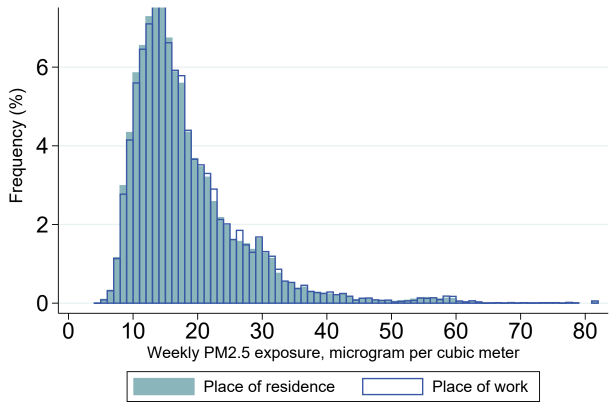
World Health Organization (2016). WHO Expert Consultation: Available evidence for the future update of the WHO Global Air Quality Guidelines (AQGs). pp. 50.

Zhang, W., H. Sun, S. Woodcock, and A. H. Anis (2017). Valuing productivity loss due to absenteeism: firm-level evidence from a Canadian linked employer-employee survey. *Health Economics Review 7*, 1–14.

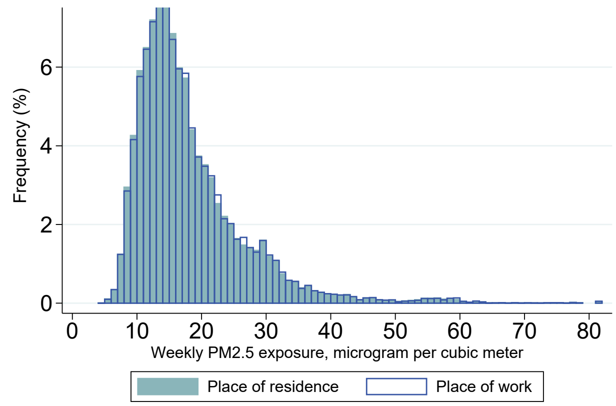
Appendix

A Additional Figures and Tables

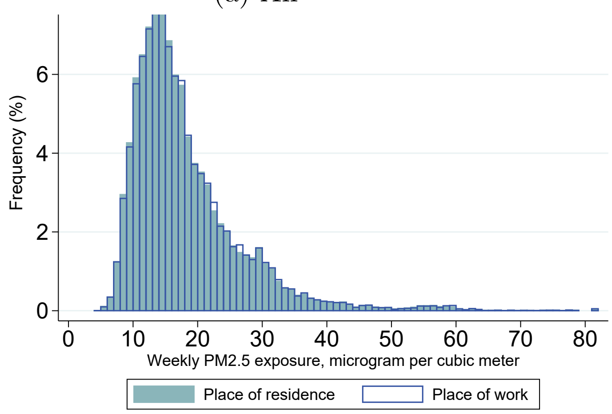
A.1 Figures



(a) All



(b) Q1



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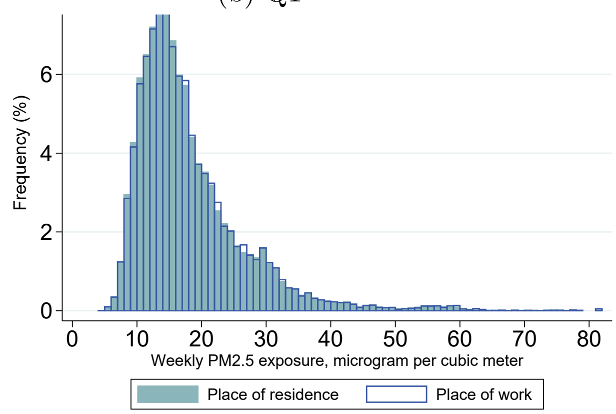

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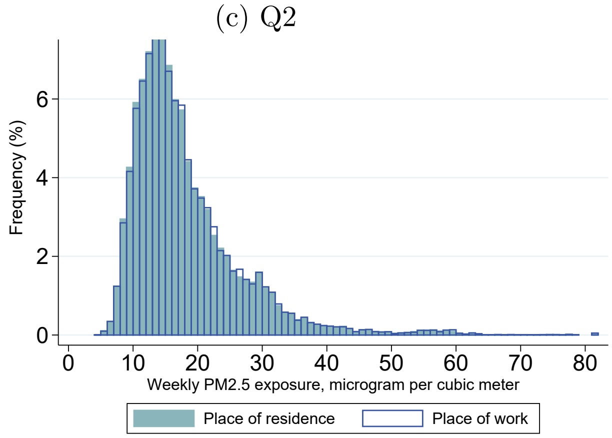

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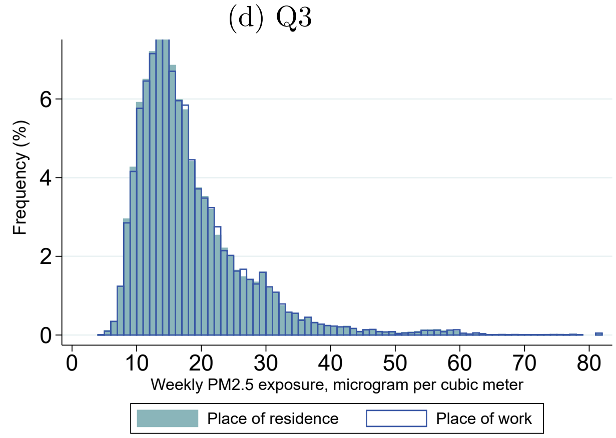
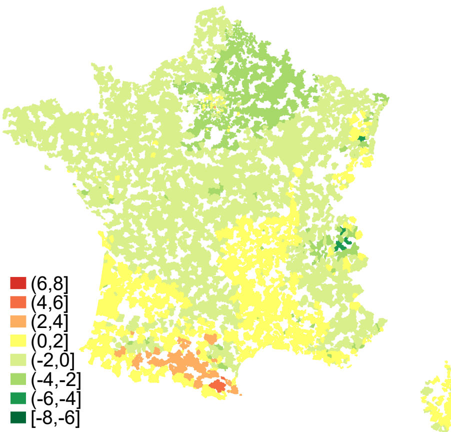


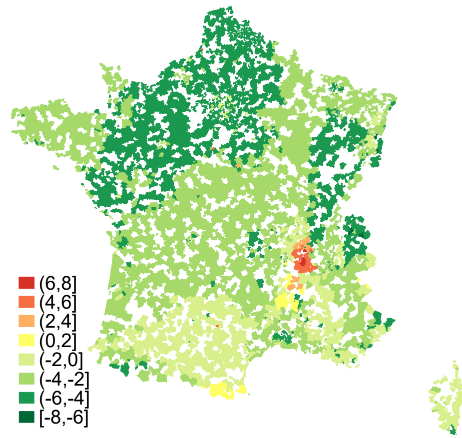
(f) Q5

Figure A.1: Distribution of pollution exposure at the municipality of residence and at the municipality of workplace

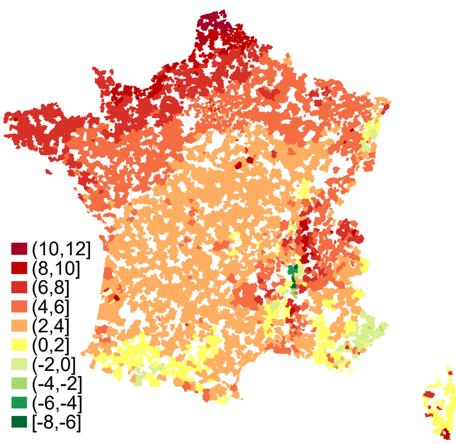
Notes: Figure presents the distribution of exposure to $PM_{2.5}$ at the place of work and at the place of residence for all private sector workers in France, and for workers by wage quintile.



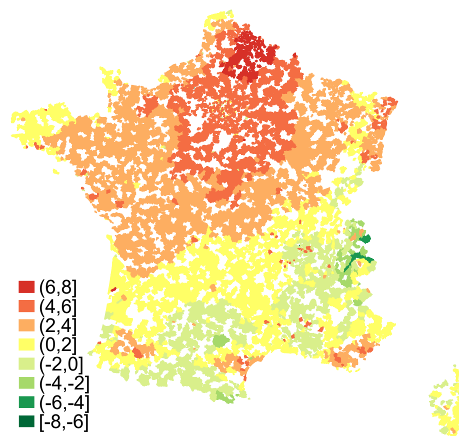
(a) South wind



(b) West wind



(c) East wind



(d) North wind

Figure A.2: Deviation from daily mean PM 2.5 for each wind direction

Notes: Figure shows for each municipality the component of the instrument Z_{jgyt} which described the variation from daily mean pollution levels on days where the dominant wind blows from direction j.

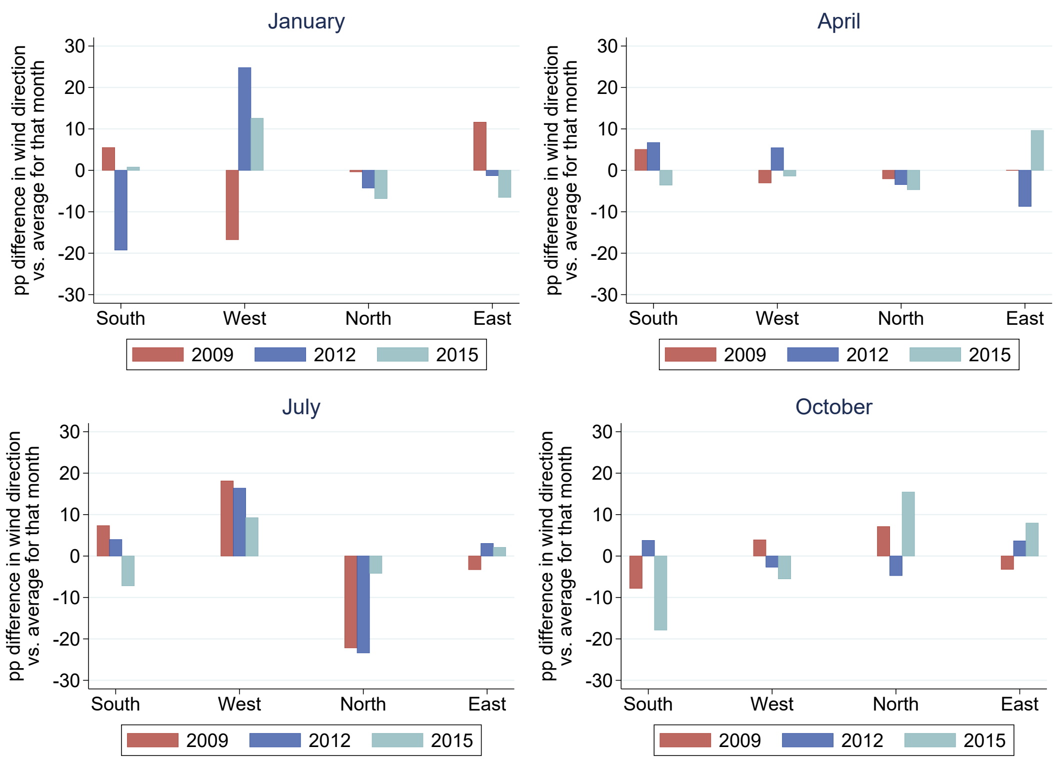


Figure A.3: Within-calendar month variation in wind direction, Paris

Notes: Figure shows the share of hours in a month in which the wind blows from a given direction, demeaned by the average for the month, for four different months (Month 3=March, Month 6=June, Month 9=September, Month 12=December and three different years (2009, 2012, 2015).

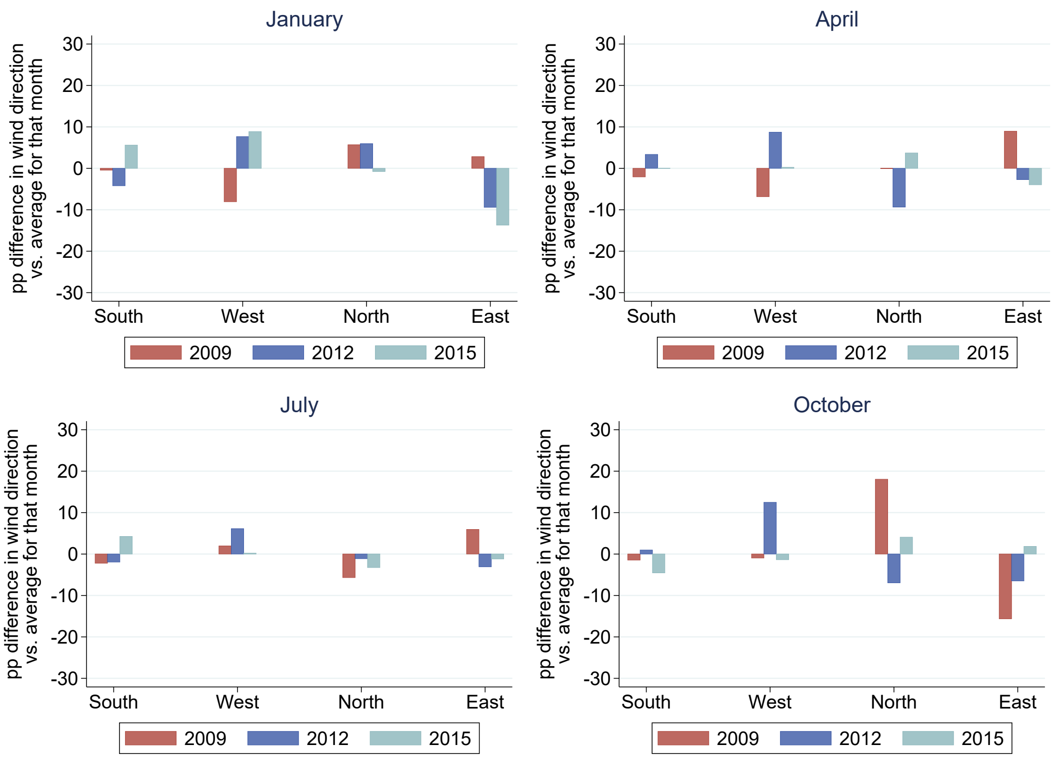
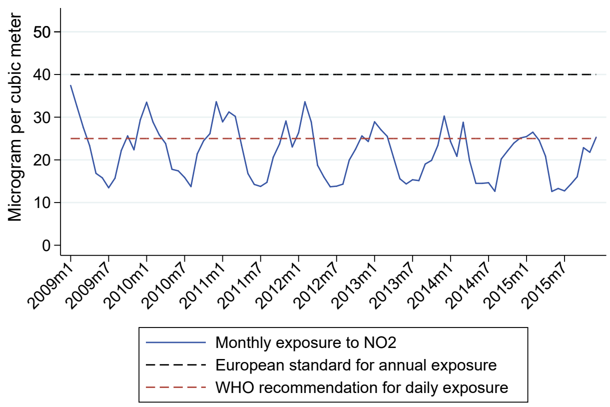
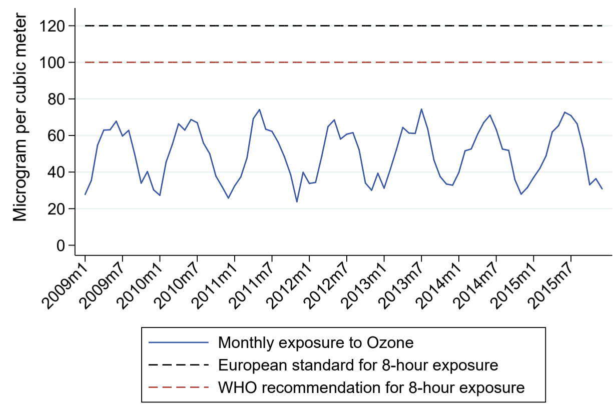


Figure A.5: Within-calendar month variation in wind direction, Marseille (South-East of France)

Notes: Figure shows the share of hours in a month in which the wind blows from a given direction, demeaned by the average for the month, for four different months (Month 3=March, Month 6=June, Month 9=September, Month 12=December and three different years (2009, 2012, 2015).



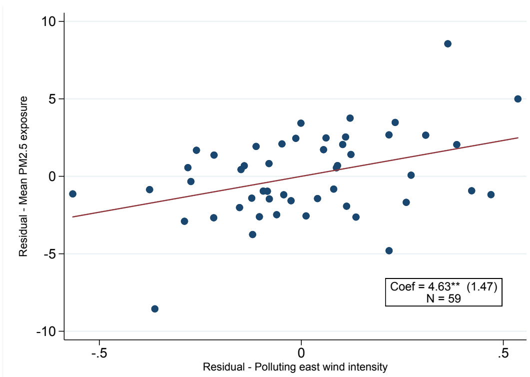
(a) NO_2



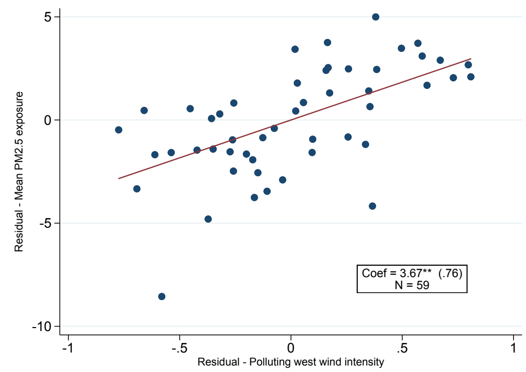
(b) Ozone

Figure A.7: Average monthly exposure to other pollutants

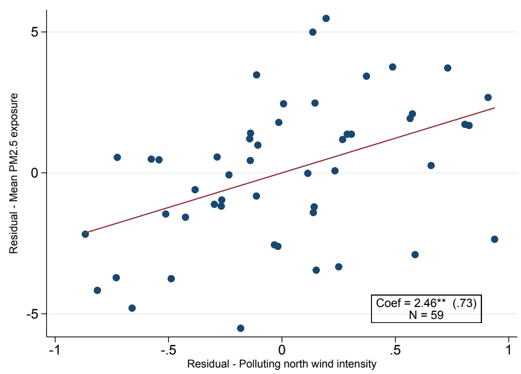
Notes: Figure presents the monthly average of workers' exposure to $PM_{2.5}$ measured at workers' municipalities. The sample of workers is the one used for the analysis of pollution effects on sickness leaves described in section 2.2 (unbalanced panel, N≈450,000). For NO_2, the European standard for annual exposure is 40µg/m^3 while the WHO's recommendation for daily exposure is 25µg/m^3. For ozone, the European standard for 8-hour exposure is 120µg/m^3 while the WHO's recommendation for 8-hour exposure is 100µg/m^3. Exposure in each municipality is weighted by the number of workers working in that municipality.



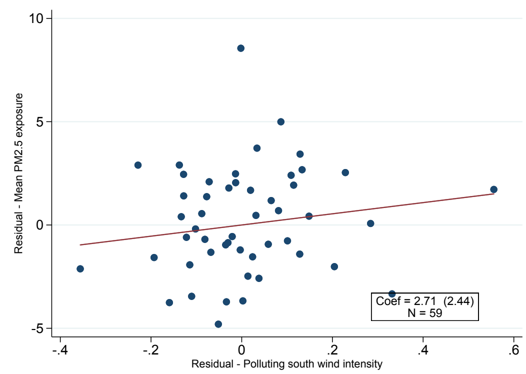
(a) East wind



(b) West wind



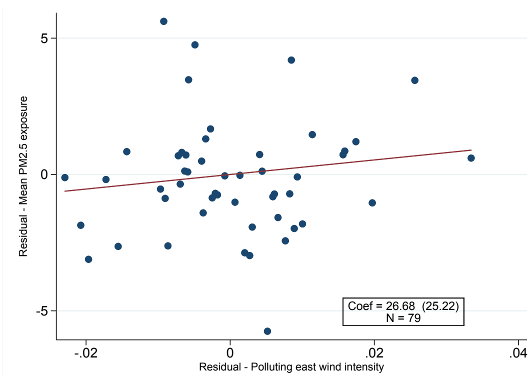
(c) North wind



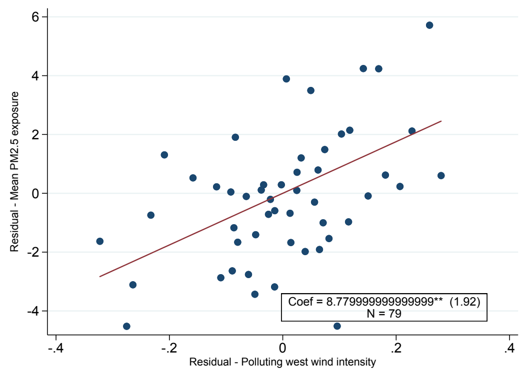
(d) South wind

Figure A.8: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations, Paris

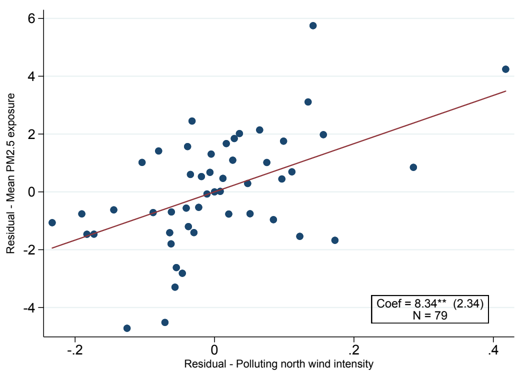
The times series is split into equal-sized bins based on the value of the x-variable – the Z instruments. Each data point shows the mean residual of that bin for the x-axis and y-axis variables after controlling for calendar quarter and year, as well as all weather variables (and their interactions) and holidays. The graph is done using the stata command *binscatterhist* by Pinna (2022).



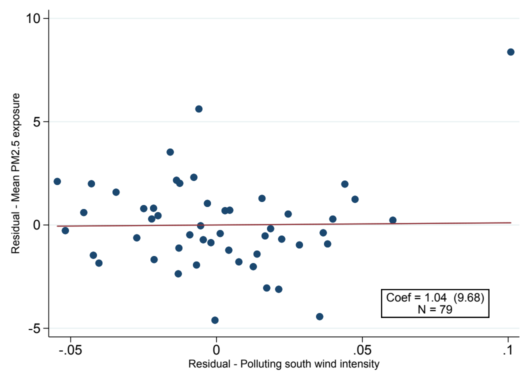
(a) East wind



(b) West wind



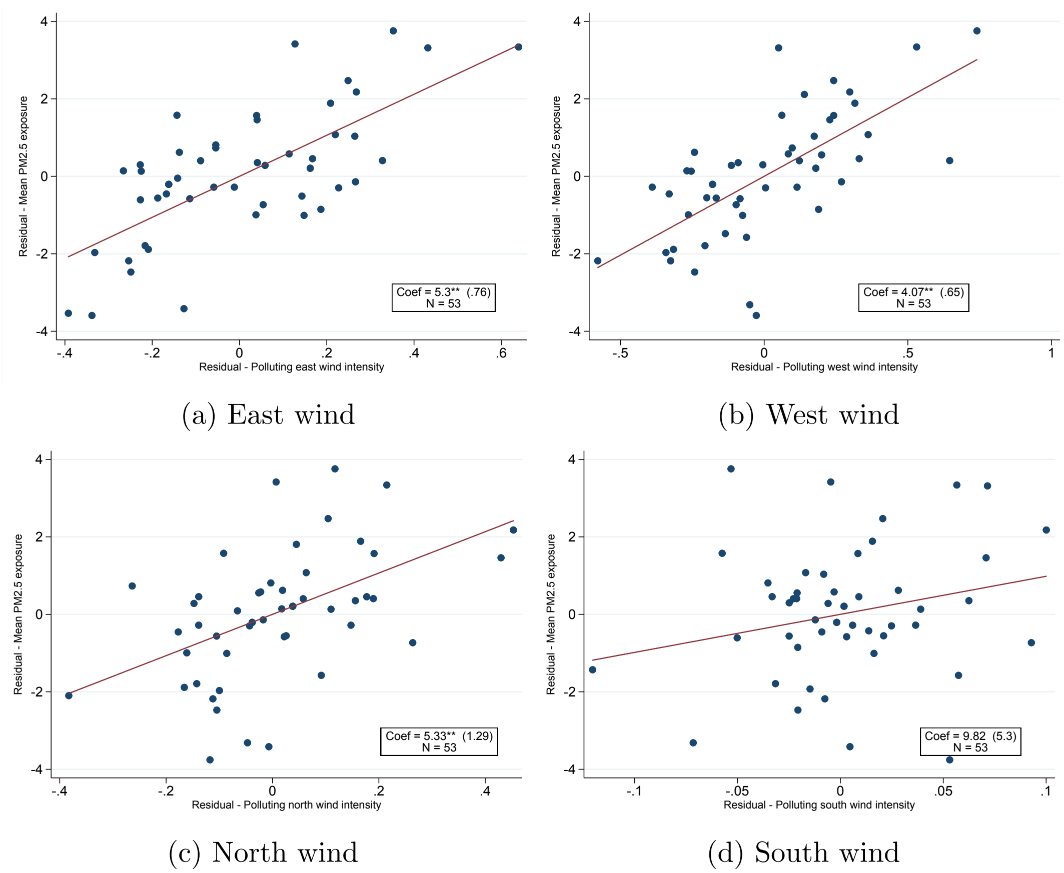
(c) North wind



(d) South wind

Figure A.10: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations, Marseille

The times series is split into equal-sized bins based on the value of the x-variable – the Z instruments. Each data point shows the mean residual of that bin for the x-axis and y-axis variables after controlling for calendar quarter and year, as well as all weather variables (and their interactions) and holidays. The graph is done using the stata command *binscatterhist* by Pinna (2022).



(a) East wind

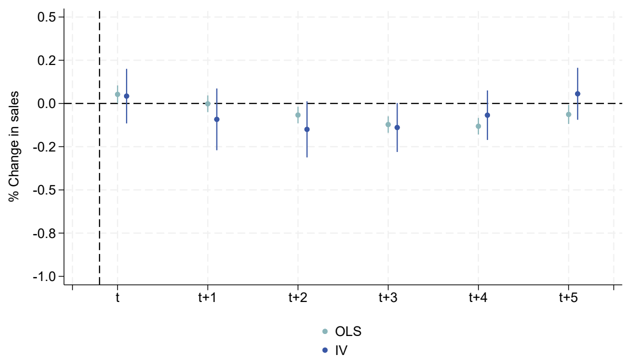
(b) West wind

(c) North wind

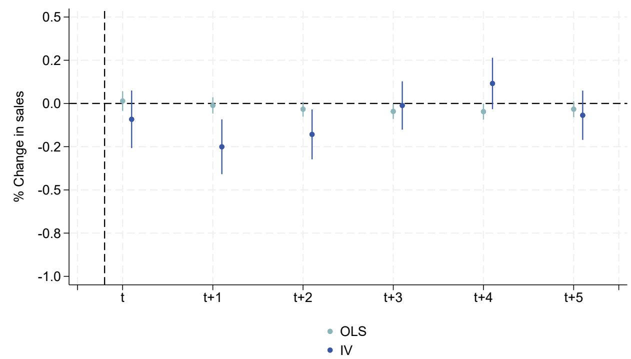
(d) South wind

Figure A.12: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations, rural area in center of France

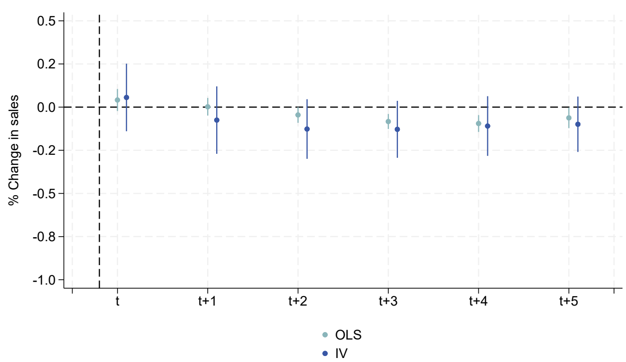
The times series is split into equal-sized bins based on the value of the x-variable – the Z instruments. Each data point shows the mean residual of that bin for the x-axis and y-axis variables after controlling for calendar quarter and year, as well as all weather variables (and their interactions) and holidays. The graph is done using the stata command *binscatterhist* by Pinna (2022).



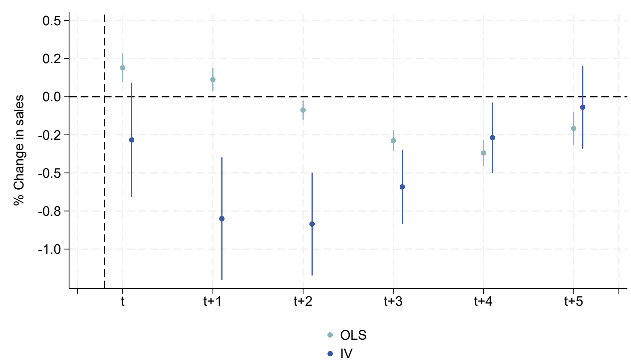
(a) Manufacturing



(b) Construction



(c) Business-to-Business Trade & Services



(d) Business-to-Consumer Trade & Services

Figure A.14: Dynamic effects of $PM_{2.5}$ on sales of single-establishment firms, by sector

Notes: Figure shows the OLS and IV point estimates and 95% confidence intervals from equation (8) for the effect of contemporaneous and lagged $PM_{2.5}$ (up to $t-5$) firms' sales at t by sector, using the polynomial distributed lag method. All regressions include month-by-year-by-industry fixed effects, firm-by-year fixed effects, quarter-by-departement fixed effects, weather controls, and holidays controls. Controls for weather and holidays at all the relevant leads and lags are added. The confidence intervals are based on standard errors clustered at the Copernicus grid cell level.

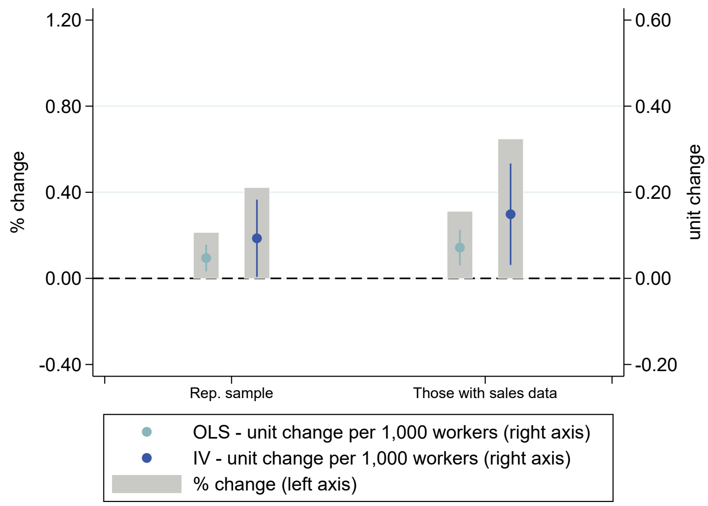


Figure A.16: Absenteeism results for the sample of workers employed at firms included in our firm sample, compared to the representative sample of workers included in the absenteeism dataset

A.2 Tables

Table A.1: Workers' characteristics (aggregated at establishment level), 2009-2015

Sample	All establishments with absenteeism		Only those with sales data	
	Mean	Sd	Mean	Sd
Age	40.4	8.9	40.2	8.7
Annual wage	25,911.0	20,547.4	28,542.0	20,576.1
Annual total medical expenditures	462.5	819.8	442.0	809.8
Works in a single-establishment firm	-	-	41%	0.49
Works in: Manufacturing	17%	0.37	28%	0.45
Construction	7%	0.26	12%	0.32
Business-to-business services	20%	0.40	33%	0.47
Business-to-consumer services	16%	0.32	27%	0.39
Others	40%	0.49	0%	-
Exposure to $PM_{2.5}$ ($\mu g/m^3$)	**15.4**	6.3	**15.3**	6.3
Workers falling sick each month (per 1,000)	23.9	111.3	24.7	113.4
incl: for <93 days	**22.1**	107.0	**23.0**	109.2
N	16,409,124		8,233,440	

Notes: Table reports descriptive statistics on workers, aggregated at the establishment level applying worker weights, for the representative sample of private sector employees (left) and for the sample for whom we have sales data (right).

Table A.2: The Effect of Lagged $PM_{2.5}$ on Contemporaneous Firm-level Sales, All Sectors, single-establishment firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	IV	IV	IV	IV	OLS	IV
$PM_{2.5t-1}$	0.0467	-0.657***	-0.598***	-0.588***	-0.266***	0.109***	-0.255***
	(0.0292)	(0.111)	(0.108)	(0.112)	(0.0263)	(0.0811)	(0.0811)
Firm-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	No	No	No	No	No
Month-by-year-by-sector FE	No	No	Yes	No	Yes	No	No
Month-by-year-by-industry FE	No	No	No	Yes	No	Yes	Yes
Quarter-by-departement FE	No	No	No	No	Yes	Yes	Yes
N	6,072,220	6,072,220	6,072,220	6,072,032	6,072,220	6,072,032	6,072,032
R-squared	0.9319	0.9318	0.9323	0.9334	0.9327	0.9338	0.9338

Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation 8 for single-establishment firms in all sectors. The instrument used is the set of Z_{jgyt} wind instruments defined in equation 9. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at t and $t+1$. The confidence intervals are based on standard errors clustered at the Copernicus grid cell level. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.3: Heterogeneous Responses to Lagged $PM_{2.5}$ by Sector, subsample of single-establishment firms

	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV
Panel A: Manufacturing					
$PM_{2.5t-1}$	-0.0464	-0.367***	-0.347***	0.0178	-0.0811
	(0.0296)	(0.0802)	(0.0779)	(0.0249)	(0.0571)
N	1,234,100	1,234,100	1,233,994	1,233,994	1,233,994
R-squared	0.9524	0.9523	0.9532	0.9535	0.9535
Panel B: Construction					
$PM_{2.5t-1}$	-0.124***	-0.371***	-0.386***	0.0131***	-0.114**
	(0.0304)	(0.0668)	(0.0672)	(0.0267)	(0.0564)
N	1,074,588	1,074,588	1,074,588	1,074,588	1,074,588
R-squared	0.9158	0.9158	0.9160	0.9162	0.9162
Panel C: Business-to-Business Trade and Services					
$PM_{2.5t-1}$	0.0230	-0.301***	-0.286***	0.0370	-0.103
	(0.0344)	(0.0807)	(0.0806)	(0.0253)	(0.0652)
N	1,498,452	1,498,452	1,498,370	1,498,370	1,498,370
R-squared	0.9148	0.9148	0.9155	0.9156	0.9156
Panel D: Business-to-Consumer Trade and Services					
$PM_{2.5t-1}$	0.202***	-0.873***	-0.873***	0.248***	-0.396**
	(0.0482)	(0.186)	(0.196)	(0.0475)	(0.141)
N	2,265,078	2,265,078	2,265,078	2,265,078	2,265,078
R-squared	0.9313	0.9313	0.9331	0.9345	0.9345
Firm-by-year FE	Yes	Yes	Yes	Yes	Yes
Month-by-year FE	Yes	Yes	No	No	No
Month-by-year-by-industry FE	No	No	Yes	Yes	Yes
Quarter-by-departement FE	No	No	No	Yes	Yes

Notes: Table reports the OLS and IV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation 8 for single-establishment firms for each sector. The instrument used is the set of Z_{jgyt} wind instruments defined in equation 9. All regressions include weather and holidays controls at $t-1$, t, and $t+1$, as well as instrumented pollution at t and $t+1$. The confidence intervals are based on standard errors clustered at the Copernicus grid level. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A.4: Pollution and Sickness Leave Episodes, Varying Unit and Time Dimensions

	Nb. of workers falling sick		Nb. of sick days		Sickness leave spending	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel a: 10% Sample and Individual Fixed Effects						
$PM_{2.5}$	0.106**	0.256***	0.912	5.024**	19.96	159.0**
	(0.0439)	(0.0912)	(1.037)	(2.217)	(28.98)	(66.89)
N	2,531,172	2,531,172	2,531,172	2,531,172	2,531,172	2,531,172
R-squared	0.0525	0.0525	0.0301	0.0301	0.0257	0.0257
Panel b: Weekly Outcomes and Pollution						
$PM_{2.5}$	0.00459***	0.0132***	0.0509	0.391***	1.448	12.86***
	(0.00160)	(0.00376)	(0.0306)	(0.0776)	(0.904)	(2.233)
Dependant variable mean	5.2	5.2	85	85	2,079	2,079
N	1,711,430	1,711,430	1,711,430	1,711,430	1,711,430	1,711,430
R-squared	0.0645	0.0644	0.0226	0.0225	0.0178	0.0177

Notes: Table reports OLS and IV estimates from equation (8) for the effect of $PM_{2.5}$ on the number of workers taking a sick leave in a municipality (columns 1 and 2), on the number of sick days associated with this leave (columns 3 and 4), and on the sickness leave spending (columns 5 and 6). Panel a reports estimates from a 10% sample of Hygie using worker fixed effects instead of municipality fixed effects. Panel b reports estimates when outcomes and all controls are defined at the weekly level and using quarter-by-year fixed effects instead of month-by-year fixed effects.Observations are weighted by the number of workers in each municipality. Standard errors in parentheses are clustered at the Copernicus grid cell level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table A.5: Pollution and Sickness Leave Episodes, the exclusion restriction and the role of Ozone

	(1)	(2)	(3)
	Baseline	O3 only	AQI index
$PM_{2.5}$ exposure	0.145^{***}		
	(0.0313)		
Ozone exposure		0.0342^{**}	
		(0.0171)	
Air quality index (higher: worse air quality)			2.922^{***}
			(0.495)
N	393,755	393,755	393,755
R-squared	0.2299	0.2300	0.2300

Notes: Table reports IV estimates from equation (8) for the effect of $PM_{2.5}$ on the number of workers taking a sick leave in a municipality using the baseline specification (column 1), for the effect of ozone only (column 2), and considering the effect of a one-unit increase in the French air quality index ranging from 1 (best air quality) to 6 (worst air quality), instead of a one-unit increase in $PM_{2.5}$ (column 3). All regressions include month-by-year fixed effects, weather controls, holidays and flu controls, and municipality fixed effects. Observations are weighted by the number of workers in each municipality. Standard errors in parentheses are clustered at the Copernicus grid cell level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

B Data Appendix

B.1 Sickness Leave Episodes

We obtain data on sickness leave episodes (SLE) from the Hygie dataset, which follows roughly 900,000 employees during the period 2009-2015. To build a representative sample of workers with information on pollution exposure, we make three restrictions. First, we only keep individuals to whom we are able to assign a place of work based on the establishment's unique identifier. This makes us discard individuals with no employment history declared between 2009 and 2015, who represent 25% of the sample. Although we cannot check the exact reason for missing information, these individuals are probably retired, unemployed or out of the labor force over the whole period. Two-thirds of them should be retired in 2009 given their age. We also discard individuals for whom we do not have an establishment identifier despite the fact that they did work and contribute to the pension system over the 2009-2015 period, who represent 6% of the sample. Two third of these individuals have zero employers declared over the period. They may have switched to the public sector or to the agricultural sector or started their own business, or they may work in the domestic care sector, where there is no establishment-level identifier (since they are employed by private individuals).

Second, we discard individuals whose establishment identifier corresponds to a public institution such as hospital or schools, because we want to focus the analysis on private sector employees. Some individuals working in these institutions have a private sector type of contract and are thus eligible to enter the Hygie sample.

Third, we discard a few individuals who did not work enough to contribute to the public pension system for any of the years included in the period. Each year, these individuals worked less than 150 equivalent hours valued at the minimum wage per year, which is the minimum to contribute to public pension. With such a low labor supply, they are unlikely to experience sickness leave episodes.

We make an additional restriction for the main sample used throughout the analysis: that workers are employed by a firm that is included in our firm-level sales dataset.

We assign each worker to the municipality of her workplace (there are around 6,000 municipalities in France). Figure B.17 shows the geographic distribution of the employees' workplaces in 2009, which is consistent with the distribution of the French population across the territory.

We use the exhaustive matched employer-employee data (DADS-Postes) to compare the characteristics of our representative sample of workers to the characteristics of the whole population of private sector employees. Applying the same restrictions as in the Hygie dataset,[33] we find that

[33] Namely, we keep private sector employees born between 1935 and 1989, less those older than 71 who should be retired. Note that in the matched employer-employee data, a worker having two different employers appears twice.

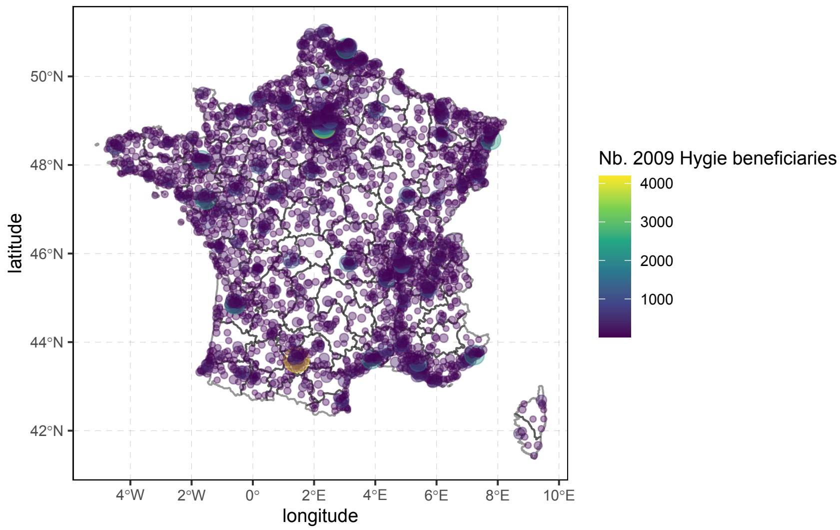


Figure B.17: Location of workers from the Hygie dataset based on the workplace municipality, in 2009

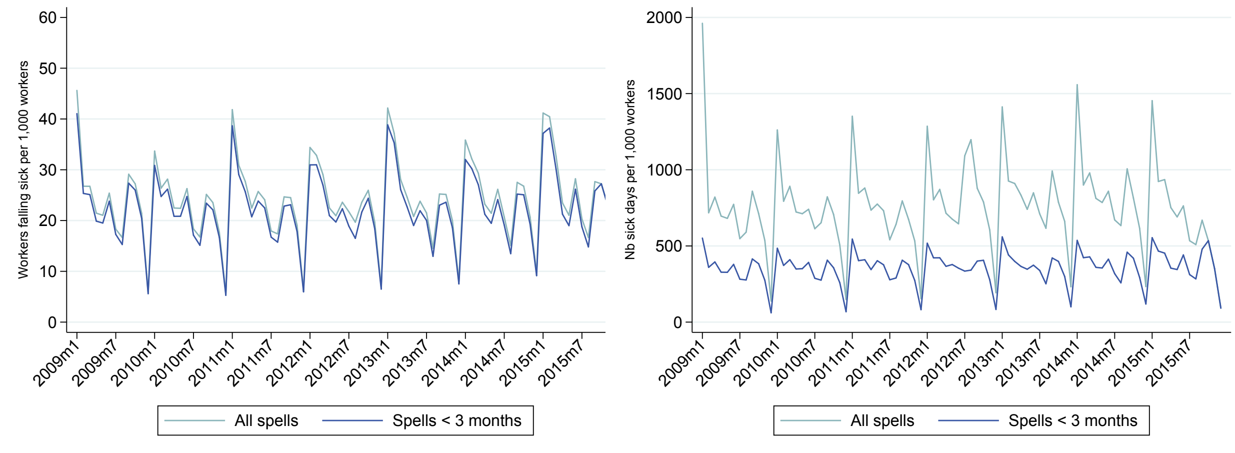
those workers representing the population from which our sample is drawn are 55% male, 41 on average, and earn an average annual gross wage of €26,204. Thus, the average individual in our final worker sample – as shown in Table **??** – is very close to the average private sector employee.

In our sample, 21 percent of employees take at least one sickness leave episode within a year. By comparison, a national survey on Working Conditions estimated that 28 percent of private sector employees in France took at least one sick leave during 2013.[34]

We

We aggregate wage information at the worker level, summing up the wages she receives from different employers.

[34]Source: https://www.fonction-publique.gouv.fr/files/files/statistiques/rapports_annuels/2015/RA2015_dossier_1.pdf



(a) Number of workers falling sick (b) Number of sick days

Figure B.18: Number of workers falling sick and number of sick days per 1,000 workers

Notes: Figure presents the average number of workers falling sick and average number of sick days per 1,000 workers over time. While the spells larger than 3 months represent a small proportion of total spells, their tend to strongly increase the average number of sick days.

B.2 Firm-Level Sales

We compute firms' monthly sales by adding up different components included in the VAT records, following the methodology of France Stratégie and Inspection générale des Finances (2021). In the raw data, total sales are broken down into different components based on two main criteria that determine VAT liability: the location of the buyer (whether in France, in another EU country, or in a non EU-country) and whether the buyer is herself liable to VAT. In addition, the sales value of goods and services subject to specific tax rules is reported separately.[35] Our measure of sales includes both domestic sales and exports to EU and non-EU countries. The French tax administration imposes monthly declarations to firms with annual sales above €818,000 for the manufacturing sector and the hospitality industry and to those with annual sales above €247,000 for the other sectors. Firms below this threshold are allowed to fill declarations on a quarterly basis.

We discard the entire firm-year series for firms not reporting sales each month within a year. However, we make one exception for zero sales records in July since it is a relatively common pattern in the data. A large number of French firms close for vacation during some weeks in August, the month where the July VAT declaration is expected since the VAT declaration corresponding to the business month t is typically made on month $t + 1$. French tax authorities allow firms

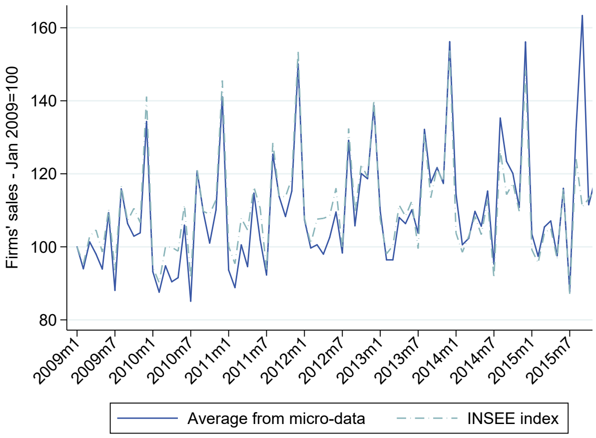
[35] For instance, the sales of natural gas and electricity is subject to a specific VAT rule in the French tax code, so they have their own subcomponent in the VAT records. See https://www.impots.gouv.fr/sites/default/files/formulaires/3310-ca3-sd/2022/3310-ca3-sd_3947.pdf

to report their July sales together with the August sales.[36] We indeed observe in the data that when the sales are 0 in July, the sales for August are frequently twice as high as those in June or September. We re-allocate sales for July and August by splitting August sales in two.

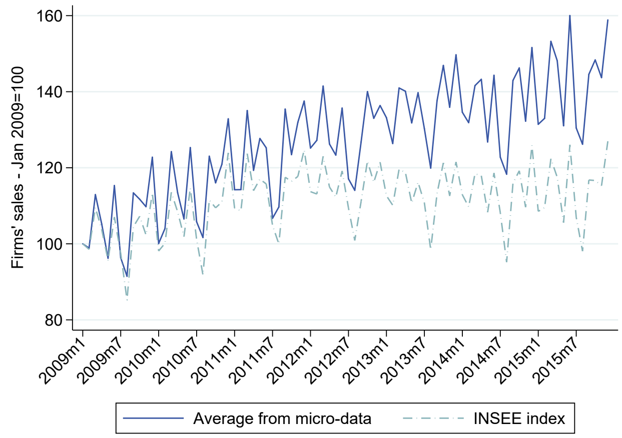
We determine sectors of activity based on the sectoral classification available at the establishment level and we use the mode of sector categories across establishments for multi-establishment firms. We define 4 sectors of interest: manufacturing, construction, business-to-consumer trade and services, and business-to-business services. We discard firms belonging to the financial services sector, to the health, education and charitable sectors, which are often not-for-profit, as well as business-to-consumer services for which the timing and location of sales is often disconnected from the timing and location of consumption, such as hotels and transport.

We check the quality of the reported data in two different ways. First, for a few large French companies for which annual financial reports are publicly available, we manually check that the sum of monthly sales of a given year is close to the official annual sales value. Second, we compare the time series of monthly sales value aggregated by economic sector to the data published at the industry level by the French statistical institute, using the same source. Figure B.19c shows the time series of monthly sales in construction (B.19a), manufacturing (B.19b) and all services (B.19c) as constructed from the VAT micro-data compared with the INSEE index. Differences may arise between our sales value and the statistical agency's because of different choices in data cleaning or the subcomponents entering the sales variable, but the correlation between the two series are above 0.9 for the three broad sectors.

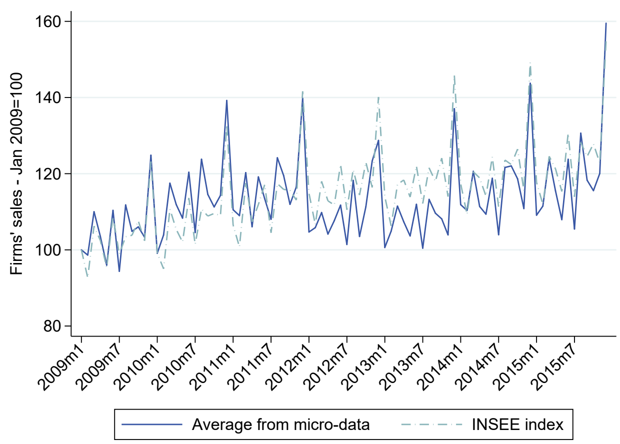
[36]See https://www.impots.gouv.fr/professionnel/questions/comment-declarer-ma-tva-en-periode-de-conges-pa



(a) Construction



(b) Manufacturing



(c) Services

Figure B.19: Average firms' nominal sales in construction, manufacturing and service sector, 2009=100

Notes: Figure presents the average nominal sales from our VAT micro-data in blue for construction, manufacturing, and services and the INSEE sales index in dashed green, using January 2009 as the reference point. We exclude several service industries (trade - sector G in NACE classification, banking - sector K and health - sector Q) to compare with the INSEE index which also excludes these industries.