The Cost of Air Pollution for Workers and Firms

Marion Leroutier*, Hélène Ollivier†

September 2024

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

JEL codes: Q53, I1, J22

*Institute for Fiscal Studies. Email: marion.leroutier@ifs.org.uk.

†Paris School of Economics, CNRS. Email: helene.ollivier@psemail.eu.

We are grateful to Tatyana Deryugina, Gregor Singer, Geoffrey Barrows, Abhijeet Singh, Antoine Dechezleprêtre, Maiting Zhuang, Jonathan Lehne, Paul Dutronc-Postel, Sampreet Goraya and Martina Bjorkman-Nyqvist for valuable feedback, as well as attendees at numerous conferences and seminars. We thank Augustin Colette and Elsa Real for sharing the INERIS air pollution data for France, Camille Regaert for help with the Hygie data, and Tom Verrier for outstanding research assistance. Authorization to use the Hygie data was granted from CNIL in September 2019 (decision DR-2019-286). The results contain modified Copernicus Climate Change Service information from 2022. Neither the European Commission nor ECMWF is responsible for any use that may be made of the Copernicus information or data it contains. Funding from the Mistra foundation and from a subsidy managed by the French National Research Agency under the ANR-17-EURE-001 programme are gratefully acknowledged.

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., 2022a). 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. Yet knowing the economic costs of air pollution is crucial to understand the full societal cost of this externality and to inform cost-benefit analyses of environmental regulations.

In this paper, we estimate the causal effects of monthly air pollution exposure on firms' monthly sales in France, using confidential tax and social security data covering half of the country's private sector (excluding agriculture and financial services). We identify three main channels through which air pollution shocks can influence sales in the private sector in the short run. First, air pollution can reduce labor supply, either through work absenteeism or through a reduction in working hours. Second, it can lower non-absent workers' productivity, either because they suffer from mild health symptoms or reduced cognitive capacities or because their work is disrupted by the absence of co-workers who took a sick leave. Finally, it can lower demand if consumers also exposed to these air pollution shocks choose to reduce their consumption. Using granular data, we measure the overall firm-level response to air pollution exposure and examine the contribution of these channels with different degrees of precision.

We assemble a unique dataset which combines the monthly sales of 160,000 firms, granular measures of air pollution and weather conditions at the workplace, as well as sickness leave episodes of a representative sample of private sector employees between 2009 and 2015. We focus on exposure to fine particulate matter pollution ($PM_{2.5}$) a pollutant that can penetrate deep into the respiratory tract and enter the brain, with detrimental effects on respiratory and cardio-vascular health, and cognitive skills.[2] Particulate pollution can also easily penetrate indoors and affect air quality at the workplace. Two key challenges with identifying the causal effects of pollution

[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.

exposure on firms and workers are that air pollution is often a co-product of production, and individual exposure to pollution 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 or municipality level—there are 6,328 postcode areas in metropolitan France.

The identifying assumption of our instrumental variable (IV) approach is that, after flexibly 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 the influence of wind direction on air pollution. The benefit of our approach is that it neither requires identifying the sources of pollution in each area nor does it impose the same relationship between specific wind directions and pollution over large areas. Instead, we allow cardinal wind directions to influence pollution differently in each municipality. Our analysis thus employs a similar strategy to Graff Zivin et al. (2023), inspired by Deryugina et al. (2019). If all firms owned a single establishment, we could easily attribute to them pollution exposure based on their location and build an instrument for $PM_{2.5}$ concentration based on their municipality-specific relationship with wind directions. However, in our dataset, thirty-six percent of firms own several establishments located in different municipalities. As a result, we build an instrument for firm-level pollution exposure 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 an establishment.

Among the three main channels through which air pollution exposure affects firms' sales in the short run, we precisely measure the labor supply channel using worker-level data on sickness leave episodes. Using social security data, we identify the exact workplace of each private sector employee in the sample, which allows us to link workers' absenteeism information to their employing firms' sales. In France, taking a sickness leave requires a medical certificate signed by a general practitioner on the first day of absence. Thus, if a worker chooses to go to work while shortening her number of hours per day, we cannot measure this supply response and attribute it to the lower productivity channel (thus implying that we measure a lower bound of the labor supply channel). Comparing the magnitude of this supply channel based on formal sick leaves with the magnitude of the overall sales' response reveals the potential role played by the productivity and demand channels. Exploiting industry heterogeneity in stock management in manufacturing allows us to highlight the supply side nature of air pollution shocks, thereby providing evidence for the productivity channel in this sector. By contrast, we study the demand channel—which only arises from consumers living in the neighborhood of shops and businesses—by focusing on the heterogeneity

[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.

in consumer goods in the retail sector, contrasting staples (i.e., goods whose consumption cannot be foregone, such as food) and discretionary goods (such as furniture or clothing).

Our study provides evidence that firm-level exposure to $PM_{2.5}$ has widespread negative effects on sales. 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 following two months. The effects differ by economic sector: sales in manufacturing and in business-to-business trade and services decrease by about 0.20 percent, construction sales decrease by 0.12 percent, while sales in business-to-consumer industries decrease by about 0.70 percent. In all sectors smaller firms employing 25 workers or less incur larger sales losses than larger firms, for which the effect is significantly negative only in business-to-consumer industries. The negative effects on sales last about two to three months after the pollution shock, and the effect dies down after five months, without rebound. These results are robust to restricting our sample to only single-establishment firms, for which pollution exposure is measured more accurately. Additionally, 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 specification of weather controls.

We then proceed to examine the mechanisms that could explain this pollution-induced decrease in sales. First, we find evidence that labor supply decreases due to an increase 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 strong and statistically significant in manufacturing, whereas we cannot rule out a null effect in the other sectors. These heterogeneous effects on work absenteeism do not coincide with the heterogeneous effects on sales. As a result, the labor supply channel cannot be the only channel at play. Otherwise, the economic sectors with the strongest pollution-absenteeism response would likely be the ones experiencing the largest sales decrease. Even the magnitudes of the effects do not match: in manufacturing, where we observe the strongest absenteeism effect, the sales losses implied by the pollution-induced lost days of work are several orders of magnitude smaller than our estimate of pollution-induced sales losses. These discrepancies suggest that the other channels—productivity and demand reductions—contribute to the effect on sales losses.

Second, we provide evidence of the productivity channel in manufacturing. We evaluate heterogeneous responses to air pollution shocks on sales and absenteeism of firms with high versus low stock levels. Having large stocks allows firms to smooth temporary supply-side shocks by selling existing stocks, thereby dampening their effect on sales. However, having large stocks does not insure firms against demand-side shocks. Thus, comparing firms in industries that tend to have large inventories with firms in industries with low inventories indicates whether the air pollution shock affects more the supply side or the demand side. We find that the effect of air pollution on manufacturing sales is entirely driven by firms with low stock levels. However, firms with different stock levels face the same absenteeism response from their employees. These findings reveal that air pollution shocks affect mostly the supply side in manufacturing, and some manufacturing firms are able to smooth these supply-side shocks with large inventories, thereby dampening their effects on sales. By contrast, firms with low stock levels experience both workers' absenteeism and lower productivity, without any buffer provided by stocks, and thus see their sales decline with these supply-side shocks.

Third, after noticing the large magnitudes of the sales response in the retail and consumer services sector, we explore the demand channel in this sector. Intuitively, we expect larger demand-side responses to air pollution exposure in the retail and consumer services sector which often serves a local demand. In such case, consumers are affected by the same air pollution shocks as workers and firms. We also expect that consumers with high air pollution exposure will adjust their demand for discretionary goods more than their demand for staple goods such as groceries. We show that the sales response is slightly stronger for firms selling discretionary goods than for firms selling staples—but the difference is not statistically significant—while both incur no significant decrease in labor supply. Ruling out a decrease in labor supply and assuming a similar decline in worker productivity, these results provide suggestive evidence of the demand channel.

Finally, we put our findings in perspective and show that sales losses due to air pollution are economically significant. We quantify the benefits associated with meeting the WHO's guidelines of not exceeding 15 µg/m^3 for daily exposure to PM2.5. In our sample, meeting the guidelines implies reducing pollution levels by 25%. Based on our estimates, such an improvement in air quality would have avoided around 27 billion euros of foregone sales (1.5% of total private sector sales) every year between 2009 and 2015. These estimates do not account for the distribution of costs and benefits across firms and regions, long-term effects, or potential general equilibrium effects. There is no readily available cost counterpart to this economic benefit from air quality improvements, but reducing $PM_{2.5}$ emissions by 33% was estimated to cost 0.77 billion euros annually in France. Thus, tightening air pollution regulation to align it with WHO standards is likely to generate economic benefits that largely exceed the cost of regulation on average.

To the best of our knowledge, this paper provides the first countrywide estimates of the effect of air pollution on both firms' performance and their workers' response in a high-income country. The literature examining 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; Holub and Thies, 2023) and decision-making (Meyer and Pagel, 2017; Dong et al., 2019), is largely based on specific settings of one or two firms, where workers are paid by the hour or productivity is easy to observe.[4] A few studies use representative

[4]This point was highlighted in a review paper by Aguilar-Gomez et al. (2022b).

data on workers and/or firms, with a focus on high-pollution middle-income countries or cities (Aragón et al., 2017; Hoffmann and Rud, 2024; Fu et al., 2021). We contribute to this literature by leveraging matched employer-employee data for a representative sample of the private sector in a high-income country and by combining worker-level and firm-level outcomes. We expect air pollution to affect workers' health, labor supply and productivity differently in high-income countries, where the levels and saliency of air 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 four to five times lower than in India or China, similar to those in Europe and fifty percent above those in the US.[5]

Our paper sheds light on other channels beside the effect of air pollution on worker productivity, through which air pollution generates economic losses. We thus contribute to a small literature studying the labor supply response to air pollution shocks in settings with moderate pollution levels. Borgschulte et al. (2022) estimate the effect of wildfire-induced pollution on labor market outcomes in the US using county-level earnings and employment data. They show that part of the decrease in earnings among workers exposed to wildfire smoke is attributable to a decrease in labor supply as workers exit the labor force. We find a similar pollution-induced decline in labor supply, but through temporary absenteeism authorized by institutionalized sick leave. Another closely related paper is Holub et al. (2021) which estimates the effects of PM_{10} on sickness leaves in Spain and the cost associated with pollution-induced work loss days. Leveraging the matched employer-employee data, we contribute to this literature by showing that the cost of pollution in terms of foregone sales is much larger than the cost related to sick leave only, which is insufficient to explain the large drops in sales in some sectors. Finally, Dechezleprêtre et al. (2019) quantifies the economic cost of air pollution in the European context using regional GDP data. While we also show large economist costs of air pollution, our firm-level data allow us to reveal heterogeneous effects by sectors and by firm characteristics.

Beyond air pollution, our paper is related to the literature estimating the impact of environmental and climate shocks on firms. A growing body of the literature highlights the negative effects of extreme temperature shocks on workers, through a decrease in productivity (Somanathan et al., 2021), in labor supply (Graff Zivin and Neidell, 2014), or through work accidents (Park et al., 2021). One study by Addoum et al. (2020) focuses on the effects of temperature shocks on the sales of US publicly listed firms, but fails to detect any impact. Temperature shocks are more salient and easier to adapt to than air pollution shocks, given the widespread adoption of air conditioning in the US. We thus contribute to this literature by focusing on low-saliency environmental

[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.

shocks for which adaptation measures are not widespread (few firms in France have adopted air filtering systems). We also find that the negative effects of air pollution shocks are concentrated on smaller firms, thereby revealing the lower vulnerability of large firms.

The rest of the paper is organized as follows. Section 2 provides a brief background on fine particulate matter and presents an analytical framework that formalizing the potential channels through which pollution can affect firms' sales. Section 4 presents the data and describes our empirical strategy. Section 5 presents the main results. Section 6 discusses the channels, and section 7 concludes.

2 Background and Framework

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

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).[6] 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 supply-side mechanisms 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; Hill et al., 2024). 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

[6] $PM_{2.5}$ 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.

(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). In the context of developing countries where high air pollution levels are salient to workers and managers, a few studies find that firms can dampen the productivity loss from their most affected employees by reallocating tasks among employees (Adhvaryu et al., 2022), or by hiring new employees (Fu et al., 2021). Demand-side mechanisms have received less attention than supply-side mechanisms. In the context of China, (Barwick et al., 2018) find that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ over the past 14 days decreases the number of daily card transactions at supermarkets by 0.45%, which the authors interpret as evidence for avoidance behaviors whereby consumers reduce shopping trips to reduce exposure to air pollution.

Unlike in previous studies, air pollution in France remains a low-salience issue for several reasons. First, monitoring and regulation primarily focused on PM_{10} until 2009, with $PM_{2.5}$ only gradually incorporated thereafter. Regulation is driven by European Union directives, employing a command-and-control approach with maximum concentration thresholds for various pollutants. While PM_{10} is regulated by both annual and 24-hour thresholds, $PM_{2.5}$ is limited to an annual threshold of 25 $\mu g/m^3$, which is rarely exceeded and thus never triggers air quality alerts. Second, like many high-income countries, France has experienced significant improvements in air quality over the past decades (Champalaune, 2020; Sicard et al., 2021; Currie et al., 2023).

Nevertheless, pollution levels are relatively high compared to public health recommendations and regulatory standards: in our sample workers are exposed to daily concentrations exceeding the WHO recommended threshold of 15 $\mu g/m^3$ on 37% of worker-days.[7] In addition, persistent non-compliance with EU air quality standards has led the European Commission to refer France to the Court of Justice of the EU for systematic failure to meet regulations and implement effective pollution reduction plans.[8]

The low saliency of air pollution shocks in France, coupled with moderate pollution levels (significantly lower than in India or China), has ambiguous effects on firms' economic outcomes. While moderate pollution may result in fewer workers experiencing severe health issues or reduced productivity, suggesting minimal impact on output, the reduced visibility of pollution shocks could hinder managers' ability to effectively mitigate potential declines in productivity.

Moreover, labor market institutions likely influence how workers and firms react to air pollution shocks. Workers' ability to take sick leave varies across countries, sectors, and firms, influenced

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

[8] 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).

by differing levels of job protection. In France, private sector employees are eligible for sickness allowances under specific conditions, as long as they provide a medical certificate and they have worked at least 150 hours in the past three months. These allowances include: (1) public benefits from the fourth day of leave, covering about 50% of the gross daily wage, (2) mandatory employer contributions from the eighth day, providing 40% of the wage for the first 30 days,[9] and (3) optional employer allowances negotiated through collective agreements. Survey data show that two-thirds of private-sector employees receive a full wage replacement from the first day of leave (Pollak, 2015).

2.2 Analytical Framework

In this section, we develop a stylized model linking individual exposure to air pollution with firms' sales. Building on the existing literature, we incorporate two supply-side mechanisms: reductions in labor supply and productivity. Additionally, we introduce a third, demand-side mechanism, accounting for the impact of consumers residing in the same area as the firms they patronize.

Demand. We consider an economy in which a representative consumer divides expenditures between a set of differentiated products available in different industries, denoted by $i \in \{1, ..., \mathcal{I}\}$. The utility function takes the following form:

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

where X_{fit} denote the consumption at time t of variety f in industry i and u_{fit} is an *ex post* variety-specific demand shock (realized at the point of sales).[10] The utility function has two tiers. The top tier 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 assume varieties are imperfect substitutes within an industry and ρ_i is the parameter that governs the substitutability of varieties in industry i, with $0 < \rho_i < 1$.

On the demand side, two variables may be influenced by air pollution shocks. First, the ex-post variety-specific demand shock, $u_{fit}(c)$, depends on the level of air pollution exposure, c. Mild or severe health effects from being exposed to air pollution may lead consumers to alter their spending behavior, such as by staying home and postponing purchases. The sign of the derivative

[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.

[10] For simplicity, we assume that $E[e^{u_{fit}}] = 0$ for all firms.

$u'_{fit}(c)$ is ambiguous, however, since consumers may decide to buy more or less of each variety (e.g., staying home may induce a higher demand for food delivery services).

Second, in a developed country context with established sickness leave rights and provisions, consumers' income in the period following pollution exposure may be impacted. Therefore, income is given by $Y_t(c) \equiv \big(1 - \zeta \bar{a}_t(c)\big) w L_t$, where ζ represents the income loss due to partial sick leave compensation (with $\zeta = 0$ indicating full compensation), $\bar{a}_t(c)$ denotes the average worker absence rate across firms, w represents the wage rate, and L_t denotes the contractual number of hours worked per employee.[11] We expect $\bar{a}'_t(c) \geq 0$ as higher pollution concentrations likely worsen health effects. However, the impact of air pollution exposure on consumers' income depends critically on their decisions regarding sick leave and the level of compensation provided by the social security system—the impact being null if $\zeta = 0$.

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 that depends on air pollution exposure, c, through at least the demand-side mechanism:

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

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

Production. On the supply side, air pollution exposure influences output through two mechanisms that concur in reducing effective labor, which is the only factor of production. First, workers exposed to pollution shocks may be less productive due to health symptoms and cognitive impairments. Second, some workers may decide to take a sick leave. We assume that each firm produces a single differentiated variety, allowing f to represent both varieties and firms interchangeably. As a result, the production technology for output Q is[12]

$$Q_{fit} = L^A_{fit}(c) \exp(\omega_{fit}) = \lambda_{fit}(c)[1 - a_{fit}(c)]^{\theta} L_{fit} \exp(\omega_{fit}), \tag{3}$$

where L^A_{fit} denotes effective labor, L_{fit} denotes the number of workers employed at time t, and ω_{fit} is a Hicks-neutral productivity shock that is exogenous to air pollution exposure. Effective labor, L^A_{fit}, responds to air pollution exposure, c, through firm f's marginal productivity of workers at time t without absenteeism, $\lambda_{fit}(c)$, and through firm f's average worker absence rate at time t,

[11] In a context where wages are flexibly adjusted based on output per hour, air pollution exposure could affect a third variable, the wage rate $w(c)$. However, in France, such adjustments are infrequent because low-skilled workers are typically paid a regulated minimum wage, and high-skilled workers often negotiate their wages on a long-term basis.

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

$a_{fit}(c)$, combined with a parameter reflecting the attendance impact on marginal productivity, θ. Both mechanisms worsen with higher air pollution levels: $\lambda'_{fit}(c) \leq 0$ and $a'_{fit}(c) \geq 0$.

While the number of workers employed by firm f at time t may not follow the short-term fluctuations of air pollution shocks, it varies with the the marginal cost of labor, which depends on the wage rate, the firm's average worker absence rate and the share of sickness leave benefits that remain privately funded. We express the firm-specific marginal cost of labor as $w[1-\eta a_{fit}(c)]$, where 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).

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 $1/\rho_i$. This yields the pricing rule

$$p_{fit} = \frac{w[1-\eta a_{fit}(c)]e^{-\omega_{fit}}}{\rho_i \lambda_{fit}(c)[1-a_{fit}(c)]^{\theta}}. \tag{4}$$

Effects of Pollution Shocks on Firms' Sales. Combining (2) with (4) yields the following expression for firm f's sales at time t:

$$y_{fit} = \left(\frac{w[1-\eta a_{fit}(c)]e^{-\omega_{fit}}}{\rho_i \lambda_{fit}(c)[1-a_{fit}(c)]^{\theta}}\right)^{\frac{\rho_i}{\rho_i-1}} (P_{it})^{\frac{\rho_i}{1-\rho_i}} e^{\frac{u_{fit}(c)}{1-\rho_i}} \nu_i Y_t(c), \tag{5}$$

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

$$\log y_{fit} \quad = \quad \underbrace{\frac{\rho_i}{1-\rho_i}\log\lambda_{fit}(c)}_{\text{Productivity effect}} + \underbrace{\frac{\rho_i(\eta-\theta)}{1-\rho_i}a_{fit}(c)}_{\text{Absenteeism effect}} + \underbrace{\frac{u_{fit}(c)}{1-\rho_i} + \log Y_t(c)}_{\text{Demand effect}} + \delta_{it} + \epsilon_{fit}, \tag{6}$$

with $\delta_{it} \equiv \frac{\rho_i}{1-\rho_i}\log P_{it} + \frac{\rho_i}{\rho_i-1}\log\left(\frac{w}{\rho_i}\right) + \log\nu_i$ and $\epsilon_{fit} \equiv \frac{\rho_i}{1-\rho_i}\omega_{fit}$. Equation (6) summarizes the three mechanisms through which air pollution affects firms' sales. First, air pollution may decrease the marginal productivity of workers, resulting in sales losses. Second, the labor effectively supplied by employees may decrease with air pollution exposure, especially if they take sick leaves. This mechanism also lower sales if and only if $\eta < \theta$, which we assume to reflect the negative impact of absenteeism on firms' sales.[13] The social security system partially compensates firms for the negative cost of worker absenteeism, as reflected by η. Third, firms' sales may fluctuate following an air pollution shock due to consumer behavior changes and the income effect resulting from

[13]To illustrate, we computed the public contribution share in France for a 5-day sickness leave episode with full replacement rate as being equal to 0.2. Zhang et al. (2017) obtain an estimate of θ equal to 0.46 on Canadian private sector employees. Using the same value yields $\eta - \theta = -0.26$.

workers taking sick leave without a full replacement rate.

From this model, we can draw three main implications for the empirical analysis. First, sales will decrease with high pollution levels either if all three channels move together or if the productivity and absenteeism effects dominate an opposite demand effect. Following the literature, we will focus on the reduced-form effect of air pollution on firms' sales and explore separately the absenteeism effect. The second implication is related to the less-studied demand-side mechanism. While we expect the income effect to be limited in the French context since two thirds of private sector employees are granted a full replacement rate during sick leaves, we cannot predict the behavioral response from consumers. Few studies have explored consumers' behaviors following air pollution shocks, especially in a context where air pollution is not very salient. Lacking the data on consumers, we explore this channel through the heterogeneous effects of air pollution on the sales of specific goods. Third, the magnitude of all three channels varies with the elasticity of substitution across varieties within an industry. Industries with large elasticities, consistent with low profit margins, will experience larger supply-side and demand-side effects. For example, Harrigan et al. (2024) find particularly large elasticities in wholesale and retail in France, with $\sigma_i = 1/(1-\rho_i)$ being estimated at 8.93 and 6.03, respectively. By contrast, they find lower elasticities for manufacturing (with average σ_i of 3.89) and construction (2.67). We can thus expect that lower productivity, absenteeism and lower demand have magnified effects on firms' sales in low-profit-margins industries.

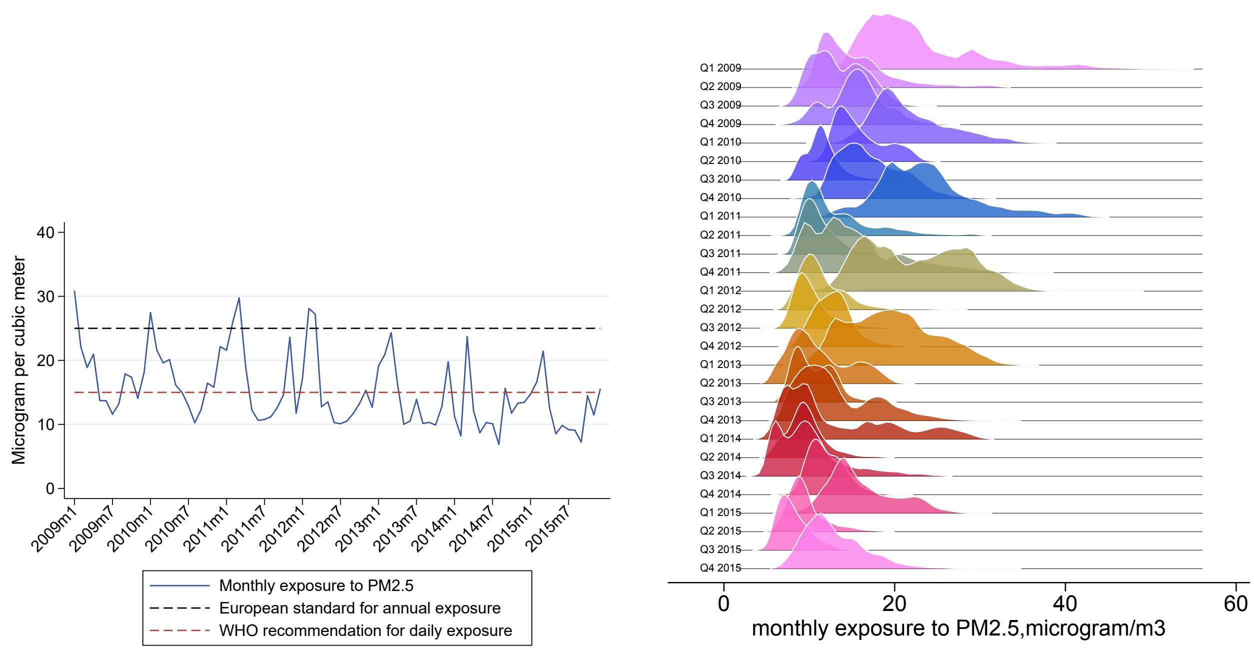
3 Data

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 gridded reanalysis pollution data produced by the French National Institute for Industrial Environment and Risks (INERIS). The dataset combines background measurements of air quality from monitoring stations with modelling from the chemistry-transport model CHIMERE, using geolocated emission inventory and weather parameters (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 the pollutants at the monthly level for all 33,252 grid cells located in metropolitan France.

Gridded reanalysis pollution data are in principle better suited to capture the average pollution exposure of local residents than pollution-monitor readings. Monitors are sparse and sometimes strategically placed, so their readings may not take into account all polluting sources.By contrast, reanalysis data combine monitor readings with a chemistry-transport model that uses emission inventory as an input and takes account all sources of pollution to give a measure of average exposure. To deal with the sparseness of the $PM_{2.5}$ monitoring network, the data uses a co-kriging method to also include PM_{10} readings – for which the network is less sparse – in the prediction of $PM_{2.5}$.[14] In section 5.3, we replicate our main results using $PM_{2.5}$ exposure based on a spatial interpolation of monitor readings, instead of reanalysis data.

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 A.1 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 exposure to $PM_{2.5}$ (µg/m^3)

Notes: Figure a) shows municipality-level $PM_{2.5}$ exposure in 2009-2015, weighted by the number of workers employed in each municipality in the absenteeism dataset. Figure b) shows the unweighted distribution of monthly exposure to $PM_{2.5}$.

[14]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.

Weather. We use gridded reanalysis weather data from the Copernicus Climate Change Service (C3S) (ERA5 dataset).[15] We obtain hourly precipitations, surface temperature, 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 temperature and hourly wind speed, 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 sick leave dataset, and from four broad economic sectors: 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).[16] The final sample includes 158,223 firms totalling €1.9 sales in 2013, which represents 52% of all French firms' sales (excluding the agriculture and financial sectors).

Sickness leave episodes. We obtain data on sickness leave episodes (SLE) for a representative sample of private sector employees born between 1935 and 1989 and affiliated to France's universal sickness-leave insurance (Hygie dataset).[17] 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

[15] 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`

[16] 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).

[17] 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).

consider SLEs lasting less than three months, which represent 93% of the spells.[18] We restrict our dataset to employees that we can match to their exact workplace via an establishment-level identifier denoted SIRET (see Appendix C 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.

Allocation of $PM_{2.5}$ exposure We have two levels of analysis corresponding to the scale at which information on sales and information on sick leave is available. Sick leave is available at the establishment level. Thanks to the establishment-level identifier, we are able to allocate to each worker and establishment the pollution and weather exposure from her municipality of employment, after allocating to each municipality the $PM_{2.5}$ exposure of the nearest Chimere grid cell and the weather variables of the nearest Copernicus grid cell. 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.[19]

Sales are only available at the firm level. Sixty-four percent of the firms in our sample have a single establishment, and we simply allocate to them the pollution and weather exposure of their municipality. The remaining thirty-six percent of firms own more than one establishment and are larger – they jointly represent 75% of total sales in our sample. To allocate them a measure of pollution exposure, we use exhaustive matched employer-data (DADS-postes) giving for each firm the number and location of all its establishments and the number of workers employed in each establishment each year. 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 establishment owned by the firm.

Descriptive statistics Panel a of table 1 shows that the average firm in our sample 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.

[18] In our data, the average sickness leave episode lasts 29 days whereas the median duration is only 9 days. Figure C.16 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.

[19] 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.2)

Panel b of table 1 shows descriptive statistics for the sample of workers included in the sick leave dataset and employed by a firm present in the sales dataset. It includes around 400,000 individuals working in 353,155 private sector establishments over the period 2009-2015. Workers are 40 year old on average; they earn an average annual gross wage of €28,542. On average, each month 23 per 1,000 of the workers enter sick leave for less than three months.

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 $PM_{2.5}$ ($\mu g/m^3$)	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 $PM_{2.5}$ ($\mu g/m^3$)	15.34	6.33	8,239,344

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

4 Empirical Strategy

4.1 Baseline model at the firm level.

Our objective is to identify the short-term causal effect of $\mathrm{PM}_{2.5}$ on firms' sales and on their employees' absenteeism due to sick leave. Our main identification challenge is that there may be unobserved time-invariant determinants of both local air pollution and firms' sales and workers' absenteeism. This includes time-invariant characteristics such as local intensity of economic activity, and time-varying factors such as weather conditions or construction works. To address these concerns, our econometric specification combines a rich set of fixed effects with instrumental variables.

We model the relationship between firm sales and pollution exposure using the following regression equation:

$$Y_{fisgyt} = \beta PM_{2.5gyt-1} + W'_{gyt-1}\gamma_1 + W'_{gyt}\gamma_2 + W'_{gyt+1}\gamma_3 + \nu_{fy} + \theta_{isyt} + \delta_{dq} + \epsilon_{fisgyt}, \quad (7)$$

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.[20] 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-county (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 a firm, which we only observe at the annual level. Industry-by-month-by-year fixed effects θ_{isyt} capture monthly shocks that are common across all firms in the same industry. We use the 2-digit level of the European Union industry classification

[20] 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.

to identify 88 industries grouped into the four main sectors described in the data section. Quarter-by-county fixed effects δ_{dq} capture seasonality in pollution (or wind patterns for the instrumented version) specific to a county which may be correlated with local seasonal fluctuations in economic activity.[21] It captures for instance the seasonal demand variation in ski or sea resort areas.

The vectors W'_{gyt-1}, W'_{gyt}, and W'_{gyt+1} include two types of time-varying municipality-specific controls. To account for the joint influence of weather on air pollution (different climatic conditions can lead to different air pollution levels) and sales (due to a decrease in activity on hot days for instance) within firm-years, we generate indicators for monthly averages of daily maximum temperatures, wind speed and precipitation in each municipality, and include in W'_{gyt} the set of indicators for all possible interactions of these weather parameters.[22] To account for the lower economic activity and pollution levels during school holiday periods, we also include the monthly count of school holiday days in each municipality.[23] 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.

4.2 Wind direction instruments.

Despite the use of high-dimensional fixed effects, OLS estimates of equation (7) are prone to bias due to the potential influence of reverse causality, measurement error in air pollution exposure, and omitted variables. Indeed, higher sales are likely to increase air pollution as a by-product of higher production. When the effects of pollution on sales are channelled through workers' productivity and labor force, there is also measurement error arising from measuring pollution exposure based on the workplace location only. 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). A last 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

[21]We refer to county for the 96 French *départements* of metropolitan France, the second smallest administrative subdivision before municipality.

[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.

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 affect air pollution differently in different regions of France, depending on the location of polluting sources. Following Graff Zivin et al. (2023), we compute four instruments Z_{jgyt}, one for each wind direction as follows:

$$\mathrm{Z}_{jgyt} = \underbrace{\mathrm{WIND}_{jgyt}}_{\text{A: Time-varying}} \underbrace{\left(\frac{1}{N_j}\sum_{d\in T_j} PM_{2.5gd} - \frac{1}{N}\sum_{d\in T} PM_{2.5gd}\right)}_{\text{B: Time-invariant}} \tag{8}$$

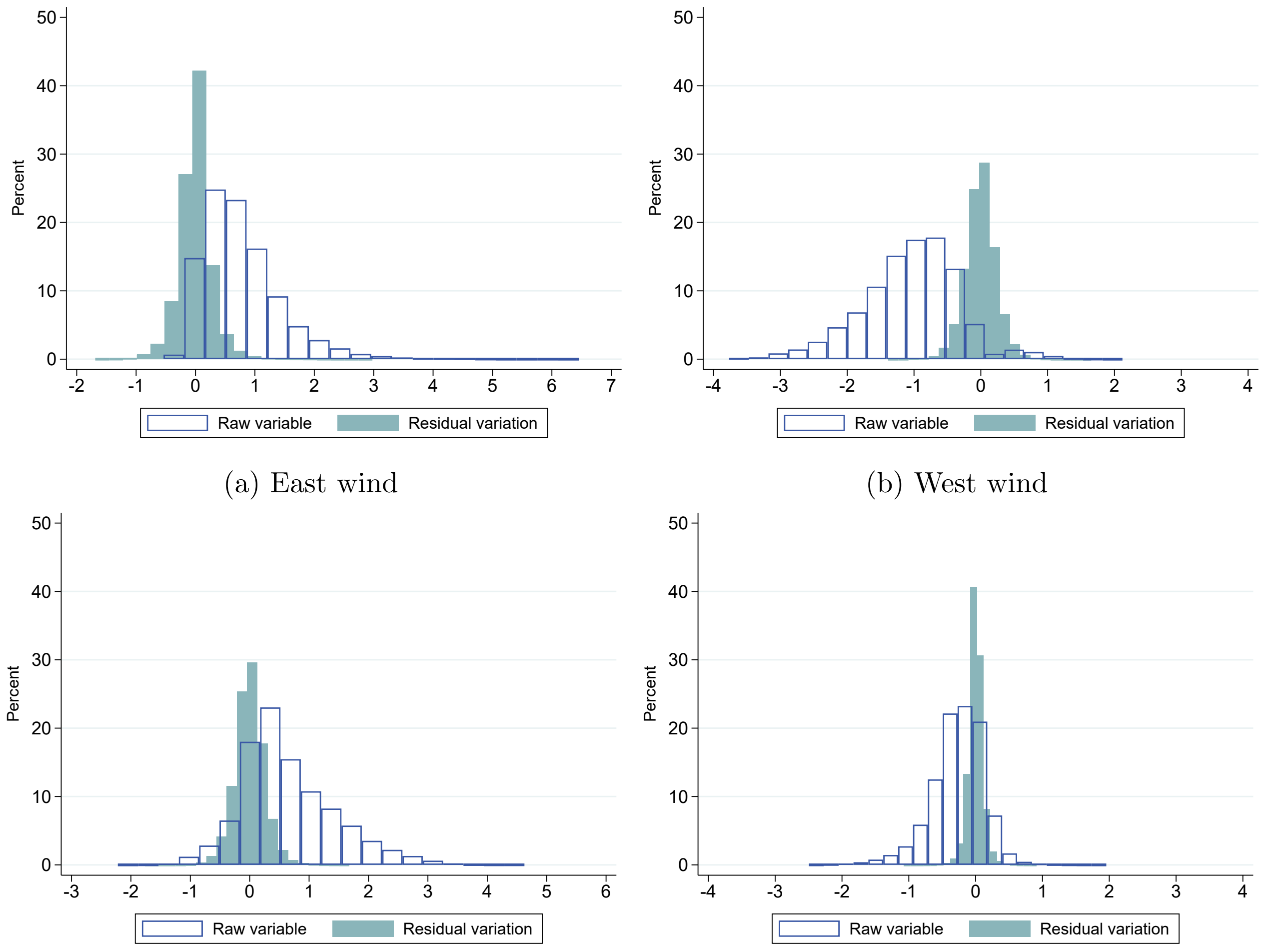
where WIND_{jgyt} identifies the share of hours in calendar month t in year y where the wind blows from direction j in municipality g, while the B term reflects the average deviation from daily mean pollution levels on days where the wind blows from direction j in municipality g, across the entire sample period. N_j and T_j are the number and set of days where the dominant wind blows from j, and N and T are the total number and set of days over the period of analysis. Figure A.3 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 monotonic effects across France: East (West) winds increase (decrease) pollution in the vast majority of municipalities. There is still a lot of variation in the magnitude of the increase (decrease). On the other hand, winds blowing from the North and the South have different 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:

$$PM_{2.5gyt} = \sum_{j=1}^{4} \beta_j \mathrm{Z}_{jgyt} + W'_{gyt}\gamma + \nu_{fy} + \theta_{isyt} + \delta_{dq} + u_{gyt}, \tag{9}$$

where the parameters of interest are β_js. For a given wind direction j, β_j captures the effect of a marginal increase in the intensity of wind j, where intensity captures both the frequency of wind j and how much wind j typically increases or decreases pollution in each municipality.

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-by-county-specific variation, industry-specific national trends in exposure, and after controlling for weather parameters other than wind direction. Figure 2 plots the distribution of the raw and residualized wind instrument variables, and shows that there remains substantial variation in each instrument after partialling out the fixed effects and controls. There is also substantial variation within a given municipality, as illustrated in figures A.4 and A.6 showing the variation in wind direction within a given calendar month in the two largest French cities, Paris in the North and Marseille in the South-East. Throughout all the analyses at the single-establishment level, we cluster standard errors at the Copernicus grid cell level, the scale at which the A component of the wind instrument varies.



(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 9: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-county fixed effects, and firm-by-year fixed effects

Identification assumptions The validity of our research design requires that three conditions are met. 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 monotonicity assumption should hold if we want to interpret our estimates as local average treatment effects (LATE). Indeed, the assumption of constant treatment effects is not plausible in our setting since 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. Under heterogeneous treatment effects, we can only interpret our two-stage-least-square estimate as a (LATE) if the monotonicity assumption holds. Below we discuss the plausibility of these three conditions.

Instrument relevance: Table 2 report the first stage results. 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 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, our wind direction instruments need to be as-good-as-randomly assigned: there should be no weather or seasonal patterns influencing sales which co-vary with the instrument. 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. Our quarter-by-county fixed effects also net out quarter- and county-specific wind and sales patterns. Second, the exclusion restriction must hold: the wind instruments should only affect firms sales 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. PM_{10} is highly correlated with $PM_{2.5}$ (Pearson correlation coefficient: ρ=0.93) and actually includes $PM_{2.5}$, so our causal estimates could also reflect the effect of PM_{10}. On the other hand, ozone 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 run two robustness tests. In the first one, we show that replacing

[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 $Z_{NorthAyt}$ and $Z_{NorthByt}$ 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

[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.11 illustrate this anti-correlation by showing the reverse seasonality of ozone vs $PM_{2.5}$ and NO_2 concentrations.

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-county 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

$PM_{2.5}$ with a multi-pollutant air quality index including ozone does not affect the magnitude of the results. In a second test, we show that the results hold when the sample period excludes the "ozone season" where ozone is highest, between April and September (see Table B.5).

Instrument monotonicity: we test for instrument monotonicity by plotting the relationship between residualized instruments and residualized $PM_{2.5}$ exposure. Figures A.8 shows the binned scatter plots of residualized variables using the firm-level panel of single-establishment firms. The relationship is monotonically increasing except at the tails of the distribution, and approximately linear.

4.2.1 Multi-establishment firms.

For multi-establishment firms, we need an instrumented counterpart to the endogenous worker-weighted pollution exposure. We generate a plausibly exogenous predicted pollution exposure using the first stage results. We save the vector of estimated $\widehat{\beta}_j$ and compute the predicted pollution exposure as $\widehat{PM_{2.5}}_{gyt} = \sum_{j=1}^{4} \widehat{\beta}_j \mathrm{Z}_{jgyt}$. We then compute the firm-level predicted pollution exposure, $\overline{\widehat{PM_{2.5}}}_{fyt}$, as the weighted average of $\widehat{PM_{2.5}}_{gyt}$ across locations g where firm f owns establishments in year y. We use $\overline{\widehat{PM_{2.5}}}_{fyt}$ as an instrument for $\overline{PM_{2.5}}_{fyt}$ in the following regression equation, which is similar to equation 7 except that pollution and weather and holiday controls are weighted averages of the values at establishments owned by the firm.[27]

$$Y_{fisyt} = \beta \overline{PM_{2.5}}_{fyt-1} + \overline{W'}_{fyt-1}\gamma_1 + \overline{W'}_{fyt}\gamma_2 + \overline{W'}_{fyt+1}\gamma_3 + \nu_{fy} + \theta_{isyt} + \delta_{dq} + \epsilon_{fisyt}, \tag{10}$$

We cluster the standard errors at the firm level, the scale at which the instrument varies. Figure A.10 shows the distribution of residualized predicted $PM_{2.5}$, and its relationship with residualized $PM_{2.5}$ exposure, using the entire firm-level sample. The monotonicity assumption also seems to hold with this instrument.

4.2.2 Analysis of worker absenteeism at the establishment level.

Compared to sales, worker absenteeism is available at the establishment level, including for multi-establishment firms, with a precise measure of pollution exposure. Another difference is that we expect a contemporaneous effect of pollution on absenteeism rather than a lagged effect, given the extensive literature showing a short-term effect of pollution on health (within the same day or week). Thus we run a regression linking contemporaneous pollution and worker absenteeism at

[27]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).

the establishment level:

$$Y_{eisgt} = \beta^A PM_{2.5gyt} + W'_{gyt}\gamma + \nu_e + \theta_{isyt} + \delta_{dq} + \epsilon_{eisgt}, \tag{11}$$

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 (7). Firm-year fixed effects are replaced with an establishment fixed effects ν_e, which isolates monthly variation in pollution exposure within an establishment and absorbs any time-invariant establishment-specific characteristic.

5 Effects of PM 2.5 on Firms' Sales

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

Effect For All Sectors. Table 3 shows that lagged monthly $PM_{2.5}$ negatively affects firm sales on t and t+1. 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 industry-specific time-varying shocks and local seasonality in sales and pollution, 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), the effect of pollution on sales becomes negative and statistically significant at the 1% level. From column (2), a one unit (1 µg/m^3) increase in firm-level $PM_{2.5}$ exposure decreases firm-level sales by 0.26 percent in the two following months. These results imply an elasticity of firm sales to pollution of -0.04: a 10 percent increase in pollution exposure decreases sales by 0.40 percent on average. Table A.2 shows the effect of adding stricter and stricter fixed effects in the specification. The IV point estimate is consistently significant and negative across specifications; adding the quarter-by-county fixed effects reduces the magnitude of the effects compared to only using firm-by-year and month-of-sample-by-industry fixed effects.

In columns (3) and (4) of table 3, we run the same analysis for the subset of single-establishment firms. The pollution exposure is more precise for these firms, since it is defined at a single location rather than averaged across locations. In column (4), we use the four wind direction instruments as instrumental variables rather than the predicted pollution exposure. The magnitude of the OLS and IV point estimates are very similar to that using the sample of all firms.

Heterogeneous Response by Sector. We expect the 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 spe-

Table 3: The effect of lagged $PM_{2.5}$ on firm-level sales in the next two Months, all sectors

	(1)	(2)	(3)	(4)
	All firms		Single-establishment firms	
	OLS	IV	OLS	IV
$PM_{2.5t-1}$	0.0822***	-0.259***	0.109***	-0.255***
	(0.0100)	(0.0264)	(0.0811)	(0.0811)
Firm-by-year FE	Yes	Yes	Yes	Yes
Month-by-year-by-industry FE	Yes	Yes	Yes	Yes
Quarter-by-county FE	Yes	Yes	Yes	Yes
N	9,403,047	9,403,047	6,072,032	6,072,032
R-squared	0.9470	0.9470	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 (10) for all firms in all sectors in columns (1) and (2), and all single-establishment firms in all sectors in columns (3) and (4). 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 instrument used in column (2) is the predicted pollution measure at firm-level. The instruments used in column (4) are the 4 wind direction instrument at single-establishment firm-level. The confidence intervals are based on standard errors clustered at the firm level for columns (1) and (2), and at the Copernicus grid cell level for columns (3) and (4). We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

cific 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 positive association between lagged $PM_{2.5}$ and contemporaneous sales when the model is run with OLS, especially in the business-to-consumer trade and services sector. When pollution is instrumented with the change in wind directions as in column (2), the effect of pollution on sales is negative and statistically significant at the 1% level, except for the construction sector where the effect is smaller and less precise.

With our baseline specification shown in column (2), 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 0.080 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 in column (4) give point estimates with a similar magnitude, but less precisely estimated.

Heterogeneity by firm size. Smaller firms are generally found to be less productive and more vulnerable to financial shocks than larger firms (Miranda, 2013; Gertler and Gilchrist, 1994). We test whether small firms are also may be more vulnerable to environmental shocks by comparing the effect of air pollution on firms' sales for firms with 25 employees or less and those with more than 25 employees. We choose the threshold of 25 employees as a middle ground between the definition of micro-enterprises having less than 10 employees and the definition of small-and-medium enterpreises having less than 50 employees[28] Table A.3 shows that firms with fewer than 24 employees are the most affected. Except in the business-to-consumer trade and services sector, we cannot reject that firms with more than 25 workers incur no significant sales losses.

Economic benefits of reducing air pollution 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

[28]The median number of employees across all firms in our sample is 12. 25 corresponds to the median size for the manufacturing firms in our sample, which are larger than in te other sectors.

$PM_{2.5}$ 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 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.

[29] https://ec.europa.eu/environment/archives/air/pdf/Impact_assessment_en.pdf The estimated cost can be found in part 3, page 43.

Table 4: Heterogeneous sales responses to lagged $PM_{2.5}$ by sector

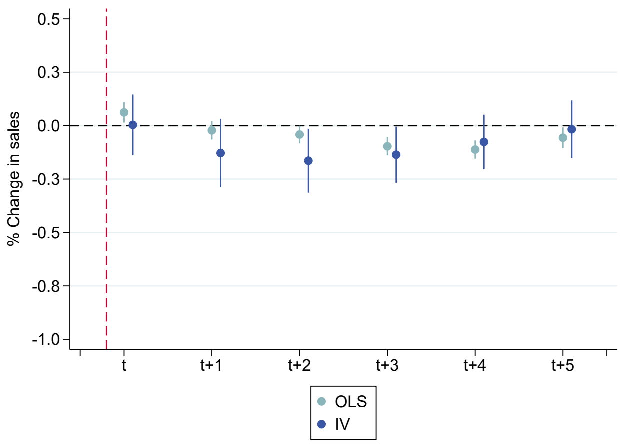
	(1)	(2)	(3)	(4)
	All firms		Single-establishment firms	
	OLS	IV	OLS	IV
Panel A: Manufacturing				
$PM_{2.5t-1}$	0.0352*	-0.137***	0.0178	-0.0811
	(0.0191)	(0.0462)	(0.0249)	(0.0571)
N	1,880,387	1,880,387	1,233,994	1,233,994
R-squared	0.9641	0.9641	0.9535	0.9535
Panel B: Construction				
$PM_{2.5t-1}$	0.0188	-0.0802*	0.0131	-0.114**
	(0.0200)	(0.0480)	(0.0267)	(0.0564)
N	1,531,685	1,531,685	1,074,588	1,074,588
R-squared	0.9351	0.9351	0.9162	0.9162
Panel C: Business-to-Business Trade and Services				
$PM_{2.5t-1}$	0.00642	-0.127***	0.0370	-0.103
	(0.0193)	(0.0469)	(0.0253)	(0.0652)
N	2,875,221	2,875,221	1,498,370	1,498,370
R-squared	0.9339	0.9339	0.9156	0.9156
Panel D: Business-to-Consumer Trade and Services				
$PM_{2.5t-1}$	0.216***	-0.463***	0.248***	-0.396**
	(0.0177)	(0.0498)	(0.0475)	(0.141)
N	3,124,507	3,124,507	2,265,078	2,265,078
R-squared	0.9459	0.9459	0.9345	0.9345
Firm-by-year FE	Yes	Yes	Yes	Yes
Month-by-year-by-industry FE	Yes	Yes	Yes	Yes
Quarter-by-county FE	Yes	Yes	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 (10) for all firms by sector in columns (1) and (2), and all single-establishment firms by sector in columns (3) and (4). 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 instrument used in column (2) is the predicted pollution measure at firm-level. The instruments used in column (4) are the 4 wind direction instrument at single-establishment firm-level. The confidence intervals are based on standard errors clustered at the firm level for columns (1) and (2), and at the Copernicus grid cell level for columns (3) and (4). We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

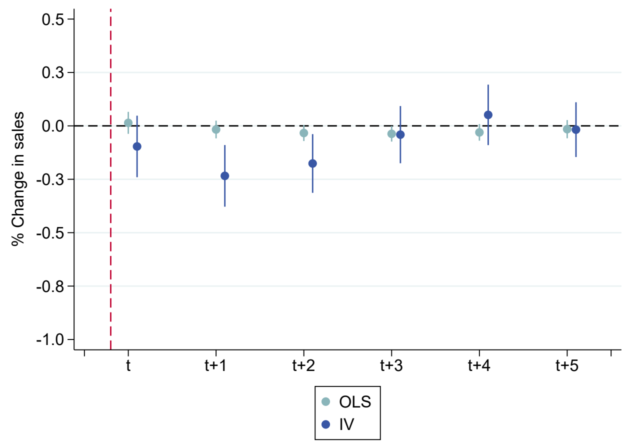
5.2 Dynamic Effects on Sales

Given the granularity of our data at the monthly level, we explore the dynamic effects of air pollution by sector. To reduce the noise due to the serial correlation in wind direction and pollution exposure over time, we use a polynomial distributed lag (PDL) specification (Schwartz, 2000; He et al., 2019) and impose a smooth polynomial function on the lag structure to discipline the coefficients. We examine in a single regression the effects of pollution at t, $t-1$,... up to $t-5$ on sales at t by sector, assuming a cubic polynomial functional form on the coefficients β_l, for $l \in \{0, .., 5\}$: $\beta_l = \sum_{k=0}^{3} \gamma_k l^k$.For example, $\beta_0 = \gamma_0$, $\beta_1 = \gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$, 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.

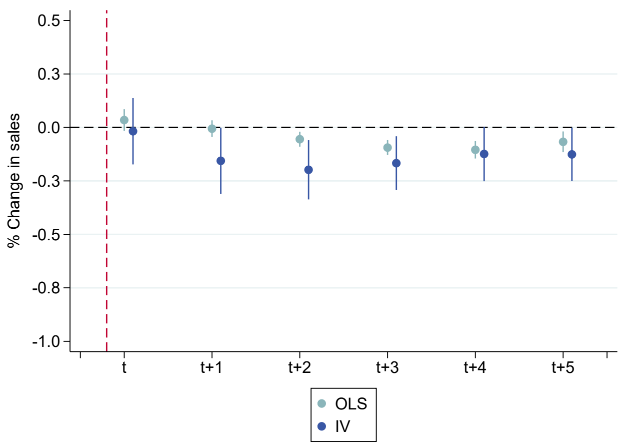
We report in figure 4 the estimates for β_0 with label t, β_1 with label $t+1$, up to β_5 with label $t+5$. The IV results at $t+1$ are generally larger than in main results described above, and the effects for construction become closer to those for manufacturing. But the relative effects across the 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.12 reports the result for the subsample of single-establishment firms, which are very similar to the results for the whole sample.



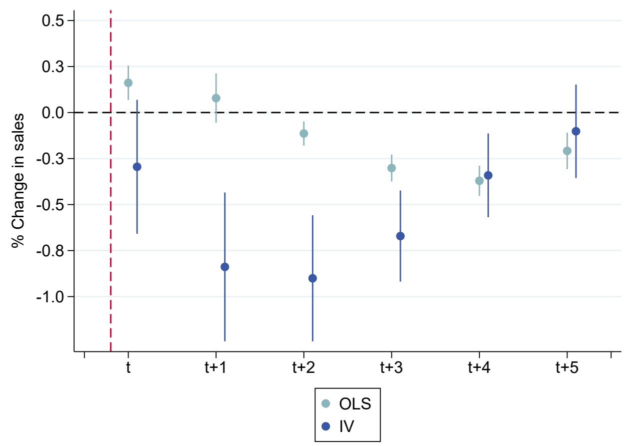
(a) Manufacturing



(b) Construction



(c) Business-to-Business Trade & Services



(d) Business-to-Consumer Trade & Services

Figure 4: 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 (7) 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-county 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.

5.3 Robustness checks

In this section we rule out the main identification concerns. First, we assess the risk that our effect is driven by a spurious correlation by running a falsification test. Second, we test the risk of having a violation of the exclusion restriction due to ozone pollution. Third, we check that our results are not driven by air quality alerts and the behavioral reactions to them. Finally, we check how sensitive our results are to the specification of weather variables and to outliers. Finally, we check that our wind instruments are not mechanically strong just because we use modeled $PM_{2.5}$ data where wind patterns are used as an input in the model.

Falsification test: Since future air pollution shocks should have no effect on current sales, we run a placebo test by studying the effect of pollution at time $t+2$ on sales at time t, while including controls for the period t to $t+2$. Table 5 shows the results. The only sector in which we find a marginally significant effect, with a low magnitude, is the business-to-consumer trade and services sector.

Table 5: Falsification test: effect of future air pollution shocks on contemporaneous sales

	All	Manuf	Const.	B2B	B2C
$PM_{2.5t+2}$	-0.0154	-0.0457	0.00655	0.0124	-0.0973**
	(0.0237)	(0.0474)	(0.0524)	(0.0483)	(0.0411)
Firm-by-year FE	Yes	Yes	Yes	Yes	Yes
Month-by-year-by-industry FE	Yes	Yes	Yes	Yes	Yes
Quarter-by-county FE	Yes	Yes	Yes	Yes	Yes
N	9,402,279	1,880,385	1,531,601	2,874,733	3,124,309
R-squared	0.9470	0.9643	0.9354	0.9339	0.9460

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 (10) for all firms, by sector. All regressions include weather and holidays controls at t, $t+1$, and $t+2$ and instrumented pollution at $t+1$ and t.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 $p < 0.01$.

The exclusion restriction and the case of ozone: 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 columns (2) and (3), we address the risk of violation of the exclusion restriction, and that ozone acts as an omitted variable in the instrumented regression. We expect that if ozone exposure also negatively affects sales, omitting ozone is likely to bias our estimate downward, since a wind direction that increases $PM_{2.5}$ will generally decrease ozone. In this case, we expect to find that using a multi-pollutant index instead of $PM_{2.5}$ as endogenous variable will give a larger effect size than our main estimate. On the other hand, if ozone has no effect on sales, or only a mild effect, we expect to find a smaller effect size when using a multi-pollutant air quality index, because the index variation will partly be due to a variation in ozone. We build a synthetic air quality index similar to the regulatory index used in France,at daily level. Then we take the monthly average in each municipality. Although the index is based on 6 pollutants, its variation is mostly driven by $PM_{2.5}$ in fall and winter and by ozone in spring and summer.[30] Column (2) shows the effect of this AQI, instrumented by the same 4 wind instruments as before. The magnitude of the coefficient is not directly comparable to our main estimate using $PM_{2.5}$, given the difference in the scale of AQI index and $PM_{2.5}$. 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 $PM_{2.5}$ and half of the year to an increase in ozone. If ozone has no significant impact on sales, the effect of $PM_{2.5}$ becomes diluted when we use AQI as a measure of pollution.

We use the fact that ozone and $PM_{2.5}$ are only anti-correlated in winter (both with and without controlling for weather and fixed effects), not in summer (where the raw correlation is positive and the correlation after partialling out weather and fixed effects is close to 0), to provide another test: if the anti-correlation with ozone biases our estimate downward, we should find that restricting the sample to winter months should give a lower point estimate. However, doing so in column (3) gives a very similar point estimate as the main result. All in all, these two tests make us confident that even is ozone is also affected by wind direction, it does not affect sales to a large enough magnitude so as to threaten the validity of our estimate of the $PM_{2.5}$ - sales relationship.

The role of air quality alerts: 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' behavioral 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

[30]Following the official methodology, 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

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.

Results' sensitivity to outliers and weather controls: 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 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) Winter months	(4) No PM_{10} alert	(5) Winsorized outcome	(6) continuous weather	(7) Two-way clustering
$PM_{2.5t-1}$	-0.259***		-0.346***	-0.272***	-0.270***	-0.424***	-0.259**
	(0.0264)		(0.0501)	(0.0298)	(0.0262)	(0.0280)	(0.105)
AQI index$_{t-1}$		-3.192***					
		(0.438)					
N	9,403,173	9,411,803	5,705,091	8,959,529	9,411,935	9,411,803	9,403,173

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 (10) 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-county 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 (7) where they are double-clustered at the firm level and across time. We denote * for $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Modeled $PM_{2.5}$ data versus $PM_{2.5}$ data from monitors In table 7, we compare our main estimate where the source of $PM_{2.5}$ measure is reanalysis data, with a measure of $PM_{2.5}$ exposure entirely based on observations from monitoring stations. Withe the latter we can rule out that the strength of the first stage linking wind direction and $PM_{2.5}$ could be partly driven by the use of weather parameters as input in the chemistry transport model used to produce the $PM_{2.5}$ reanalysis data. Following the literature, we build a municipality-level measure of $PM_{2.5}$ equal to

restrictions in car traffic were issued on 0.7% of the days only.

the weighted average of $PM_{2.5}$ measures at neighboring monitors. For a given municipality, we exclude monitors located more than 150 kilometres away, and we use as weights the inverse distance between the centroid of the municipality and each monitor. Due to availability of $PM_{2.5}$ monitor-level data, we restrict the sample to the 2011-2015 period.[32] The monitor-based exposure measure is highly correlated with the reanalysis-data-based measure ($\rho = 0.95$). Using the monitor-based measure as the endogenous variable in our main regression in column (2), we find a point estimate similar to the one based on $PM_{2.5}$ reanalysis data.

Table 7: The effect of lagged $PM_{2.5}$ on contemporaneous firm-level sales, all Sectors, $PM_{2.5}$ data from monitors instead of reanalysis data, 2011-2015

	(1) Baseline reanalysis	(2) PM2.5 monitors
$PM_{2.5t-1}$	-0.304***	-0.292***
	(0.0310)	(0.0294)
N	6,693,045	6,693,045

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 (10) 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-county fixed effects and industry-by-month-by year fixed effects. 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 $p < 0.01$.

6 Identifying Channels

The temporary decline in sales following a month of high $PM_{2.5}$ levels can arise due to different channels explored in our analytical framework: an increase in worker absenteeism, a decrease in workers' productivity and a decrease in demand. 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.

[32]The data can be downloaded from here: https://eeadmz1-downloads-webapp.azurewebsites.net/

6.1 Pollution-induced sickness absenteeism

Table 8 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 (11). The OLS estimate indicates that a one-unit increase in average $PM_{2.5}$ exposure 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, a 0.15 increase, consistent with the OLS estimate being downward bias due to omitted variable and attenuation bias from classical measurement error. Given the baseline average of 23 per 1,000 workers, our IV results imply that a 10 percent increase in monthly PM2.5 increases absenteeism by 1 percent, a 0.1 elasticity of sick leave flows to pollution.

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 estimates are very similar.

Table 8: The effect of $PM_{2.5}$ 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***	0.0644**	0.148**
	(0.0211)	(0.0603)	(0.0207)	(0.0613)
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 (11) 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-county 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.14 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, with Spanish data on sick leave and PM_{10} pollution in urban areas, Holub et al. (2021) estimate that a 10% increase in weekly pollution increases 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.

Does the pollution-driven decrease in labor supply due to sick leave explain our results on sales? Looking at heterogeneous effects by sector suggests that worker absenteeism is not the only channel at play. Note that heterogeneous effects of pollution on absenteeism by sector 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.

Figure 5 reproduces the absenteeism results on subsamples 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. Comparing tables 4 and figure 8, there is no correlation between the magnitude of the absenteeism effect and the magnitude of the sales 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.

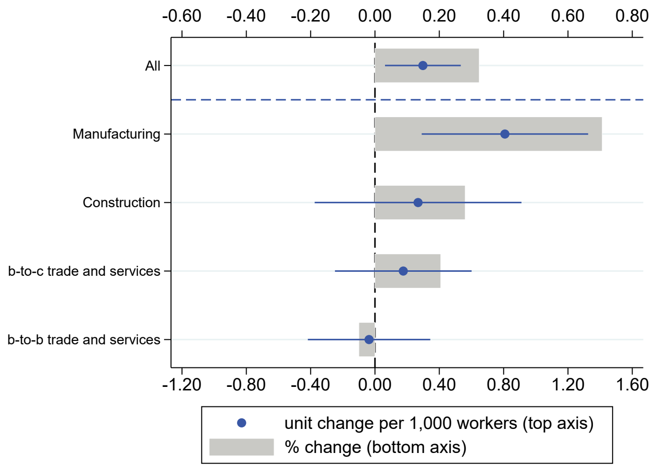


Figure 5: Contemporaneous effect of a one-unit increase in $PM_{2.5}$ on sick leave episodes

Section B shows the same set of robustness checks as for the sales outcome. The effect of air pollution on sick leave does not seem driven by a confounding effect of ozone, by air quality alerts, or by the specification of weather controls.

6.2 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.[33] 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

[33]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

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 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.

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 (10) 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-county 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 $p < 0.01$.

Demand: We would expect demand responses to be stronger in the consumer retail and services sector, where demand is local. 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 shopping. If such demand effect is at play, we would expect industries selling discretionary goods, such as furniture or clothing, to be more affected than industries selling essential goods, such as groceries, for which consumption is more costly to forego. Table 10 shows that pollution decreases sales slightly more for firms selling discretionary goods than for firms selling staples. Note that the point estimates are quite imprecise and we cannot reject that the effects are the same. The two types of firms also 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 (10) 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-county 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 $p < 0.01$.

7 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 two months, with an average elasticity of sales to pollution of -0.04. Worker air pollution exposure increase their sickness-related absenteeism, with an elasticity of 0.1. We highlight the significant role played by two other mechanisms: the decrease in worker productivity and the decrease in demand.

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 results suggest that tightening air pollution standards to align them with WHO recommendations would yield benefits greater than the cost of regulation on average. Understanding which firms would win and lose from such regulation is a promising area for future research. A related point is that 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.

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.

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 (2022a). This Is Air: The "Nonhealth" Effects of Air Pollution. *Annual Review of Resource Economics 14*(1), 403–425.

Aguilar-Gomez, S., H. Dwyer, J. S. Graff Zivin, and M. J. Neidell (2022b). This is Air: The "Non-Health" Effects of Air Pollution. Working Paper 29848, National Bureau of Economic Research. Series: Working Paper Series.

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 (2018). The Healthcare Cost of Air Pollution: Evidence from the World's Largest Payment Network. Technical Report 24688, National Bureau of Economic Research, Inc. Publication Title: NBER Working Papers.

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.

Gertler, M. and S. Gilchrist (1994). Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms∗. *Q. J. Econ. 109*(2), 309–340.

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.

Harrigan, J., A. Reshef, and F. Toubal (2024). Techies and Firm Level Productivity. *mimeo*.

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).*

Hill, A. E., J. Burkhardt, J. Bayham, K. O'Dell, B. Ford, E. V. Fischer, and J. R. Pierce (2024). Air pollution, weather, and agricultural worker productivity. *Amer. J. Agr. Econ. 106*(4), 1329–1353.

Hoffmann, B. and J. P. Rud (2024). The Unequal Effects of Pollution on Labor Supply. *Econometrica 92*(4), 1063–1096.

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

Holub, F. and B. Thies (2023). Air Quality, High-Skilled Worker Productivity and Adaptation: Evidence from Github. [Online; accessed 19. Sep. 2024].

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.

Miranda, T. C. F. &. J. H. &. R. S. J. &. J. (2013). How Firms Respond to Business Cycles: The Role of Firm Age and Firm Size. *IMF Economic Review 61*(3), 520–559.

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.

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

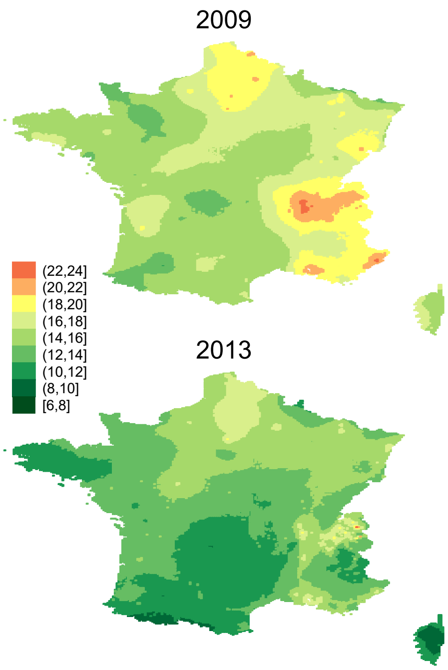
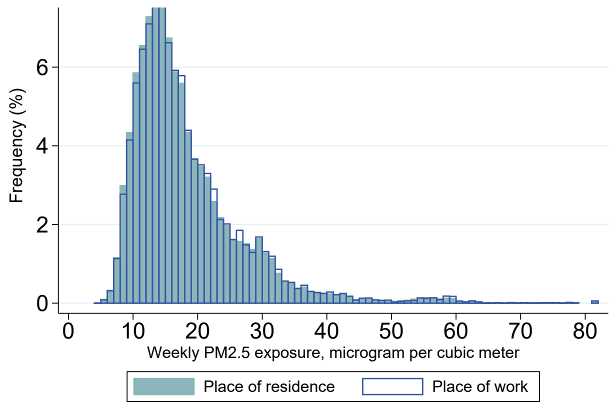
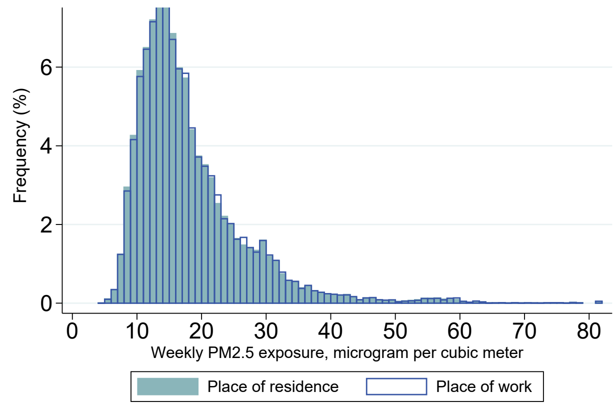


Figure A.1: Average annual concentrations of $PM_{2.5}$ (µg/m^3)

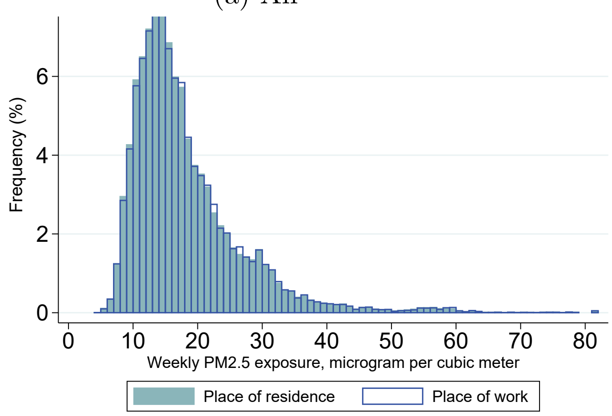
Notes: Figure shows the average annual concentration of $PM_{2.5}$ measured at the 4km x 4 km grid cell level using the reanalysis CHIMERE data, for selected years. There are 33,252 Chimere grid cells in metropolitan France.



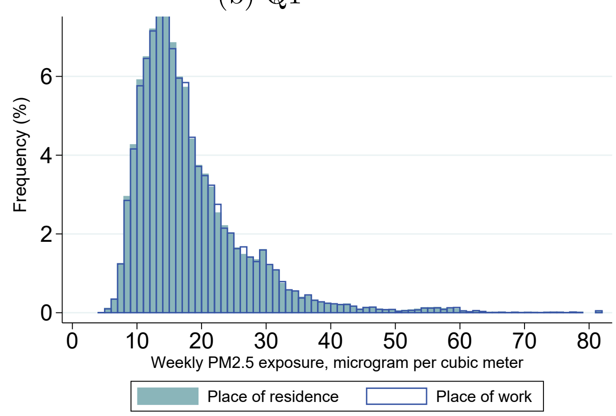
(a) All



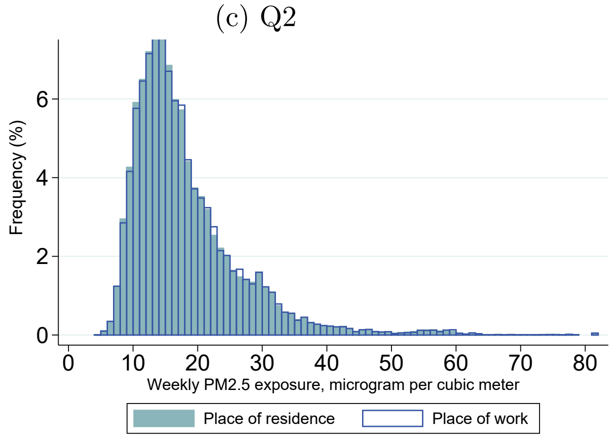
(b) Q1



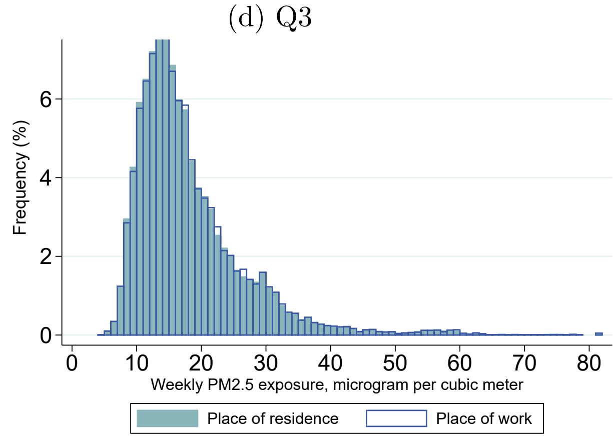
(c) Q2



(d) Q3



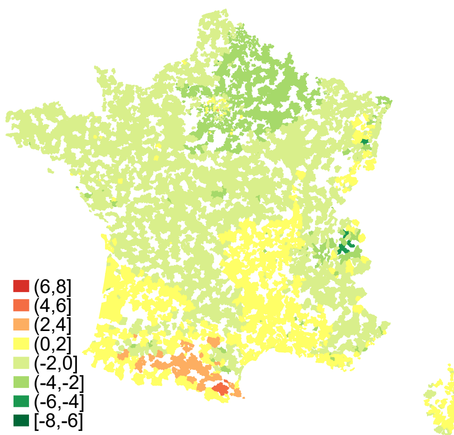
(e) Q4



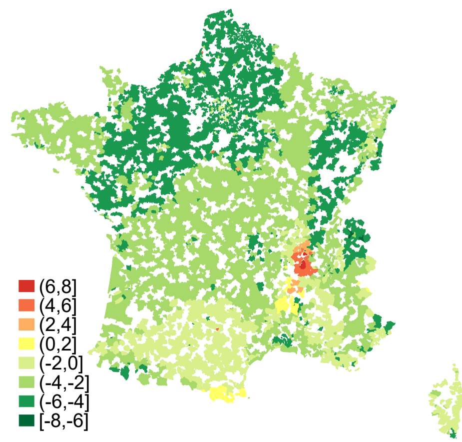
(f) Q5

Figure A.2: Distribution of pollution exposure at the municipality of residence and at the municipality of workplace

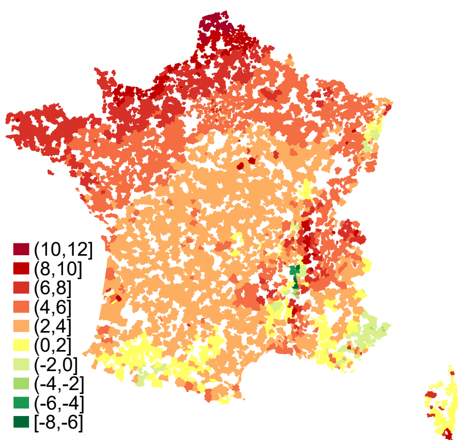
Notes: Figure presents the distribution of exposure to $PM_{2.5}$ at the place of work and at the place of residence for all private sector workers in France, and for workers by wage quintile.



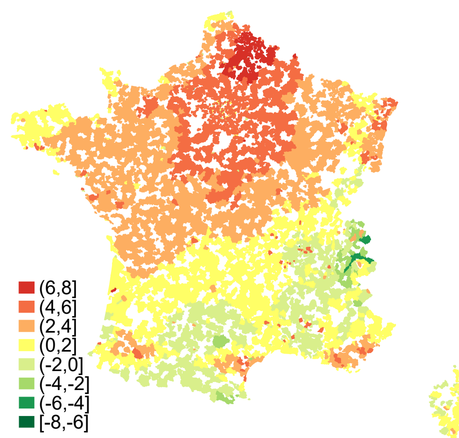
(a) South wind



(b) West wind



(c) East wind



(d) North wind

Figure A.3: 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.

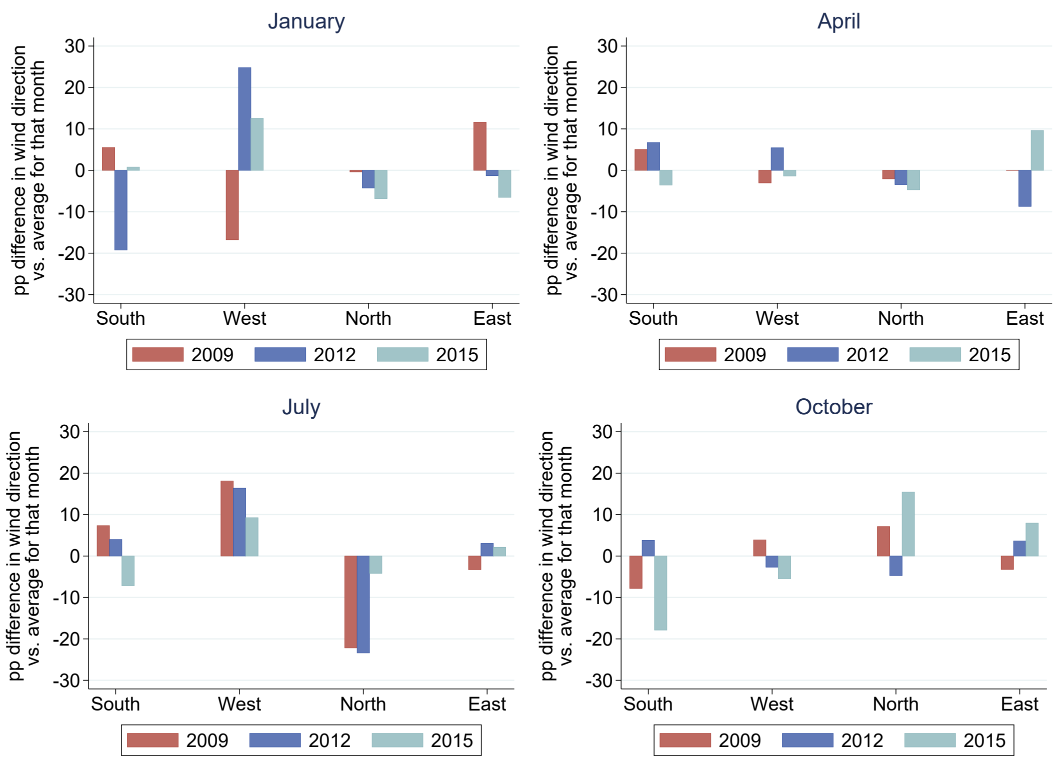


Figure A.4: Within-calendar month variation in wind direction, Paris

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).

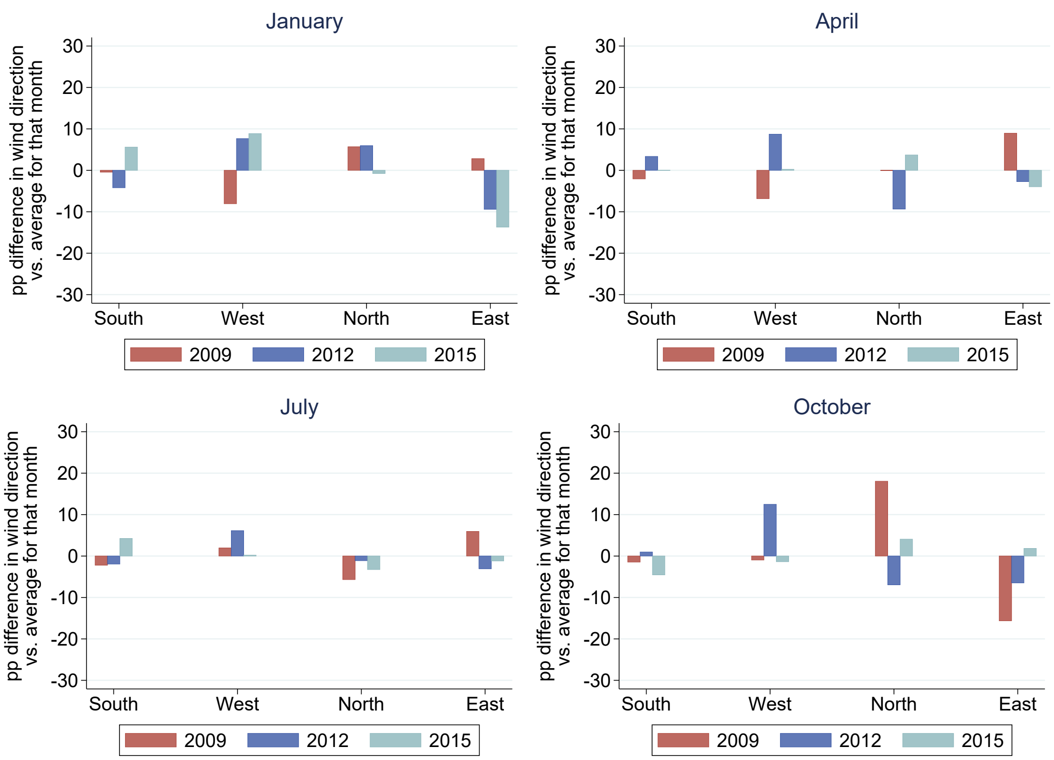
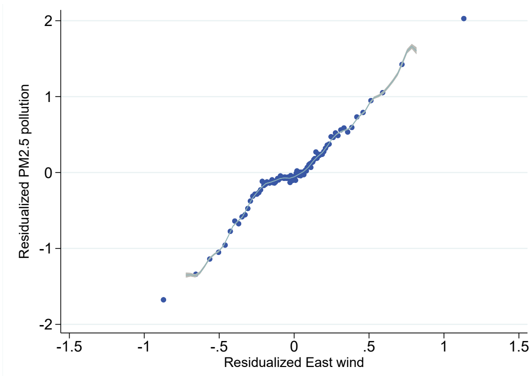
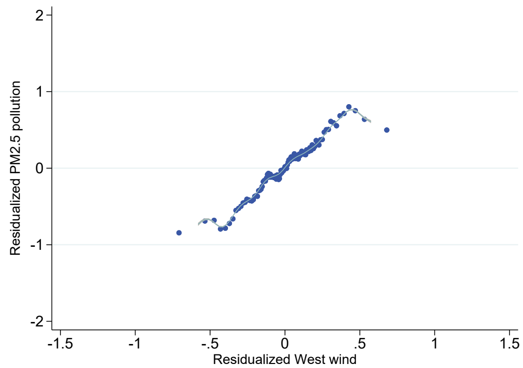


Figure A.6: Within-calendar month variation in wind direction, Marseille (South-East of France)

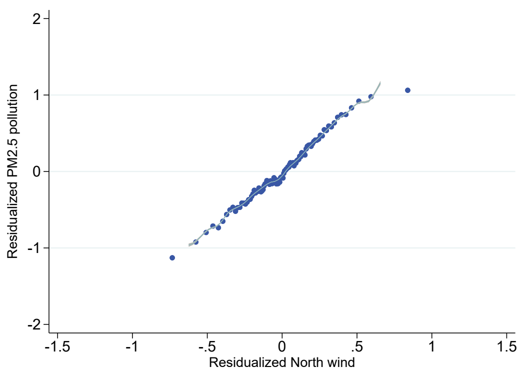
Notes: Figure shows the share of hours in a month in which the wind blows from a given direction, demeaned by the average for the month, for four different months (Month 3=March, Month 6=June, Month 9=September, Month 12=December and three different years (2009, 2012, 2015).



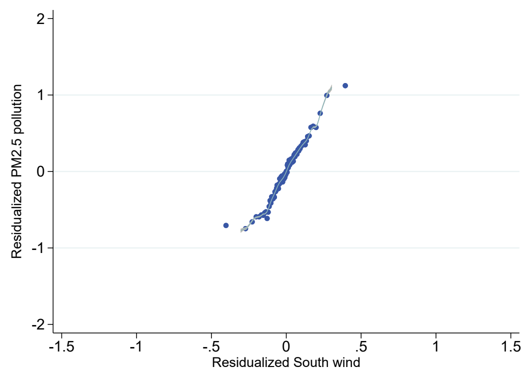
(a) East wind



(b) West wind



(c) North wind



(d) South wind

Figure A.8: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations 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 9: weather and holiday controls, industry-by-month-by-year fixed effects, quarter-by-county 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).

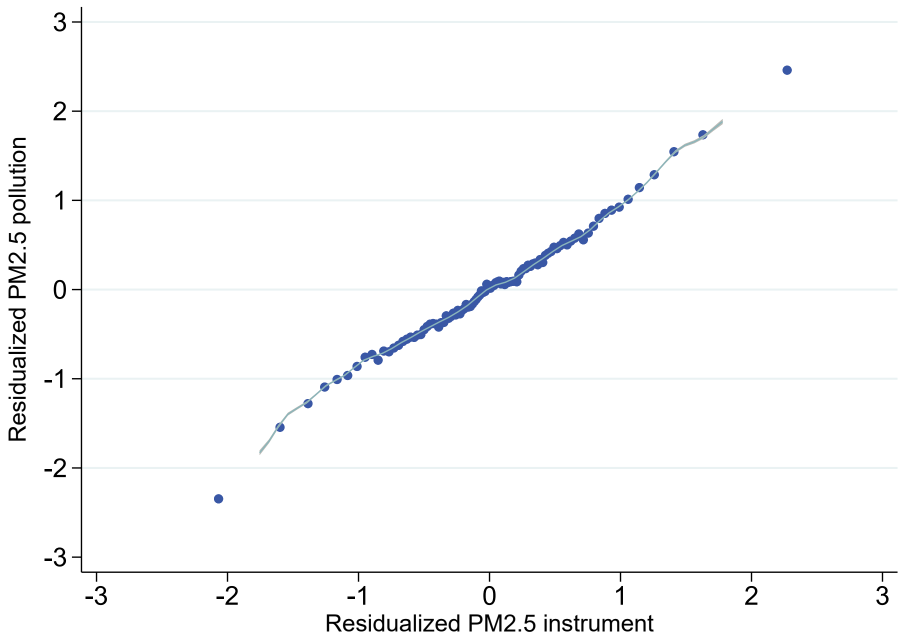
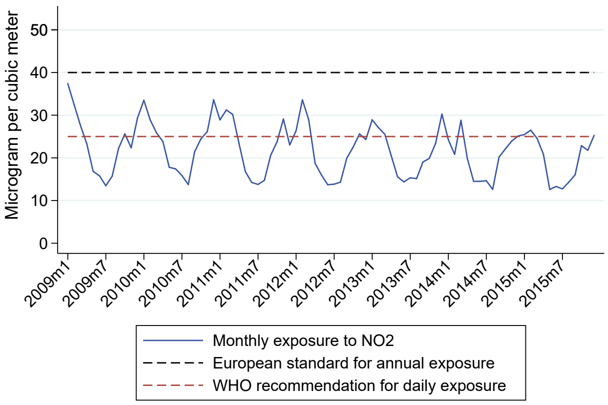
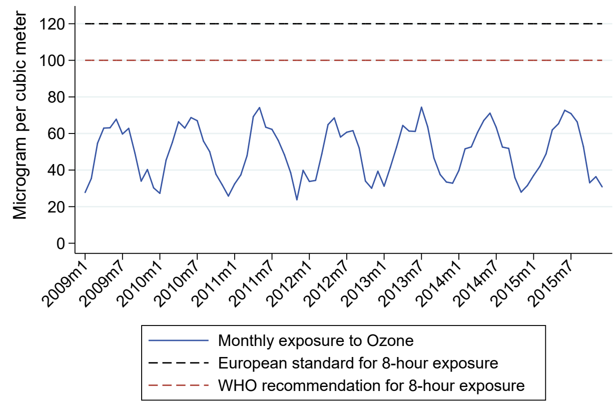


Figure A.10: Residualized binned scatter plot between wind instruments and $PM_{2.5}$ concentrations and local polynomial fit

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 9: 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).



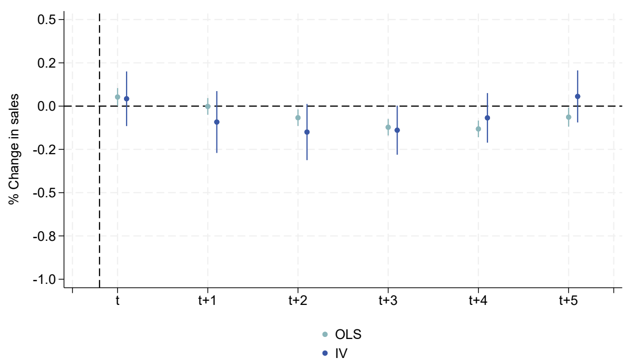
(a) NO_2



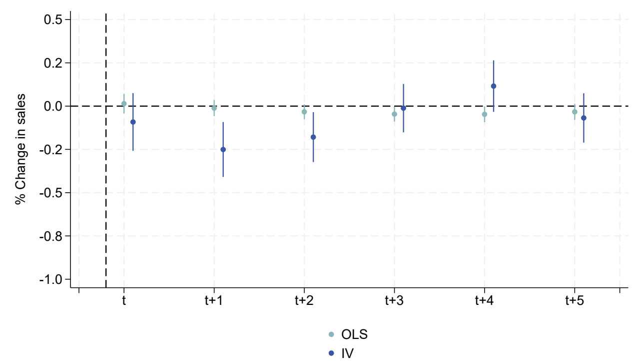
(b) Ozone

Figure A.11: Average monthly exposure to other pollutants

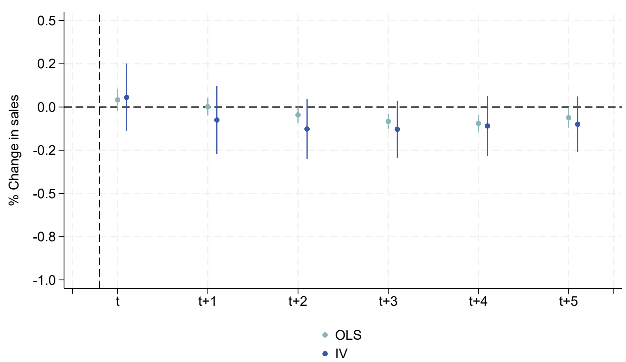
Notes: Figure presents the monthly average of workers' exposure to $PM_{2.5}$ measured at workers' municipalities. The sample of workers is the one used for the analysis of pollution effects on sickness leaves described in section 3 (unbalanced panel, N≈450,000). For NO_2, the European standard for annual 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.



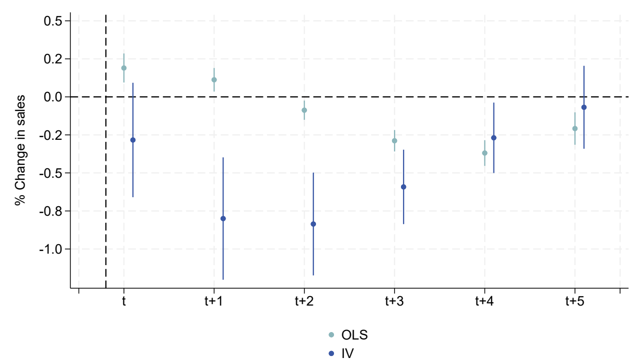
(a) Manufacturing



(b) Construction



(c) Business-to-Business Trade & Services



(d) Business-to-Consumer Trade & Services

Figure A.12: 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 (7) 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-county 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.

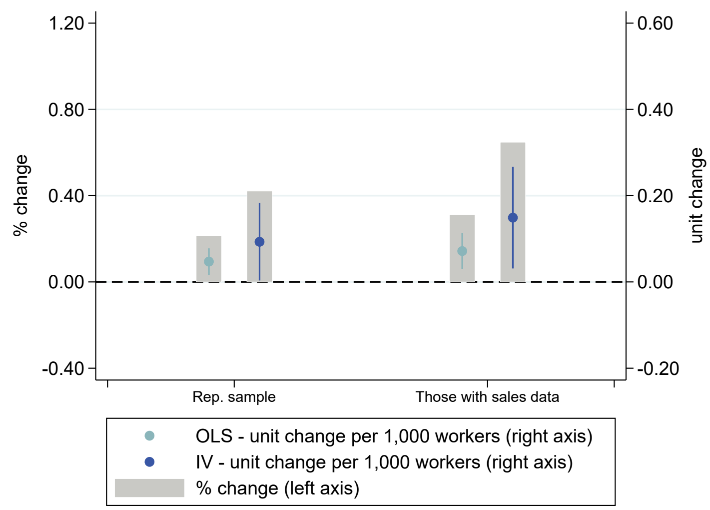


Figure A.14: Absenteeism results for the sample of workers employed at firms included in our firm sample, compared to the representative sample of workers included in the absenteeism dataset

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 Firm-level Sales in the next Two Months, All Sectors

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV	IV	IV	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 (10) 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 $p < 0.01$.

Table A.3: Heterogeneous sales responses to lagged $PM_{2.5}$ by firm size, measured by average number of employees over the sample period

	(1) Below 25	(2) Above 25
Panel A: All firms		
$PM_{2.5t-1}$	-0.312***	-0.0811*
	(0.0419)	(0.0327)
N	6,606,718	2,795,991
R-squared	0.8983	0.9530
Panel B: Manufacturing		
$PM_{2.5t-1}$	-0.239***	0.0203
	(0.0666)	(0.0618)
N	998,239	877,789
R-squared	0.9028	0.9533
Panel C: Construction		
$PM_{2.5t-1}$	-0.142**	0.0758
	(0.0588)	(0.0761)
N	1,145,798	384,555
R-squared	0.8705	0.9302
Panel D: Business-to-Business Trade and Services		
$PM_{2.5t-1}$	-0.143**	-0.0490
	(0.0565)	(0.0831)
N	1,962,452	910,863
R-squared	0.9339	0.9323
Panel E: Business-to-Consumer Trade and Services		
$PM_{2.5t-1}$	-0.489***	-0.309***
	(0.0565)	(0.0989)
N	2,500,225	622,769
R-squared	0.9066	0.9496
Firm-by-year FE	Yes	Yes
Month-by-year-by-industry FE	Yes	Yes
Quarter-by-county FE	Yes	Yes

Notes: Table reports theIV estimates of the effect of a one unit increase in $PM_{2.5}$ at $t-1$ on the sales outcome at t from equation (10) for the subsample of firms with fewer than 25 workers over the sample period (column (1)) and those with more than 25 workers (column (2)). 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 $p < 0.01$.

Table A.4: 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 (7) 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 Robustness Checks for the results on absenteeism

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 B.5 shows the baseline estimate for the specification at the establishment level (same as column (2) of table 8). Column (2) shows the effect using the AQI index instead of $PM_{2.5}$. increases the number of workers entering sick leave that month by 2.1 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, while the effect of $PM_{2.5}$ corresponds to a 0.93 SD increase. The two effects are of a similar order of magnitude. Columns (3) to (5) show that the estimated effect of $PM_{2.5}$ 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 B.5: 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 (11) 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 county 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 $p < 0.01$.

C Data Appendix

C.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 C.15 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,[34] we find that 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

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

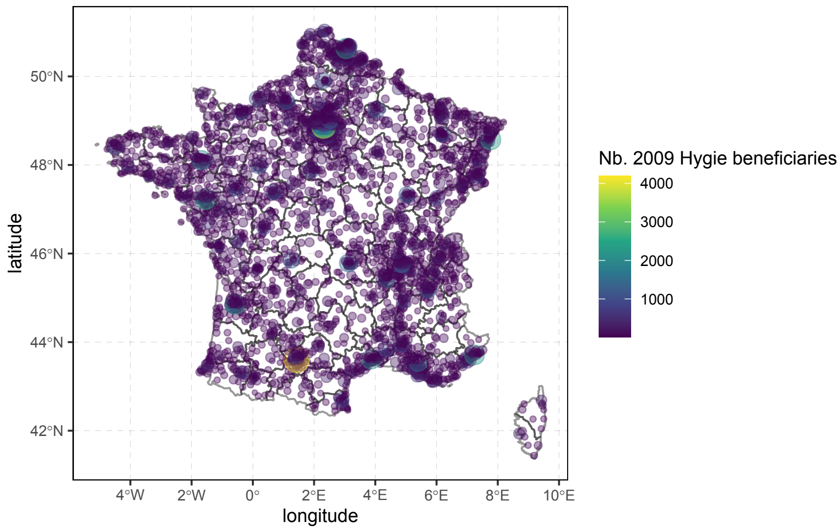
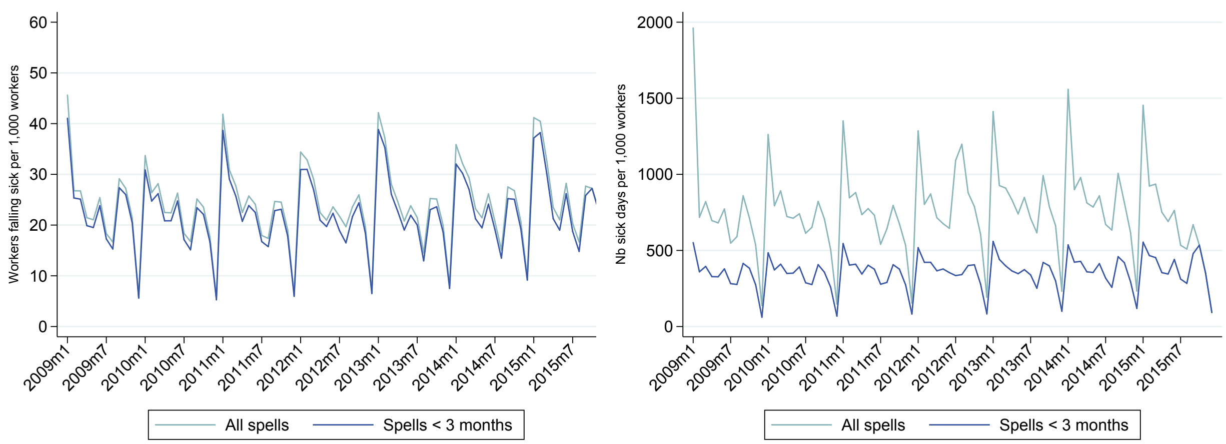


Figure C.15: Location of workers from the Hygie dataset based on the workplace municipality, in 2009

sector employees in France took at least one sick leave during 2013.[35]

We



(a) Number of workers falling sick

(b) Number of sick days

Figure C.16: 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.

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

C.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.[36] 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 to report their July sales together with the August sales.[37] 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.

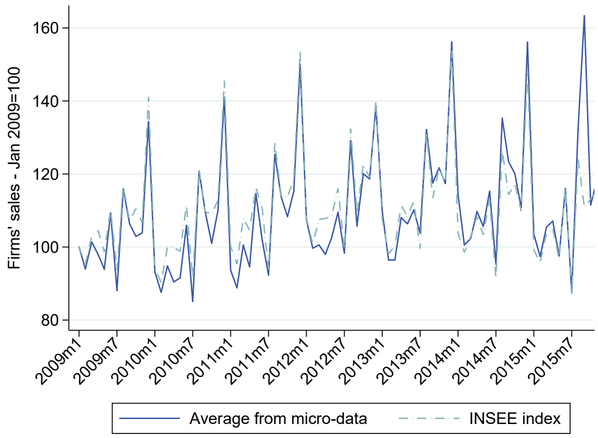
We determine sectors of activity based on the sectoral classification available at the establishment level and we use the mode of sector categories across establishments for multi-establishment firms. We define 4 sectors of interest: manufacturing, construction, business-to-consumer trade and services, 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 C.17c shows

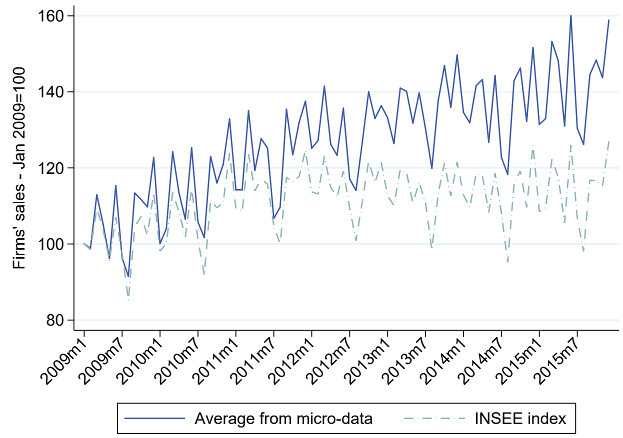
[36] For instance, the sales of natural gas and electricity is subject to a specific VAT rule in the French tax code, so they have their own subcomponent in the VAT records. See https://www.impots.gouv.fr/sites/default/files/formulaires/3310-ca3-sd/2022/3310-ca3-sd_3947.pdf

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

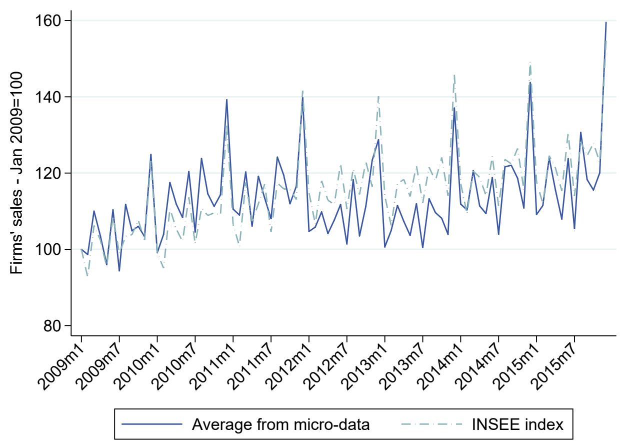
the time series of monthly sales in construction (C.17a), manufacturing (C.17b) and all services (C.17c) as constructed from the VAT micro-data compared with the INSEE index. Differences may arise between our sales value and the statistical agency's because of different choices in data cleaning or the subcomponents entering the sales variable, but the correlation between the two series are above 0.9 for the three broad sectors.



(a) Construction



(b) Manufacturing



(c) Services

Figure C.17: 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.